A Dynamic Capabilities Perspective of Big Data Analytics in Healthcare in South Africa

BY

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DECLARATION

I, Dakalo Tshifhiwa Mathivha, hereby declare that this thesis for the Master of Commerce in Business Information Systems submitted to the Business Information Systems Department at the University of Venda has not been submitted previously for any degree at this or another university. It is original in design and in execution my own work, and all reference materials contained therein have been duly acknowledged.

Student ……………………………….. **Date** **……….**04/03/2022………

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ABSTRACT

The healthcare domain has constantly been swamped with a vast amount of complex data coming in swiftly. Big Data could be a term for tremendous data sets with expansive, more shifted, complex structures with troubles putting away, analyzing, and visualizing distinctive processes or results. Big Data Analytics may be a modern era of innovations and models planned to financially extract value from large volumes of a wide variety of data by empowering high-velocity capture, discovery, and analysis.

An immeasurable sum of data is created in several healthcare industry divisions, such as data from clinics, hospitals, healthcare suppliers, medical insurance, medical equipment, life sciences, and medical research. With the progression in innovation technology, there is endless potential for utilizing this data to transform healthcare.

The study aims to analyze how Big Data Analytics can be used for Data Management in Healthcare Organizations in South Africa to improve service delivery. The study reviewed the concept of BDA in healthcare, sources of Big Health Data, potential benefits and challenges, BDA capabilities, BDA technologies and techniques within healthcare, and Dynamic Capabilities Theory. The Dynamic Capabilities Theory was used as a theoretical lens to study Big Data Analytics in Healthcare.

This research used primary data. A positivist research paradigm was used in this study. To achieve the aim of the study, 170 questionnaires were distributed for data collection, but only 102 responded. SPSS 25 was used to analyze data.

The study found that the healthcare sector can spot, interpret, and pursue environmental opportunities. It can oversee and ideally synchronize resources, partners, deliverables, and tasks concerning tasks or necessities. It moreover can gather, understand, and exploit knowledge to make progressed decisions. Furthermore, it has processes that permit more effective problem-solving by combining different organizational resources. The findings further revealed that the healthcare sector could make strategic decisions and rapidly enact or execute against these by repositioning resources better to adjust the organization to the external or market environment.

Keywords: Big Data Analytics, Dynamic Capabilities Theory, Dynamic Capabilities, Healthcare, Data management, Service delivery

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TABLE OF CONTENTS

LIST OF TABLES/FIGURES

List of tables page

List of figures page

LIST OF ABBREVIATIONS

BDA	Big Data Analytics
BDAC	Big Data Analytics Capabilities
BD	Big Data
IT	Information Technology
DC	Dynamic Capabilities
DCT	Dynamic Capabilities Theory
RBV	Resource Based View
RB	Resource Base
KBV	Knowledge Based View
EHR	Electronic Health Records
EMR	Electronic Medical Records
BI	Business Intelligence
BA	Business Analysts
LIMS	Laboratory Information Management System
MRI	Magnetic Resonance Imaging
EEG	Electroencephalogram
ECG	Electrocardiogram
EMG	Electromyography
EFA	Exploratory Factor Analysis
PCA	Principal Component Analysis
KMO	Kaiser Meyer Olkin

CHAPTER 1: INTRODUCTION

1.1. Background of the study

Healthcare in South Africa differs from the foremost fundamental primary health care, offered for free by the government, to exceedingly specialized, hi-tech health services accessible within the public and private sectors. The private sector is run on commercial lines and caters to centre- and high-income workers who are members of medical schemes. The private sector, moreover, draws in most of the country's well-experienced health professionals. This two-tiered system is not only biased and inaccessible to a large portion of the citizens of South Africa, but organizations within the public sector have suffered poor management, underfunding, and deteriorating infrastructure (Brandsouthafrica. com,2012). Whereas access to healthcare facilities has progressed, healthcare quality has fallen.

The bulk of health-sector financing comes from the South African National Treasury. The government's expenditure on health remains a crucial need, with R205.4bn spent in 2018/19. R205.4bn Is allocated and divided split between the following focus areas: district health services (R90.2bn), central hospital services (R38.6bn), local hospital services (R34.3bn), other health services (R33.8bn) and facilities management and maintenance (R8.5bn) (Chowles, 2018). Despite this high expenditure, performing the health sector in South Africa remains poor compared to comparable middle-income nations. This can largely be attributed to the inequities in specialized practitioners and the financial budget between the public and private sectors.

Historically, the healthcare industry creates vast volumes of data driven by record keeping, compliance, regulatory requirements, and patient care. While most data is stored in complex copy files, the trend is toward rapid digitization of these vast volumes of data (Raghupathi & Raghupathi, 2014). To demonstrate data volume size, the health data blast from 500 petabytes in 2012 will reach 163 zettabytes in 2025 (Galetsi, Katsaliaki & Kumar, 2020).

The healthcare industry is data intensive and could utilize collaborative, dynamic Big Data platforms with innovative technologies and tools to advance patient care and services (Panagiota et al., 2020). Much of the profoundly valuable healthcare data is unstructured or semi-structured (Mehta & Pandit, 2018). The complex, dynamic and diverse characteristics of the data render it difficult to extract valuable information using traditional data analysis tools and techniques. There is a finite human capacity to process this data without effective decision support. This creates the need for the integration of Big Data Analytics into healthcare.

Raghupathi & Raghupathi (2014) characterize Big Data in healthcare as electronic health data sets that are so huge and complex; that they are difficult or impossible to oversee with traditional software and hardware be effortlessly overseen with traditional data management tools and techniques. According to (Shams & Solima, 2019), the concept of Big Data Analytics is based on 5Vs, which are a high volume of data, intense velocity in the appearance of a vast amount of data, tremendous but confusing variety in the perspectives, and potentials of data, data veracity, and data value.

This study used the Dynamic Capabilities Theory as a theoretical lens to study Big Data Analytics in Healthcare. The purpose of relying on the Dynamic Capabilities Theory is the overall management of data veracity and data value management. Both must be managed by organizational processes and different firm resources to pursue the firm's strategic direction. Such organizational processes, resources, and path dependences are the fundamental constituents in forming organizational Dynamic Capabilities (Shams & Solima, 2019). Dynamic Capabilities are an organization's ability to integrate, build and reconfigure internal and external competencies to address transforming environments (Teece, 2012).

1.2. Context of the Study

South Africa has an estimated 58 78 million population (Statssa, 2019). Most people access health services through government-run public clinics and hospitals (Graham, 2015). There are over 5000 healthcare facilities in South Africa. The health system comprises the public sector (run by the state) and the private sector. Public health services are divided into primary, secondary, and tertiary through health facilities managed by the local departments of health (Graham, 2015). Clinics treat everyday health needs, known as 'primary health care. Clinics refer patients to hospitals when a patient needs further treatment. Clinics refer patients to hospitals when a patient needs further treatment. Specially trained primary health care nurses run clinics. There are distinctive sorts of clinics, such as mobile and satellite clinics. Clinics are in the primary tier. In the secondary tier, we have Community Health Centres, which are larger clinics and usually have doctors and nurses. In the tertiary sector, we have hospitals for surgery, emergency treatment, and severe illness that cannot be treated at the Clinic. Clinics and doctors refer patients to hospitals, and individuals can only present themselves without a referral if it is an emergency (constitution, 1996). The local departments are the direct employers of the health workforce, while the National Ministry of Health is responsible for policy development and coordination (Graham,2019).

According to Section 27 of the Bill of Rights, every South African citizen is guaranteed access to health services. In any case, everybody can get both public and private health services. However, access to private health services depends on an individual's capacity to pay. The Vision of The National Department of Healthcare of South Africa is to grant a long and healthy life for all citizens. Their Mission is to enhance health status through preventing illnesses and the promotion of healthy lifestyles and to consistently improve the healthcare delivery system by focusing on access, equity, efficiency, quality, and sustainability. All these will lead to a more incredible and healthier country.

Graham(2015) found that the private health sector gives health services through individual practitioners who run private surgeries or through private hospitals. Most of them tend to be in urban areas. Most patients get health services through the public sector District Health System, the preferred state mechanism for health provision within a primary healthcare approach. Furthermore, this study found that the private sector serves 16% of the country's population while the public sector serves 84%. The country's population distribution indicates that about 64.7% inhabit the primarily rural provinces. Some of these provinces contain large cities, but most of the population lives in rural communities (Graham, 2015).

Big Data within the South African eco-system is not too different from any other developing country. South Africa has a strategy to implement Big Data for the healthcare sector to improve the lives of its citizens. According to the (*National Digital Health Strategy for South Africa 2019 - 2024 1*, 2019), eHealth can be defined as the use of ICT for health to treat patients, pursue research, educate students, track diseases and monitor public health. These advancements are conducted and led by the World Health Organisation (WHO), which has an emphasis on digital consumers, with a more extensive range of smart devices and connected equipment being used, along with other advanced and dynamic concepts such as that of Internet of Things (IoT) and the more widespread use of Artificial Intelligence (AI), and Big Data and Analytics.

Furthermore, they demonstrate that the key challenges facing digital health in South Africa, over the years, remain value for money on systems obtained and implemented, as well as broken and poorly coordinated systems. However, the Council for Scientific and Industrial Research (CSIR) conducted information systems assessments in 2015, revealing that many individual systems had been created to address different health system perspectives. However, there need to be more advancements in architecture and an integrated platform to make them interoperable.

Meanwhile, the healthcare department has implemented a Health Patient Registration System (HPRS) Project as an initial prerequisite for developing a patient Electronic Health Record (EHR). The diagnostic, treatment, and billing modules needed for an EHR in the context of NHI are yet to be created (*National Digital Health Strategy for South Africa 2019 - 2024 1*, 2019).

Other challenges distinguished amid the past eHealth Strategy evaluation include a lack of funds and investments for digital health; cybersecurity; high market-driven costs of broadband connectivity and network infrastructure; insufficient human resource capacity to obtain and implement complex eHealth solutions; and poor ICT infrastructure and unavailability of a broadband network (*National Digital Health Strategy for South Africa 2019 - 2024 1*, 2019).

1.3. Problem statement and research questions

There is a critical need in healthcare for systems that precisely support or enhance clinical experts' decision-making ability to diagnose complex diseases or pathologies (Galetsi et al., 2020). However, the public sector is stretched and under-resourced in some places. Minister Doctor Aaron Motsoaledi, during his speech, for the Health Department Budget Vote 2017/18, said the following: "pre- or post-Apartheid, South Africa has never had a patient information system that allows for tracking a patient from one facility to the other”. “This means that one patient can visit as many facilities as possible per day and collect the same medicine/services without us knowing because there is no system to detect it". This means there is poor decision-making and poor services rendered in healthcare services due to a lack of data management systems. The study of (Mehta, Pandit, & Shukla, 2019) found that the healthcare domain has constantly been swamped with a vast amount of complex data coming in swiftly. An immeasurable sum of data is created in several healthcare industry divisions, such as data from clinics, hospitals, healthcare suppliers, medical insurance, medical equipment, life sciences, and medical research. However, technological advancements are required to achieve the potential benefits of unstructured data in healthcare according to the growth rate of data (Adna, Akbar, Khor, & Ali, 2019).

Therefore, the problem is about immeasurable health data and traditional data analytical tools, making it difficult for clinical practitioners and other health data users to decide. This means the service delivery will not be as effective and efficient as it should be. The researcher will try to solve this problem by answering the following primary research question: How can Big Data Analytics be used for Data Management in Healthcare Organizations in South Africa to improve service delivery?
Sub-research questions:

- How can Big Data Analytics be used to sense opportunities to improve healthcare service delivery?
- To what extent can Big Data Analytics be used to coordinate resources for improved healthcare data Management?

- To what extent will Healthcare Data users learn about Big Data Analytics as a tool to improve healthcare services?
- How will the Healthcare sector integrate BDA to improve service delivery?
- How can Big Data Analytics be used in Reconfiguring Healthcare Data Management to improve healthcare services?

1.4. Research aims and objectives

The study's main objective is to analyze how Big Data Analytics can be used for Data Management in Healthcare Organizations in South Africa to improve service delivery.

The primary objective will be achieved through the following sub-objectives identified:

- To explore how Big Data Analytics is sensed in the healthcare sector.
- To identify how Big Data Analytics can be used to coordinate resources to improve healthcare service delivery.
- To explore how health Data users can learn about Big Data Analytics capabilities and tools to improve healthcare service delivery.
- To explore how the healthcare sector integrates Big Data Analytics to improve service delivery.
- To explore how Big Data Analytics can be used in Reconfiguring Healthcare Data Management to improve healthcare services.

1.5. Justification of the research

This study will provide valuable insights to the public and healthcare practitioners on the best ways to adopt and use BDA technologies within the public healthcare delivery system in South Africa. The designed strategies may be used by the management when they design their strategies towards adopting BDA. This will help improve the quality of services rendered at healthcare organizations. The study will provide new insights into how healthcare organizations can redesign their strategies towards adopting BDA, exploit their capabilities and potential to improve healthcare services, mitigate risks, reduce costs, grasp new opportunities, and expand research in the healthcare industry.

1.6. Delimitations of the study

The research study took place in South Africa, and it focused on the healthcare sector. The researcher looked specifically at this sector to analyze Big Data Analytics based on the Dynamic Capabilities Theory. Using the DCT will help the researcher to sense, coordinate, learn, integrate, and reconfigure Big Data Analytics in the healthcare sector of South Africa to improve the delivery of services.

1.7. Operational definitions

- **Dynamic Capabilities** are an organization's ability "to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments" (Teece, 2012). Dynamic Capability is an organization's capacity to purposefully create, extend, and change its resource base (Helfat & Peteraf, 2009). For this study, the view taken by (Teece et al., 2019) is most suitable as it recommends the enablement of outputs of Big Data Analytics platforms that directly impact firm performance and competitiveness, as has previously been asserted.
- **Big Data Analytics** could be a form of enhanced analytics, which includes complex applications with components such as predictive models, statistical algorithms, and what-if analysis powered by high-performance analytics systems. The study by (Mikalef et al., 2019) characterizes Big Data Analytics as a modern era of technologies and architectures designed to economically extract value from massive volumes of a wide range of data, enabling high-velocity capture, discovery, and analysis. The researcher defines Big Data Analytics in healthcare as an analytical tool to help healthcare associations have progressed understanding of data and settle on educated decisions.

1.8. Structure of the thesis

Chapter 1: Introduction and background

This chapter includes the background of the study, motivation, purpose and objectives, the study's problem statement and research questions, the research scope, the justification of the study, and the main definitions of the operational terms.

Chapter 2: Literature review

This review chapter reviews literature from previous research papers, CDs, DVDs, articles, historical data, government and business reports, and others.

Chapter 3: Research Design and Methodology

This chapter clarifies the type of research, the method used in the research, the target population, the sample, and the techniques used to find the target sample, and the data collection methods used to get data from the targeted sample.

Chapter 4: Presentation and discussion of the research findings

This chapter deals with the presentation of the data collected from the respondents using the instruments in a tabular and narrative form. It entails the discussion of the results, analysis, and interpretation of the findings and linkages with the literature review.

Chapter 5: The chapter features a summary, conclusions, and recommendations of the study.

1.9. Chapter Summary

This chapter systematically presented the foundation of the topic under examination, explored issues for articulation, clarified the research scope, legitimized the exploration, and gave the examination and inquiries destinations. It additionally gave a concise outline of the research strategies and instruments used to lead the examination or gather the examination information from the respondents.

CHAPTER 2: LITERATURE REVIEW

2. Overview

This literature review chapter examines and reviews the existing literature from sources such as previous research papers, CDs, DVDs, articles, historical data, government and business reports, and others on Big Data Analytics in the healthcare sector.

2.1. Big Data Analytics in Healthcare

Big Data (BD) permeates every element of human life in the twenty-first century, including biology and medicine (Baro et al.,2015). Mehta and Pandit (2018) claim that the notion of BD was developed in the late 1990s. BD refers to an explosion in quantity and, occasionally, quality of readily accessible and possibly helpful information. Big data is defined as large volume, high velocity, and/or a wide variety of information assets that call for novel kinds of processing to enable improved decision-making, insight finding, and process optimization, according to the studies by Mehta & Pandit (2018) and Shams & Solima (2019). (Feldman, Martin, & Skotnes, 2012) identified authenticity as another crucial component of BD in healthcare.

Based on these criteria, there are now many definitions of BD. However, according to (Scruggs et al., 2015), the definition of BD should go beyond these features and include the possibility of utility and reuse, the ability to accrue value over time, and the innovation of a multidimensional, systems-level understanding. Mehta and Pandit (2018) assert that BD in medicine contains diverse, multi-spectral, partial, and imprecise observations gathered from many sources employing incongruent sampling. For instance, the identification, demographics, care, and prevention of illness, injury, disease, and disabilities of the body and mind.

According to (Auffray et al., 2016), some of these data are structured and focus on genotype, phenotype, genomics data, and ICD codes. Memos, clinical notes, medications, medical imaging, Electronic Health Records (EHR), lifestyle, environmental, and health economics data are among the unstructured data (Auffray et al., 2016). Auffray et al. (2016) discovered that dealing with this diverse data to produce insights for better healthcare outcomes is an issue for Big Data Analytics (BDA).

Authors like (Raghupathi & Raghupathi, 2014) underlined the need for analytical and management tools, while (Auffray et al., 2016) concentrated on the many types of healthcare data. The vast and complicated electronic health data sets that, at times, are impossible to manage with conventional software and/or hardware are described by the study of (Raghupathi & Raghupathi, 2014) as BD in healthcare. This data cannot be easily managed with conventional or widely used data management tools and techniques. Big Data Analytics (BDA) is a new generation of technologies and architectures that can enable high-velocity data capture, discovery, and/or analysis.

According to the study by Mikalef et al. (2019), BDA is used to economically extract value from large quantities of a wide range of data. Additionally, (Shams & Solima, 2019) show that the 5Vs—high volume of data, intense velocity in the appearance of vast amounts of data, tremendous yet perplexing variation in the perspectives and potentials of data, data veracity, and data value—are included in the definition of BDA. The 5Vs are the characteristics of BDA; that is, volume, velocity, variety, veracity, and value.

The study by (Mehta & Pandit, 2018) defines the characteristics of BDA in healthcare. Volume refers to the quantity of BD in healthcare, estimated to increase dramatically to 35 zettabytes by 2020. Variety refers to the types of healthcare BD collected, including their heterogeneous characteristics and the structured and unstructured nature of medical data. Velocity is the speed of data generation (i.e., real-time patient data) and data collection. Veracity refers to sources that influence accuracies, such as inconsistencies, missing data, ambiguities, deception, fraud, duplication, spam, and latency. Veracity and data quality issues are of acute concern in healthcare because life or death decisions depend on having accurate information (Mehta & Pandit, 2018). Lastly, the value represents the cost-benefit of the decision-maker through the ability to take meaningful action based on insights derived from data.

(Rajabion, et al.,2019) Stated that BD has caused many challenges in a wide range of research field. It holds patients' data to help them select the best choice and to support the medicinal treatment plans. However, they have also made healthcare data much more significant and harder to manipulate and process.

From these definitions, the researcher posits that there is still a lack of consensus on the operational definition of BDA in healthcare. Therefore, the researcher defines BDA in healthcare as an analytical tool to help healthcare associations have an improved understanding of data and settle on educated decisions. The examination of definitions from previous studies allows discernment of the common elements.

2.2. Sources of big health data

Sometimes, healthcare data is not disseminated or organized, comes from diverse sources, and has varying structures (Mehta & Pandit, 2018). The use of BDA in the healthcare industry entails techniques for analyzing vast amounts of electronic data about patient health and wellbeing. Data on physiological, behavioral, molecular, clinical, and environmental exposure, medical imaging, illness management, drug prescription history, diet, or exercise characteristics are all included in healthcare business intelligence (BD) (Mehta & Pandit, 2018). This data is complex and challenging for conventional software or hardware to measure (Panagiota Galetsi et al., 2020).

According to a study by Mehta and Pandit (2018), genomics-driven BD (genotyping, gene expression, and sequencing data) and payer-provider BD are the two main sources of health BD (electronic health records, insurance records, pharmacy prescription, patient feedback, and responses). Furthermore, (Mehta & Pandit, 2018) categorize BD streams into (a) traditional medical data obtained from Electronic Medical Records (EMR), medication history, and lab reports which assist in a better understanding of disease outcomes and optimizing healthcare delivery; (b) Omics" data including genomics, micro "biomics, proteomics, and metabolomics, which helps in understanding the mechanisms of diseases and accelerates the individualization of medical treatments and; (c) Data from social media, wearables, and sensors which provides the information about behavior and lifestyle of individuals.

This data may be available internally in health services (e.g., EHR, LIMS) or come from external sources (e.g., insurance companies, pharmacies, government) and could be in a structured format (e.g., tables with laboratory results) or unstructured format (e.g., the text of medical notes in EHR) (Panagiota Galetsi et al., 2020). Data resources in healthcare, such as clinical, patient, pharmaceutical data, etc., must be appropriately processed and analyzed to create capabilities translated into business values. According to (Raghupathi, 2013), data is also accumulated in various web 2.0 and social media applications such as Twitter, Facebook, YouTube, blogs, and wikis, as applications such as Twitter, Facebook, YouTube, blogs, and wikis, as well as email messages and mobile applications. These high volumes of data are collected for compliance and regulatory reporting.

2.3. Big Data Analytics Capabilities in Healthcare

Several definitions for Big Data Analytics Capabilities (BDAC) have been developed in the literature (Wang, Kung, & Anthony, 2018). BDAC refers to managing a vast volume of disparate data to allow users to implement data analysis and reaction. The studies of (Panagiota Galetsi et al., 2020) and (Wamba et al., 2017) have identified BDAC for healthcare as follows:

- **Better diagnosis for the provision of more personalized healthcare** refers to the BDA's capability to direct to better case diagnosis from collecting more data and therefore offer more targeted therapy or health service to the individual.
- **Supporting/replacing professionals' decision-making with automated algorithms** is about mining knowledge from large data sets and training algorithms to pattern matching. This means the better automatic categorization of new information entering the analysis process and improved decision-making regarding diagnosis and choice of therapeutic scheme.
- **New business models, products, and services** refer to the development of new business models, products, and services through the capabilities offered by BDA, such as new visualization software with real-time statistical analyses of brain images for better patient diagnosis.
- **Enabling experimentation, exposing variability, and improving performance** from using BDA allows researchers to acquire a deeper understanding of all possible interrelationships between variables, develop scenarios for further experimentation with their models, and expose new health information.
- **Healthcare information sharing and coordination** are gained by coordinating and sharing health information across healthcare services or even countries to improve health professionals' decision-making.
- **Creating data transparency** is about the ability of BDA to collect big data and format them standardized. This capability reduces data identification and

analysis time and assists the previous value of coordinating meaningful and comprehensive health-related information.

- **Identifying patient care risk** refers to the capability of running the big data in advanced statistical techniques, such as logistic regression models and regression trees, which can identify scenarios of risk patterns and send an alert for areas of health risk prevention.
- **Offering customized actions by segmenting populations** refers to using BDA to identify additional factors, through clustering and other methods, for segmenting populations differently or in more categories and offering more targeted health services or products.
- **Reducing expenditure while maintaining quality** focuses on the capability of analytics through process mining, visualization techniques, and collaborative tools to propose ways to reduce health organizations' costs, from better resource utilization eliminating non-value-added actions, capturing hospital underpayments, etc.
- **Protecting** privacy is about how BDA can offer data security in ways such as the identification of privacy breaches, the capability to extract data by eliminating ID recognition from electronic medical records, and others.

2.4. Big Data Analytics Potential Benefits and Challenges

BDA has shown distinctive advantages in improving healthcare efficiency in the healthcare sector. BDA can recognize individuals' healthcare conditions, identify risks for serious health problems, and provide personalized healthcare services (Wu et al., (2017). BDA has the potential to transform business and clinical models for intelligent and efficient delivery of care (Mehta & Pandit, 2018) because it enables the integration of de-identified health information to allow secondary uses of data. In addition, BDA also has the potential to reduce healthcare costs by identifying healthcare resource waste, providing closer monitoring, and increasing healthcare efficiency. Recognizing patterns and deciphering associations can facilitate autonomous decision-making (Mehta & Pandit, 2018).

BDA can help with early disease detection, accurate disease trajectory prediction, identification of deviation from a healthy state, changed disease trajectories, and fraud detection. Providing this information helps healthcare organizations in the personalization of predictions, targeted treatment and cost-effectiveness of care, and reduction in waste of resources; and by giving actionable recommendations to individuals, it encourages them to be in good health (Mehta & Pandit, 2018). The studies of (Wu et al., 2017) and (Rajabion et al., 2019) state that by adding BDA into the healthcare sector, it is predicted that at least 300–450 billion dollars a year will be saved by healthcare industries.

Some healthcare leaders have already captured the value of BD. BDA can analyze a wide variety of complex data and generate valuable insights which otherwise would not have been possible. When applied to healthcare data, it can identify patterns, lead to improved healthcare quality, reduce costs, and enable timely decision-making (Mehta & Pandit, 2018). The benefits of analytics in healthcare have been summarized in the ability to provide comparative effectiveness research to determine more clinically appropriate and cost-effective ways to diagnose and treat patients (Panagiota Galetsi et al., 2020). The application of BD in healthcare services is still in its growing stages. The deployment of BD in healthcare services improves healthcare results and the patient's safety (Rajabion, Shaltooki, Taghikhah, Ghasemi, & Badfar, 2019).

Even with substantial potential benefits, the healthcare industry is in its nascent stage for adopting BDA. With the vast amount of data available, there are more challenges to be faced, and there is a lack of knowledge about which data to use and for what purpose (Mehta & Pandit, 2018). Another major challenge that healthcare faces are the lack of appropriate IT infrastructure and the transition from using paper-based records to using distributed data processing (Mehta & Pandit, 2018). The resistance to redesigning processes and approving technology that influences the health care system and the need for substantial initial investment makes it more challenging to utilize BD technology. The study by (Mehta & Pandit, 2018) shows that because of the lack of knowledge about the best algorithm and tool for analysis and the unavailability of trained clinical scientists and BD managers to interpret BD outcomes, healthcare remains far from realizing the potential of BDA. Furthermore, they indicated that the major concern with using BDA in healthcare is processing information without human supervision, which might lead to erroneous conclusions. According to (Raghupathi &

Raghupathi, 2014), there is a need for a simple, convenient, and transparent BDA system which can be applied to real-time cases.

From the technical point of view, challenges include integrating structured, semi-structured, and unstructured data from various resources. Studies show that the main technical issues in BDA include siloed/fragmented data, limitations of observational data, validation, data structure issues, data standardization issues, data inaccuracy and inconsistency (veracity), data reliability, semantic interoperability, network bandwidth, scalability, and cost (Mehta & Pandit, 2018). The problems such as missing data and the risk of false-positive associations also add to it. Furthermore, Mehta & Pandit (2018) found that security issues such as BD breaches can be a significant threat in healthcare. Patient privacy and confidentiality are of utmost importance in healthcare. But data sharing between various stakeholders for deriving insights can deepen the privacy concern. According to (Mehta & Pandit, 2018), informed consent and privacy are critical areas of concern. Lack of data protocols and standards are some of the governance issues faced by BDA in healthcare. (Mehta & Pandit 2018) state that one of the prominent reasons for the lack of clinical integration of BD technology is the dearth of evidence of the practical benefits of BDA in healthcare.

The application of BDA to healthcare faces various challenges, which can differ based on the applications in which the techniques are used. The following are common challenges in this area, according to the studies of (Khanra et al., 2020) and (Renugadevi et al., 2021):

- **Big Data format conversion** - Due to the data sources' diversity in BD, heterogeneity limits data format conversion effectively. Therefore, applications must be able to create more values if format conversions are effective.
- **Big Data allocation** - BD allocation comprises data generation, transformation, storage, and acquisition under a specific domain. Improvement in Big Data productivity is considered a crucial factor.
- **Initial investment -** The deployment of the requisites to leverage the benefits of BD incurs huge initial costs for organizations providing healthcare.

- **Quality of data -** The lack of trained personnel and resistance to change in organizational routines may affect the quality of BD accumulated by the organization.
- **Quality of insights** - The poor quality of heterogeneous biomedical data has the potential drawback of yielding inadequate insights and misleading suggestions.
- **Privacy and security** - Scholars warn about patients' privacy and security concerns regarding exposure to unauthorized data access during intersystem exchanges. Personal as well as private data are stored safely to prevent leakage. It is considered illegal even if the worker's permission is obtained.

(Shamim, Zenga, Shariq, & Khana, 2019) State that the use of BD itself cannot yield its maximum benefits until firms overcome the related managerial challenges, i.e., leadership focus, harnessing talent and technology management, and company culture, which are even bigger contributing factors than the technical ones.

2.5. Big Data analytical techniques and technologies in healthcare

As BD in healthcare continues to develop, the amount of raw data will continue to increase. By 2020, it is estimated that the data will take up to 25 petabytes of storage space. The data cleaning, mining, and extraction algorithms, as well as the machine and deep learning processes still in their infancy today, will require significant computing power. However, the exact values of both data sides or the power needed are not yet known. (Mikalef et al. (2019) state that BD requires novel technologies capable of handling large amounts of diverse and fast-moving data. The multidimensional healthcare data medical images (X-ray,–MRI images), biomedical signals (EEG, ECG, EMG, etc.), audio transcripts, handwritten prescriptions, and structured data from EMRs and their dynamicity and complexity makes it difficult to analyze them (Mehta & Pandit, 2018). There is a lack of analytical strategies to handle such heterogeneous data and facilitate decision-making. A study by (Mehta & Pandit, 2018) identifies some analytical approaches that can be applied to healthcare and medicine. By incorporating descriptive and comparative analytics, healthcare organizations have improved the quality of care (Mehta & Pandit, 2018). However, they state that long-term tangible benefits can be accrued using predictive analytics.

