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The employees' perception on the adoption of big data analytics by selected medical aid organisations in Durban

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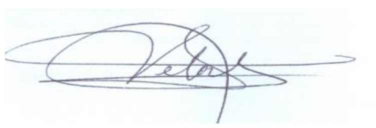

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ABSTRACT

The increase of number of data available in today's world has prompted different industries to find a way to get the value out of the data available. Big data analytics is a term used to describe the analysis of the enormous amount of data. Therefore, practitioners and researchers are trying to understand the adoption of this new technology by companies, government, universities.

Big data analytics has been used by some medical aid companies to improve the quality of schemes and products provided to clients by collecting, analysing accurate data. However, the rate of acceptance and use of big data analytics by medical aids organisations in South Africa is still unknown. In this dissertation, we discuss the employees' perceptions on the adoption of big data analytics by medical aid organizations in Durban. The benefits and challenges of big data analytics in medical aid organizations was also discussed.

A conceptual framework was developed to structure the problem being investigated in this dissertation. To this end, five perceived factors that might influence the employees' perception on the adoption of big data analytics were examined: - perceived performance expectancy, - perceive price value, - perceived social influence, - perceived facilitating conditions, - perceived characteristic of Innovation.

A survey research was used as a research strategy. An exploratory nature of the study was chosen. Thus, there is no conclusive outcomes in this dissertation. Results show that generally employees have a positive perception on the adoption of big data analytics. Constructs such as perceived performance expectancy, perceived price value, and the perceived characteristics of innovation proved to be influencing the employees' attitudes towards the adoption of big data analytics.

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CHAPTER 1

INTRODUCTION TO THE STUDY

1.1. Introduction

Big data is an emerging technology in the IT community. Business domains such as web companies, health care sectors, governments, IT specialists, and marketing gurus are trying to understand the phenomenon and benefit from it. The amount of data available is causing all sectors to find a way to analyse the data and gain knowledge. Offering good and better services to customers and businesses has become more effective due to the importance given to data by organisations (Buhl, Röglinger, Moser & Heidermann, 2013).

From web companies to traditional enterprises, everyone is experiencing an extraordinary increase in the amount of data available, as well as the opportunities that big data hold for the world (Borkar, Carey, & Li, 2012). Many organisations are trying to explore the potential of big data to create value for organisations, individuals, communities and governments.

Fan and Bifet (2013) define big data analytics as the ability to extract valuable information from large datasets or stream of data, while (Russom, 2011) defines it as advanced analytic techniques operating on large datasets.

Russom (2011) states that most organisations considered big data as a complex technology but now it is seen as an opportunity for businesses to achieve competitive advantage. Furthermore, Cumbley & Church (2013) consider big data as both a threat and opportunity for users; big data provides instant access to an immense quantity of information and at the same time has potential of violating users privacy.

Many companies in the world have become data driven using big data analytics to get new insights, discover new business trends, improve decision making, improve profitability and achieve competitive advantage (McAfee, Brynjolfsoon, Davenport, Patil & Barton, 2012). According to Botha (ITweb, 2014), big data is not yet widely adopted in South Africa, and citing a report from Gartner which revealed that 64% of organisations have invested or are planning to adopt big data; but only 8% have already started using big data. As it stands, the real state of adoption of big data analytics in South Africa is still not clear. According to Bhoola, Kruger, Peick, Pio, & Tshabalala

(2014), the e-skills UK has estimated the adoption of big data analytics for larger organisations worldwide as follows: 14% in 2012, 20% in 2013, 24% in 2014, 26% in 2015, 28% in 2016, and 29% in 2017. According to Buhl *et al*. (2013), a broad adoption of big data is expected within the next five years. With all the benefits big data analytics can bring to businesses, its adoption by businesses can only help to serve people better, management will be able to implement data driven decisions, and businesses will be able to design custom products.

The KwaZulu-Natal health department has put in place a health performance plan project to improve the health care system of the province. Some of the outcomes expected are to improve access, efficiency, effectiveness, and equity of health services as well as to improve the information systems and process, data quality, and performance monitoring (KZN Health, 2014). Therefore the adoption of big data analytics can contribute to achieve these objectives, and a focus is needed in exploring the perceptions towards the adoption of big data analytics by medical aid organisations.

The availability of unstructured and structured data to the insurance industry is growing rapidly (Bhoola *et al*., 2014). Data and information is the cornerstone of the insurance industry as well as the medical aid companies. The medical scheme act defines medical aid as the business of undertaking obligation in return for a premium or contribution. The availability of large datasets to medical aid organisations makes the medical aid industry as one of the candidates to adopt this new technique of analysis called big data analytics.