According to (Wang et al., 2018), predictive analytics can predict high-cost patients, readmissions, triage, decompensation (when a patient's condition worsens), adverse events, and treatment optimization for diseases affecting multiple organ systems. Some of the BDA Techniques used in healthcare are shown in Table 2.1.

Big Data Analytical Technique	Healthcare Application Cluster
Cluster Analysis	Determination of obesity clusters for identifying high-risk groups; Determination of population clusters with specific health determinants for treatment of chronic diseases
Data Mining	Bio-signal monitoring for health-related abnormalities; Determination of epidemics; Inductive reasoning and exploratory data analysis in healthcare
Graph Analytics	Analysis of hospital performance across various quality measures
Machine Learning	Prediction of disease risk; Assessment of the hospital performance; Determination of epidemics
Natural Language Processing (NLP)	Improving the efficiency of care and controlling costs; Providing training, consultation, and treatments; Identifying high-risk factors; Extraction of information from clinical notes; Reducing the likelihood of morbidity & mortality.
Neural Networks	Diagnosis of chronic diseases; Prediction of patients' future disease
Pattern Recognition	Improvement of public health surveillance
Spatial Analysis	Extracting meaningful population-level insights by using visual, spatial, and advanced analytics

Table 2.1: Big Data Analytical Techniques Source: (Mehta & Pandit, 2018)

Furthermore (Mehta & Pandit, 2018) highlighted some of the applications of BD technologies like MapReduce and Hadoop for healthcare analytics which other researchers supported:

- MapReduce can improve the performance of standard signal detection algorithms for pharmacovigilance at approximately linear speedup rates.
- Algorithms based on the Hadoop distributed platform can refine protein structure alignments more accurately than existing algorithms.
- MapReduce-based algorithms can improve the performance of neural signal processing.
- Image reconstruction algorithms speed up the reconstruction process.

2.6. Dynamic Capabilities Framework

During the last years, significant advances in Information Technology (IT) have caused people to produce, process, and share high volumes of information (Rajabion et al., (2019). Several studies have verified that incomplete access to patient-related information and unsuccessful communication among the care team members is the main reason for faults in healthcare domains. Therefore, pervasive access to healthcare data is vital for the correct diagnosis. So, healthcare management systems should focus on reaching such vital information anywhere and anytime to deliver welfare for patients and care team members. The application of big data in healthcare services is still in its growing stages. The deployment of big data in healthcare services improves healthcare results and patient safety (Rajabion et al., 2019).

(Niland, 2017) suggests that although research and literature on the concept of Dynamic Capability Theory (DCT) predate the seminal articles by Teece, Rumelt, Dosi, and Winter (1994) and later Teece, Pisano, and Shuen (1997), it was not until these publications that the Dynamic Capabilities (DC) view generated substantial interest and a growing flow of research. Since then, the past decade has seen DCT become a highly effective lens for strategic and IT management fields (Niland, 2017). As a field still in its relative infancy, it, like BD, has not reached a consensus in terms of a definition (Niland, 2017).

As research on DC has developed, so has the definition of DC. While building on earlier definitions, later definitions have sought to make incremental improvements. (Teece & Pisano, 1994) State that DC operates on organizational skills, resources, and functional competencies. (Teece et al., 1997) view DC as being idiosyncratic factors which give rise to an organization's sustainable competitive advantage", and thus have the view that outputs should be viewed as firm performance. However, (Eisenhardt & Martin, 2000) see DC as "best practice" or "commonalities amongst enterprises." As a result, they see it as a method that gives rise to lasting competitive advantage through their resource configurations. A DC (Helfat & Peteraf, 2009) describes an organization's capacity to actively build, extend, and adjust its resource base. The organization's assets, skills, and human resources that are owned, under its control, or to which it has preferential access collectively comprise the Resource Base (RB). Since there are numerous varieties of DC, the definition has always been intentionally vague. Because different types perform different tasks, ranging from new product development to post-acquisition integration (Helfat & Peteraf, 2009), researchers should be specific in characterizing the dynamic capabilities they are investigating.

For the purposes of this study, the perspective expressed by Teece et al. (2019) is the most relevant because it demonstrates that, as previously claimed, enabling the outputs of Big Data Analytics platforms directly impacts company performance and competitiveness. The essential competency outlined by DCT, which emphasizes the critical role of strategic management in adapting, integrating, and reconfiguring internal and external organizational skills, resources, and functional competencies toward a changing environment, is also defined by this description. The Dynamic Capabilities Theory offers a comprehensive framework that may synthesize and facilitate the prescription of existing conceptual and empirical information (Teece et al., 2019). DCT is largely rooted within the theory of Resource Based View (RBV) and Knowledge-Based View (KBV) and argues that the idiosyncratic factors held by an organization allow them to alter their activity concerning market factors to maintain their competitive advantage. The RBV, according to Panagiota Galetsi et al. (2020), asserts that a corporation can develop distinctive values and skills that give it a competitive edge by accumulating valuable resources and synthesizing them effectively. They discovered that the RBV is the organizing framework for Big Data research that is most frequently applied. Over the past ten years, DCT has become one of the most significant theoretical viewpoints in the study of strategic management (Mikalef et al., 2019). (Niland, 2017) discovered that despite disagreements over terminology and points of view, the fundamental components of the DC framework were first outlined by (Teece et al., 1997). These consist of the following:

- **Sensing**: the capacity to perceive, recognize, and comprehend threats and opportunities in a business environment (Niland, 2017). According to (Teece et al., 2019), sensing entails analytical systems that scan, search, and explore various marketplaces and technologies.
- **Coordinating**: the capacity to coordinate and, ideally, manage resources, stakeholders, deliverables, and tasks concerning needs or tasks. This competence allows identifying opportunities and synergies inside and outside the organization that may be further capitalized on through cooperation (Niland, 2017). According to (Teece et al., 2019), seizing requires evaluating current

and developing capabilities and potential investments in pertinent designs and technologies that are most likely to succeed in the market.

- **Learning**: the ability to acquire, comprehend, and use knowledge so that better decisions can be made (Niland, 2017).
- **Integrating**: the method that makes it possible to solve problems more quickly by more effectively combining all of the organization's resources (Niland, 2017).
- **Reconfiguring**: The organization's capacity to quickly implement or carry out strategic decisions by reallocating resources to better match the organization with the external or market environment (Niland, 2017). According to (Teece et al., 2019), transformation involves ongoing realignment and alignment of tangible and intangible assets.

Although the literature on DCT has expanded significantly and includes important areas of effect like those mentioned above, empirical research on how dynamic capabilities positively affect business performance appears to be relatively scarce (Niland, 2017). The DC approach, however, offers a coherent framework that may integrate both the existing conceptual and empirical knowledge and facilitate prescription (Teece & Pisano, 1994). There are recognizable characteristics of solid theoretical foundations in literature, even though DCT may still only provide enough basis to be defined as an "approach" to understanding change and absorption in business rather than a fully-fledged "theory" (Helfat & Peteraf, 2009). The study will follow the theoretical framework by (Teece, 2007), which focuses on specific types of DC, using a chain of logic that expands upon that in (Teece et al., 1997). In the last article, DC of opportunity identification ('sensing') and investment in these opportunities ('seizing') lead to new positions and paths, which then affect firm performance in terms of growth, profits, and competitive advantage. After the investment, DC for recombination and reconfiguration can further alter the accumulated asset base of the organization further, leading to an additional effect on firm performance, competitive advantage, and new positions and paths.

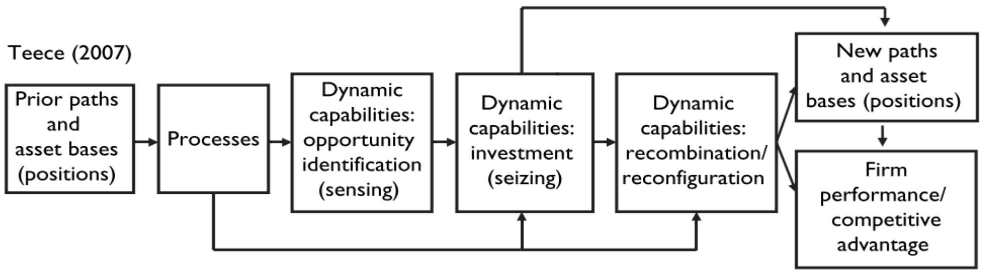


Figure 2.1: Dynamic Capabilities Theory Source: (Teece,2007)

The proposed conceptual framework for this study was adapted from the DCT presented in Figure 2.1 by (Teece, 2007) and (Teece et al., 1997). This work aims to propose a recognizable set of dynamic capabilities by extending this logic and drawing on the strategic management and decision sciences pieces of literature. Starting points are the unique capabilities Teece et al. (1997) described for reconfiguring, learning, integrating, and coordinating, and by Teece (2007) for detecting the environment to take advantage of opportunities and reconfigure assets. This study has reconciled the various labels and meanings from the literature and grouped them under a concise set to reflect (Teece et al.,1997) .'s and Teece's (2007) conceptualization, our interpretation of the literature, and the relevance of Big Data Analytics in healthcare. This is because different labels have been used in the literature to refer to similar capabilities or similar labels for different capabilities.

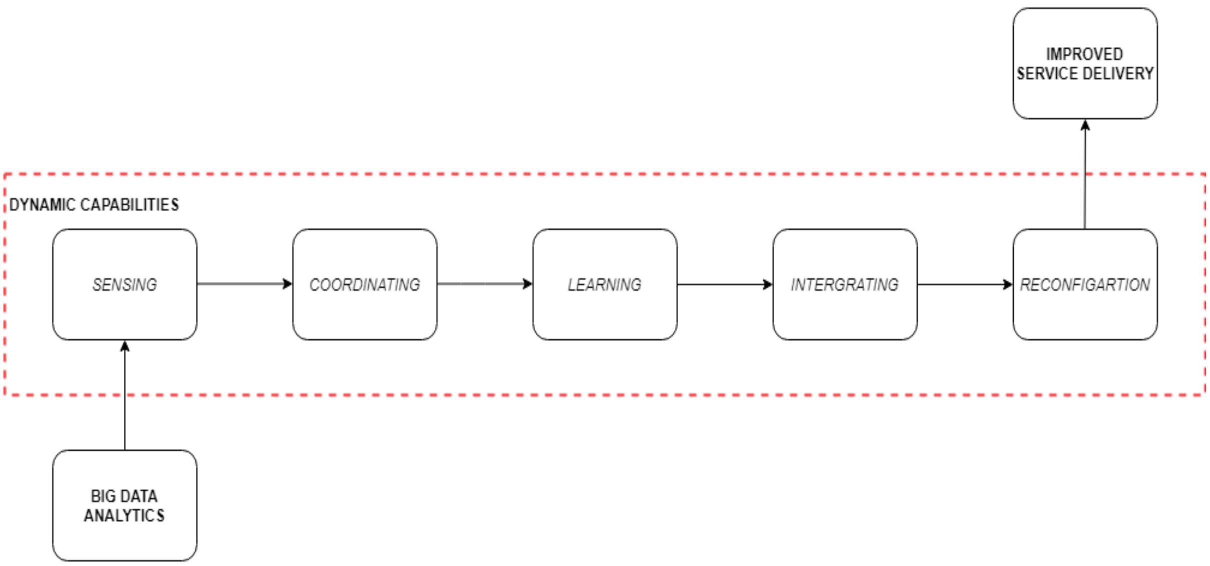


Figure 2.2: A framework for representing the proposed measurable model of dynamic capabilities.

Capability	Description	Construct indicators
Sensing	The ability to spot, interpret, and pursue opportunities in the environment.	Generating Industry intelligence, Disseminating Industry intelligence, and Responding to industry intelligence (Pavlou & Sawy, 2011)
Coordinating	The ability to manage and ideally synchronize resources, stakeholders, deliverables, and tasks about tasks or requirements.	Appointing the right persons to the right tasks, Orchestrating activities (Pavlou & Sawy, 2011)
Learning	The capacity to gather, understand and exploit knowledge such that improved decisions may be made	Acquiring, assimilating, transforming, and exploiting knowledge (Pavlou & Sawy, 2011) Systematic in-house learning knowledge development, Effective team-working, and well-organized "on-the-job training" (Protogerou et al., 2011).
Integrating	The processes allow for more efficient problem resolution by more effectively combining the various resources of the organization.	Contributing individual knowledge to the industry, Representation of individual & group knowledge, and Interrelation of diverse knowledge inputs to the collective system (Pavlou & Sawy, 2011)
Reconfiguration	The ability of the organization to make strategic decisions and rapidly enact or execute against these by repositioning resources to better align the organization with the external or market environment.	Adoption of new management methods, Renewal of business. (Wilden et al., 2013)
Big Data Analytics	An analytical tool to help the healthcare industry have an improved understanding of data and settle on educated decisions.	Analytics Extraction Organizing Decision making

Table 2.2: Existing scales for measuring Dynamic Capabilities (as conceptualized by Teece)

1.1. Chapter Summary

The researcher extensively reviewed the literature on Big Data Analytics in healthcare and the Dynamic Capabilities Theory in this chapter.

CHAPTER 3: RESEARCH METHODOLOGY

3.1. Introduction

This chapter aims to examine a Dynamic Capabilities perspective of Big Data Analytics in healthcare in South Africa. This chapter outlines all the significant steps in the research process and the methods employed. Research is based on collecting data, analyzing it with various tools, and interpreting the results to answer multiple research questions (Neville, 2007). This chapter provides a methodology overview, including a description of where the study was to be conducted, study design, intended audience, methods, sampling techniques, data collection procedures, data analysis tools and techniques, and ethical considerations.

3.2. Research Paradigm

This study adopted a positivist paradigm. A positivist paradigm is a type of inquiry that believes that there is a single reality that can be measured and known. Therefore, the use of quantitative methods seems ideal. The positivist research paradigm can be described as quantitative research. Quantitative research includes statistical and numerical measurements. The studied phenomenon was observed and measured. Quantitative approaches have been used to develop knowledge using post-positive assertions that use surveys and collect data statistically using prescribed tools (Creswell, 2003). According to Muijs (2010), quantitative research methods aim to reveal existing realities. This method also evaluates the cause and effect of various variable relationships.

3.4. Research Design

In this study, the researcher used a survey as a design. According to (Maree & Pietersen, 2010), in survey design, researchers select a sample of respondents before conducting the questionnaire and analyze the respondents' attitudes, values, habits, thoughts, demographics, feelings, and opinions. A survey design assesses status, opinions, beliefs, and attitudes through questionnaires or interviews with a general population (Maree & Pietersen, 2010). (Mathiyazhagan & Nandan, 2010) stated that this design is identified as a descriptive design used to collect data based on verbal responses or written explanations from the target group of respondents.

3.5. Data Collection

(Yount, 2006) states that a population comprises events, persons, and objects, which are cases that might make up a known whole. The targeted respondents are healthcare institutions and people who are knowledgeable about BDA in South Africa.

3.5.1. Sampling Design

The study used a purposive sampling technique. (Maree & Pietersen, 2010) State that purposive sampling techniques are used in special situations where sampling is done for a specific purpose. This study focused on healthcare Data Management Systems. This meant that the target population was the medical sector, and researchers used individuals as representatives, as the medical sector is the target population for this study. This includes administrators, clinicians, nurses, pharmacists, doctors, other medical professionals, IT professionals, and anyone with knowledge about Big Data and Big Data Analytics, such as IT/IS students, research professors, and other IT/IS personnel.

Table 3.1: Healthcare tier

Healthcare tier	Targeted respondents
Primary	administrators, clinicians, nurses, pharmacists, physicians and other healthcare practitioners, IT experts
Secondary	administrators, clinicians, nurses, pharmacists, physicians and other healthcare practitioners, IT experts
Tertiary	administrators, clinicians, nurses, pharmacists, physicians and other healthcare practitioners, IT experts

Descriptions of targeted respondents

Administrator: The individual responsible for the administration of the hospital

Clinician: A physician who has direct contact with patients and is not involved in theoretical or experimental research.

Nurse: An individual specially trained in a hospital to care for the sick and infirm.

Pharmacist: A person who is professionally qualified to dispense and dispense pharmaceuticals.

Physician: A person qualified to practice medicine, specializing in diagnosis and treatment other than surgery.

Healthcare practitioner: An individual other than a medical doctor licensed or licensed by the state to provide medical services.

Purposive sampling requires personal judgment to select cases that answer research questions and help achieve research goals. According to (Yount, 2006), sampling is the process of drawing a small percentage from a larger group as respondents representing the whole group.

3.5.2. Sample frame and size

A sample is a subset of a population containing a given number of sample sizes in units randomly selected from the population (Maree & Pietersen, 2010). A sampling frame is a list of all units in the population, each with a unique number. An appropriate sampling frame allows researchers to capture defined target populations without worrying about contaminating records with erroneous input (Maree & Pietersen, 2010).

South Africa has over 5000 medical facilities. The healthcare system comprises a public sector run by the government and a private sector. Public health services are divided into primary, secondary, and tertiary through medical institutions affiliated with and managed by state departments of health (Graham, 2015). The provincial departments are, therefore, direct employers of health workers, and national health departments are responsible for policy development and coordination (Graham, 2019).

The study includes South African private and public healthcare organizations, universities, colleges, IT organizations, and local governments. Questionnaires were distributed to healthcare practitioners, clinicians, those who work in the dispensary, blood banks, data management workers where patients are registered, IT experts, database administrators, IT students, IT lecturers, pharmacists, hospital receptionists, administrators, Etc. There was no restriction on selecting respondents, such as position, gender, age, working experience, Etc. In total, 170 questionnaires were distributed to the target population. Only 102 questionnaires were returned. Therefore, the response rate was 68%. These organizations and enterprises were selected from several enterprises and organizations that know BDA. Data collected for this study was not patient health data but data about the BDA tools and systems used within the healthcare facilities of South Africa.

3.6. Data collection

To achieve the main objective of the research, data was collected based on the researcher's questions. The study aimed to design a framework for Big Data Analytics in Healthcare Organizations in South Africa, based on the Dynamic Capabilities theory, to improve healthcare service delivery. This research used both primary and secondary data. According to (Currie, 2005), primary data are data that researchers collect directly for a specific study and have never been collected. The primary data can be collected using different approaches.

In this study, primary data were collected using an electronic questionnaire. The researcher distributed them to acquire data from the respondents. A sample questionnaire is attached as Appendix 2 at the end. A questionnaire was designed to explore BDA within the South African healthcare sector. The questionnaire design was based on an extensive literature review of the BDA-related literature. The questionnaire consists of a subset of BDA questions. Some questions include answers based on a 7-point Likert scale, with 1 being 'strongly disagree' and 7 being 'strongly agree' to measure the responses. On the other hand, secondary data were used for the literature review, and this will be obtained using published articles, websites, books, and other secondary sources.

3.6.1. Instruments for data collection

This study used an electronic questionnaire for data collection. The questionnaire was conducted in English as this is the medium of instruction for the conduct of the work. This will be easy for respondents to complete the questionnaires. The respondents used their own time to complete the questionnaires. According to (Uys, 2005), questionnaires provide respondents with the convenience of time and place and reduce bias in results. The questionnaire was designed to be efficiently completed by respondents, and basic English was used.

The questionnaire used a more legible font to make myopic respondents' understanding easier.

- The questions are grouped in a way they are related to the section.
- A logical order in questions so that respondents may not lose interest.
- A simple layout of the questions will be used to avoid respondents skipping questions.

The main cover page of the questionnaire explains and clarifies the following:

- The reasons for conducting research
- The researcher who is conducting the study Importance of responding
- Researchers contacts
- Assurance of Confidentiality to Respondents.

The questionnaire design was so that the respondents would easily understand and readable. The sections of the questionnaire are arranged as follows:

- Section 1: *Demographic Information* involves personal information, but because personal information is kept at a minimum to ensure anonymity, personal information such as the name and surname of respondents will not be included.
- Section 2: Sensing, in this section, the researcher asks questions to find out if the Healthcare sector can identify, interpret, and opportunities in the environment.
- Section 3: *Coordinating*, in this section, the researcher asks questions to find out if the Healthcare sector can orchestrate and deploy tasks, resources, and activities in the new operational capabilities and newly identified opportunities
- Section 4: *Learning*, in this section, the researcher asks questions to determine if the Healthcare sector can revamp existing operational capabilities with new knowledge.
- Section 5: *Integrating*, in this section, the researcher asks questions to determine if the Healthcare sector can embed new knowledge into the new

operational capabilities by creating a shared understanding and collective sense-making.

- Section 6: *Reconfiguration,* in this section, the researcher tries to find the ability of the healthcare sector to make strategic decisions and rapidly enact or execute against these by repositioning resources to better align the organization with the external or market environment.

3.6.2. Data Collection Procedure

The researcher distributed questionnaires to respondents. The reason is that the respondents do not fully understand the language used in the questionnaire. The researcher may have to read and explain the questions to the respondents so that they may understand them. The questionnaires were distributed in paper and electronic versions.

3.6.3. Pilot study

A pilot study was conducted to validate whether the questionnaire was easy to use, comprehensive, and suitable for data collection. Pre-testing was conducted to eliminate errors in the creation of the questionnaire. (NC3Rs 2006) defined a pilot study as an experiment to test logistics and gather information prior to a larger study to improve quality and efficiency.

In this study, the researcher conducted a pilot study by inviting 10 practitioner experts from various organizations and academics to confirm the questionnaire's effectiveness. This pre-test was conducted using at least 5 organizations in South Africa. These individuals were university IT/IS faculty or employees who have rich work experience in the IT field.

3.7. Data analysis

Quantitative data analysis was used in this study. The data are based on numbers that achieve range frequencies and averages of the data, and various tools such as IBM SPSS (version 25) and Excel are available for data analysis. The study used the IBM Statistical Package for Social Sciences (SPSS) (version 25) program to analyze the data. SPSS is a statistical tool to manipulate and analyze data concerning variance mean mode and standard deviation. SPSS also uses descriptive tools to create various tables and frequencies that are later used to present results. The respondent's responses were captured for coding, and validation for each code was ensured to check if the data collected was valid before analyzing it.

3.7.1. Reliability and validity

(Maree & Pietersen, 2010) State that Reliability has to do with the consistency or repeatability of a measure. High Reliability is obtained when the measure will give the same results if the research is repeated on the same sample. A test is valid if it measures what it is supposed to measure and nothing else. For the results to be trustworthy, the measure should have a high degree of internal and external validity.

In this study, the Cronbach coefficient alpha (α) was used to assess the Reliability of the measurements. (Cooper & Schindler 2006) States that Cronbach's coefficient alpha is a metric used to measure the internal consistency of all items measuring the same structure. It also shows how to do domain sampling. Therefore, Cronbach's coefficient alpha is one of the most popular internal consistency methods and determines the average reliability factor of all methods of splitting a set of elements in half. As a result, the Cronbach alpha coefficient is considered one of the most important estimates of multiitem scale reliability.

3.7.2. Normality tests

Before performing detailed data analysis, we first checked the normality of the data. According to (Coakes, 2005), the normality of data can be determined using the Kolmogorov-Smirnov test (for sample sizes greater than 100) and the Shapiro-Wilks test (for sample sizes less than 100). The Kolmogorov-Smirnov test was used in this study because the sample size was over 100.

3.7.3. Exploratory Factor Analysis

According to (Child, 2006), Exploratory Factor Analysis (EFA) seeks to uncover complex patterns by examining data sets and testing predictions. EFA is usually the first step towards building a scale or new metric. EFA is used when researchers discover the number of factors that influence variables and want to analyze which variables "match" (Yong & Pearce, 2013). Furthermore, the basic hypothesis of EFA is that common 'latent' factors need to be discovered in the dataset, and the goal is to find the minimum number of common factors that explain the correlation.

EFA was used in this study. This is because observing "groups" of variables can reduce large data sets of multiple variables. The recommended sample size for this study was at least 170 participants, and variables undergoing factor analysis should contain at least 5-10 observations each. EFA works better with larger sample sizes because larger sample sizes reduce the error in the data. Researchers should conduct studies with large samples at specific time points to ensure the Reliability of factors. Pooling results from multiple samples or the same sample at different time points is not recommended, as these methods can skew the results. Factor analysis is helpful for studies containing a few or hundreds of variable items from a questionnaire or a set of tests that can be reduced to a small set to reach underlying concepts and facilitate interpretation (Young & Pearce, 2013).

3.8. Considerations for ethics

Ethical considerations are one of the most important parts of research. The paper may even fail if this part is missing. According to (Bryman & Bell, 2007), the following principles represent the most important principles regarding ethical considerations in dissertations.:

3.8.1. Participants' consent and voluntary

Respondents must participate based on informed consent. The principle of informed consent requires that researchers provide sufficient information and assurances about participation so that individuals understand the implications of participation and are fully informed as to whether to participate without pressure or coercion. It needs to be obtained, considered, and free to choose (Saunders, Lewis & Thornhill, 2012). The voluntary participation of respondents in surveys is important. Participants have the right to discontinue the study at any time if necessary. Research participants should not be harmed in any way.

3.8.2. Privacy, anonymity, and confidentiality

Ensure respondents that the information they provide will not disclose their identity. The questionnaires did not collect information such as the respondent's name or contact information. Researchers must obtain the full consent of participants before starting research to ensure that the privacy and anonymity of individuals and participating organizations are protected. Confidentiality of research data should also be guaranteed. Researchers have not misrepresented or exaggerated the aims and objectives of their research. Researchers must ensure that all types of research-related communications are honest and transparent and strive to avoid misleading information and biased representations of primary data results.

3.9. Chapter Summary

This chapter describes how researchers can answer research questions and fill gaps in the health research industry.

CHAPTER 4: ANALYSIS OF RESULTS

4.1. Introduction

This Chapter is dedicated to illustrating the results of this study. The data is presented using graphs, tables and pie charts and interpreted for better understanding and it was analysed using IBM SPSS Statistics. The main objective of the study was to analyse how Big Data Analytics can be used for Data Management in Healthcare Organizations in South Africa to improve service delivery. A total number of 170 closed-ended questionnaires were distributed, that is, some were self-administered, and some were sent out as electronic surveys to respondents. Out of the 170 distributed questionnaires, a total of 135 responses were collected, 102 were returned completed, 33 questionnaires were incomplete, hence, these were not included in data analysis, while 35 questionnaires were not returned by the respondents. Respondents came from all three tiers of the healthcare sector, with little responses coming from the primary tier.

4.2 Section 1: Demographic characteristics

This section presents the demographic characteristics of the organisation and of the respondents who took part this study. 102 people from different organisations took part in the study and their profiling was done and presented in graphs as shown in the preceding sections.

4.2.1. Awareness of Big Data Analytics Capability

The respondents were asked to indicate their awareness of BDA. 62% of the respondents indicated yes, which implies that they are aware of BDA. A further 38% of the respondents indicated that they are not aware of BDA. This denotes that not all respondents in this study are aware of BDA.

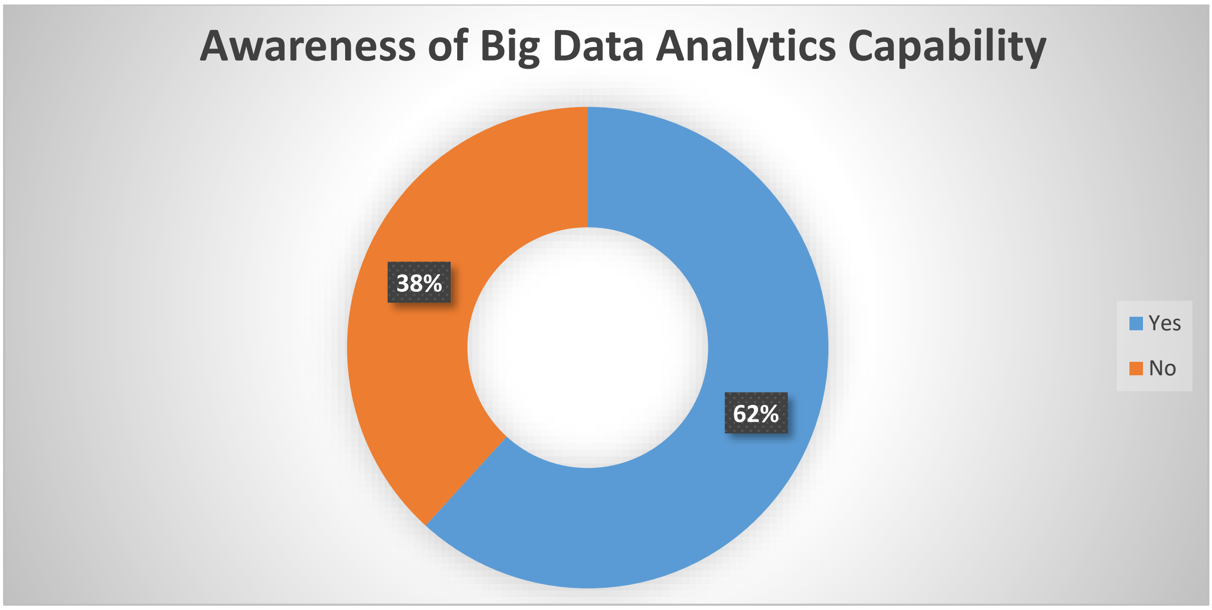


Figure 4.1: Association with a Big Data Analytics Capability

4.2.2 Type of industry

In terms of the type of industry, the study identified five, which are teaching and learning, public sector, corporate, higher learning and training, and healthcare as indicated in the figure 4.2.

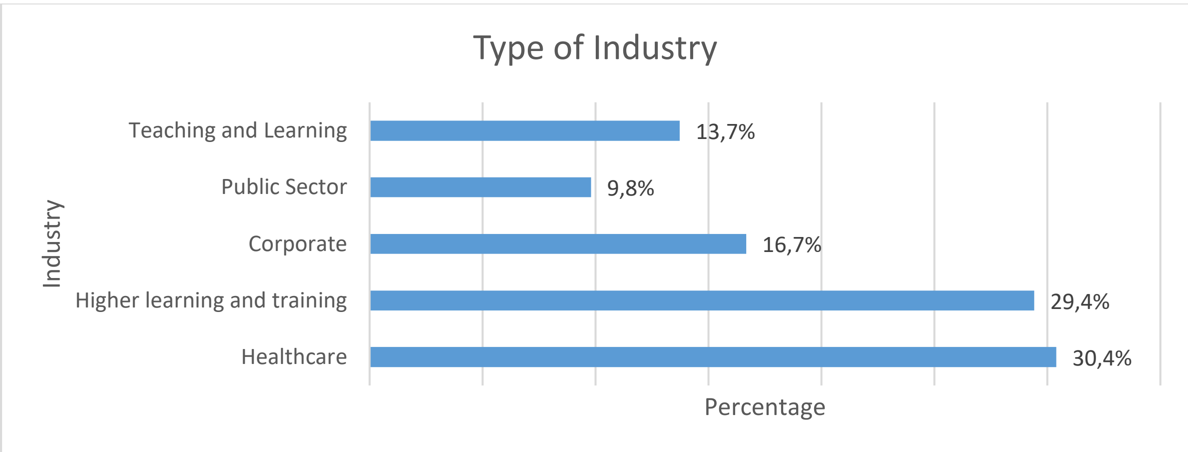


Figure 4.1: Type of industry

30.4% of respondents were in the healthcare sector, followed by 29.4% of the respondents who were in higher learning and training, followed by 16.7% of the respondents who were in the corporate. A further 13.7% were in the teaching and learning industry whilst 9.8% were in the public sector. The data provides trustworthy information considering that most of the participants were from the healthcare sector.

4.2.3 Personal experience in BDA

Another aspect that we considered was that of the respondents' term relative to the field of BDA, as a measure of the level of direct experience that respondents had regarding the environment being considered.

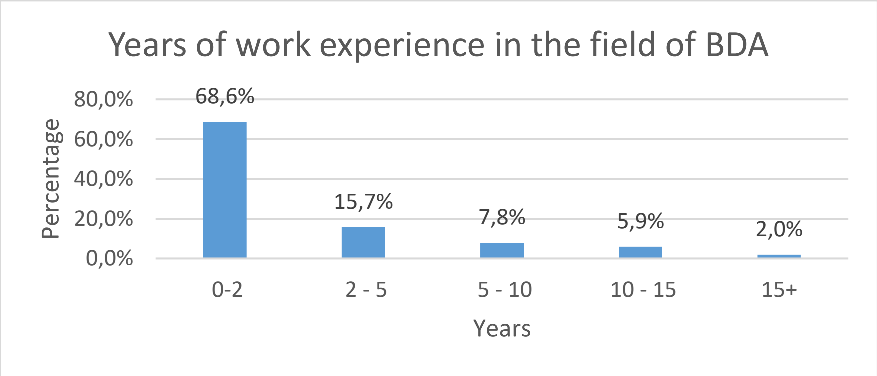


Figure 4.2: Years of experience in the Field of BDA

As shown in figure 4.3, 68.6% of respondents reported between 0-2 years' experience with the BDA environment, whilst 15.7% reported 2-5 years' experience. Similarly, to that result, a further 7.8% reported between 5-10 years' experience in BDA, with 7.9% suggesting they had more than 10 years' experience in BDA.

4.2.4. Organisation's tenure in BDA

The descriptive measure of the organisations themselves describes the time that these organisations have actively pursued BDA. The years were categorised into 0–2 years, 2–4 years,4-6 years, 6–8 years, and 8 and above, as shown in figure 4.4.

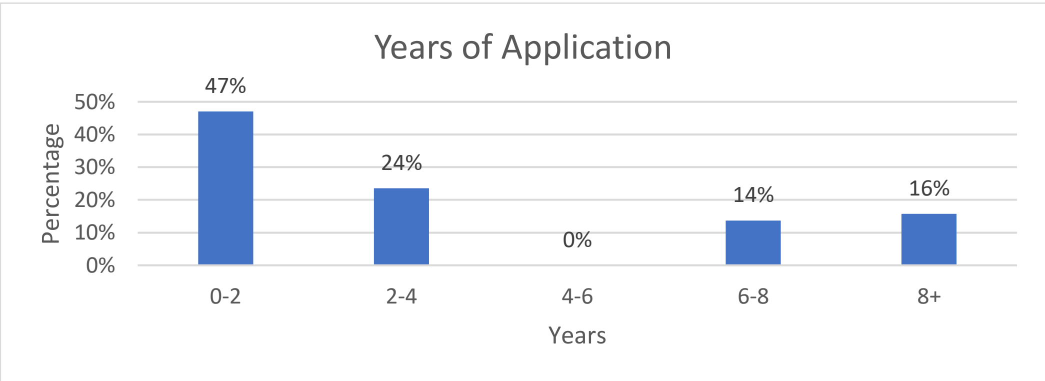


Figure 4.3: Years for which respondents organisations have actively pursued BDA

47.1% of organisations are within “0-2” years of deploying BDA capability, while a further 23.5% of organisation have reportedly actively pursued BDA capability for “2-4” years. 13.7% of organisations indicated that they have actively pursued BDA capabilities for “6-8” years, and 15.7% of organisations specified “8 years or more” use of BDA capabilities.

4.2.5. Association to the BDA environment

The respondent’s association or type of role relative to the BDA environment was also considered. This measure was intended to describe the relative position from which respondents considered the BDAC and was intended to describe context toward the expressed perceptions of respondents toward organisational, technical, or analytical competencies of the organisation.

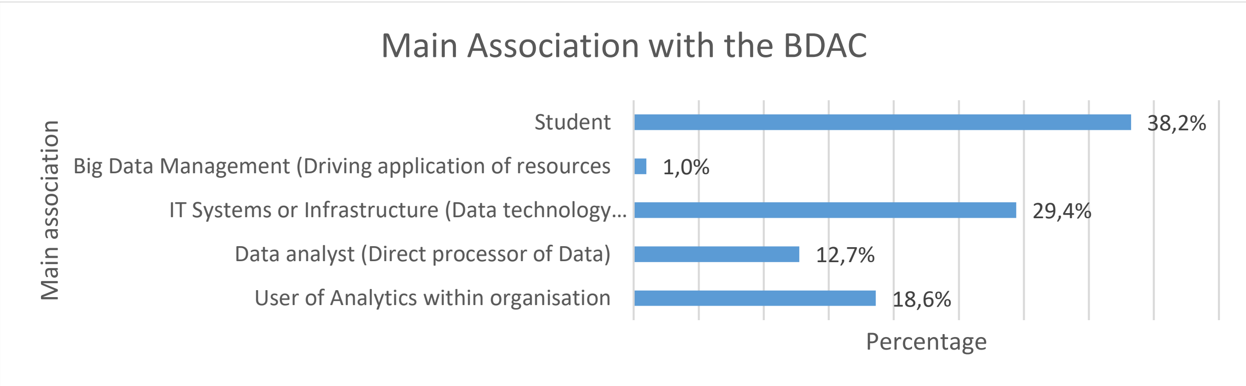


Figure 4.4: Main Association with the BDAC

The findings illustrated in figure 4.5, that 38,2% of respondents were students or consultants, while 29.4% were in IT system or infrastructure. A further 18.6% of respondents were using analytics within the organisations and 12.7% were data analysts involved in the direct processing of data. The remaining 1% of respondents was the big data management involved in the driving application of resources.

4.2.6. Relative organisation size

Each of the industries described are predominated by large organisations, which is reflected in the headcount of employees as illustrated in Figure 4.6. Five categories were identified, 1–99, 100–499, 500–999, 1000+ and “don’t know”.

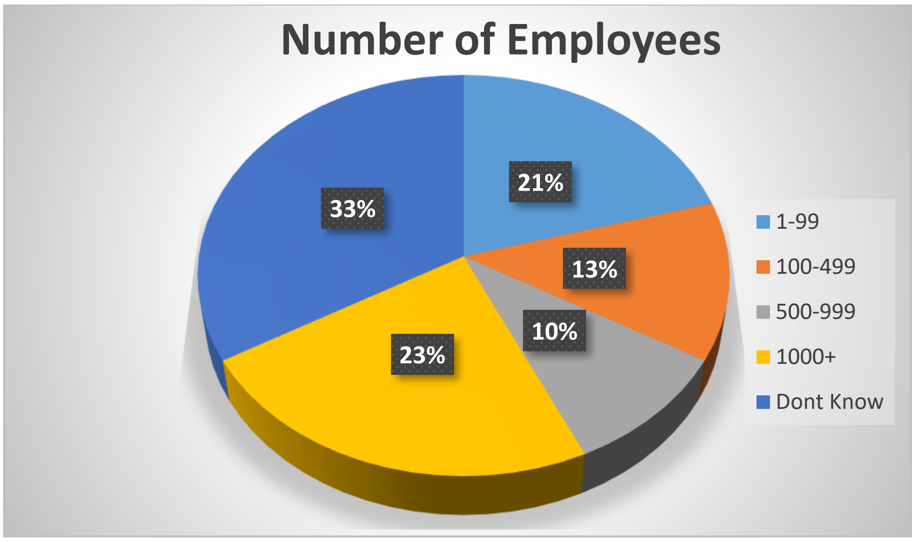


Figure 4.5: Number of employees within respondent's organisation

23% of the respondents came from organisations with 1000 or more employees, whilst a further 10% come from organisations with over 500 employees, which amounts to 33% of the sample combines. The 33% of the respondents which came from organisations which they could not estimate the headcount of the employees within their organisations.

4.2.7. Respondents' seniority in organisations

Moving on to descriptions of the respondents themselves, the following figures consider aspects which relate to the association or respondents themselves with the BDA environment. Respondents who participated in this study were categorized as students, entry-level employees, intermediate-level employees, middle managers, senior managers as well as owners/executives/C-level employees.

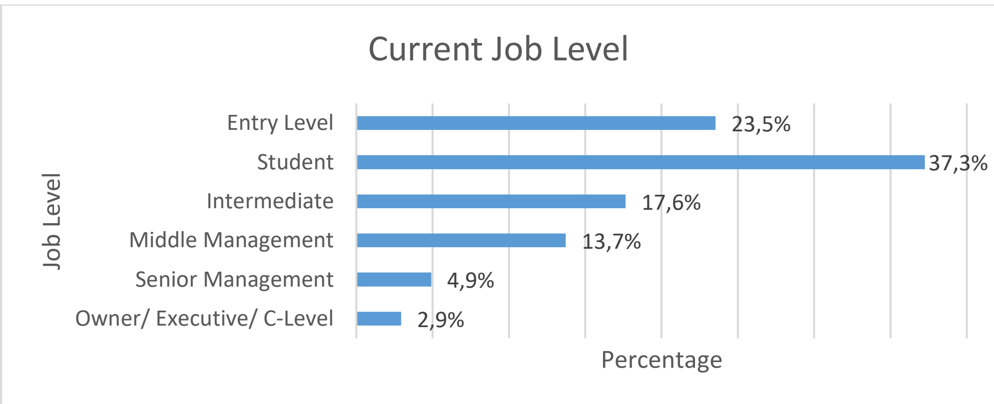


Figure 4.6: Current job level of respondents

As is illustrated in figure 4.7, which describes the relative seniority of positions held by respondents in their respective organisations, 23.5% reported themselves as being entry level, with a relatively even split across the remaining five levels described of 37.3%, 17.6%, 13.7%, 4.9% and 2.9% respectively for student, intermediate, middle management, senior management, and finally owner, executive or C-suite level.

4.2.8. Organisational location

When asked which regions they work in, respondents indicated that their organisations are located both in rural and urban areas.

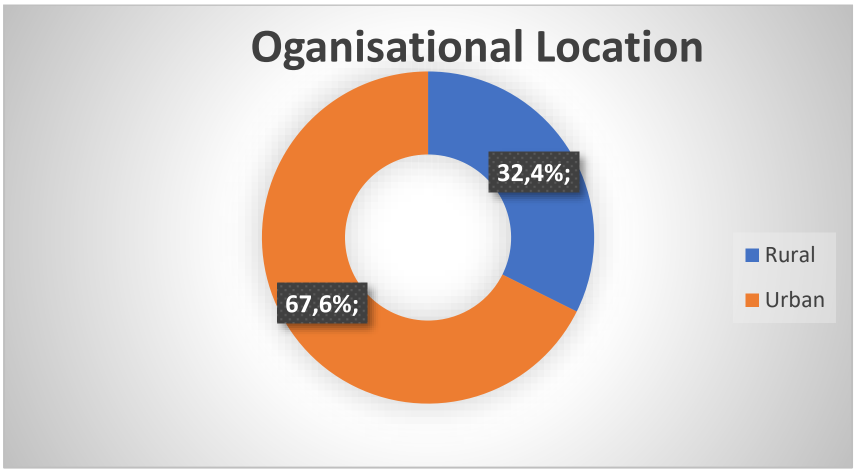


Figure 4.7: Organisational location

As illustrated in figure 4.8, 67.6% of respondents whose data were applied in the analysis work in organisations in urban areas while the remaining 32.4% work in organisations in rural areas.

4.3 Section 2: Assessment of survey sections as constructs

Section 1 of the survey, which included questions which are related to demographic characteristics of respondents and their organisations, was not included in the following as it pertains to descriptive characteristics rather than constructs assessed by Likert scale as ordinal variables.

4.3.1. Reliability and Validity Analysis

The internal reliability of data sets was assessed using Cronbach's coefficient alpha (α). Cronbach's alpha is a commonly applied measure of internal consistency, or reliability of measures or scales, and is often used where multiple Likert questions are present in a questionnaire, as in this study (Vale et al., 1997). Assessment constructs was performed as distinct sections of the questionnaire to determine internal reliability prior to further application in the study. The results of those assessments are summarised in Table 4.1. It is evident that all sections assessed returned Cronbach alpha scores over 0.7, thus all constructs were reliable.

Table 4.1: Table showing reliability statistics results

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.842	0.836	38

From our results in the above table, we can see that Cronbach's alpha is **0.842**, which indicates a high level of internal consistency for our scale with our sample of 38 questions. The table below, table 4.2, presents the value that Cronbach's alpha would be if that item was deleted from the scale. We can see that removal of 13 questions (question 1, 2, 4, 5, 6, 7, 8, 10, 11, 12, 25, 26, and 36) would lead to a small improvement in Cronbach's alpha, and we can also see that the "Corrected Item-Total Correlation" values were low (from -0.209 to 0.190) for these items. This might lead us to consider whether we should remove this item.

4.3.2. Normality test

In the table below, table 4.2, the Kolmogorov-Smirnov tests indicate that the data for the tools used to collect big health data do not follow a normal distribution, D (102) = 0.336, p = 0.00. Similarly, it can be concluded that all variables used in this study do not follow a normal distribution. Expectations were that healthcare organisations will want to invest heavily in various clinical and operational Information Systems (e.g., Electronic Health Record Systems (EHRS), which is an important way in which they can improve their information processing capability (service delivery). More expectations were that organisations would be competing to adopt BDA as it has capabilities of improving overall firms' performance. However, part of the reasons for this study's results to not be normal could be politics, unskilled employees, ignorance, poor management, lack of research and no investments in BDA by healthcare organisations. Other studies in BDA, for instance, the study by Niland (2017) also reported a presumption of a not normally distributed test, thus, the results for this study were acceptable.

Table 4.2: Table with normality tests

	N	Normal Parameters[a,b]		Most Extreme Differences			Test Statistic	Asymp. Sig. (2-tailed)
		Mean	Std. Deviation	Absolute	Positive	Negative		
form of data collection	102	2.34	0.790	0.336	0.203	-0.336	0.336	.000[c]
Sources of data collection	102	2.64	1.413	0.272	0.272	-0.139	0.272	.000[c]
Ability for prediction	102	1.67	0.926	0.411	0.411	-0.239	0.411	.000[c]
Awareness of BDA	102	1.64	0.854	0.380	0.380	-0.228	0.380	.000[c]
Executive support for BDA	102	4.40	1.154	0.254	0.254	-0.197	0.254	.000[c]
Executive ability to appraise BDA	102	2.08	0.270	0.536	0.536	-0.386	0.536	.000[c]
Investment on BD tools	102	4.76	1.321	0.238	0.238	-0.193	0.238	.000[c]
BD Knowledge capability	102	4.88	1.253	0.201	0.201	-0.143	0.201	.000[c]
BD for decision making capability	102	5.00	1.126	0.167	0.167	-0.167	0.167	.000[c]
Organization's capacity to learn BD capabilities	102	4.91	1.313	0.218	0.145	-0.218	0.218	.000[c]
Employees' orientation on how new tech will improve service delivery	102	5.25	1.316	0.259	0.156	-0.259	0.259	.000[c]
Organization's investment on teaching and training employees about BD	102	4.98	1.210	0.203	0.160	-0.203	0.203	.000[c]
Employees encouraged to develop and apply knowledge on BD	102	4.94	1.296	0.234	0.217	-0.234	0.234	.000[c]

Employees are knowledgeable about adopted technological tools	102	4.57	1.239	0.157	0.157	-0.156	0.157	.000[c]
Ability to adopt new practices to improve service delivery	102	5.90	1.139	0.234	0.168	-0.234	0.234	.000[c]
Knowledgeable that Innovation is necessary for the future of the Organisation	102	5.57	1.231	0.185	0.168	-0.185	0.185	.000[c]
Internal politics influences decision making about new policies and practices	102	6.03	1.214	0.288	0.212	-0.288	0.288	.000[c]
BD improves Service delivery	102	5.93	1.229	0.288	0.192	-0.288	0.288	.000[c]
BD improves overall financial performance	102	6.06	1.150	0.244	0.207	-0.244	0.244	.000[c]
There is a central database?	102	5.15	1.607	0.179	0.124	-0.179	0.179	.000[c]
BD tools available	102	4.75	1.601	0.184	0.130	-0.184	0.184	.000[c]
Technological tools can be used across the Organisation	102	5.47	1.123	0.192	0.192	-0.152	0.192	.000[c]
Our user interfaces provide transparent access to all platforms and applications	102	4.92	1.287	0.211	0.172	-0.211	0.211	.000[c]
Reusable software modules are widely used in new analytics model development	102	4.76	1.380	0.195	0.125	-0.195	0.195	.000[c]
End-users can use software provided to create their own analytics applications	102	4.87	1.716	0.235	0.148	-0.235	0.235	.000[c]
Data is sourced from outside and is easily analyzed	102	4.85	1.498	0.209	0.124	-0.209	0.209	.000[c]
Decisions are made easily because of the new adapted technology	102	5.17	1.313	0.218	0.135	-0.218	0.218	.000[c]
The legacy system within our Organisation restricts the development of new applications	102	4.63	1.560	0.167	0.111	-0.167	0.167	.000[c]
Our analytics personnel are very capable in terms of programming skills	102	4.94	1.209	0.184	0.184	-0.159	0.184	.000[c]
Our analytics personnel are very capable in terms of teaching others in our business	102	5.06	1.304	0.177	0.154	-0.177	0.177	.000[c]

4.3.3. Exploratory Factor Analysis test

The Exploratory Factor Analysis (EFA) test was run on the data from questions 9 to 38 (only demographical information was excluded from the data for the test to be conducted). A statistical technique using EFA requires a large amount of data. Therefore, sufficient data must be tested first before performing further analysis using EFA. The Kaiser–Meyer–Olkin (KMO) test and Bartlett's test are EFA instruments used to measure the sufficiency of data. (Handoyo et al., 2021) indicated that to conduct EFA, the KMO value must be higher than 0.6 and Bartlett's test should be less than 0.05. The information outlined in Table 4.3 is the output of the KMO test and Bartlett's test.

Table 4.3: KMO and Barlett's tests results

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.670
Bartlett's Test of Sphericity	Approx. Chi-Square	2012.568
	Df	435
	Sig.	0.000

The Kaiser-Meyer-Olkin Measure of sampling (KMO) value is 0.670 which is > 0.06 and the Bartlett's test is significant ($p = 0.000$), indicating that the requirement for data adequacy for factor analysis has been fulfilled. EFA with a Principal Component Analysis (PCA) was employed. A KMO value with a range ≥ 0.80 indicates that the adequacy of the data to perform EFA is excellent (Handoyo et al., 2021). Bartlett's test of sphericity shows a significant indication ($p < 0.05$). The results of the KMO test and Bartlett's test imply that the amount of data in this study is adequate for conducting factor analysis.

Table 4.4 shows the Initial Eigenvalues. We look at only components that have total Initial Eigenvalues greater than 1. In our case, only nine components have Total Initial Eigenvalues greater than 1. The nine components with the values greater than 1 explain 74.54% of the variance. Therefore, we conclude that there are nine factors.

Table 4.4: Table with variance explained by the principal components

Total Variance Explained							
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	**8.451**	28.170	28.170	8.451	28.170	28.170	6.079
2	**2.566**	8.552	36.722	2.566	8.552	36.722	2.602
3	**2.420**	8.068	44.790	2.420	8.068	44.790	3.882
4	**2.006**	6.687	51.477	2.006	6.687	51.477	4.400
5	**1.722**	5.740	57.217	1.722	5.740	57.217	1.744
6	**1.483**	4.944	62.162	1.483	4.944	62.162	1.854
7	**1.302**	4.340	66.502	1.302	4.340	66.502	1.784
8	**1.264**	4.215	70.717	1.264	4.215	70.717	2.573
9	**1.146**	3.822	74.538	1.146	3.822	74.538	3.750
10	0.986	3.287	77.826				
11	0.871	2.903	80.729				
12	0.763	2.544	83.273				
13	0.678	2.261	85.534				
14	0.630	2.099	87.633				
15	0.595	1.982	89.615				
16	0.440	1.466	91.082				
17	0.406	1.352	92.433				
18	0.334	1.115	93.548				
19	0.301	1.003	94.551				
20	0.269	0.898	95.449				
21	0.252	0.840	96.289				
22	0.224	0.746	97.035				
23	0.182	0.605	97.640				
24	0.165	0.550	98.190				
25	0.151	0.503	98.693				
26	0.121	0.404	99.097				
27	0.094	0.313	99.410				
28	0.079	0.263	99.674				
29	0.064	0.215	99.888				
30	0.034	0.112	100.000				
Extraction Method: Principal Component Analysis.							

The scree in support of the total variance is given in the figure below:

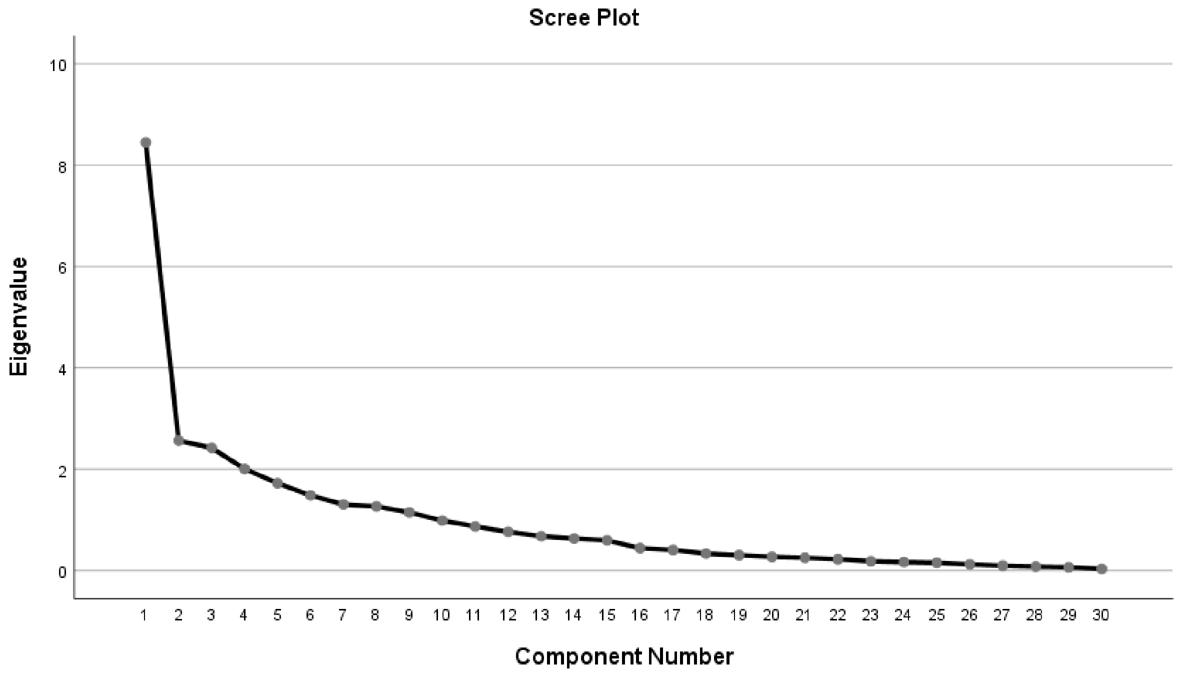


Figure 4.8: Scree plot for variance explained by components

(Comrey & Lee, 1992) suggest that the pattern/structures more than 0.71 loadings are considered excellent, 0.63 as very good, 0.55 as good, 0.45 as fair, and 0.32 to be poor. (Hair et al., 2006) suggests that there should be due consideration of the sample size when deciding on the threshold for the loadings. According to their guidelines, the ideal factor loading for a study with a small sample size should be more than 0.71 (excellent). This cut-off was considered appropriate. Cronbach's internal reliabilities were assessed for each construct. All constructs were "substantially reliable" with their alphas above 0.61 (Landis & Koch, 1977). The following are the factor weights we used for this study:

- 0 to 0.20 as "slightly reliable"
- 0.21 to 0.40 as "fairly reliable"
- 0.41 to 0.60 as "moderately reliable"
- 0.61 to 0.80 as "substantially reliable"
- 0.80 to 1.0 as "almost perfect"

Table 4.5 shows factor weights. The first component is questions 15, 16, 18, 19, 20, 21, 22 and 31. The second component is questions 23, 24, 25, 26, and 27. The third component is questions 29, 33, 34, 35 and 38. The fourth component is questions 19, 22, 27, 28, 29, 31, 32, 35, and 36. The fifth component is questions 11 and 12. The 6th component is questions 9, 24, 25 and 30. The 7th component is questions 10, 31 and 36. The 8th component is questions 12,16, 17, 24, 37 and 38. Lastly the 9th component is questions 13, 14, 15, 16 and 17.

Table 4.5: Pattern matrix for variables and components

Pattern Matrix[a]									
	Component								
	1	2	3	4	5	6	7	8	9
Organization's capacity to learn BD capabilities	0.838								
Employees encouraged to develop and apply knowledge on BD	0.744								
Employees' orientation on how new tech will improve service delivery	0.685								
Organization's investment on teaching and training employees about BD	0.684								
Employees are knowledgeable about adopted technological tools	0.670								
BD improves Service delivery		0.834							
Internal politics influences decision making about new policies and practices		0.736							
Ability to adopt new practices to improve service delivery		0.652							
BD improves overall financial performance		0.646							
Knowledgeable that Innovation is necessary for the future of the Organisation									
End users can use software provided to create their own analytics applications			0.918						
Data is sourced from outside and is easily analyzed			0.905						
There is not a central database				0.850					
BD tools are not available				-0.681					
Reusable software modules are not widely used in new analytics model development				-0.680					
Awareness of BDA					0.849				
Ability for prediction					0.750				
form of data collection						0.818			
Technological tools cannot be used across the Organisation						-0.612			
Sources of data collection							0.806		
The legacy system within our Organisation restricts the development of new applications							0.626		
Our analytics personnel are not very capable in terms of teaching others in our business								-0.578	
There is no Executive support for BDA									-0.835
There is no Executive ability to appraise BDA									-0.672
Tere is no BD for decision making capability									-0.592
There is no BD Knowledge capability									-0.577
Extraction Method: Principal Component Analysis. Rotation Method: Oblimin with Kaiser Normalization. a. Rotation converged in 18 iterations.									

Each factor was given a name according to the research questions used. The name is based on judgements made by considering the characteristics of each factor's element.

Factor 1: The variables that were considered significant were organization's capability to learn BD capabilities, employees encouraged to develop and apply knowledge on BD, employees' orientation on how new tech will improve service delivery, organization's investment on teaching and training employees about BD and employees are knowledgeable about adopted technological tools. These factors were named BDA organizational Capability knowledge. Given the factors above, BDA Organizational Capability Knowledge is important in the adoption of BDA in Healthcare organizations. BDAC is the ability to manage a huge volume of disparate data to allow users to implement data analysis and reaction. Therefore, it is important for healthcare organisations to learn and know about BDAC and their importance as it will have an influence for them to use and adopt BDA.

Factor 2: The variables that were considered significant were BD improves Service delivery, Internal politics influences decision making about new policies and practices, Ability to adopt new practices to improve service delivery and BD improves overall financial performance. These factors were named BDA benefits and challenges. In the healthcare sector, BDA has shown distinctive advantages on improving healthcare efficiency. The studies by (Mehta & Pandit, 2018), (Wu, et al., (2017), (Rajabion,et al., 2019) , (Panagiota Galetsi et al., 2020), (Khanra et al., 2020) and (Renugadevi et al., 2021) highlighted the benefits and challenges of BDA in healthcare. Even with huge potential benefits, the healthcare industry is in its emerging stage for adoption of BDA. With the huge amount of data available, there are more and more challenges to be faced. (Shamim, Zenga, Shariq, & Khana, 2019) state that the use of big data itself cannot yield its maximum benefits until firms overcome the related managerial challenges, i.e., leadership focus, harnessing talent and technology management and company culture which are even bigger contributing factors than the technical one.