The scarcity of research exploring the adoption of big data analytics by medical aid organisations has also led the researcher to focus on this industry. In this study, the aim was to find out employees' perception on the adoption of big data analytics by selected medical aid organisations in Durban. For the purpose of this study, adoption is referred to as the acceptance for implementation of big data analytics. The study explored the perceived factors that might influence the adoption of big data analytics by selected medical aid organisations. The study attempted to find out from the managers and employees their perceptions on the factors that might influence the adoption of big data analytics. Data was collected from two organisations and a comparative analysis was done to find out whether there is a significant difference between the two organisations. As requested by the selected medical aid, the name of the two selected organisations will not be revealed in this study and will be designated as company A and company B. An analysis was done for the combined companies, and then a separate analysis was conducted to find out whether there is a significant difference.

1.2. Background

In the industrial context, data is seen as an asset. The transformation of raw data, to a valuable asset to the company, requires a long and diligent process. From data analytics, business intelligence to big data analytics, companies have tried to find a way to analyse data and make it valuable to companies. One of these long and diligent processes is the adoption of big data analytics by companies. Recently, companies and especially the healthcare sector have generated a lot of data to be analysed.

Various sources of data such as social media, insurance claims, electronic health records, scans, monitoring devices and other wearable devices have made it possible for the health care sector including medical aid organisations to handle a lot of data. These examples are just showing how data are incredibly growing nowadays from diverse sources, and that is where the term big data comes from.

A report from the US indicates that US healthcare system has reached 150 Exabyte (*unit of information equal to one quintillion*) in 2011, and the country is predicting to reach the zettabyte ($10^{21}\ gigabytes$ "$unit\ of\ information\ equal\ to\ 2^{30} bytes$") in 2020. Kaiser Permanente, a health network based in California, has between 26.5 and 44 petabytes of data from its 9 million members (Raghupathi & Raghupathi, 2014).

Organisations can benefit from the huge amount of data available to reduce costs, improve profitability, achieve competitive advantage, produce better products, and to identify new trends. Many organisations around the world are starting to adopt or have adopted already big data to gain these benefits.

Organisations cannot benefit from big data without any analysis of the huge amount of data. Big data analytics is defined as the capability to explore, combine and cross reference large datasets (Lyon, 2014), while Fan and Bifet (2013) claim that big data analytics is the capability to extract useful information from large datasets.

According to Shah & Pathak (2014), a better gathering and analysis of big data will provide the health care system with a tremendous opportunity to improve in a sense that information gathered will help to identify the disease, providing the right treatment to the right individual or subgroup. Shah & Pathak (2014) further outline how healthcare can benefit and use big data effectively by integrating data, generating new knowledge, then translating knowledge into practice.

In the U.S.A, Rise Health has developed software called accountable-care-organisation (ACO) dashboard which allows providers to collect, organise, and exchange information more effectively and efficiently. The application has the potential of aligning the wealth of patient data available with the goal of each provider. Such technology can improve healthcare and create or discover new patterns (Groves, Kayyali, Knott & Kuiken, 2013).

In South Africa, the healthcare system is divided into two parts; the public sector and the private sector. The private sector services about 7 million people, which is 16.3% of the entire population and accounts for 52% of the total expenditure on healthcare, while the public sector services the rest of the population and accounts for 48% of the total spending on healthcare (Health24, 2016). The budget allocated to the healthcare system is spent mostly on the services provided and medicine. Most people do not have access to quality healthcare due to the cost of medication (Health24, 2016). For the past ten years, the cost of healthcare has increased by 300% in private health care in South Africa (Health24, 2016). The large number of the population generates a lot of data for both the public and private sector.

The usage of big data analytics will benefit the healthcare. The potential benefits can be the detection of diseases at an early stage that can lead to an effective treatment, as well as the detection of healthcare fraud, and low costs. The South Africa healthcare system can also benefit from big data analytics. The adoption of big data analytics in South Africa healthcare can reduce the difference in quality between private sector and public sector. By adopting big data analytics, medical aid organisations can reduce the cost of risk, improve the quality of schemes, grasp new business opportunities and improve the quality of service.

In general, the importance of big data analytics has become obvious which cannot be ignored by organisations. However, from the literature, there is not enough evidence of the acceptance and use (adoption) of this new way of analysis by businesses in South Africa though a lot of data is available out there.

1.3. Problem statement

Researchers and practitioners across the globe have been doing research in order to understand the new phenomenon called big data analytics. However, there is little evidence from the literature exploring the adoption of big data analytics by medical aid organisations in South Africa. The acceptance of implementation, acceptance of implanted big data analytics, use, or level of adoption of big data analytics by medical aid organisations in South Africa is still unknown. The full adoption is a process that comprises many steps. One of the steps of adoption will be explored in this study. This study makes an attempt to explore the employees' perception on the adoption (acceptance for implementation) of big data analytics by selected medical aid companies in Durban. Medical aid organisations are dealing with a lot data, and are always trying to find a way to get value out of the data available to improve performance, products (schemes), decision making and to identify new business opportunities. MacAfee et al., (2012) claim that the adoption of big data analytics will allow companies to improve their decision making, performance, and products.