Factor 3: The variables that were considered significant were, End users can use software provided to create their own analytics applications and Data is sourced from outside and is easily analysed. These factors were named Big Data Analytical Capability. Organisations need to measure their Big Data Analytics capability to yield competitive performance. According to (Alnoukari, 2020), Big Data Analytical talent capability refers to the ability of an analytics professional to perform assigned tasks in the BD environment. They further indicated that analysts should be competent in four important skills, that is: technical knowledge; technology management knowledge; business knowledge; and relational knowledge. This will enable the organisation to utilise BDA effectively.

Factor 4: The variables that were considered significant were, there is no central database, BD tools are not available and reusable software modules are not widely used in new analytics model development. These factors were named BDAC. Thus, for organisations to be able to manage a huge volume of disparate data to allow users to implement data analysis and reaction, adopting BDA is important.

Factor 5: The variables that were considered significant were, awareness of BDA, ability for prediction. These factors were named BDA awareness. Literature on BDA awareness emphasizes that awareness can help in ensuring that BDA is properly implemented in organizations. For instance, studies by (Zhang et al., 2022) indicate that organizations compete to connect Big Data capabilities with organizational learning infrastructure to respond to these new Big Data and social media developments. This means that organisations are aware that employing BDA in healthcare will allow for improved service delivery through its capability of enabling connections within different fields (Khanra et al., 2020). Another study by (Sarkar et al., 2021) indicated that the adoption rate of BDA has been one of the fastest tech-adoption phenomena in the business world. The application of BD in healthcare services is still in their growing stages.

Factor 6: The variables that were considered significant were form of data collection and technological tools can be used across the organisation. These factors were named BD tools.

Factor 7: The variables that were considered significant were, Sources of data collection, the legacy system within our organisation restricts the development of new applications. These factors were named sources of BD.

Factor 9: The variables that were considered significant were, there is no executive support for BDA, there is no executive ability to appraise BDA, there is no BD for decision making capability, and there is no BD Knowledge capability. These factors were named firms' ability to realize BDAC.

Factor 8: which only consisted of one variable was removed.

Table 4.6: Factor names and variance explained by each factor

Factor	Factor name	% variance	Description
1		28.17024	Investment on BD tools
			BD Knowledge capability
			Organization's capacity to learn BD capabilities
			Employees' orientation on how new tech will improve service delivery
			Organization's investment on teaching and training employees about BD
			Employees encouraged to develop and apply knowledge on BD
			Employees are knowledgeable about adopted technological tools
			Our user interfaces provide transparent access to all platforms and applications
2		8.551919	Ability to adopt new practices to improve service delivery
			Knowledgeable that Innovation is necessary for the future of the Organisation
			Internal politics influences decision making about new policies and practices
			BD improves Service delivery
			BD improves overall financial performance
3		8.067862	BD tools available
			End-users can use software provided to create their own analytics applications
			Data is sourced from outside and is easily analyzed
			Decisions are made easily because of the new adapted technology
			Our analytics personnel are very capable in terms of teaching others in our business
4		6.687199	Employees' orientation on how new tech will improve service delivery
			BD improves overall financial performance
			There is a central database?
			BD tools available
			Our user interfaces provide transparent access to all platforms and applications
			Reusable software modules are widely used in new analytics model development
			Decisions are made easily because of the new adapted technology
			The legacy system within our Organisation restricts the development of new applications
5		5.740169	Ability for prediction
			Awareness of BDA
6		4.944362	form of data collection
			Knowledgeable that Innovation is necessary for the future of the Organisation
			Internal politics influences decision making about new policies and practices
			Technological tools can be used across the Organisation
7		4.340468	Sources of data collection
			Our user interfaces provide transparent access to all platforms and applications
			The legacy system within our Organisation restricts the development of new applications
8		4.21462	Awareness of BDA
			BD Knowledge capability
			BD for decision making capability
			Knowledgeable that Innovation is necessary for the future of the Organisation
			Our analytics personnel are very capable in terms of programming skills (e.g., structured programming, web-based application, CASE, tools, etc
			Our analytics personnel are very capable in terms of teaching others in our business
9		3.821558	Executive support for BDA
			Executive ability to appraise BDA
			Investment on BD tools
			BD Knowledge capability
			BD for decision making capability

Table 4.7 below, with Component Correlation Matrix shows that there is a weak correlation between factors 1 and 4 and between factors 1 and 9.

Table 4.7: Component correlation matrix

Component Correlation Matrix									
Component	1	2	3	4	5	6	7	8	9
1	1.000	0.067	0.252	**-0.336**	-0.029	-0.074	0.099	-0.207	**-0.343**
2	0.067	1.000	0.036	-0.075	-0.045	-0.083	0.041	-0.045	-0.003
3	0.252	0.036	1.000	-0.209	-0.063	0.121	0.099	-0.109	-0.173
4	**-0.336**	-0.075	-0.209	1.000	0.020	0.109	-0.082	0.127	0.071
5	-0.029	-0.045	-0.063	0.020	1.000	0.011	-0.079	0.099	0.020
6	-0.074	-0.083	0.121	0.109	0.011	1.000	0.051	0.040	0.025
7	0.099	0.041	0.099	-0.082	-0.079	0.051	1.000	-0.049	-0.057
8	-0.207	-0.045	-0.109	0.127	0.099	0.040	-0.049	1.000	0.144
9	**-0.343**	-0.003	-0.173	0.071	0.020	0.025	-0.057	0.144	1.000

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.

4.4 Chi-Square Analysis

This section is aimed at addressing the research questions using the Chi-Square test. This study intends to answer the primary research question: How can Big Data Analytics be used for Data Management in Healthcare Organizations in South Africa to improve service delivery? The researcher further divided the question into sub-research questions:

- How can Big Data Analytics be used to sense opportunities to improve healthcare service delivery?
- To what extant can Big Data Analytics be used to coordinate resources for improved healthcare data Management?
- To what extent will Healthcare Data users learn about Big Data Analytics as a tool to improve healthcare services?
- How will the Healthcare sector integrate BDA to improve service delivery?
- How can Big Data Analytics be used in the reconfiguration of Healthcare Data Management to improve healthcare services?

The Chi-Square test was used in this section. The Chi-square test is used to verify the possible relationship between two categorical variables (Barceló, 2018). In this test, a two-way table is created, and the observed counts are compared to the expected counts of the cells.

4.4.1 "Sensing" Big Data Analytics Opportunities

To measure "Sensing" of BDA opportunities, four variables were considered: the form of data collection (whether manual or digital); sources of data collection (e.g., social media, medical health research, etc); ability for prediction; and awareness of BDA. The data type was categorical; therefore, the Chi-square statistic was suitable for assessing the significance of the relationship between these "sensing" variables and the demographic statistics.

4.4.1.1 Data Analytics Collection Tools

Data in healthcare are disorganized and distributed, coming from various sources and having different structures and forms (Mehta & Pandit, 2018). Three tools are used to analyse big health data. The tools are traditional data analytic tools such as a traditional Business Intelligence (BI) software installed on a stand-alone system, such as a desktop or laptop (Raghupathi & Raghupathi, 2014), used to manually record medical images (X-ray, MRI images), biomedical signals (EEG, ECG, EMG etc.), audio transcripts, handwritten prescriptions and structured data from EMRs (Mehta & Pandit, 2018), digitalized data analytics tools such as MapReduce and Hadoop (Mehta & Pandit, 2018), as well as integrated data analytical tools such as the use of stand-alone systems for lesser complicated data and mapReduce and Hadoop for more complex data. The figure below, figure 4.10 shows the usage of each tool in healthcare industry.

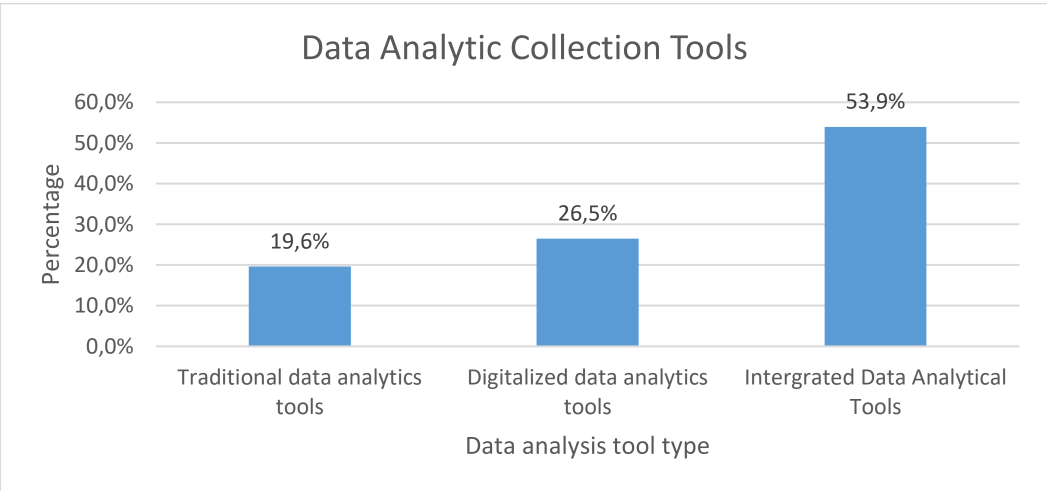


Figure 4.10: Data analytic collection tool

Results show that integrated data analytical tools are the widely used data analytic collection tools in these organisations. This is supported by the majority of 53.9% respondents who said they use the integrated data analytical collection tools. The second most used data analytic collection tools are digitalized data analytics tools which was indicated by 26.5% respondents. The least used tools are traditional data analytics tools which was mentioned by 19.6% respondents who said they use them in their organisations. A Chi-square test was further undertaken to assess the significance of the relationship between the use of these BDA tools with the demographic characteristics (Table 4.8).

Table 4.8: Test for association of BDA collection tool with demographic characteristics

Chi-Square Tests (Demographical variables and Big Data Analytics collection tool)			
Demographical variables	Pearson Chi-Square	df	P-value
Awareness of Big Data Analytics capability	4.455	2	0,11
Type of industry	21.213	8	**0,01**
Years of work experience in the field of BDA	10.670	8	0,22
Organisation's tenure in BDA	8.911	6	0,18
Association with BDA environment	12.262	8	0,14
Relative organisation size	14.001	8	0,08
Respondents' seniority in organisations	18.743	10	**0,04**
Organisational location	7.217a	2	**0,03**

The results revealed that there is an association between the type of industry and BDA collection tool. Since the p-value is less than the adopted significance level, α=0.05, the null hypothesis which says that there is no association between the type of industry and big data analytics collection tool, is rejected. The healthcare industry receives large amounts of data from a wide range of sources and most of the data is stored in hard copy form (Raghupathi & Raghupathi, 2014)., Therefore, it requires interactive, dynamic BDA platforms with innovative technologies and tools to improve the quality of healthcare service delivery while reducing the costs. There is enough evidence to suggest an association between the type of industry and BDA collection tool. Similarly, there is an association between respondents' seniority in organisations and BDA collection tools. Change is a state in which differences exist between new and old ways of thinking. In order to avoid staff resisting to change in organizations when implementing new systems such as BDA or ways of working, (Shahbaz et al., 2019) proposed that the organization should encourage employees to learn new skills, tasks, and programs. Concerning the adoption or use of BDA in the healthcare industry, (Shahbaz et al., 2019) also suggested that the systems should be easy to use and have attractive features that make it useful to the users. Furthermore, they said that employees should put the systems to work if they are available, as the use of BDA in healthcare will improve healthcare services. Furthermore, there is also an association between organisational location and BDA collection tools. As illustrated in Figure 4.8, the results show that the majority of 67.6% respondents work in organisations located in urban areas while the remaining 32.4% work in organisations located in rural areas. This means that healthcare organisations in urban areas are more advanced than those in rural areas.

4.4.1.2. Big Data sources for health

Respondents when asked where their healthcare industries find data about their industry's current situation, clients' problems and the competitors, respondents indicated that they find it from suggestion/complaints boxes, through observation, from news updates (TV and Radio), via medical health research and from social media (Facebook, Twitter, and WhatsApp).

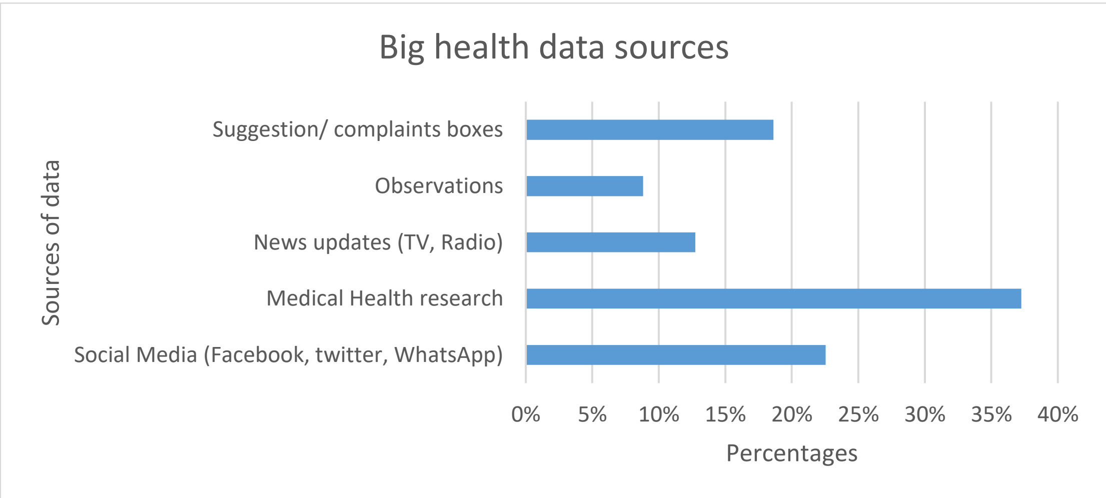


Figure 4.11: Big health data sources

Results show that mostly, the healthcare industry find data about their industry's current situation, clients' problems, and the competitors from medical health research. This is supported by the majority of over 37% respondents who said that their organisation find data from medical health research. The second most used data source is social media (Facebook, Twitter, and WhatsApp) which was mentioned by 22.5% of respondents. 18.6% respondents said that their big health data sources are suggestion/complaints boxes, 12.7% participants identified that their organisations data sources include news updates (TV and Radio) while 8.8% source big health data through observations. A chi-square test was further undertaken to assess the significance of the relationship between healthcare data sources and the demographic characteristics (Table 4.9).

Table 4.9: Test for association of Health care data sources with demographic characteristics

Chi-Square Tests (Demographical variables and Health care data sources)			
Demographical variables	Pearson Chi-Square	df	P-value
Awareness of Big Data Analytics capability	9.457	4	0,05
Type of industry	19.963	16	0,22
Years of work experience in the field of BDA	29.446	16	**0,02**
Organisation's tenure in BDA	26.266	12	**0,01**
Association with BDA environment	23.832	16	0,09
Relative organisation size	26.065	16	0,05
Respondents' seniority in organisations	42.841	20	**,002**
Organisational location	6.493a	4	0,17

The results show that there is an association between the organisation's tenure in BDA and big health data sources. From the results in the above table, we can say since the p-value is less than the significance level, α=0.05, the null hypothesis which says that there is no association between organisation's tenure in BDA and big health data sources, is rejected. Organizations that are new in adopting BDA can learn from implementation challenges that have been reported in literature to avoid similar mistakes in the past. A study by (Chauhan et al., 2021) indicate that the healthcare sector receives large data sets, from different sources (structured, unstructured, text, images) which is difficult to be managed with traditional statistical technology. While (Mehta & Pandit, 2018) categorize big health data sources as (a) traditional medical data (b); Omics; (c) Data from social media, wearables and sensors. As illustrated in figure 4.4, 47.1% of organisations are within "0-2" years of deploying BDA. Thus, the "newness" in the arena of BDA provides an opportunity to implement solutions that are much more relevant. Therefore, there is enough evidence to suggest an association between organisation's tenure in BDA and big health data sources.

Similarly, there is an association between years of work experience in the field of BDA and big health data sources and an association between respondents' seniority in organisations and big health data sources.

4.4.1.3 Future Trends Prediction

When asked whether the healthcare industry can use the data collected from external sources and internal sources to predict the future trends in the industry, varied responses were obtained which were categorized into “yes”, “no” or “maybe”.

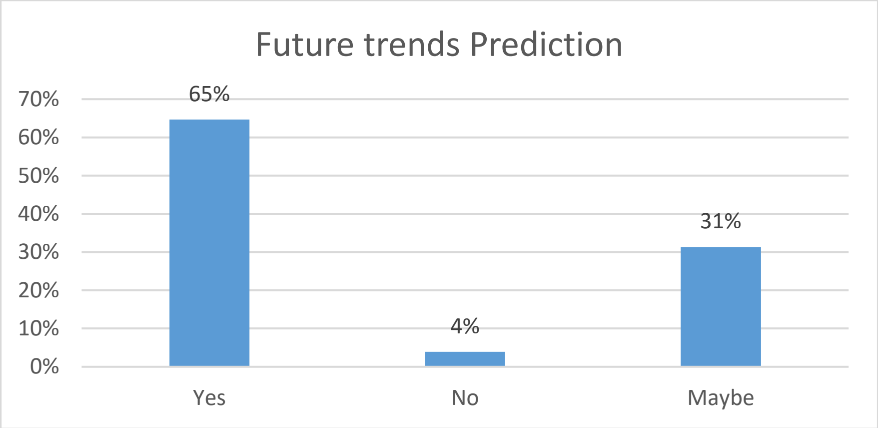


Figure 4.12: Future trends prediction

From the results in figure 4.12, it is shown that the majority of 65% respondents indicated that the healthcare industry can use the data collected from external sources and internal sources to make future trends prediction while only 4% indicated that the healthcare industry is unable to use this data for future trends prediction. 31% of respondents were not sure, they said maybe the healthcare industry can use the data collected from external and internal sources to make future trends prediction. A chi-square test was further undertaken to assess the significance of the relationship between future trends prediction and the demographic characteristics (Table 4.10).

Table 4.10: Test for association of future trends prediction with demographic characteristics

Chi-Square Tests (Demographical variables and future trends prediction)			
Demographical variables	Pearson Chi-Square	df	P-value
Awareness of Big Data Analytics capability	6.056	2	0,05
Type of industry	7.665	8	0,47
Years of work experience in the field of BDA	16.818	8	**0,03**
Organisation's tenure in BDA	22.920	6	**0,00**
Association with BDA environment	13.267	8	0,10
Relative organisation size	20.865	8	**0,01**
Respondents' seniority in organisations	15.221	10	0,12
Organisational location	8.920a	2	**0,01**

There is an association between Years of work experience in the field of BDA and future trends prediction. From the results in the above table, since the p-value is less than our significance level, α=0.05, the null hypothesis of the test which says that there is no association between period of operation and future trends prediction, can be rejected. Many studies have been used to help the healthcare industry predict future trends. The studies by (Rehman et al., 2021) indicated that healthcare informatics research is a scientific attempt that improves both health service organizations' performance and patient care outcomes. Furthermore, they listed a few research which were used by the healthcare industry through social media to predict future trends, such as studies where they "gathered 553,186,016 tweets from the Twitter. They extracted more than 9800 keywords and geographic annotations that contains HIV risk words. They revealed that social media monitor global HIV occurrence and concluded that positive correlation of greater than 0.01 was retrieved between HIV-related tweets and HIV cases" and one where they "detected and predicted the onset of post-partum depression of 165 mothers through Facebook shared data" in 2014. Therefore, it may be concluded that there is enough evidence to suggest an association between years of work experience in the field of BDA and future trends prediction. Similarly, there is an association between relative organisation size and future trends prediction, an association between organisation's tenure in BDA and future trends prediction and association organisational location and future trends prediction.

4.4.1.4. Awareness of big data and benefits

When asked whether the healthcare industry is aware of BDA and its potential benefits for the industry, three categories came out from the responses of the respondents: “yes”, “no”, and “maybe”.

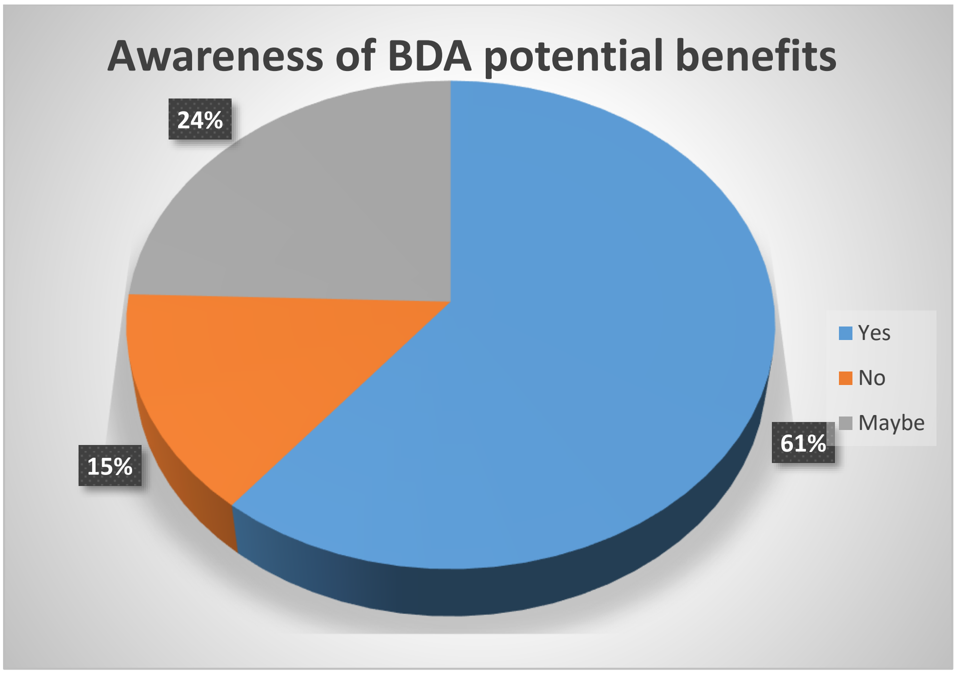


Figure 4.13: Awareness of BDA and potential benefits

Results shown in figure 4.13 show that the majority of 61% respondents said that the healthcare industry is aware of BDA and its potential benefits for the industry while 15% said that the healthcare industry is not aware. There were also 24% of respondents who said that maybe the healthcare industry is aware of BDA and its potential benefits for the industry. A chi-square test was further undertaken to assess the significance of the relationship between awareness of BDA and the demographic characteristics (Table 4.11).

Table 4.11: Test for association of awareness with demographic characteristics

Chi-Square Tests (Demographical variables and awareness)			
Demographical variables	Pearson Chi-Square	df	P-value
Awareness of Big Data Analytics capability	10.483	2	**0,01**
Type of industry	8.038	8	0,43
Years of work experience in the field of BDA	11.095	8	0,20
Organisation’s tenure in BDA	13.344	6	**0,04**
Association with BDA environment	3.270	8	0,92
Relative organisation size	19.779	8	**0,01**
Respondents’ seniority in organisations	25.203a	10	**0,00**
Organisational location	8.026	2	**0,02**

There is an association between Awareness of Big Data Analytics capability and Awareness of BDA and potential benefits. From the results in the above table, since the p-value is less than the significance level, α=0.05, the null hypothesis of the test which says that there is no association between Big Data Analytics Capability and Awareness of BDA and potential benefits, can be rejected. Studies on BDA awareness emphasize that awareness can help in ensuring that BDA is properly implemented in organizations. The studies by (Mehta & Pandit, 2018) mentioned some of the potential benefits of BDA. Potential benefits include improved service delivery, BDA reduces healthcare costs, autonomous decision making, enabling integrating of de-identified health data, and allowing secondary uses of health data. Studies by (Zhang et al., 2022) indicated that organizations compete to connect Big Data capabilities with organizational learning infrastructure to respond to these new Big Data and social media developments. This means that Organisations are aware that employing BDA in healthcare will allow for improved service delivery through its capability of enabling connections within different fields (Khanra et al., 2020). Therefore, there is enough evidence to suggest an association between Big Data Analytics Capability and awareness. Similarly, there is an association between years of work experience in the field of BDA and Awareness of BDA and potential benefits, an association between Relative organisation size and Awareness of BDA and potential benefits, association between Respondents' seniority in organisations and future Awareness of BDA and potential benefits and association organisational location and Awareness of BDA and potential benefits. Although IT-based systems replace the manual data entry in records, reports, documents, and also save time and cost associated with records, hospital data and reports on daily bases, like billing and schedules of patients. (Rehman et al., 2021) indicate that BDA is currently not practiced in small clinics, hospitals, laboratories in rural and county side areas due to its implementation.

4.4.2 Coordinating Resources for Big Data Analytics

To assess how resources for BDA can be coordinated to improve healthcare, five variables were considered: executive level support for BDA, executive ability to appraise BDA, investment in BDA tools, BDA knowledge capability, BDA for decision making capability. The data type was categorical; therefore, the Chi-square statistic was suitable for assessing the significance of the relationship between these "coordinating" variables and the demographic statistics.

4.4.2.1. Executive Support for BDA

On this theme, how often does the executive level actively and visibly supports our BDA capability, the categories that came out from responses on these themes were; “always”, “very frequently”, “frequently”, “occasionally”, “rarely” and very rarely.

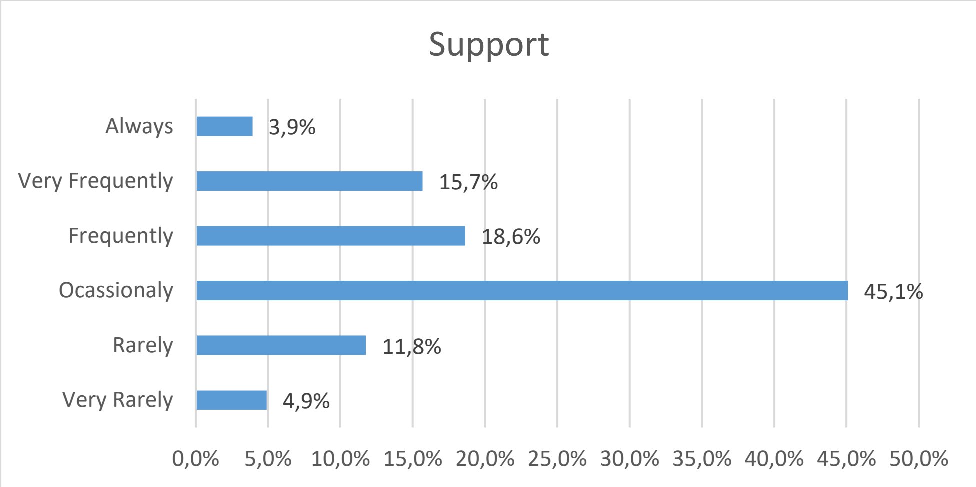


Figure 4.14: Support

Figure 4.14 shows that the majority of 45.1% respondents said that executive level occasionally actively and visibly supports BDA capability. The study had 34.5% of respondents who said that the executive level actively and visibly supports BDA capability frequently. Respondents who said the executive level rarely gives support to BDA capability constitute for 15.7% of total responses while there were 3.9% of respondents who said they are always actively and visibly supporting BDA capability.

Table 4.12: Test for association of executive support for BDA with demographic characteristics

Chi-Square Tests (Demographical variables and support)			
Demographical variables	Pearson Chi-Square	df	P-value
Awareness of Big Data Analytics capability	5.765	5	.330
Type of industry	44.549	20	**.001**
Years of work experience in the field of BDA	43.275	20	**.002**
Organisation's tenure in BDA	44.845	15	**.000**
Association with BDA environment	30.610	20	.061
Relative organisation size	46.146	20	**.001**
Respondents' seniority in organisations	72.058	25	**.000**
Organisational location	4.178	5	.524

There is an association between the type of industry and frequency at which the executive level actively and visibly supports the BDA capability. From the results in the above table, we can say since the p-value is less than our significance level, α=0.05, we can reject the null hypothesis of the test which says that there is no association between type of industry and frequency at which the executive level actively and visibly supports the BDA capability. Historically, the healthcare industry generates large volumes of data, driven by record keeping, compliance, regulatory requirements, and patient care. While most data are stored in hard copy files, the current trend is towards rapid digitization of these large volumes of data (Raghupathi & Raghupathi, 2014). With the expansion of technology, there is also a significant increase in the size of data, therefore the healthcare Big data is analysed for various insights, which lead to better decisions and business moves (Shah et al., 2019). We can therefore conclude that there is enough evidence to suggest an association between type of industry and frequency at which the executive level actively and visibly supports BDA capability.

Similarly, there is an association between years of work experience in the field of BDA, organisation's tenure in BDA, relative organisation size, organisational location and frequency at which the executive level actively and visibly supports the industry's big data analytics capability. Although IT-based systems replace the manual data entry in records, reports, documents, and also save time and cost associated with records, hospital data and reports on daily bases, like billing and schedules of patients.

(Rehman et al., 2021) indicates that BDA is currently not practiced in small clinics, hospitals, laboratories in rural and county side areas due to its implementation.

4.4.2.2. Executive ability to appraise BDA

When asked about managers' knowledge of critically appraising both internal data and evidence from scientific research, the majority of 92% of respondents said that, not all but some of their managers know how to critically appraise both internal data and evidence from scientific research while 8% said all their managers know how to critically appraise both internal data and evidence from scientific research.

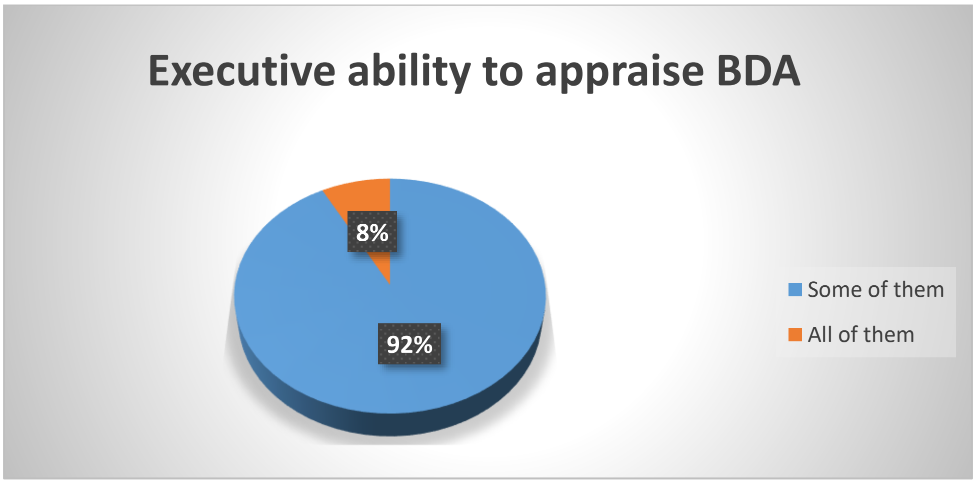


Figure 4.15: Executive ability to appraise BDA

Table 4.13: Test for association of appraise with demographic characteristics

Chi-Square Tests (Demographical variables and appraise)			
Demographical variables	Pearson Chi-Square	df	P-value
Awareness of Big Data Analytics capability	.002	1	0,96
Type of industry	4.740	4	0,32
Years of work experience in the field of BDA	25.322	4	**0,00**
Organisation's tenure in BDA	.666	3	0,88
Association with BDA environment	4.329	4	0,36
Relative organisation size	2.450	4	0,65
Respondents' seniority in organisations	26.243	5	**0,00**
Organisational location	.105	1	0,75

There is an association between years of work experience in the field of BDA and managers' knowledge on how to critically appraise both internal data and evidence from scientific research. From the results in the above table, we can say since the p-value is less than our significance level, α=0.05, we can reject the null hypothesis of the test which says that there is no association between period of operation and managers' knowledge on how to critically appraise both internal data and evidence from scientific research. Technology is advancing rapidly that provides effectiveness in every walk of life, especially in healthcare. A study by (Rehman et al., 2021) indicates that healthcare managers uses trends models and search queries on Google to detect influenza and flu-like diseases. This is one of the earlier comprehensive review papers of public healthcare informatics using social media. We can therefore conclude that there is enough evidence to suggest an association between period of operation and managers' knowledge on how to critically appraise both internal data and evidence from scientific research. Similarly, there is an association between employee position and managers' knowledge on how to critically appraise both internal data and evidence from scientific research.

4.4.2.3. Investing in BD tools to interpret data

Respondents were also asked about their views on whether their organisation or Industry invest in technological tools to Interpret data collected from external sources to be able to identify which information can be useful for their industry. Their responses were given in Likert scale from strongly disagree to strongly agree.

Table 4.14: Investing in tools to interpret data

Investing in tools to interpret data	Responses		Descriptive statistics				T-test results		
	Frequency	**%**	**N**	**Mean**	**Std. Deviation**	**Std. Error Mean**	**T**	**df**	**Sig. (2-tailed)**
Strongly Disagree	2	1.96%	102	4.76	1.32	0.13	36.42	101	0.00
Disagree	2	1.96%							
Moderately Disagree	5	4.90%							
Neutral	44	43.14%							
Moderately Agree	17	16.67%							
Agree	20	19.61%							
Strongly Agree	12	11.76%							

Association with Demographical variables

Demographical variables	Pearson Chi-Square	df	P-value
Awareness of Big Data Analytics capability	4.259	6	0,64
Type of industry	48.614	24	**0,00**
Years of work experience in the field of BDA	43.766	24	**0,01**
Organisation's tenure in BDA	28.585	18	0,05
Association with BDA environment	55.474	24	**0,00**
Relative organisation size	49.879	24	**0,00**
Respondents' seniority in organisations	51.261	30	**0,01**
Organisational location	7.457	6	0,28

From the table above, it is shown that the majority of 48.04% of respondents agree that their industry invest in technological tools to interpret data collected from external sources to be able to identify which information can be useful. This is followed by 43.14% of respondents who are neutral on the matter. These results also show that only 8.82% of respondents disagree that their industry invest in technological tools to interpret data collected from external sources to be able to identify which information can be useful for their industry.

There is an association between type of industry and an industry investing in technological tools to interpret data collected from external sources to be able to identify which information can be useful for their Industry. From the results in the above table, we can say since the p-value is less than our significance level, α=0.05, we can reject the null hypothesis of the test which says that there is no association between type of industry and an industry investing in technological tools to interpret data collected from external sources to be able to identify which information can be useful for their industry. Healthcare enterprises search for suitable technologies to streamline resources for the sake of improving the patient experience and organisational performance (Khanra et al., 2020). Applications of BDA in healthcare are gradually increasing with the growing volume of big data in this context. Implementing data in healthcare often requires the generation and collection of real-time data of high quality. Decision-makers in healthcare organisations can take meaningful action based on valuable insights derived from big data. Healthcare organisations deploy technologies to cope with the changing nature of big data. Moreover, big data in healthcare can be employed to connect different fields to comprehensively study a disease. Therefore, it is important for the healthcare industry to invest in BDA tools to interpret data collected from external sources to be able to identify which information can be useful. We can therefore conclude that there is enough evidence to suggest an association type of industry and an industry investing in technological tools to interpret data collected from external sources to be able to identify which information can be useful for their industry.

Similarly, there is an association between Years of work experience in the field of BDA, BDA environment, relative organisation size, also respondents' seniority in organisations and an industry investing in technological tools to interpret data collected from external sources to be able to identify which information can be useful for their industry.

4.4.2.4. Investing in tools to analyse data

Respondents were also asked about their views on whether their organisation or industry invest in technological tools to analyse data collected from external sources to turn it into useful and meaningful information for the industry. Their responses were also given in Likert scale from strongly disagree to strongly agree.

Table 4.15: Investing in tools to analyse data

Investing in tools to analyse data	Responses		Descriptive statistics				T-test results		
	Frequency	%	N	Mean	Std. Deviation	Std. Error Mean	T	df	Sig. (2-tailed)
Strongly Disagree	1	1.0%	102	4.88	1.25	0.12	39.35	101	0.00
Moderately Disagree	9	8.8%							
Neutral	35	34.3%							
Moderately Agree	26	25.5%							
Agree	17	16.7%							
Strongly Agree	14	13.7%							
Association with Demographical variables									

Demographical variables	Pearson Chi-Square	df	P-value
Awareness of Big Data Analytics capability	2.697a	5	0,75
Type of industry	28.394a	20	0,10
Years of work experience in the field of BDA	35.122a	20	**0,02**
Organisation's tenure in BDA	23.106a	15	0,08
Association with BDA environment	24.638a	20	0,22
Relative organisation size	69.628a	20	**0,00**
Respondents' seniority in organisations	27.761a	25	0,32
Organisational location	9.026a	5	0,11

From the results in the above table, it is shown that more than half of respondents (56%) agree that their industry invest in technological tools to analyse data collected from external sources to turn it into useful and meaningful information for the industry. This is followed by 34% of respondents who are neutral on the matter. These results also show that only 10% of respondents disagree that their industry invest in technological tools to analyse data collected from external sources to turn it into useful and meaningful information for the industry.

There is an association between Years of work experience in the field of BDA and an industry investing in technological tools to analyse data collected from external sources to turn it into useful and meaningful information for the industry. From the results in the above table, we can say since the p-value is less than our significance level, α=0.05, we can reject the null hypothesis of the test which says that there is no association between Years of work experience in the field of BDA and an industry investing in technological tools to analyse data collected from external sources to turn it into useful and meaningful information for the industry. As Big Data in healthcare continues to develop, the amount of raw data will continue to increase at an accelerating rate. By 2020, it was estimated that the data took up to 25 petabytes of storage space. Additionally, the data cleaning, data mining and extraction algorithms, as well as the machine and deep learning processes still in their infancy today, will require significant amount of computing power e although exact values of both size of the data or the power needed are not yet known. (Mikalef, et al., 2019) state that Big Data requires novel technologies that are capable of handling large amounts of diverse and fast-moving data. We can therefore conclude that there is enough evidence to suggest an association between Years of work experience in the field of BDA and an industry investing in technological tools to analyse data collected from external sources to turn it into useful and meaningful information for the industry.

Similarly, there is an association between Relative organisation size in the organisation and an industry investing in technological tools to analyse data collected from external sources to turn it into useful and meaningful information for the industry.

4.4.2.5. Investing to find solution

Respondents were also asked about their views on whether their organisation or industry invest in technological tools and knowledge to find solutions for their clients and to help improve their services and make better informed. Their responses were also given in Likert scale from strongly disagree to strongly agree.

Table 4.16: Investing to find solution

Investing to find solutions	**Responses**		**Descriptive statistics**				**T-test results**		
	Frequency	**%**	**N**	**Mean**	**Std. Deviation**	**Std. Error Mean**	**t**	**df**	**Sig. (2-tailed)**
Moderately Disagree	10	9.8%	102	5.00	1.13	0.11	44.86	101	0.00
Neutral	24	23.53%							
Moderately Agree	34	33.33%							
Agree	24	23.53%							
Strongly Agree	10	9.8%							

Association with Demographical variables			
Demographical variables	**Pearson Chi-Square**	**df**	**P-value**
Awareness of Big Data Analytics capability	2.296	4	0,68
Type of industry	32.708	16	**0,01**
Years of work experience in the field of BDA	22.828	16	0,12
Organisation's tenure in BDA	29.733	12	**0,00**
Association with BDA environment	20.464	16	0,20
Relative organisation size	53.152	16	**0,00**
Respondents' seniority in organisations	40.153	20	**0,00**
Organisational location	6.191	4	0,19

From the results in the above table, it is shown that most respondents (over 66.66%) agree that their industry invest in technological tools and knowledge to find solutions for their clients and to help improve their services and make better informed. This is followed by 23.53% of respondents who are neutral on the matter. These results also show that only 9.8% of respondents disagree that their industry invest in technological tools and knowledge to find solutions for their clients and to help improve their services and make better informed.

There is an association between the type of industry and an industry investing in technological tools and knowledge to find solutions for their clients and to help improve their services and make better informed decisions. From the results in the above table, we can say since the p-value is less than our significance level, α=0.05, we can reject the null hypothesis of the test which says that there is no association between the type of industry and an industry investing in technological tools and knowledge to find solutions for their clients and to help improve their services and make better informed decisions. Studies by (Mehta & Pandit, 2018) indicate that it is difficult to analyse the multi-dimensional healthcare data medical images (X-ray,–MRI images), biomedical signals (EEG, ECG, EMG etc.), audio transcripts, handwritten prescriptions and structured data from EMRs because of its dynamicity and complexity. They further indicated that the healthcare industry can incorporate descriptive and comparative analytics, to improve the quality of care. We can therefore conclude that there is enough evidence to suggest an association between the type of industry and an industry investing in technological tools and knowledge to find solutions for their clients and to help improve their services and make better informed decisions. Similarly, there is an association between Organisation's tenure in BDA, Relative organisation size, and respondents' seniority in organisations and an industry investing in technological tools and knowledge to find solutions for their clients and to help improve their services and make better informed decisions.

4.4.3. Learning BDA capabilities and tools

To explore how health data users can learn about Big Data Analytics capabilities and tools to improve healthcare service delivery, five variables were considered: organization's capacity to learn BD capabilities, Employees' orientation on how new tech will improve service delivery, organization's investment on teaching and training employees about BD, employees encouraged to develop and apply knowledge on BD, employees are knowledgeable about adopted technological tools. The Chi-square statistic was suitable for assessing the significance of the relationship between these "coordinating" variables and the demographic statistics.

4.4.3.1. Ability of the organisation to enable learning, accumulation, and application of BD capabilities

Respondents were also asked about their views on whether their organisation enables learning, accumulation, and application of new knowledge better than their competitors. Their responses were also given in Likert scale from strongly disagree to strongly agree.

Table 4.17: Organisation enables learning, accumulation, and application of new knowledge

Organisation enables learning, accumulation and application of new knowledge	**Responses**		**Descriptive statistics**				**T-test results**		
	Frequency	**%**	**N**	**Mean**	**Std. Deviation**	**Std. Error Mean**	**t**	**df**	**Sig. (2-tailed)**
Strongly Disagree	1	0.98%	102	4.91	1.31	0.13	37.77	101	0.00
Disagree	5	4.90%							
Moderately Disagree	7	6.86%							
Neutral	25	24.51%							
Moderately Agree	21	20.59%							
Agree	37	36.27%							
Strongly Agree	6	5.88%							

Association with Demographical variables			
Demographical variables	**Pearson Chi-Square**	**df**	**P-value**
Awareness of Big Data Analytics capability	7.126	6	0,31
Type of industry	48.202	24	**0,00**
Years of work experience in the field of BDA	39.999	24	**0,02**
Organisation's tenure in BDA	41.831	18	**0,00**
Association with BDA environment	32.600	24	0,11
Relative organisation size	52.688	24	**0,00**
Respondents' seniority in organisations	23.213	30	0,81
Organisational location	13.092	6	**0,04**

From the results in the above table, table 4.17, it is shown that most respondents (over 62.745%) agree that their organisation enables learning, accumulation, and application of new knowledge better than their competitors. This is followed by 24.51% of respondents who are neutral on the matter. These results also show that only 12.745% of respondents disagree that their organisation enables learning, accumulation, and application of new knowledge better than their competitors.

There is an association between the type of industry and the ability of an organisation to enable learning, accumulation, and application of new knowledge better than our competitors. From the results in the above table, we can say since the p-value is less than our significance level, α=0.05, we can reject the null hypothesis of the test which says that there is no association between the type of industry and the ability of an organisation to enable learning, accumulation, and application of new knowledge better than our competitors. Healthcare and Pharmaceutical companies, independently of the company size, are extracting information from different sources and with the main objective to apply the knowledge of the collected data into a better and more informed decision support processes and reveal meaningful business insights and data outputs to scrutinize business models and business approaches (Pesqueira et al., 2020). Industries should have a strategic focus on how to carry out their big data projects within themselves, including the healthcare industry. Studies by (Pesqueira et al., 2020) indicated that traditionally, organizations have developed data management strategies to manage data infrastructures, tools, applications, and services that support organizations' functions and processes. However, if organisations want to use big data business strategies, they must implement advanced Big Data technologies. In that manner the healthcare industry and Big Data transformation strategies reflect industry's' perspectives on data management and consider the technical and human resources and capabilities required to digitalize organizations' structures, products, services, processes, and business models (Pesqueira et al., 2020). We can therefore conclude that there is enough evidence to suggest an association between the type of industry and the ability of an organisation to enable learning, accumulation, and application of new knowledge better than their competitors. Similarly, there is an association between years of work experience in the field of BDA, Organisation's tenure in BDA, Relative organisation size, also between organisational location and the ability of an organisation to enable learning, accumulation, and application of new knowledge better than their competitors.

4.4.3.2. Employee Orientation programme

Respondents were also asked about their views on whether the extensive employee orientation program for new employees to ensure employees share the corporate vision and purpose. Their responses were also given in Likert scale from strongly disagree to strongly agree.

Table 4.18: Orientation programme

Employee orientation program	Responses		Descriptive statistics				T-test results		
	Frequency	%	N	Mean	Std. Deviation	Std. Error Mean	t	df	Sig. (2-tailed)
Strongly Disagree	1	1%	102	5.25	1.32	0.13	40.26	101	0.00
Disagree	7	7%							
Moderately Disagree	2	2%							
Neutral	7	7%							
Moderately Agree	37	36%							
Agree	35	34%							
Strongly Agree	13	13%							

Association with Demographical variables			
Demographical variables	**Pearson Chi-Square**	**df**	**P-value**
Awareness of Big Data Analytics capability	6.434	6	0.38
Type of industry	65.953	24	**0.00**
Years of work experience in the field of BDA	23.321	24	0.50
Organisation's tenure in BDA	25.448	18	0.11
Association with BDA environment	29.193	24	0.21
Relative organisation size	49.452	24	**0.00**
Respondents' seniority in organisations	41.111	30	0.09
Organisational location	9.220	6	0.16

From the results in table 4.18, it is shown that most respondents (83%) agree that their organisation offers an extensive employee orientation program for new employees to ensure employees share the corporate vision and purpose. This is followed by 10% of respondents who disagree that there is an extensive employee orientation program for new employees to ensure employees share the corporate vision and purpose in their organisation. These results also show that only 7% of respondents are neutral on the matter.

There is an association between relative organisation size and extensive employee orientation program for new employees to ensure employees share the corporate vision and purpose. From the results in the above table, we can say since the p-value is less than our significance level, α=0.05, we can reject the null hypothesis of the test which says that there is no association between Relative organisation size and extensive employee orientation program for new employees to ensure employees share the corporate vision and purpose. (Pesqueira et al., 2020) indicate that big data professionals within the different industries, including healthcare, should possess a range of different skills. This is because, these professionals must demonstrate critical and unique capabilities to develop novel and pioneering improvements in the way organizations are implementing and developing big data projects, which leads to achieving greater organizational effectiveness. While (Shahbaz et al., 2019b) indicated that the organizations should encourage employees to learn new skills, tasks, and programs. We can therefore conclude that there is enough evidence to suggest an association between number of employees in the organisation and extensive employee orientation program for new employees to ensure employees share the corporate vision and purpose.

4.4.3.3. Investing in assisting the organisation

Respondents were also asked about their views on whether they invest in targeted training and support at all levels of their organisation to assist their organisation to understand or know how to use data that is available. Their responses were also given in Likert scale from strongly disagree to strongly agree.

Table 4.19: Investing in assisting the organisation

Invest in assisting the organisation	**Responses**		**Descriptive statistics**				**T-test results**		
	Frequency	**%**	**N**	**Mean**	**Std. Deviation**	**Std. Error Mean**	**t**	**df**	**Sig. (2-tailed)**
Strongly Disagree	1	0.98%	102	4.98	1.21	0.12	41.56	101	0.00
Disagree	4	3.922%							
Moderately Disagree	3	2.941%							
Neutral	23	22.549%							
Moderately Agree	37	36.275%							
Agree	25	24.510%							
Strongly Agree	9	8.824%							

Association with Demographical variables			
Demographical variables	Pearson Chi-Square	df	P-value
Awareness of Big Data Analytics capability	8.849	6	0.18
Type of industry	50.065	24	**0.00**
Years of work experience in the field of BDA	68.579	24	**0.00**
Organisation's tenure in BDA	41.403	18	**0.00**
Association with BDA environment	26.178	24	0.34
Relative organisation size	71.758	24	**0.00**
Respondents' seniority in organisations	41.980	30	0.07
Organisational location	13.278	6	**0.04**

From the results in table 4.19, it is shown that most respondents (69.609%) agree that they invest in targeted training and support at all levels of their organisation to assist their organisation to understand or know how to use data that is available. This is followed by 22.549% of respondents who are neutral on the matter. These results also show that only 7.843% of respondents disagree that they invest in targeted training and support at all levels of their organisation to assist their organisation to understand or know how to use data that is available.

There is an association between the type of industry and investing in targeted training and support at all levels of the organisation to assist the organisation to understand or know how to use data that is available. From the results in the above table, we can say since the p-value is less than our significance level, $\alpha=0.05$, we can reject the null hypothesis of the test which says that there is no association between the type of industry and investing in targeted training and support at all levels of the organisation to assist the organisation to understand or know how to use data that is available. Even with huge potential benefits, the healthcare industry is in its nascent stage for adoption of Big Data analytics. The studies by (Mehta & Pandit, 2018) indicated that with the huge amount of data available, there are more challenges to be faced and there is a lack of knowledge about which data to use and for what purpose. Furthermore, to extract meaningful insights and valuable information from Big Data, Training key personnel to use BDA. To extract meaningful insights and valuable information from Big Data, healthcare professionals should be trained with BDA competencies. This is critical for healthcare, because incorrect interpretation of the reports generated could lead to unanticipated consequences.

We can therefore conclude that there is enough evidence to suggest an association between the type of industry and investing in targeted training and support at all levels of the organisation to assist the organisation to understand or know how to use data that is available. Similarly, there is an association between Years of work experience in the field of BDA, organisation's tenure in BDA, relative organisation size and organisational locationand investing in targeted training and support at all levels of the organisation to assist the organisation to understand or know how to use data that is available.

4.4.3.4. Encouraged to expand BD knowledge and capacities

Respondents were also asked about the frequency that people in their organisations are encouraged to expand their capacities to achieve more and apply new capabilities. Their responses were giving the following themes; never, rarely, very rarely, occasionally, frequently, very frequently and always.

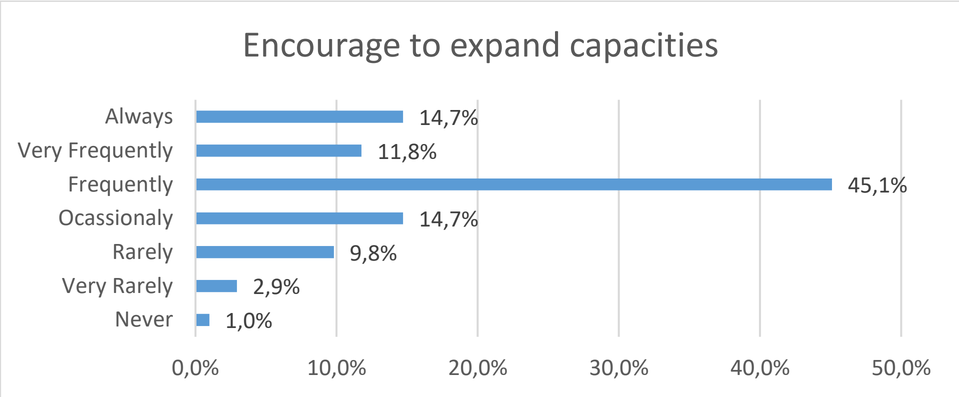


Figure 4.16: Expand capabilities

From the results in figure 4.16, it is shown that most respondents (56.9%) say that people in their organisation are frequently encouraged to expand their capacities to achieve more and apply new capabilities. 14.7% of respondents say that they are always encouraged to expand their capacities to achieve more and apply new capabilities. Another 14.7% of respondents say that they are occasionally encouraged to expand their capacities to achieve more and apply new capabilities. Respondents who say that they are rarely encouraged to expand their capacities to achieve more and apply new capabilities in their organisations account for 12.7 % of total responses. There is 1% of respondents who say they are never encouraged to expand their capacities to achieve more and apply new capabilities.

Table 4.20: Test for association of encourage and expand capabilities with demographic characteristics

Demographical variables	Pearson Chi-Square	df	P-value
Awareness of Big Data Analytics capability	7.686	6	0.26
Type of industry	35.108	24	0.07
Years of work experience in the field of BDA	20.062	24	0.69
Organisation's tenure in BDA	22.016	18	0.23
Association with BDA environment	32.785	24	0.11
Relative organisation size	47.807	24	**0.00**
Respondents' seniority in organisations	29.271	30	0.50
Organisational location	10.444	6	0.11

There is an association between continuously encouraging people in the organisation to expand their capacities to achieve more and apply new capabilities and relative organisation size. From the results in the above table, we can say since the p-value is less than our significance level, α=0.05, we can reject the null hypothesis of the test which says that there are no association continuously encouraging people in the organisation to expand their capacities to achieve more and apply new capabilities and number of employees in the organisation. The studies by (Shahbaz et al., 2019) indicated that the adoption of BDA is still in the initial stages, in which many healthcare organizations are thinking about adopting BDA systems. The present is an optimal time to adopt/implement BDA systems, especially in healthcare organizations, with an aim of providing better health-care facilities by maintaining patients' health records and formulating better strategies. Furthermore, they proposed that the organizations should encourage employees to learn new skills, tasks, and programs. We can therefore conclude that there is enough evidence to suggest an association between continuously encouraging people in the organisation to expand their capacities to achieve more and apply new capabilities and relative organisation size.

4.4.3.5. Knowledge and skills

Respondents were also asked if they were knowledgeable and skilled of the adopted technological tools. Their responses were giving the following themes; never, rarely, very rarely, occasionally, frequently, very frequently and always.

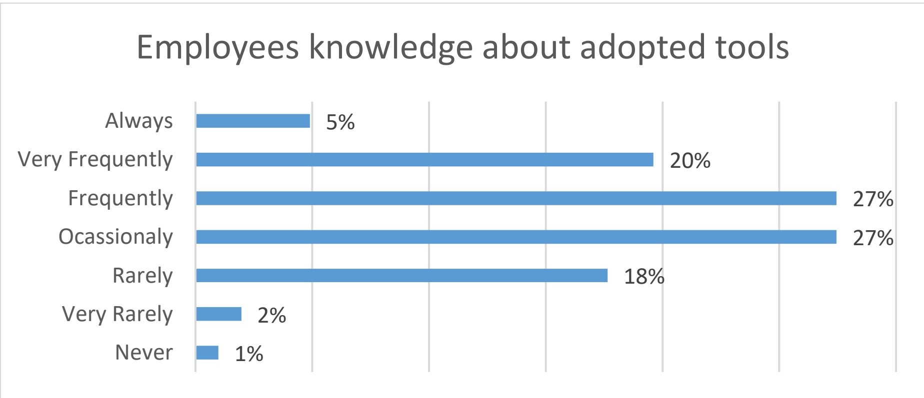


Figure 4.17: Employees knowledge about adopted tools

From the results in figure 4.17, it is shown that most respondents (37%) say that people in their organisation are frequently knowledgeable and skilled to adopt technological tools. 5% of respondents say that they are always knowledgeable and skilled of the adopted technological tools. 27% of respondents say that they are occasionally knowledgeable and skilled to adopt technological tools. Respondents who say that they are rarely knowledgeable and skilled to adopt technological tools in their organisations account for 20 % of total responses. There is 1% of respondents who say they are never knowledgeable and skilled to adopt technological tools.

Table 4.21: Test for association of acknowledgeable and skilled with demographic characteristics

Demographical variables	Pearson Chi-Square	df	P-value
Awareness of Big Data Analytics capability	9.985	6	0.13
Type of industry	56.385	24	**0.00**
Years of work experience in the field of BDA	25.906	24	0.36
Organisation's tenure in BDA	34.912	18	**0.01**
Association with BDA environment	33.936	24	0.09
Relative organisation size	50.934	24	**0.00**
Respondents' seniority in organisations	38.391	30	0.14
Organisational location	10.577	6	0.10

There is an association between knowledgeability and skilfulness of the adopted technological tools by people working in the organisation and the type of industry. From the results in the above table, we can say since the p-value is less than our significance level, $\alpha=0.05$, we can reject the null hypothesis of the test which says that there is no association between knowledgeability and skilfulness of the adopted technological tools by people working in the organisation and the type of industry. The study by (Shahbaz et al., 2019) indicated that successful adoption of BDA depends on user considerations in terms of its convenience of use, which employs processing of large-scale and heterogeneous data. However, the intensity of difficulty and ease of using BDA vary from person to person. Also, individuals with the intention to use BDA will lead to the actual use of BDA. The studies by (Pesqueira et al., 2020) Indicates that big data professionals within the different industries, including healthcare, should possess a range of different skills. We can therefore conclude that there is enough evidence to suggest an association between knowledgeability and skilfulness of the adopted technological tools by people working in the organisation and the type of industry. Similarly, there is an association between knowledgeability and skilfulness of the adopted technological tools by people working in the organisation and organisation's tenure in BDA and relative organisation size.

4.4.4. Integrating BDA in healthcare sector

To explore how the healthcare sector integrates BDA to improve service delivery, seven variables were considered: Ability to adopt new practices to improve service delivery, knowledgeable that innovation is necessary for the future of the organisation, internal politics influences decision making about new policies and practices, BD improves service delivery, BD improves overall financial performance, there is a central database, BD tools available. The data type was categorical; therefore, the Chi-square statistic was suitable for assessing the significance of the relationship between these "coordinating" variables and the demographic statistics.

4.4.4.1. Adopt new and cutting-edge practices

Respondents were also asked about their views on adoption of new and cutting-edge practices to continuously improve product or service delivery. Their responses were given in Likert scale from strongly disagree to strongly agree.

Table 4.22: Adopt new and cutting-edge practices

Adopt new and cutting-edge practices	**Responses**		**Descriptive statistics**				**T-test results**		
	Frequency	**%**	**N**	**Mean**	**Std. Deviation**	**Std. Error Mean**	**t**	**df**	**Sig. (2-tailed)**
Disagree	1	1%	102	5.90	1.14	0.11	52.33	101	0.00
Moderately Disagree	1	1%							
Neutral	11	11%							
Moderately Agree	22	22%							
Agree	26	25%							
Strongly Agree	41	40%							

Association with Demographical variables			
Demographical variables	**Pearson Chi-Square**	**df**	**P-value**
Awareness of Big Data Analytics capability	9.719	5	0.08
Type of industry	39.157	20	**0.01**
Years of work experience in the field of BDA	68.971	20	**0.00**
Organisation's tenure in BDA	17.378	15	0.30
Association with BDA environment	34.831	20	**0.02**
Relative organisation size	46.996	20	**0.00**
Respondents' seniority in organisations	47.990	25	**0.00**
Organisational location	5.729	5	0.33

From the results in table 4.22, it is shown that most respondents (87%) agree that it is important to adopt new and cutting-edge practices to continuously improve product or service delivery. This is followed by 11% of respondents who are neutral on the matter. These results also show that only 2% of respondents disagree that it is important to adopt new and cutting-edge practices to continuously improve product or service delivery.

There is an association between adopting new and cutting-edge practices to continuously improve product or service delivery and the type of industry. From the results in the above table, we can say since the p-value is less than our significance level, $\alpha=0.05$, we can reject the null hypothesis of the test which says that there is no association between adopting new and cutting-edge practices to continuously improve product or service delivery and the type of industry. BDA has shown distinctive advantages on improving healthcare efficiency. BDA can recognize individuals' healthcare conditions, identify risks for serious health problems, and provide personalized healthcare services, etc. (Wu, et al., (2017). BDA has the potential to transform business and clinical models for smart and efficient delivery of care (Mehta & Pandit, 2018). Data related to healthcare are generated at a very high pace, and existing systems are unable to store and analyse the huge volume, velocity, and variety of data. Therefore, a need exists for a system with the ability to store and analyse data with high volumes, velocities, and variety, all of which are provided by BDA systems (Shahbaz et al., 2019). We can therefore conclude that there is enough evidence to suggest an association between adopting new and cutting-edge practices to continuously improve product or service delivery and the type of industry.

Similarly, there is an association between adopting new and cutting-edge practices to continuously improve product or service delivery and years of work experience in the field of BDA. Also, association with BDA environment, relative organisation size and organisational location.

4.4.4.2. Innovation is a necessity for the organisation's future

Respondents were also asked about their views on whether innovation is a necessity for the organisation's future. Their responses were given in Likert scale from strongly disagree to strongly agree.

Table 4.23: Innovation is a necessity for the organisation's future

Innovation is a necessity for the organisation's future	**Responses**		**Descriptive statistics**				**T-test results**		
	Frequency	**%**	**N**	**Mean**	**Std. Deviation**	**Std. Error Mean**	**t**	**df**	**Sig. (2-tailed)**
Strongly Disagree	2	2%	102	5.57	1.23	0.12	45.69	101	0.00
Moderately Disagree	2	2%							
Neutral	10	10%							
Moderately Agree	36	35%							
Agree	24	24%							
Strongly Agree	28	27%							

Association with Demographical variables

Demographical variables	**Pearson Chi-Square**	**df**	**P-value**
Awareness of Big Data Analytics capability	9.780	5	0.08
Type of industry	20.396	20	0.43
Years of work experience in the field of BDA	40.586	20	**0.00**
Organisation's tenure in BDA	8.179	15	0.92
Association with BDA environment	36.393	20	**0.01**
Relative organisation size	46.236	20	**0.00**
Respondents' seniority in organisations	35.171	25	0.09
Organisational location	8.979	5	0.11

From the results in the table above, it is shown that most respondents (86%) agree that innovation is an absolute necessity for the organisation's future. This is followed by 10% of respondents who are neutral on the matter. These results also show that only 4% of respondents disagree that innovation is an absolute necessity for the organisation's future.

There is an association between organisation's belief, innovation and the type of industry. From the results in the above table, we can say since the p-value is less than our significance level, α=0.05, we can reject the null hypothesis of the test which says that there is no association between organisation's belief innovation and the type of industry. The volume of data related to healthcare organizations has grown dramatically in past years and is expected to increase in coming years due to the use of innovative technologies (Shahbaz et al., 2019). Technological competency is fundamental in facilitating the use of big data for analysis. Studies by (Shamim et al., 2019) indicated that Big data decision making requires the use of the most effective and cutting-edge technologies to collect, store, analyse and visualise data. BDA techniques can be applied to the massive amount of prevailing patient-related medical information to analyse outcomes for improvement of the healthcare industry. Recent years have seen improvements in the tools, including open source software, needed to handle the velocity, volume and variety of Big Data (Shamim et al., 2019). We can therefore conclude that there is enough evidence to suggest an association between organisation's belief innovation and the type of industry. Similarly, there is an association between organisation's belief innovation and association with BDA environment. There is an association between organisation's belief innovation and Relative organisation size.

4.4.4.3. Influence

Respondents were also asked about their views on the influence of Internal politics and power struggles on the way decisions are made about policies and practices. Their responses were given in Likert scale from strongly disagree to strongly agree.

Table 4.24: Influence

Influence	Responses		Descriptive statistics				T-test results		
	Frequency	%	N	Mean	Std. Deviation	Std. Error Mean	T	df	Sig. (2-tailed)
Disagree	2	1.96%	102	6.03	1.21	0.12	50.15	101	0.00
Moderately Disagree	2	1.96%							
Neutral	7	6.86%							
Moderately Agree	20	19.61%							
Agree	20	19.61%							
Strongly Agree	51	50.00%							

Association with Demographical variables			
Demographical variables	**Pearson Chi-Square**	**df**	**P-value**
Awareness of Big Data Analytics capability	10.073	5	0.07
Type of industry	36.431	20	**0.01**
Years of work experience in the field of BDA	9.308	20	0.98
Organisation's tenure in BDA	21.324	15	0.13
Association with BDA environment	21.473	20	0.37
Relative organisation size	35.406	20	**0.02**
Respondents' seniority in organisations	35.046	25	0.09
Organisational location	25.537	5	**0.00**

From the results in the table above, it is shown that most respondents (89.22%) agree that internal politics and power struggles influence the way we make decisions about policies and practices. This is followed by 6.86% of respondents who are neutral on the matter. These results also show that only 3.92% of respondents disagree that internal politics and power struggles influence the way we make decisions about policies and practices.

There is an association between the influence of internal politics and power struggles on way the organisation makes decisions about policies and practices and the type of industry. From the results in the above table, we can say since the p-value is less than our significance level, α=0.05, we can reject the null hypothesis of the test which says that there is no association between the influence of internal politics and power struggles on the way the organisation makes decisions about policies and practices and the type of industry. The studies by (Shamim et al., 2019) indicated that the use of big data itself does not yield its maximum benefits until organisations overcome the related managerial challenges, such as leadership focus, internal politics, harnessing talent and technology management and company culture which are even bigger contributing factors than the technical ones. In the big data era, firms are successful not only because they have access to more and better data but mainly because they employ leadership teams who have a clear vision and set clear goals. They further indicated that organisational culture is one of the main challenges for big data management, as employees will not regularly do things that are not part of organisational norms. Thus, Big Data initiative failures are related to organisational culture rather than to data characteristics and technological factors. We can therefore conclude that there is enough evidence to suggest an association between the influence of internal politics and power struggles on the way the organisation and the type of industry. Similarly, there is an association between the influence of internal politics and power struggles on the way the organisation makes decisions about policies and practices and relative organisation size and organisational location.

4.4.4.4. Improve services

Respondents were also asked whether using big data analytics has/will improve services relative to competitors. Their responses were given in Likert scale from strongly disagree to strongly agree.

Table 4.25: Improve services

Improve services	Responses	Descriptive statistics	T-test results

	Frequency	%	N	Mean	Std. Deviation	Std. Error Mean	t	df	Sig. (2-tailed)
Moderately Disagree	4	3.9%	102	5.93	1.23	0.12	48.75	101	0.00
Neutral	12	11.8%							
Moderately Agree	20	19.6%							
Agree	17	16.7%							
Strongly Agree	49	48.0%							

Association with Demographical variables

Demographical variables	Pearson Chi-Square	df	P-value
Awareness of Big Data Analytics capability	5.229	4	0.26
Type of industry	15.834a	16	0.46
Years of work experience in the field of BDA	12.659	16	0.70
Organisation's tenure in BDA	18.068	12	0.11
Association with BDA environment	10.608a	16	0.83
Relative organisation size	22.626	16	0.12
Respondents' seniority in organisations	39.200	20	**0.01**
Organisational location	11.422	4	**0.02**

From the results in the table above, it is shown that most respondents (84.3%) said that using BDA will improve services relative to competitors. This is followed by 11.8% of respondents who are neutral on the matter. These results also show that only 3.9% of respondents are saying that using big data analytics has not improved/will not improve services relative to competitors.

There is an association between whether using BDA will improve services relative to competitors and Respondents' seniority in organisations. From the results in the above table, we can say since the p-value is less than our significance level, α=0.05, we can reject the null hypothesis of the test which says that there is no association between whether using BDA will improve services relative to competitors and Respondents' seniority in organisations. The studies by (Panagiota Galetsi et al., 2020) indicated that the benefits from the analytics in healthcare have been summarized in the ability to provide comparative effectiveness research to determine more clinically relevant and cost-effective ways to diagnose and treat patients. Furthermore, they indicated capabilities from the use of BDA in the health industry such as better diagnosis for provision of more personalized healthcare, supporting/replacing professionals' decision-making with automated, new business models, products and services, enabling experimentation, expose variability and improve performance, healthcare information sharing and coordination, creating data transparency, identifying patient care-risk, offering customized actions by segmenting populations, reducing expenditure while maintaining quality, and protecting privacy. We can therefore conclude that there is enough evidence to suggest an association between whether using big data analytics has/will improve services relative to competitors and employee position. Similarly, there is an association between the location of the organisation and whether using BDA will improve services relative to competitors.

4.4.4.5. Improve overall financial performance

Respondents were whether using big data analytics will improve overall financial performance relative to competitors. Their responses were given in Likert scale from strongly disagree to strongly agree.

Table 4.25: Improve overall financial performance

<table>
<tr><th rowspan="2">Improve overall financial performance</th><th colspan="2">Responses</th><th colspan="4">Descriptive statistics</th><th colspan="3">T-test results</th></tr>
<tr><th>Frequency</th><th>%</th><th>N</th><th>Mean</th><th>Std. Deviation</th><th>Std. Error Mean</th><th>t</th><th>df</th><th>Sig. (2-tailed)</th></tr>
<tr><td>Strongly Disagree</td><td>1</td><td>1.0%</td><td rowspan="7">102</td><td rowspan="7">6.06</td><td rowspan="7">1.15</td><td rowspan="7">0.11</td><td rowspan="7">53.19</td><td rowspan="7">101</td><td rowspan="7">0.00</td></tr>
<tr><td>Disagree</td><td>1</td><td>1.0%</td></tr>
<tr><td>Moderately Disagree</td><td>1</td><td>1.0%</td></tr>
<tr><td>Neutral</td><td>5</td><td>4.9%</td></tr>
<tr><td>Moderately Agree</td><td>18</td><td>17.6%</td></tr>
<tr><td>Agree</td><td>30</td><td>29.4%</td></tr>
<tr><td>Strongly Agree</td><td>46</td><td>45.1%</td></tr>
<tr><th colspan="10">Association with Demographical variables</th></tr>
</table>

Demographical variables	Pearson Chi-Square	df	P-value
Awareness of Big Data Analytics capability	5.531	6	0.48
Type of industry	24.059	24	0.46
Years of work experience in the field of BDA	58.088	24	**0.00**
Organisation's tenure in BDA	18.259	18	0.44
Association with BDA environment	23.683	24	0.48
Relative organisation size	26.894	24	0.31
Respondents' seniority in organisations	27.747	30	0.58
Organisational location	6.122	6	0.41

From the results in the table above, it is shown that most respondents (92.1%) said that using BDA will improve overall financial performance relative to competitors. This is followed by 4.9% of respondents who are neutral on the matter. These results also show that only 3% of respondents said that using BDA will not improve overall financial performance relative to competitors.

There is an association between the improvement of overall financial performance relative to competitors by using BDA and Years of work experience in the field of BDA. From the results in the above table, we can say since the p-value is less than our significance level, α=0.05, we can reject the null hypothesis of the test which says that there is no association between the improvement of overall financial performance relative to competitors by using big data analytics and Years of work experience in the field of BDA. Studies by (Mehta & Pandit, 2018), (Rajabion, et al., 2019) and (Yu et al., 2021) indicated several challenges and opportunities that have been experienced in BDA implementation. (Rajabion, et al., 2019) indicated that by implementing BDA into the healthcare industry, it is predicted that at least 300–450 billion dollars a year is saved by healthcare industries. (Mehta & Pandit, 2018) indicated that BDA helps the healthcare industry with personalization of predictions, targeted treatment and cost-effectiveness of care, and reduction in waste of resources. Thus, when applied to the healthcare data, it has the potential to identify patterns and lead to improved healthcare quality and reduced costs and enable timely decision-making. We can therefore conclude that there is enough evidence to suggest an association between the improvement of overall financial performance relative to competitors by using big data analytics and Years of work experience in the field of BDA.

4.4.4.6 Offices are connected to the central office for analytics

Respondents were also asked whether all other (e.g., remote, branch, and mobile) offices are connected to the central office for analytics. Their responses were given in Likert scale from strongly disagree to strongly agree.

Table 4.26: Offices are connected to the central office for analytics

Offices are connected to the central office for analytics	**Responses**		**Descriptive statistics**				**T-test results**		
	Frequency	**%**	**N**	**Mean**	**Std. Deviation**	**Std. Error Mean**	**t**	**df**	**Sig. (2-tailed)**
Strongly Disagree	7	6.9%							
Moderately Disagree	4	3.9%							
Neutral	18	17.6%	102	5.15	1.61	0.16	32.35	101	0.00
Moderately Agree	28	27.5%							
Agree	21	20.6%							
Strongly Agree	24	23.5%							

Association with Demographical variables			
Demographical variables	**Pearson Chi-Square**	**df**	**P-value**
Awareness of Big Data Analytics capability	10.590	5	0.06
Type of industry	36.907	20	**0.01**
Years of work experience in the field of BDA	42.159	20	**0.00**
Organisation's tenure in BDA	25.062a	15	0.05
Association with BDA environment	52.298a	20	**0.00**
Relative organisation size	44.142a	20	**0.00**
Respondents' seniority in organisations	39.668a	25	**0.03**
Organisational location	6.845	5	0.23

From the results in the table above, it is shown that most respondents (71.6%) agree all other (e.g., remote, branch, and mobile) offices are connected to the central office for analytics. This is followed by 17.6% of respondents who are neutral on the matter. These results also show that only 10.8% of respondents disagree that all other (e.g., remote, branch, and mobile) offices are connected to the central office for analytics.

There is an association between the offices being connected to the central office for analytics and type of industry. From the results in the above table, we can say since the p-value is less than our significance level, $\alpha=0.05$, we can reject the null hypothesis of the test which says that there is no association between the offices being connected to the central office for analytics and type of industry. The studies by (Mehta & Pandit, 2018) indicated that much of the highly valuable healthcare data is in unstructured or semi-structured form and it is difficult to extract useful information using traditional data analytical tools & techniques. Furthermore, they indicated that because of large data sets, it is has become impossible for the human ability to process this data without effective decision support systems, this has created a need for the incorporation of BDA into healthcare as it can analyse a wide variety of complex data and generate valuable insights. BDA enables the incorporation of longitudinal patient data with data from different, structured, and unstructured Big Data sources (Mehta & Pandit, 2018). By linking data from different sources and discerning patterns the predictive power can be used for transforming real-time data from different departments into valuable information which will lead to improved service delivery. We can therefore conclude that there is enough evidence to suggest an association between the offices being connected to the central office for analytics and type of industry.

Similarly, there is an association between the offices being connected to the central office for analytics and years of work experience in the field of BDA. (Mehta & Pandit, 2018) indicated that even with huge potential benefits, the healthcare industry is in its developing stage for adoption of BDA, thus, the “newness” in the arena of BDA provides an opportunity to implement solutions that are much more relevant. There is an association between the offices being connected to the central office for analytics and association with BDA environment. (Pesqueira et al., 2020) indicated that Big Data professionals within the different industries, including healthcare, should possess a range of different skills, thus, to enable them to demonstrate critical and unique capabilities to develop new improvements in the way these organizations are implementing and developing Big Data projects, which leads to achieving greater organizational effectiveness or improved service delivery. There is also an association between the offices being connected to the central office for analytics and relative organisation size and an association between the offices being connected to the central office for analytics and respondents' seniority in organisations.

4.4.4.7. Analytics systems

Respondents were also asked whether their organisation has the foremost available analytics systems compared to rivals within their industry. Their responses were given in Likert scale from strongly disagree to strongly agree.

Table 4.27: Analytics systems

<table>
<tr><th rowspan="2">Analytics systems</th><th colspan="2">Responses</th><th colspan="4">Descriptive statistics</th><th colspan="3">T-test results</th></tr>
<tr><th>Frequency</th><th>%</th><th>N</th><th>Mean</th><th>Std. Deviation</th><th>Std. Error Mean</th><th>t</th><th>df</th><th>Sig. (2-tailed)</th></tr>
<tr><td>Strongly Disagree</td><td>6</td><td>5.9%</td><td rowspan="7">102</td><td rowspan="7">4.75</td><td rowspan="7">1.60</td><td rowspan="7">0.16</td><td rowspan="7">30.00</td><td rowspan="7">101</td><td rowspan="7">0.00</td></tr>
<tr><td>Disagree</td><td>7</td><td>6.9%</td></tr>
<tr><td>Moderately Disagree</td><td>4</td><td>3.9%</td></tr>
<tr><td>Neutral</td><td>22</td><td>21.6%</td></tr>
<tr><td>Moderately Agree</td><td>22</td><td>21.6%</td></tr>
<tr><td>Agree</td><td>32</td><td>31.4%</td></tr>
<tr><td>Strongly Agree</td><td>9</td><td>8.8%</td></tr>
<tr><th colspan="10">Association with Demographical variables</th></tr>
<tr><th colspan="6">Demographical variables</th><th colspan="2">Pearson Chi-Square</th><th>df</th><th>P-value</th></tr>
<tr><td colspan="6">Awareness of Big Data Analytics capability</td><td colspan="2">16.297</td><td>6</td><td>0.01</td></tr>
<tr><td colspan="6">Type of industry</td><td colspan="2">59.710</td><td>24</td><td>0.00</td></tr>
<tr><td colspan="6">Years of work experience in the field of BDA</td><td colspan="2">52.709a</td><td>24</td><td>0.00</td></tr>
<tr><td colspan="6">Organisation's tenure in BDA</td><td colspan="2">44.596</td><td>18</td><td>0.00</td></tr>
<tr><td colspan="6">Association with BDA environment</td><td colspan="2">52.478</td><td>24</td><td>0.00</td></tr>
<tr><td colspan="6">Relative organisation size</td><td colspan="2">64.565</td><td>24</td><td>0.00</td></tr>
<tr><td colspan="6">Respondents' seniority in organisations</td><td colspan="2">66.395</td><td>30</td><td>0.00</td></tr>
<tr><td colspan="6">Organisational location</td><td colspan="2">6.314</td><td>6</td><td>0.39</td></tr>
</table>

From the results in the table above, it is shown that most respondents (61.8%) agree that their organisation has the foremost available analytics systems compared to rivals within their industry. This is followed by 21.6% of respondents who are neutral on the matter. These results also show that only 16.7% of respondents disagree that their organisation has the foremost available analytics systems compared to rivals within their industry.

There is an association between availability of foremost available analytics systems in the organisation and Awareness of Big Data Analytics capability. From the results in the above table, we can say since the p-value is less than our significance level, $\alpha=0.05$, we can reject the null hypothesis of the test which says that there is no association between availability of foremost available analytics systems in the organisation and Awareness of Big Data Analytics capability. Studies indicated that BDA awareness emphasizes that awareness of BDA can help in ensuring that BDA is properly implemented in organizations. For instance, (Khanra et al., 2020) that healthcare organisations search for suitable technologies to streamline resources for the sake of improving the patient experience and organisational performance. They further indicated that advances in new peripheral technologies may increase the quality of the insights derived by BDA in healthcare. Zhang et al. (2022) indicated that organizations compete to connect Big Data capabilities with organizational learning infrastructure to respond to these new Big Data and social media developments. This means that organisations are aware that employing BDA in healthcare will allow for improved service delivery through its capability of enabling connections within different fields (Khanra et al., 2020). We can therefore conclude that there is enough evidence to suggest an association between availability of foremost available analytics systems in the organisation and awareness or association with a Big Data Analytics Capability within the organisation.

Similarly, there is an association between availability of foremost available analytics systems in the organisation and type of industry. (Khanra et al., 2020) indicated that BDA seemingly helps hospital management improve their efficiency in delivering health-care services and in providing customised care to patients, thus BDA awareness is vital in the healthcare industry. There is an association between availability of foremost available analytics systems in the organisation and years of work experience in the field of BDA, an association between availability of foremost available analytics systems in the organisation and organisation’s tenure in BDA, an association between availability of foremost available analytics systems in the organisation and association with BDA environment, an association between availability of foremost available analytics systems in the organisation and relative organisation size and an association between availability of foremost available analytics systems in the organisation and respondents’ seniority in organisations.

4.4.5. Analytics platforms Reconfiguration

To explore how BDA can be used in the reconfiguration of Healthcare Data Management to improve healthcare services, nine variables were considered: technological tools can be used across the organisation, our user interfaces provide transparent access to all platforms and applications, reusable software modules are widely used in new analytics model development, end-users can use software provided to create their own analytics applications, data is sourced from outside and is easily analyzed, decisions are made easily because of the new adapted technology, the legacy system within our organisation restricts the development of new applications, our analytics personnel are very capable in terms of programming skills, our analytics personnel are very capable in terms of teaching others in our business. The data type was categorical; therefore, the Chi-square statistic was suitable for assessing the significance of the relationship between these “coordinating” variables and the demographic statistics.

4.4.5.1. Multiple analytics platforms

Respondents were also asked about the frequency that software applications are transported and used across multiple analytics platforms within the organisation. Their responses were giving the following themes; never, rarely, very rarely, occasionally, frequently, very frequently and always.

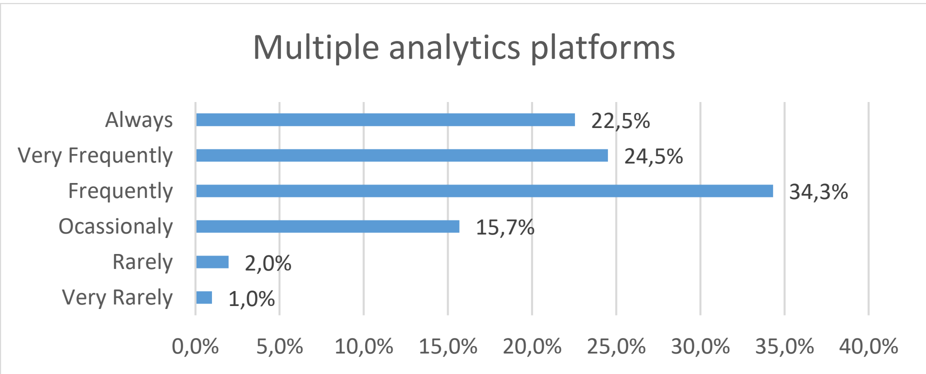


Figure 4.18: Bar graph of analytics platforms

From the results in the graph above, it is shown that most respondents (58.8%) say that software applications are frequently transported and used across multiple analytics platforms within the organisation. 5% of respondents say that they are always knowledgeable and skilled of the adopted technological tools. 15.7% of respondents say that software applications are occasionally transported and used across multiple analytics platforms within the organisation. Respondents who say that software applications are rarely transported and used across multiple analytics platforms within the organisation account for 3 % of total responses.

Table 4.28: Association between multiple analytics platforms with demographical characteristics

Demographical variables	Pearson Chi-Square	Df	P-value
Awareness of Big Data Analytics capability	21.577	5	**0.00**
Type of industry	41.984	20	**0.00**
Years of work experience in the field of BDA	22.742	20	0.30
Organisation's tenure in BDA	26.983	15	**0.03**
Association with BDA environment	26.932	20	0.14
Relative organisation size	31.059	20	0.05
Respondents' seniority in organisations	42.609	25	**0.02**
Organisational location	5.256	5	0.39

There is an association between the ability to easily transport software applications and use them across multiple analytics platforms within the organisation and Awareness of Big Data Analytics capability. From the results in the above table, we can say since the p-value is less than our significance level, α=0.05, we can reject the null hypothesis of the test which says that there is no association between the ability to easily transport software applications and use them across multiple analytics platforms within the organisation and Awareness of Big Data Analytics capability. In healthcare, growth comes both from digitizing existing data and from generating new forms of data. Overwhelming volume of existing healthcare data includes personal medical records, radiology images, clinical trial data, FDA submissions, human genetics and population (Feldman et al., 2012). The study by (Sarkar et al., 2021) indicated that the adoption rate of Big Data capabilities has been one of the fastest tech-adoption phenomena in the business world. The study by (Panagiota Galetsi et al., 2020) identified BDA capability that enables healthcare information sharing and coordination. This is gained by the coordination and sharing of health information across healthcare services or even countries to improve of health professionals' decision-making, leaving organisations able to use software applications across multiple platforms. We can therefore conclude that there is enough evidence to suggest an association between the ability to easily transport software applications and use them across multiple analytics platforms within the organisation and Awareness of Big Data Analytics capability.

Similarly, there is an association between the ability to easily transport software applications and use them across multiple analytics platforms within the organisation and type of industry, In the case of the healthcare industry, data comes from clinical and operational information systems (Panagiota Galetsi et al., 2020), thus BDA enables users to use and access data from different departments. There is an association between the ability to easily transport software applications and use them across multiple analytics platforms within the organisation and organisation’s tenure in BDA, organizations that are new in adopting BDA can learn from implementation challenges that have been reported in literature to avoid similar mistakes in the past. Studies by (Mehta & Pandit, 2018), (Chauhan et al., 2021) and (Yu et al., 2021) indicate several challenges and opportunities that have been experienced in BDA implementation and an association between the ability to easily transport software applications and use them across multiple analytics platforms within the organisation and respondents’ seniority in organisations. The study by (Sarkar et al., 2021) indicated that Graduates Digital Upskilling in a competitive environment is essential as healthcare organisations require the skills for improved services.

4.4.5.2. Transparent access

Respondents were also asked about the frequency at which their user interfaces provide transparent access to all platforms and applications. Their responses were giving the following themes; never, rarely, very rarely, occasionally, frequently, very frequently and always.

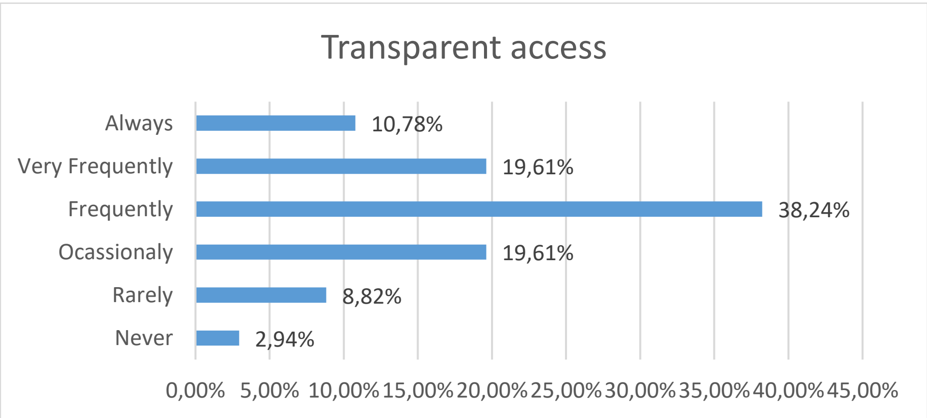


Figure 4.19: Transparent access

From the results in the graph above, it is shown that most respondents (57.85%) say that their user interfaces frequently provide transparent access to all platforms and applications. 10.78 % of respondents say that their user interfaces always provide transparent access to all platforms and applications. 19.61% of respondents say that their user interfaces occasionally provide transparent access to all platforms and applications. Respondents who say that their user interfaces rarely provide transparent access to all platforms and applications account for 8.82% of total responses. There is 2.94% of respondents who say their user interfaces provide transparent access to all platforms and applications.

Table 4.29: Test for association of access transparency with demographic characteristics

Demographical variables	Pearson Chi-Square	df	P-value
Awareness of Big Data Analytics capability	16.198	5	**0.01**
Type of industry	37.531	20	**0.01**
Years of work experience in the field of BDA	25.337	20	0.19
Organisation's tenure in BDA	24.450	15	0.06
Association with BDA environment	20.648	20	0.42
Relative organisation size	40.513a	20	**0.00**
Respondents' seniority in organisations	28.462	25	0.29
Organisational location	5.224	5	0.39

There is an association between the frequency by which user interfaces provide transparent access to all platforms and applications and Awareness of Big Data Analytics capability. From the results in the above table, we can say since the p-value is less than our significance level, α=0.05, we can reject the null hypothesis of the test which says that there is no association between the frequency by which user interfaces provide transparent access to all platforms and applications and Awareness of Big Data Analytics capability. Creating data transparency is a BDA Capability identified by (Panagiota Galetsi et al., 2020). It is about the ability of BDA to collect big data and format them in a standardized way. This capability reduces data identification and analysis time and assists the previous value of coordinating meaningful and comprehensive health-related information. BDA provides transparent access to all departments and applications. We can therefore conclude that there is enough evidence to suggest an association between the frequency by which user interfaces provide transparent access to all platforms and applications and Awareness of Big Data Analytics capability. Similarly, there is an association between the frequency by which user interfaces provide transparent access to all platforms and applications and type of industry. There is also an association between the frequency by which user interfaces provide transparent access to all platforms and applications and relative organisation size.

4.4.5.3. Reusable software modules

Respondents were also asked about the frequency at which reusable software modules are widely used in new analytics model development. Their responses were giving the following themes; never, rarely, very rarely, occasionally, frequently, very frequently and always.

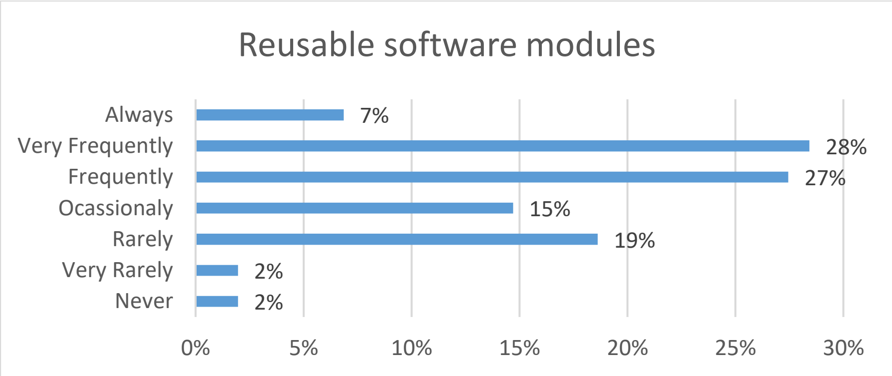


Figure 4.20: Reusable software modules

From the results in the table above, it is shown that most respondents (55%) say that reusable software modules are frequently used in new analytics model development. 7% of respondents say that reusable software modules are always used in new analytics model development. 15% of respondents say that reusable software modules are occasionally used in new analytics model development. Respondents who say that reusable software modules are rarely used in new analytics model development account for 21% of total responses. There is 2% of respondents who say that reusable software modules are never used in new analytics model development.

Table 4.30: Test for association of reusable software modules with demographic characteristics

Demographical variables	Pearson Chi-Square	df	P-value
Awareness of Big Data Analytics capability	16.392	6	**0.01**
Type of industry	42.920	24	**0.01**
Years of work experience in the field of BDA	23.967	24	0.46
Organisation's tenure in BDA	30.069	18	**0.04**
Association with BDA environment	40.466	24	**0.02**
Relative organisation size	69.792	24	**0.00**

Respondents' seniority in organisations	42.631	30	0.06
Organisational location	6.914	6	0.33

There is an association between frequency by which reusable software modules are widely used in new analytics model development and Awareness of Big Data Analytics capability. From the results in the above table, we can say since the p-value is less than our significance level, α=0.05, we can reject the null hypothesis of the test which says that there is no association between frequency by which reusable software modules are widely used in new analytics model development and Awareness of Big Data Analytics capability. The "newness" in the arena of BDA provides an opportunity to implement solutions that are much more relevant and as Big Data in healthcare continues to develop, the amount of raw data will continue to increase at an accelerating rate. (Mehta & Pandit, (2018) highlighted some of the applications of Big Data Technologies like MapReduce and Hadoop for healthcare analytics which can be reused widely in new model development. We can therefore conclude that there is enough evidence to suggest an association between frequency by which reusable software modules are widely used in new analytics model development and Awareness of Big Data Analytics capability.

Similarly, there is an association between frequency by which reusable software modules are widely used in new analytics model development and the type of industry, Organisation's tenure in BDA, Association with BDA environment and Relative organisation size.

4.4.5.4. Software provided

Respondents were also asked about the frequency at which end-users can use software provided to create their own analytics applications. Their responses were giving the following themes; never, rarely, very rarely, occasionally, frequently, very frequently and always.

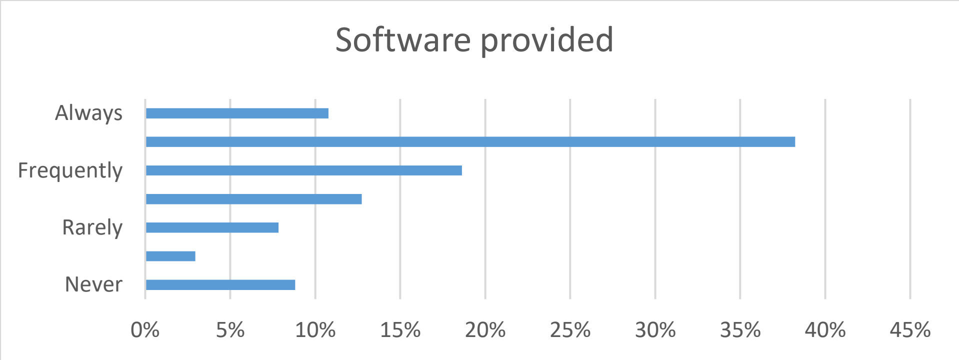


Figure 4.21: Software provided

From the results in the table above, it is shown that most respondents (56.87%) say that end-users frequently use software provided to create their own analytics applications. 10.78% of respondents say that end-users always use software provided to create their own analytics applications. 12.75% of respondents say that end-users occasionally use software provided to create their own analytics applications. Respondents who say that end-users rarely use software provided to create their own analytics applications account for 10.78 % of total responses. There is 8.82% of respondents who say they end-users never use software provided to create their own analytics applications.

Table 4.31: Test for association of software provision with demographic characteristics

Demographical variables	Pearson Chi-Square	df	P-value
Awareness of Big Data Analytics capability	11.371	6	0.08
Type of industry	31.994	24	0.13
Years of work experience in the field of BDA	21.226	24	0.63
Organisation's tenure in BDA	29.604	18	**0.04**
Association with BDA environment	49.032	24	**0.00**
Relative organisation size	43.623	24	**0.01**
Respondents' seniority in organisations	43.034	30	0.06
Organisational location	16.579	6	**0.01**

There is an association between frequency by end-users can use software provided to create their own analytics applications and Organisation's tenure in BDA. From the results in the above table, we can say since the p-value is less than our significance level, α=0.05, we can reject the null hypothesis of the test which says that there is no association between frequency by end-users can use software provided to create their own analytics applications and Organisation's tenure in BDA. Organizations that are new in adopting BDA can learn from implementation challenges that have been reported in literature to avoid similar mistakes in the past. Thus, the "newness" in the arena of BDA provides an opportunity to implement solutions that are much more relevant. (Mehta & Pandit, 2018) and (Chauhan et al., 2021) and (Yu et al., 2021) indicate several challenges and opportunities that have been experienced in BDA implementation. For instance, (Chauhan et al., 2021) indicated that the healthcare sector receives large data sets, from varied resources (structured, unstructured, text, images) which is difficult to be managed with traditional statistical technology. Furthermore, they indicated privacy as a challenge for big healthcare databases, focusing on issues of data authentication, integrity, encryption, auditing, and the availability of data. Furthermore, (Mehta & Pandit, (2018) highlighted some of the applications of Big Data Technologies like MapReduce and Hadoop for healthcare analytics which new organisations can adopt and do away with traditional data analytics tools. We can therefore conclude that there is enough evidence to suggest an association between frequency by end-users can use software provided to create their own analytics applications and Organisation's tenure in BDA. Similarly, there is an association frequency by end-users can use software provided to create their own analytics applications and years of application of big data analytics and association with BDA environment, relative organisation size and organisational location.

4.4.5.5. Data is easily analysed

Respondents were also asked about the frequency at which data is sourced from outside and is easily analysed. Their responses were giving the following themes; never, rarely, very rarely, occasionally, frequently, very frequently and always.

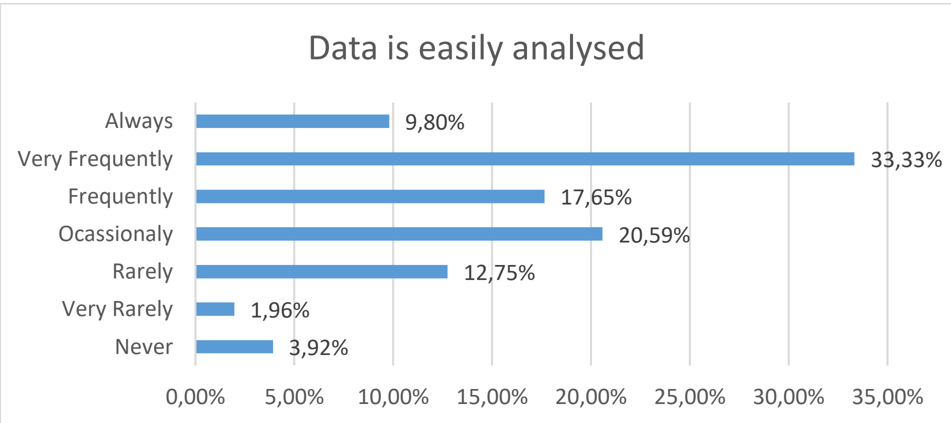


Figure 4.22: Data is easily analysed

From the results in the table above, it is shown that most respondents (50.98%) say that data is frequently sourced from outside and is easily analysed. 9.8% of respondents say that data is always sourced from outside and is easily analysed. 20.59% of respondents say that data is sourced occasionally from outside and is easily analysed. Respondents who say that data is rarely sourced from outside and is easily analysed account for 14.71 % of total responses. There is 3.92% of respondents who say that data is never sourced from outside and is easily analysed.

Table 4.32: Test for association of frequency at which data is sourced from outside and is easily analysed with demographic characteristics

Demographical variables	Pearson Chi-Square	df	P-value
Awareness of Big Data Analytics capability	24.124	6	**0.00**
Type of industry	48.242	24	**0.00**
Years of work experience in the field of BDA	47.851	24	**0.00**
Organisation’s tenure in BDA	35.936	18	**0.01**
Association with BDA environment	49.363	24	**0.00**
Relative organisation size	63.779	24	**0.00**
Respondents’ seniority in organisations	45.254	30	**0.04**
Organisational location	6.194	6	0.40

There is an association between frequency at which data is sourced from outside and is easily analysed and Awareness of Big Data Analytics capability. From the results in the above table, we can say since the p-value is less than our significance level, α=0.05, we can reject the null hypothesis of the test which says that there is no association between frequency at which data is sourced from outside and is easily analysed and Awareness of Big Data Analytics capability. Literature has indicated that big health data comes from various sources and different structures and forms. For instance, the study by (Mehta & Pandit, 2018) which identified two main sources of health big data to be genomics-driven big data and a payer provider big data. Although the application of big data in healthcare services is still in their growing stages. The study by (Sarkar et al., 2021) indicated that the adoption rate of Big Data capabilities has been one of the fastest tech-adoption phenomena in the business world. This means organisations are aware of BDA. We can therefore conclude that there is enough evidence to suggest an association between frequency at which data is sourced from outside and is easily analysed and Awareness of Big Data Analytics capability.

Similarly, there is an association frequency at which data is sourced from outside and is easily analysed and type of industry. Years of work experience in the field of BDA, Organisation's tenure in BDA, Association with BDA environment Relative organisation size Respondents' seniority in organisations.

4.4.5.6. Decisions are made easily

Respondents were also asked about the frequency at which decisions are made because of the new adapted technology. Their responses were giving the following themes; never, rarely, very rarely, occasionally, frequently, very frequently and always.

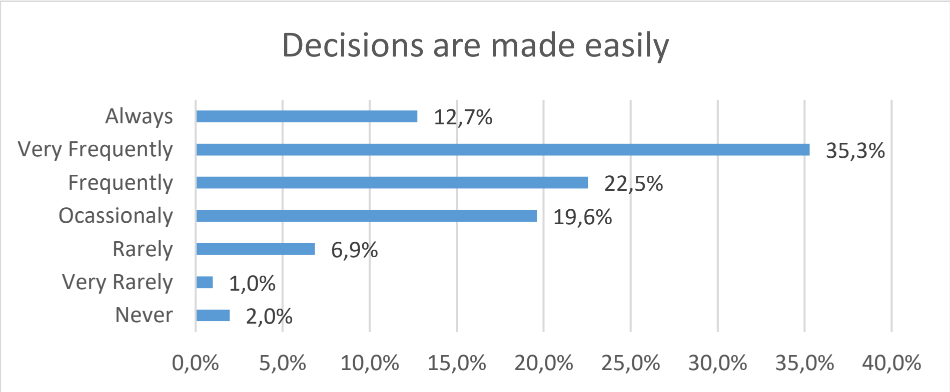


Figure 4.23: Bar graph of decision making

From the results in the table above, it is shown that most respondents (57.8%) say that decisions are frequently made easily because of the new adapted technology. 12.7% of respondents say that decisions are always easily made because of the new adapted technology. 19.6% of respondents say that decisions are occasionally made because of the new adapted technology. Respondents who say decisions are rarely made because of the new adapted technology account for 7.9% of total responses. There is 2% of respondents who say that decisions are never easily made because of the new adapted technology.

Table 4.33: Test for association of decision making with demographic characteristics

Demographical variables	Pearson Chi-Square	df	P-value
Awareness of Big Data Analytics capability	12.981	6	**0.04**
Type of industry	45.770	24	**0.00**
Years of work experience in the field of BDA	37.453	24	**0.04**
Organisation's tenure in BDA	28.995	18	0.05
Association with BDA environment	25.872	24	0.36
Relative organisation size	43.849	24	**0.01**
Respondents' seniority in organisations	42.036	30	0.07
Organisational location	9.507	6	0.15

There is an association between frequency at which decisions are made easily because of the new adapted technology and Awareness of Big Data Analytics capability. From the results in the above table, we can say since the p-value is less than our significance level, α=0.05, we can reject the null hypothesis of the test which says that there is no association between frequency at which decisions are made easily because of the new adapted technology and Awareness of Big Data Analytics capability. Several literatures have indicated that BDA can analyse a wide variety of complex data and generate valuable insights which otherwise would not have been possible using traditional analyses tools. Furthermore, literature on BDA awareness emphasizes that awareness can help in ensuring that BDA is properly implemented in organizations. The healthcare sector is aware of the potential benefits and capabilities of BDA as indicated in the study by (Khanra et al., 2020). BDA has many benefits when applied to the healthcare data. It has the potential to identify patterns and lead to improved healthcare quality & reduced costs and enable timely decision-making (Mehta & Pandit, 2018). Thus, decisions are made easily because of the new adapted technology and Awareness of Big Data Analytics capability. We can therefore conclude that there is enough evidence to suggest an association between frequency at which decisions are made easily because of the new adapted technology and Awareness of Big Data Analytics capability.

Similarly, there is an association frequency at which decisions are made easily because of the new adapted technology and type of industry. Historically, the healthcare industry generates large volumes of data, driven by record keeping, compliance, regulatory requirements, and patient care. While most data is stored in hard copy files, the current trend is towards rapid digitization of these large volumes of data Raghupathi & Raghupathi, (2014). Furthermore, Galetsi et al.,(2020) indicated that healthcare industry could use interactive dynamic Big Data platforms with innovative technologies and tools to advance patient care and services. There is an association frequency at which decisions are made easily because of the new adapted technology and years of work experience in the field of BDA and relative organisation size.

4.4.5.7. The legacy system restricts the development of new applications

Respondents were also asked whether the legacy system within their organisation restricts the development of new applications. Their responses were given in Likert scale from strongly disagree to strongly agree.

Table 4.34: The legacy system restricts the development of new applications

The legacy system restricts the development of new applications	**Responses**		**Descriptive statistics**				**T-test results**		
	Frequency	**%**	**N**	**Mean**	**Std. Deviation**	**Std. Error Mean**	**t**	**df**	**Sig. (2-tailed)**
Strongly Disagree	4	4%	102	4.63	1.56	0.15	29.96	101	0.00
Disagree	11	11%							
Moderately Disagree	3	3%							
Neutral	26	25%							
Moderately Agree	23	23%							
Agree	27	26%							
Strongly Agree	8	8%							

Association with Demographical variables			
Demographical variables	**Pearson Chi-Square**	**df**	**P-value**
Awareness of Big Data Analytics capability	17.585	6	**0.01**
Type of industry	73.578	24	**0.00**
Years of work experience in the field of BDA	49.442	24	**0.00**
Organisation's tenure in BDA	26.141	18	0.10
Association with BDA environment	41.159	24	**0.02**
Relative organisation size	47.873	24	**0.00**
Respondents' seniority in organisations	70.943	30	**0.00**
Organisational location	24.909	6	**0.00**

From the results in the table above, it is shown that most respondents (57%) said that the legacy system within their organisation restricts the development of new applications. This is followed by 25% of respondents who are neutral on the matter. These results also show that only 18% of respondents said that the legacy system within their organisation does not restrict the development of new applications.

There is an association between restrictions of the development of new applications by the legacy system within the organisation and all demographic factors in this study except for organisation's tenure in BDA. This is supported by the p-value of less than 0.05 between restrictions of the development of new applications by the legacy system within the organisation and most demographic factors except organisation's tenure in BDA. We can reject the null hypothesis of the test which says that there is no association between restrictions of the development of new applications by the legacy system within the organisation and most demographic factors except for organisation's tenure in BDA. (Shamim et al., 2019) indicated that the use of big data itself does not yield its maximum benefits until organisations overcome the related managerial challenges, such as leadership focus, internal politics, harnessing talent and technology management and company culture which are even bigger contributing factors such as the organisational legacy systems. In the big data era, firms are successful not only because they have access to more and better data but mainly because they employ leadership teams who have a clear vision and set clear goals. We can therefore conclude that there is enough evidence to suggest an association between restrictions of the development of new applications by the legacy system within the organisation and most demographic factors except for organisation's tenure in BDA.

4.4.5.8. Capable in terms of programming skills

Respondents were also asked about the capability of their analytics personnel in terms of programming skills (e.g., structured programming, web-based application, CASE, tools, etc. Their responses were given in Likert scale from strongly disagree to strongly agree.

Table4.35: Capable in terms of programming skills

Capable in terms of programming skills	**Responses**		**Descriptive statistics**				**T-test results**		
	Frequency	**%**	**N**	**Mean**	**Std. Deviation**	**Std. Error Mean**	**T**	**df**	**Sig. (2-tailed)**
Disagree	4	4%	102	4.94	1.21	0.12	41.27	101	0.00
Moderately Disagree	2	2%							
Neutral	35	34%							
Moderately Agree	28	27%							
Agree	21	21%							
Strongly Agree	12	12%							

Association with Demographical variables

Demographical variables	**Pearson Chi-Square**	**df**	**P-value**
Awareness of Big Data Analytics capability	6.554	5	0.26
Type of industry	36.935	20	**0.01**
Years of work experience in the field of BDA	19.857	20	0.47
Organisation's tenure in BDA	23.178	15	0.08
Association with BDA environment	22.754	20	0.30
Relative organisation size	47.792	20	**0.00**
Respondents' seniority in organisations	44.793	25	**0.01**
Organisational location	14.152	5	**0.01**

From the results in table 4.35, it is shown that most respondents (60%) said that their analytics personnel are very capable in terms of programming skills (e.g., structured programming, web-based application, CASE, tools, etc. This is followed by 34% of respondents who are neutral on the matter. These results also show that only 6% of respondents said that their analytics personnel are not capable in terms of programming skills (e.g., structured programming, web-based application, CASE, tools, etc.

There is an association between capability of analytics personnel in terms of programming skills and the type of industry. From the results in the above table, we can say since the p-value is less than our significance level, $\alpha=0.05$, we can reject the null hypothesis of the test which says that there is no association between capability of analytics personnel in terms of programming skills and the type of industry. The growing need for Big Data specialists with analytical capabilities is also increasing tremendously in healthcare. (Pesqueira et al., 2020) indicated that the need of professional skills development as a resource and competence in Healthcare and Pharmaceutical organizations has been progressively noticed. Furthermore, Big Data professionals within the different industries, including healthcare, should possess a range of different skills as these professionals must demonstrate critical and unique capabilities to develop novel improvements in the way organizations are implementing and developing Big Data projects. Technology and processes relevant skills, including programming, data visualization, and management expertise, and the software management field is essential for professionals to take on Big Data roles and focus on innovation that can bring all necessary outcome and data insights applied to the Healthcare (e.g., drugs development, clinical research, etc.). (Verma et al., 2019) analysed different positions for analytics jobs within healthcare industry, included in their analyses is the business analyst (BA), business intelligence analyst (BIA), data analyst (DA), and data scientist (DS). They further discovered that the most desired skill for these analytics positions is decision making. Moreover, (Verma et al., 2019) support other skills such as organization, communication, structured data management, domain knowledge, knowledge of statistical and programming skills is also so relevant to analytics positions. Therefore, professionals involved directly or indirectly with Big Data need a variety of skills for successful practice and successful execution of the necessary Big Data Projects. We can therefore conclude that there is enough evidence to suggest an association between capability of analytics personnel in terms of programming skills and the type of industry. Similarly, there is an association between relative organisation size and capability of analytics personnel in terms of programming skills. There is an association between respondents' seniority in organisations and capability of analytics personnel in terms of programming skills and an association between capability of analytics personnel in terms of programming skills and organisational location.

4.4.5.9. Capable in terms of teaching

Respondents were also asked about the capability of their analytics personnel in terms of teaching others in their business. Their responses were given in Likert scale from strongly disagree to strongly agree.

Table 4.36: Capable in terms of teaching

Capable in terms of teaching	Responses		Descriptive statistics				T-test results		
	Frequency	%	N	Mean	Std. Deviation	Std. Error Mean	t	df	Sig. (2-tailed)
Strongly Disagree	1	1%	102	5.06	1.30	0.13	39.19	101	0.00
Disagree	3	3%							
Moderately Disagree	4	4%							
Neutral	29	28%							
Moderately Agree	23	23%							
Agree	28	27%							
Strongly Agree	14	14%							

Association with Demographical variables			
Demographical variables	**Pearson Chi-Square**	**df**	**P-value**
Awareness of Big Data Analytics capability	18.992	6	**0.00**
Type of industry	52.109	24	**0.00**
Years of work experience in the field of BDA	38.812	24	**0.03**
Organisation's tenure in BDA	41.387	18	**0.00**
Association with BDA environment	45.917	24	**0.00**
Relative organisation size	49.769	24	**0.00**
Respondents' seniority in organisations	45.795	30	**0.03**
Organisational location	15.665	6	**0.02**

From the results in table 4.36, it is shown that most respondents (64%) said that their analytics personnel are very capable in terms of teaching others in their business. This is followed by 28% of respondents who are neutral on the matter. These results also show that only 8% of respondents said that their analytics personnel are not capable in terms of teaching others in their business. There is an association between capability of analytics personnel in terms of teaching others in the business and all demographic factors in this study (Awareness of Big Data Analytics capability, Type of industry, Years of work experience in the field of BDA, organisation's tenure in BDA, association with BDA environment, relative organisation size, respondents' seniority in organisations and organisational location). From the results in the above table, we can say since the p-value is less than our significance level, $\alpha=0.05$, we can reject the null hypothesis of the test which says that there is no association between capability of analytics personnel in terms of teaching others in the business and all eight demographic factors. The healthcare industry is data intensive and could use interactive dynamic big data platforms with innovative technologies and tools to advance patient care and services (Panagiota Galetsi et al., 2020). Thus, the healthcare industry manages a wide amount of data every day from clinical and operational information systems, such as Electronic Health Records (EHR) and Laboratory Information Library Systems (LIMS). (Raghupathi & Raghupathi, (2014) defined Big Data in healthcare as the electronic health data sets that are so large and complex that they are difficult and sometimes impossible to manage with traditional software and/ or hardware. These data cannot be easily managed with traditional or common data management tools and methods. (Mehta & Pandit, 2018) indicated that with the huge amount of data available, there are more and more challenges to be faced and there is a lack of knowledge about which data to use and for what purpose. Furthermore, to extract meaningful insights and valuable information from Big Data, Training key personnel to use Big Data analytics. To extract meaningful insights and valuable information from Big Data, healthcare professionals should be trained with Big Data analytics competencies. This is critical for healthcare, because incorrect interpretation of the reports generated could lead to unanticipated consequences. We can therefore conclude that there is enough evidence to suggest an association between capability of analytics personnel in terms of teaching others in the business and the type of industry.

4.4. Chapter summary

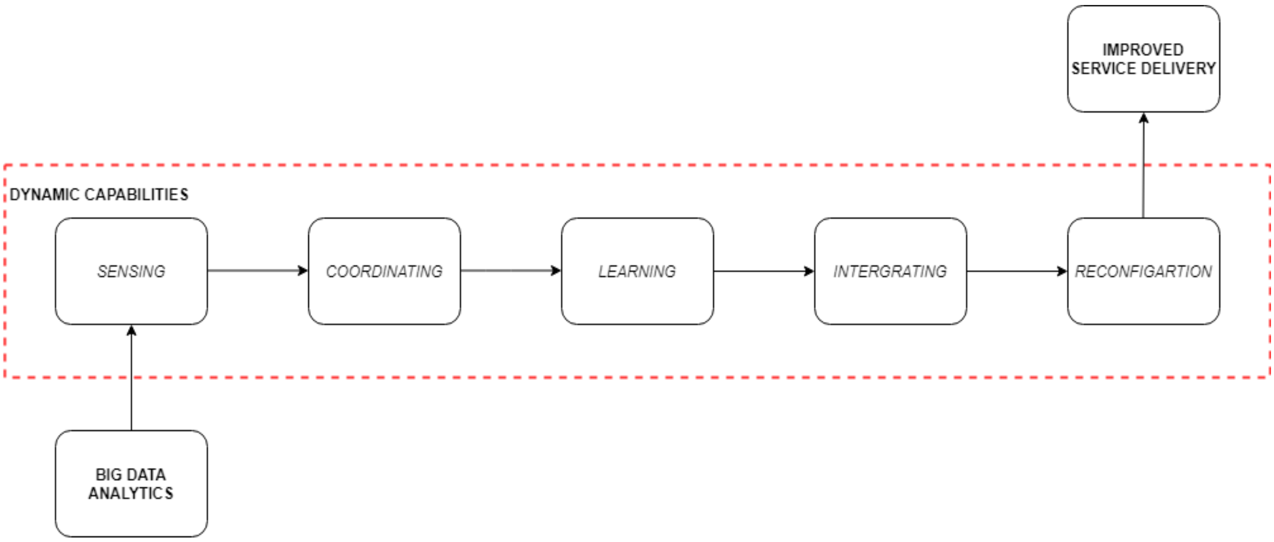
In conclusion, this chapter focused on the presentation of data analysed. Data were presented, using graphs, charts and tables. The data was interpreted based on the research objectives and the literature reviewed.

CHAPTER 5: DISCUSSIONS OF FINDINGS AND CONCLUSIONS

5.1. Introduction

Chapter 4 provided the analysis and presentation of data using of bar graphs, tables, and pie charts. This chapter presents the discussion based on the findings of the analysis, presentation, and interpretation in chapter 4. The discussion presented in this chapter was based on the objectives and literature review of the study. In this research, the primary aim was to design a framework for Big Data Analytics in Healthcare Organizations in South Africa, based on Dynamic Capabilities Theory, to improve healthcare service delivery.

THEORETICAL FRAMEWORK:



The conceptual framework for this research was adapted from the DCT presented on Figure 2.1 by Teece (2007) and Teece et al. (1997). Extending this logic and drawing upon the strategic management and decision sciences literatures, this study aimed at identifying a set of dynamic capabilities for big data analytics for healthcare. The starting point is Teece et al.'s (1997) (reconfiguring, learning, integrating, and coordinating) and Teece's (2007) (sensing the environment to seize opportunities and reconfigure assets) distinct capabilities. Because different labels have been used in the literature to refer to similar capabilities, or similar labels for different capabilities, this study have reconciled the various labels and meanings from the literature and grouped them under a parsimonious set to reflect Teece et al.'s (1997) and Teece's (2007) conceptualization, our own interpretation of the literature, and relevance Big Data Analytics in healthcare.

The main objective of the study was to analyse how Big Data Analytics can be used for Data Management in Healthcare Organizations in South Africa to improve service delivery.

Sub-objectives:

- To explore how Big Data Analytics are sensed in the Healthcare's sector.
- To identify how Big Data Analytics can be used to coordinate resources to improve Healthcare's service delivery.
- To explore how health Data users can learn about Big Data Analytics capabilities and tools to improve healthcare service delivery.
- To explore how the healthcare sector integrates BDA to improve service delivery.
- To explore how BDA can be used in the reconfiguration of Healthcare Data Management to Improve healthcare services

5.2. Summary of findings

This section discusses the findings of the data analysed on chapter 4. The discussion presented in this section is based on the objectives and literature review of the study. The structure of the discussion is as follows:

- Findings related to sensing BDA in healthcare
- Findings related to BDA coordinating in healthcare
- Findings related to learning BDA for healthcare
- Findings related to integrating BDA capabilities in healthcare
- Findings related to the ways of reconfiguring BDA in healthcare sector

5.2.1 Findings related to sensing BDA

The Chi-Square analysis reported that 61% of the respondents were aware of BDA capabilities and benefits for healthcare organizations. Several studies have indicated that awareness is essential for BDA adoption. For instance, (Willet et al., 2022) found that lack of BDA awareness hinders adoption of BDA in SMEs. (Zhang et al. 2022) indicate that organizations compete to connect Big Data capabilities with organizational learning infrastructure to respond to these new Big Data and social media developments. This means that organisations are aware that employing BDA in healthcare will allow for improved service delivery through its capability of enabling connections within different fields (Khanra et al., 2020). Another study by (Sarkar et al., 2021) indicated that the adoption rate of Big Data capabilities has been one of the fastest tech-adoption phenomena in the business world. Thus, awareness is critical for BDA adoption. Therefore, the study findings, in relation to BDA awareness have grounding in literature, confirming the role that awareness plays an important role in the adoption of BDA in healthcare organizations.

The respondents also indicated that BDA is a useful innovation for making predictions, for instance, (Batko & Ślęzak, 2022) indicated that the results of Big Data Analysis can be used to predict the future and help creating trends about the past. (Rehman et al., 2021) listed few researches which were used by the healthcare industry through social media to predict future trends. From these researches, they found that the healthcare sector can use keywords and geographic annotations from Facebook and twitter to diagnose HIV, depression, and anxiety. The use of BDA in healthcare predictions is well grounded in the literature and points to the increasing dependence on such technologies to improve healthcare service delivery.

Further, 54% of the respondents preferred that healthcare organizations use integrated data analytics data collection tools; and that the sources of healthcare data should mostly be from medical health research (37% of respondents) and social media (23% of the respondents). From the respondents' perspective, a single data collection tool cannot inform BDA in healthcare organizations. Healthcare Big Data includes data on physiological, behavioural, molecular, clinical, environmental exposure, medical imaging, disease management, medication prescription history, nutrition, or exercise parameters (Mehta & Pandit, 2018). This data is diverse and difficult to measure by traditional software or hardware (Panagiota Galetsi et al., 2020). Thus, healthcare data requires integrated data collection tools. Studies have demonstrated that the integration of BDA with other health systems such as Electronic health (E-Health) systems, Telehealth systems and health care ecosystems, in general, improve healthcare. For instance, cloud-based data collection has been proposed by several scholars (Batko & Ślęzak, 2022), (Edu & Agozie, 2020) and (Rajabion et al., 2019).

Therefore, the findings, in relation to sensing BDA, confirm that the healthcare sector can spot, interpret, and pursue opportunities in the environment.

5.2.2. Findings related to BDA resources coordinated in healthcare sector

The Chi-Square analysis reported that 34.5% of the respondents said that executive level actively and visibly supports BDA capability. Literature indicates that organisations whose executive actively support BDAC are more likely to remain competitive in the industry. For instance, (Olabode et al., 2022) indicate that a firm's ability to develop a strong BDAC can contribute to superior market performance as BDAC enables firms to view the market using a different lens. However, 45.1% of the respondents indicated that the executive level occasionally actively and visibly supports BDAC. Studies indicates that BDA capability is still in its infancy, having only gained prominence since around 2011, Lee, (2017), and in the early stages of the BDAC functions establishment, as a significant input of effort, time and alignment of diverse entities within the business is necessary, which is a feature which cannot be underestimated, and is something that requires good management and string leadership (Niland, 2017). Therefore, the study findings, in relation to the executive's level to support BDAC have grounding in literature, confirming that there is a limitation in the ability to effectively apply BDA, as the executive level occasionally actively and visibly support BDAC. If the executive level does not understand BDA, and are currently in small clinics, hospitals, laboratories in rural where (Rehman et al., 2021) indicated that BDA is currently not practiced, they will not support BDAC in their organisations.

The 92% of respondents also indicated that some executive level (managers) can critically appraise both internal data and evidence from scientific research. Several studies on BDA in healthcare indicate that eternal data and scientific research is useful for improving healthcare service delivery. For instance, (Rehman et al., 2021) indicated that healthcare managers use trends models and search queries on Google to detect influenza and flu-like diseases. Other studies include the studies by (Khanra et al., 2020); (Mehta & Pandit, 2018); (Imran et al., 2021) and (P. Galetsi et al., 2019). Therefore, the study findings, in relation to the executive level ability to appraise BDA, have a grounding in literature, confirming that the executive level (managers) can appraise eternal data and scientific research to improve healthcare services.

Further, 48,04% respondents indicated their views on whether their organisation invests in technological tools to interpret data collected from external sources. 56% respondents agreed that their organisation invests in technological tools to analyse data collected from external sources to turn it into useful and meaningful information for the industry. Several studies indicate that as the healthcare industry receives huge amount of data from different sources, it is difficult to analyse healthcare data using traditional data analytics tools. Therefore, employing BDA to extract, transform and load data will improve service delivery while saving costs. For instance, (Mehta & Pandit, 2018) indicated that it is difficult to analyse the multi-dimensional healthcare data medical images (X-ray,–MRI images), biomedical signals (EEG, ECG, EMG etc.), audio transcripts, handwritten prescriptions and structured data from EMRs because of its dynamicity and complexity. Also, (Khanra et al., 2020) indicate that healthcare enterprises search for suitable technologies to streamline resources for the sake of improving the patient experience and organisational performance. Healthcare organizations see the opportunity to grow through investments in Big Data Analytics (Batko & Ślęzak, 2022). Therefore, the findings in relation to organisational ability to invest in technological tools to interpret data collected from external sources, have a grounding in literature, confirming that it is important for the healthcare industry to invest in BDA tools to interpret data collected from external sources to be able to identify which information can be useful.

Therefore, the study findings are related to BDA resources coordinated in healthcare sector, which confirm that the healthcare sector can manage and ideally synchronise resources, stakeholders, deliverables, and tasks in relation to tasks or requirements.

5.2.3. Findings related to Learning BDA

The Chi-Square analysis reported that 62,745% of the respondents agree that their organisation enables learning, accumulation, and application of new knowledge better than their competitors. Literature indicates that organizations are looking for ways to use the power of Big Data to improve their decision making, competitive advantage or business performance. For instance, the study by (Batko & Ślęzak, 2022) indicates that the digitization and effective use of Big Data in healthcare can bring benefits to every stakeholder in this sector. Furthermore, there are potential opportunities to achieve benefits and effects from Big Data in healthcare such as improving the quality of healthcare services, supporting the work of medical personnel, supporting scientific and research activity, and business and management. Therefore, the findings, related to the organisations' ability to enable learning, accumulation and application of new knowledge better than their competitors, have a grounding in literature, confirming that it is necessary for healthcare organisations to learn, accumulate and apply BD capabilities in order to remain competitive in the era of large healthcare data.

A further 83% respondents indicated that their organisation offers extensive employee orientation program for new employees to ensure that they share the corporate vision and purpose. 60.609% respondents agree that their organisations invest in targeted training and support at all levels of their organisations to assist their employees to understand and know how to use data that is available. Also, 56.9% respondents indicated that people in their organisation are frequently encouraged to expand their capacities to achieve more and apply new capabilities, while a further 37% respondents agreed that in their organisation, they are knowledgeable and skilled of the adopted technological tool. Several studies indicates that, employees in BDA should be knowledgeable and skilled to be productive, while new employees require orientation of the position they hold. For instance, (Shahbaz et al., 2019) indicated that the organizations should encourage employees to learn new skills, tasks, and programs, and the study by (Pesqueira et al., 2020) which explains the useful skills required to be able to associate an individual with BDA environment, and the study by (Verma et al., 2019) which analysed the job descriptions for the types of analytics positions. Therefore, the findings, related to the organisations' ability to offer extensive employee orientation program for new employees to ensure that they share the corporate vision and purpose, have a grounding in literature, confirming that it is important for organisations to employ skilled and knowledgeable people, employees should be offered orientation program and it is the duty of the organisation to do so, because if employees do not get the orientation program, they will not have knowledge about the corporate vision and mission of the organisation and this will lead to poor service rendering, as they will not know about the tools and how to utilise them for productivity.

Therefore, the study findings, related to Learning BDA, confirm that the healthcare sector has the capacity to gather, understand and exploit knowledge such that improved decisions may be made.

5.2.4. Findings related to BDA's integration within healthcare

The Chi-Square analysis reported that 87% of the respondents agreed that it is important for their organisations to adopt new and cutting-edge practices to continuously improve product or service delivery. A further 86% of the respondents agreed that innovation is a necessity for their organisation's future. 84.3% of the respondents agreed that employing and using BDA will improve services relative to competitors. Also, 92.1% of the respondents agreed that employing and using BDA will improve the overall financial performance relative to competitors. Several studies indicated the potential benefits adopting new technologies, BD capabilities and necessary technological tools to improve products and service delivery. For instance, (Panagiota Galetsi et al., 2020) which indicated the different BD capabilities, such as better diagnosis for provision of more personalized healthcare, reducing expenditure while maintaining quality, creating data transparency and enabling experimentation, expose variability and improve overall firm performance. The study by (Edu & Agozie, 2020) found that application of new technologies will enhance and improve healthcare delivery quality, efficiency and patients monitors. Therefore, the findings, related to adoption of new cutting-edge technologies, and usage of BDA to improve services and overall financial performance, have a grounding in literature, confirming that it is important for healthcare organisations to adopt new cutting-edge BDA technologies such as Hadoop, MapReduce and Apache as this will improve their overall firm performance.

Further 89.22% of respondents agreed that internal politics and power struggles influence the way they make decisions about policies and politics. Literature indicates that for organisations which are successful have employed leadership teams who understands the organisation's vision and mission. For instance, (Shamim et al., 2019) indicated that the use of big data itself does not yield its maximum benefits until organisations overcome the related managerial challenges, such as leadership focus, internal politics, harnessing talent and technology management and company culture which are even bigger contributing factors than the technical ones. Therefore, the findings, related to internal politics and power struggles influencing the way the organisation makes decision about policies and politics, have a grounding in literature, confirming that it is important for healthcare organisations employ leadership teams who understands the organisation's vision and mission.

There is 71.6% of the respondents agreed that all other offices are connected to the central office for analytics. Also, 61.8% of the respondents agreed that their organisation has the foremost available analytics systems compared to competitors. Literature indicates that linking data from different sources and discerning patterns the predictive power can be used for transforming real-time data from different departments into valuable information which will lead to improved service delivery. For instance, the study by (Mehta & Pandit, 2018) indicates that BDA enables the incorporation of longitudinal patient data with data from different, structured, and unstructured big data sources. Furthermore, it indicated that technology is emerging every day, therefore, new analytics systems are being developed which also require compatible peripheral technologies. The study by (Khanra et al., 2020) indicates that healthcare organisations search for suitable technologies to streamline resources for the sake of improving their patient experience and organisational performance. They further indicated that advances in new peripheral technologies may increase the quality of the insights derived by BDA in healthcare. Therefore, the findings, related organisation's ability to access data from different offices, analyse it and generate real-time accurate information, and organisation's use of the foremost available analytics systems compared to competitors, have a grounding in literature, confirming that it is important to adopt and use BDA as it allows for improved service delivery through its capability of enabling connections within different fields. Also new and foremost available analytics systems such as Electronic Health Records (EHRs), Sensors, and real-time alerting, and wearable devices will also improve healthcare service delivery, however they will require compatible peripherals.

Therefore, the study findings, related to BDA's integration within healthcare, confirms that the healthcare sector has the processes that allow for more efficient problem resolution by more effectively combining the various resources of the organisation.

5.2.5. Findings related to ways of reconfiguring BDA in healthcare

The Chi-Square analysis reported that 58.8% of the respondents indicated that software applications are transported and used across multiple analytics platforms within the organisation. Several studies indicates that the healthcare sector receives huge data sets from different sources. For instance, the study by (Panagiota Galetsi et al., 2020) found that BDA capability enables healthcare information sharing and coordination. This is gained by the coordination and sharing of health information across healthcare services or even countries to improve of health professionals' decision-making, leaving organisations able to use software applications across multiple platforms. Therefore, the finding related to software applications are transported and used across multiple analytics platforms within the organisation, have a grounding in literature, confirming that it is important for software applications to be used across multiple analytics platforms within the organisation. Software applications Including AWS, Cloudera, Hortonworks, and MapR Technologies—distribute open-source Hadoop platforms (Raghupathi & Raghupathi, 2014).

57.85% of the respondents indicated that their user interfaces frequently provide transparent access to all platforms and applications. The study by (Panagiota Galetsi et al., 2020) indicates that BDA has the capability for creating data transparency, BDA collects big data and format them in a standardized manner. Therefore, the finding related to user interface ability to provide transparent access to all platforms and applications, have a grounding in literature, confirming that it is important for organisations to employ user-interfaces with transparent access as it reduces data identification and analysis time and assists the previous value of coordinating meaningful and comprehensive health-related information.

A further 55% of the respondents indicated that reusable software modules are frequently used in new analytics model development. Further 56.87% of the respondents indicated that end-users frequently use software provided to create their own analytics applications. (Mehta & Pandit, (2018) highlighted some of the applications of Big Data Technologies like MapReduce and Hadoop for healthcare analytics which can be reused widely in new model development. A study by (Pesqueira et al., 2020) indicate that big data professionals within the different industries, including healthcare, should possess a range of different skills. Therefore, the findings related to reusable software modules are frequently used in new analytics model development, and the ability of end-users to use software provided to create their own analytics have a grounding in literature, confirming that is important to use reuse software modules in the development of new models as it will give you an idea on what to develop. These technologies can be used to create personal analytics given that they have the knowledge and skills to use them.

Also 50.9% of the respondent's indicated data is frequently sourced from outside and is easily analysed. Also 57.8% of the respondent's indicated that decisions are frequently made easily because of the new adapted technology. Several literatures have indicated that BDA can analyse a wide variety of complex data and generate valuable insights which otherwise would not have been possible using traditional analyses tools. For instance, several studies indicated the potential benefits of healthcare sector (Khanra et al., 2020), (Wu, et al., (2017), (Rajabion,et al., (2019) and (Panagiota Galetsi et al., 2020).. Therefore, the finding related to data is sourced from outside and is easily analysed, and that decisions are made easily because of the new adapted technology, have a grounding in literature, confirming that there are several health data sources however BDA has the ability to easily extract, transform and load structured and unstructured data, making it easier for Big Health data to interpret and make decisions that are sound in a short space of time.

Also 57% of the respondent's indicated that the legacy system within their organisation restricts the development of new applications. The studies by (Shamim et al., 2019) indicated that the use of big data itself does not yield its maximum benefits until organisations overcome the related managerial challenges, such as leadership focus, internal politics, harnessing talent and technology management and company culture which are even bigger contributing factors such as the organisational legacy systems. Therefore, the findings related to the legacy system within their organisation the development of new applications, have a grounding in literature, confirming that the legacy system within their organisation restricts the development of new applications.

Further 60% of respondents indicated that their analytics personnel are very capable in terms of programming skills (e.g., structured programming, web-based application, CASE, tools, etc. Also, 64% of the respondents indicated that that their analytics personnel are very capable in terms of teaching others in their business. Literature indicated that BDA personnel should possess a range of different skills and be able to transfer the skills to others within the organisation. For instance, a study by (Mehta & Pandit, 2018) indicated that with the huge amount of data available, there are more challenges to be faced and there is a lack of knowledge about which data to use and for what purpose, thus healthcare professionals should be trained with Big Data analytics competencies. Furthermore, a study by (Pesqueira et al., 2020) indicates that big data professionals within the different industries, including healthcare, should possess a range of different skills. This is because, these professionals must demonstrate critical and unique capabilities. While a study by (Verma et al., 2019) analysed the skills required in the analytics position, they include decision making, knowledge of statistical and programming skills are also so relevant to analytics positions. Therefore, the finding related to organisations capability of their analytics personnel in terms of programming skills, and teaching others, has a grounding in literature, confirming that having correct skills for analytics position will result in improved healthcare service delivery.

Therefore, the study findings, related to ways of reconfiguring BDA in healthcare, confirms that the healthcare sector has the ability of the organisation to make strategic decisions and rapidly enact or execute against these by repositioning resources to better align the organisation with the external or market environment.

5.3 Conclusions and Recommendations

The aim of the study was to analyse how Big Data Analytics can be used for Data Management in Healthcare Organizations in South Africa to improve service delivery, based on Dynamic Capabilities theory. To address this aim, a deductive approach using the Dynamic Capabilities Theory (DCT) was adopted. The conclusions that are detailed below are derived from the testing of a DCT. Based on the summary of findings above, several conclusions and recommendations can be advanced:

The first relates to “Sensing” BDA opportunities to improve service delivery in healthcare organizations. In “Sensing” BDA opportunities, it was established that BDA is critical for predictions in health diagnosis; and, that awareness enhances adoption of BDA. A key deduction that emerges to ensure better utilization of BDA is the need to implement integrated data analytics collection tools to ensure effective use of BDA in healthcare organizations. The recommendations that can be considered to realize the implementation of integrated data analytics tools include research on all possible benefits and capabilities and values that integrated data analytics tools.

Second relates to BDA resources coordinated in healthcare sector to improve service delivery. In coordinating BDA resources, it was established that there is a limitation in the ability to effectively adopt BDA in healthcare organisations. There is the ability to appraise external data and scientific research to improve healthcare services; it is important for the healthcare industry to invest in BDA tools to interpret data collected from external sources to be able to identify which information can be useful. A key deduction that arises is to ensure that BDAC is actively and visibly supported by the healthcare. The recommendations that can be considered to realize BDAC is to employ leaders who are willing to adopt new technologies which will enable the organisation to be able to appraise external data and scientific research.

Third, relates to learning BDA to improve healthcare's service delivery. In learning BDA, it was established that there is a necessity for healthcare organisations to learn, accumulate, and employ BD capabilities, and it is critical for healthcare organisations to train and teach their new employees about the tasks they are designated to do. A key deduction that emerges is to ensure that healthcare organisations are learning and employing BD capabilities to improve service delivery. The recommendations that can be considered is for healthcare organisations to invest in trainings for their employees so that they may have full knowledge about BDA, and they will exploit all possible capabilities to improve service delivery.

Forth, relates to BDA's integration within healthcare. In integrating BDA, it was established that it is crucial for healthcare organisations implement BDA to improve overall firm performance, healthcare organisations struggle to make decisions related to new technologies because of policies and policies. Key deduction that emerges is to influence healthcare organisations to adopt new cutting-edge technologies such as Hadoop, and MapReduce, for healthcare organisations to enjoy BD capability which allows them to access data from different offices. The recommendations that can be considered is for healthcare organisations to employ leadership teams which understand their mission and vision and aim at remaining above their competitors within the market and to invest in new technologies, to develop their healthcare central database which will connect even other organisations.

Fifth, relates to ways of reconfiguring BDA in healthcare sector. In reconfiguring BDA, it was established that it is crucial to healthcare organisations to implement software applications to be used across multiple analytics platforms, also user-interfaces which are transparent, the organisation should be aware of all the possible health data there is and that the legacy system within their organisation restricts the development of new applications. Key deduction that emerges is the ability of the organisation to make strategic decisions and rapidly enact or execute against these by repositioning resources to better align the organisation with the external or market environment. The recommendations that can be considered is for healthcare organisations to adopt technologies, such as BDA, which has the capabilities to be used across multiple platforms, offers transparent data access, and can be reused in the development of new models. This will improve service delivery.

The healthcare sector has the ability to spot, interpret, and pursue opportunities in the environment. They are aware of BDA and its potential benefits, values and what may be the challenges. The healthcare sector can manage and ideally synchronise resources, stakeholders, deliverables, and tasks in relation to tasks or requirements. Mostly in private healthcare organisations, they have started to implement BDA to improve patients care services. The healthcare sector has the capacity to gather, understand and exploit knowledge such that improved decisions may be made. There are offered trainings for new technologies which are being adopted. The healthcare sector has fewer processes that allow for efficient problem resolution by more effectively combining the various resources of the organisation. In South Africa, there is still a struggle in adopting new processes, these include the policies and strategies being used in the healthcare sector, lack of team leaders who will lead towards better services for all, and also the political policies. Healthcare sector Organisations have the ability to make strategic decisions and rapidly enact or execute against these by repositioning resources to better align the organisation with the external or market environment. However, there are rules and policies they need to get through before they can adopt to technologies which allow for such abilities. They also need to consider the costs of the technologies together with the potential benefits of these technologies.

5.4 Evaluations the Contributions of the Study

This section presents the contributions of the study in Information Systems body of knowledge. The three contributions made by this study are theoretical, practical, and contextual.

5.4.1. Theoretically:

The study followed a conceptual framework adapted from the DCT presented on by Teece (2007) and Teece et al. (1997). Extending this logic and drawing upon the strategic management and decision sciences literatures, this study aimed at proposing an identifiable set of DC. The starting point is Teece et al.'s (1997) (reconfiguring, learning, integrating, and coordinating) and Teece's (2007) (sensing the environment to seize opportunities and reconfigure assets) distinct capabilities. Because different labels have been used in the literature to refer to similar capabilities, or similar labels for different capabilities, this study reconciled the various labels and meanings from the literature and grouped them under a parsimonious set to reflect Teece et al.'s (1997) and Teece's (2007) conceptualization, our own interpretation of the literature, and relevance Big Data Analytics in healthcare.

5.4.2. Practical /Policy Contributions:

Practically, this study briefly explains BDA to healthcare. The study observed the state of the country's healthcare sector and realised that there is a need to adopt and implement BDA within the organisations. The study asks people who are working in healthcare sector through the questionnaire, the questions made these people aware of what they could use. The study also emphases that the healthcare should adopt BDA to render best services while saving costs. The study can be used by the executives in the healthcare sector to assist them in awareness and adoption of BDA.

5.5 Limitations of the Study

Just like any other study, the current study reported in this thesis was faced with certain limitations. One of the limitations was from the purposive sampling technique adopted which gave rise to research bias. This is because; purposive sampling may not always be representative of the populations under study. Another limitation was data collection methods. Data for this study was collected during the South African Lockdown level 4. The researcher could not distribute the questionnaires directly to the participants. This resulted in having to use an electronic survey as a tool for data collection. Acquiring participants email addresses or any other means I could use to send the survey was difficult as people were not in their offices and were limited to move around. The survey was sent through emails. The survey was sent to only 170 emails, only 102 surveys were returned.

5.6 Recommendations for Future Research

Future research in the healthcare field has virtually endless possibilities. First, for future studies, researchers might try integrating the theory with other theories. Second, future research, researchers may address the same research aim but from a different paradigm or theories such as the Resource Based View (RVB), and thirdly, future research may be conducted reflecting on the global and national policy around BDA in the South African healthcare eco-system.

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APPENDICES

Appendix A: Research Ethical Clearance: University of Venda

ETHICS APPROVAL CERTIFICATE

RESEARCH AND INNOVATION
OFFICE OF THE DIRECTOR

NAME OF RESEARCHER/INVESTIGATOR:
Ms DT Mathivha

STUDENT NO:
14008115

PROJECT TITLE: **A dynamic capabilities perspective of big data analytics in healthcare in South Africa.**

PROJECT NO: SMS/20/BIS/06/0807

SUPERVISORS/ CO-RESEARCHERS/ CO-INVESTIGATORS

NAME	INSTITUTION & DEPARTMENT	ROLE
Prof NM Ochara	University of Venda	Supervisor
Dr W Munyoka	University of Venda	Co - Supervisor
Ms DT Mathivha	University of Venda	Investigator – Student

Type: **Masters Research**
Risk: **Minimal risk to humans, animals or environment**
Approval Period: **July 2020 – July 2022**

The Research Ethics Social Sciences Committee (RESSC) hereby approves your project as indicated above.

General Conditions
While this ethics approval is subject to all declarations, undertakings and agreements incorporated and signed in the application form, please note the following.

- The project leader (principal investigator) must report in the prescribed format to the REC:
  - Annually (or as otherwise requested) on the progress of the project, and upon completion of the project
  - Within 48hrs in case of any adverse event (or any matter that interrupts sound ethical principles) during the course of the project.
  - Annually a number of projects may be randomly selected for an external audit.
- The approval applies strictly to the protocol as stipulated in the application form. Would any changes to the protocol be deemed necessary during the course of the project, the project leader must apply for approval of these changes at the REC. Would there be deviated from the project protocol without the necessary approval of such changes, the ethics approval is immediately and automatically forfeited.
- The date of approval indicates the first date that the project may be started. Would the project have to continue after the expiry date; a new application must be made to the REC and new approval received before or on the expiry date.
- In the interest of ethical responsibility, the REC retains the right to:
  - Request access to any information or data at any time during the course or after completion of the project,
  - To ask further questions; Seek additional information; Require further modification or monitor the conduct of your research or the informed consent process.
  - withdraw or postpone approval if:
  - Any unethical principles or practices of the project are revealed or suspected.
  - It becomes apparent that any relevant information was withheld from the REC or that information has been false or misrepresented.
  - The required annual report and reporting of adverse events was not done timely and accurately,
  - New institutional rules, national legislation or international conventions deem it necessary

ISSUED BY:
UNIVERSITY OF VENDA, RESEARCH ETHICS COMMITTEE
Date Considered: July 2020

Name of the RESSC Chairperson of the Committee: Mashau Takalani Samuel

Signature:

Director Research and Innovation

Signature: ....

UNIVERSITY OF VENDA
OFFICE OF THE DIRECTOR
RESEARCH AND INNOVATION
2020 -07- 10
Private Bag X5050
Thohoyandou 0950

University of Venda
PRIVATE BAG X5050, THOHOYANDOU, 0950, LIMPOPO PROVINCE, SOUTH AFRICA
TELEPHONE [illegible]

Appendix B: Research Questionnaire

University of Venda

School of Management Sciences

Introduction

I am conducting research with aim to design a framework for Big Data Analytics in Healthcare Organizations in South Africa, based on Dynamic Capabilities theory, to improve healthcare service delivery. The research will review the concept of Big Data Analytics (BDA) in healthcare, sources of Big Health Data, BDA potential benefits and challenges, BDA capabilities, BDA technologies and techniques within healthcare and Dynamic Capabilities Theory. To this end, you are asked to complete a short survey should take no more than 15 minutes.

In addition to all data being collected anonymously and confidentially, your participation is voluntary, and you can withdraw at any time. By completing the survey, you indicate that you voluntarily participate in this research.

If you have any concerns, please contact myself or my research supervisor with the following details:

Researcher name: Mathivha Dakalo
Email: dakimathivha@gmail.com
Phone: 0829426613
Research Supervisor: Professor Ochara M.
Email: Muganda.ochara@univen.ac.za

Instructions: Please select the most appropriate answer according to the scale provided in each question below:

A: CONTEXT OF ORGANISATION AND RESPONDENT

1. Are you aware of or associated with a Big Data Analytics Capability within the organisation?

   Yes ☐ No ☐

2. Which of the following best describes the principal industry of your organisation?

Healthcare	
Higher learning and training	
Corporate	
Other (specify)	

3. How long have you been associated with the field of big data or data analytics?

0-2	2-5	5-10	10-15	15+

4. How long has your organisation actively pursued or applied big data analytics to its business?

0-2	2-4	4-6	6-8	8+

5. What is your main association with the data analytics capability?

User of Analytics within organisation	
Data analyst (Direct processor of Data)	
IT Systems or Infrastructure (Data technology environment)	

Big Data Management (Driving application of resources	
Other (specify)	

6. What is the approximate total number of employees within your organisation?

1-99	100-499	500-999	1000 +	Don't know

7. Which of the following best describes your current job level?

Owner/ Executive/ C-Level	
Senior Management	
Middle Management	
Intermediate	
Entry Level	
Other(specify)	

8. In which region do you work?
Rural ☐ Urban ☐

B: Sensing

9. What is the healthcare industry using to **collect big** health data?(form of data collection)

Traditional data analytics tools	
Digitalized data analytics tools	

10. Where does the Healthcare Industry find data about the industry's current situation, clients' problems and the competitors? Please select possible ways (sources of data collection)

Social Media (Facebook, twitter, WhatsApp)	
Medical Health research	
News updates (TV, Radio)	
Observations	
Suggestion/ complaints boxes	
Other (specify)	

11. Is the healthcare industry able to use the data collected from external sources and internal sources to predict the future trends in the industry? (ability for prediction)

YES		NO	

12. Is the Healthcare industry aware of Big Data Analytics and its potential benefits for the industry? (awareness of Big Data Analytics)

YES		NO	

C: Coordinating

		Never	Very Rarely	Rarely	Occasionally	Frequently	Very Frequently	Always
13	Our executive level actively and visibly supports our big data analytics capability? (executive support for BDA)							

		None of them	Some of them	All of them
14	Our managers know how to critically appraise both internal data and evidence from scientific research? (Executive Ability to appraise BDA)			

		Strongly Disagree	Disagree	Moderately Disagree	Indifferent	Moderately Agree	Agree	Strongly agree
15	The Organisation or Industry invest in Technological tools to Interpret data collected from external sources to be able to identify which information can be useful for their Industry (Investment in BD tools)							
16	The organisation or industry invest in Technological tools to Analyse data collected from external sources to turn it into useful and meaningful information for the industry (BD knowledge capability)							
17	The organisation or industry invest in Technological tools and knowledge to find solutions for their clients and to help improve their services and make better informed decisions (BD for decision Making capability)							

D: Learning

		Strongly Disagree	Disagree	Moderately Disagree	Indifferent	Moderately Agree	Agree	Strongly agree
18	Our organisation enables learning, accumulation, and application of new knowledge better than our competitors? (							

19	There is an extensive employee orientation program for new employees to ensure employees share the corporate vision and purpose?							
20	We invest in targeted training and support at all levels of our organisation to assist our organisation to understand or know how to use data that is available?							

		Never	Very Rarely	Rarely	Occasionally	Frequently	Very frequently	Always
21	People in our organisation are continuously encouraged to expand their capacities to achieve more and apply new capabilities							
22	people working in the organisation are knowledgeable and skilled of the adopted Technological tools							

E: Integrating

		Strongly Disagree	Disagree	Moderately Disagree	Indifferent	Moderately Agree	agree	Strongly agree
23	We believe it is important to adopt new and cutting-edge practices to continuously improve product or service delivery?							
24	Our organisation has a widely held belief that innovation is an absolute necessity for the organisation's future.							
25	Internal politics and power struggles influence the way we make decisions about policies and practices?							

26	Using big data analytics has/will improve services relative to competitors							
27	Using big data analytics will improve overall financial performance relative to competitors							
28	All other (e.g., remote, branch, and mobile) offices are connected to the central office for analytics							
29	Compared to rivals within our industry, our organisation has the foremost available analytics systems							

F: Reconfiguration

		Never	Very Rarely	Rarely	Occasionally	Frequently	Very Frequently	Always
30	Software applications can be easily transported and used across multiple analytics platforms within the organisation							
31	Our user interfaces provide transparent access to all platforms and applications							
32	Reusable software modules are widely used in new analytics model development							
33	End-users can use software provided to create their own analytics applications							
34	Data is sourced from outside and is easily analysed							
35	Decisions are made easily because of the new adapted technology							

		Strongly Disagree	Disagree	Moderately Disagree	Indifferent	Moderately Agree	Agree	Strongly Agree

36	The legacy system within our organisation restricts the development of new applications							
37	Our analytics personnel are very capable in terms of programming skills (e.g., structured programming, web-based application, CASE, tools, etc.							
38	Our analytics personnel are very capable in terms of teaching others in our business							

Appendix 3: Research plan