The aim is to find out the employees' perception on the adoption of big data analytics. Further, this research makes an effort to address this main research question: What are the perceptions of the employees of medical aid organisations in Durban that influence the attitude towards the adoption of big data analytics? This main question is broken down into six research questions.

1.4. Research Questions & Research Objectives

1.4.1. Research Questions

1. What is the perception of performance expectancy among the employees towards the adoption of big data analytics in selected medical aid organisations in Durban?
2. What are the perceived facilitating conditions influencing the adoption of big data analytics by selected medical aid organisations in Durban?
3. How does the employees' perception on price value influence the adoption of big data analytics in selected medical aid organisations in Durban?
4. How does the employees' perception of social factors influence the adoption of big data analytics in selected medical aid organisations in Durban?
5. What are the perceived characteristics of innovation influencing the employees' attitude towards the adoption of big data analytics by selected medical aid organisations in Durban?

6. How does the employees' attitude towards big data analytics influence its adoption by selected medical aid organisations in Durban?

1.4.2. Research Objectives

1. To determine the perceived performance expectancy that is influencing the adoption of big data analytics by selected medical aid organisations in Durban.
2. To determine the perceived facilitating conditions that is influencing the adoption of big data analytics by selected medical aid organisations in Durban.
3. To understand how the perception of price value influences the adoption of big data analytics in selected medical aid organisations in Durban.
4. To understand how the perceived social factors influence the adoption of big data analytics in selected medical aid organisations in Durban.
5. To determine the perceived characteristics of innovation influencing the employees' attitude towards the adoption of big data analytics by selected medical aid organisations in Durban.
6. To understand the attitudes of the employees towards the adoption of big data analytics.

1.5. Research Rationale

The explosion in data availability has made it possible for many industries to analyse and get valuable information to improve profitability. Many companies are starting to utilise this emerging technology called big data analytics. The evidence of the use of big data analytics by companies in South Africa is not well known. This study attempts to explore the employees' perception on the adoption of big data analytics. The research will contribute to the reduction of inequality between the healthcare private sector and the public sector with regards to funds spent and the quality of health services in South Africa by providing a better understanding of the adoption of big data analytics. The study will contribute towards the understanding of the adoption process of big data analytics by medical aid organisations. The study is likely to contribute to the scarce literature on big data analytics in South Africa.

1.6. Significance/Contribution of the study

To the researcher's best knowledge, not much research is carried out exploring the adoption of big data analytics by organisations in Durban. The study attempts to explore the perception of employees on the adoption of big data analytics. Furthermore, the study attempts to find out which perceived factors influence the employees' perception on the adoption of big data analytics. Therefore, the study will contribute towards a more comprehensive understanding of big data analytics as a tool to achieve competitive advantage; which may lead businesses to implement big data analytics more effectively leading to better products, better services, and better decision making. Medical aid organisations will be aware of the employees' perception on the adoption of big data analytics. Moreover, companies will be aware of perceived factors that influence the attitudes towards the adoption of big data analytics. This will allow them to efficiently and successfully adopt this emerging technology that will benefit patients by having appropriate and better schemes and products from medical aid organisations.

1.7. Dissertation structure

The dissertation comprises of five chapters.

Chapter 1 gives a synopsis of the study. The chapter highlights the research problem, questions and objectives. In addition, the background and the significance of the study were discussed.

Chapter 2 reviews the literature, identifies the knowledge gap, and establishes the need for this research. An in-depth review of big data analytics is discussed and the conceptual framework is discussed in this chapter.

Chapter 3 describes in detail the methodology used in the study. Other procedures followed in this study are also discussed in detail.

Chapter 4 analyses the data collected and presents the results.

Chapter 5 discusses the findings and concludes the study with recommendations.

1.8. Justification of the study

The study will contribute towards an in-depth understanding of the emerging technology (big data analytics) and will contribute towards an understanding of the employees' perception on the adoption of this emerging technology. The factors influencing the employees' perception on the adoption of big data analytics will be identified. It will also create awareness to the industry in South Africa, improve medical schemes, and be a step forward in achieving smart health by medical aid organisations in South Africa.

1.9. Summary

The chapter establishes the need to perform this study. It provides a general understanding of big data analytics. A discussion on the background of the adoption of big data analytics was provided, the context of the study was discussed as well as the problem being investigated. To this end, the research questions and research objectives were developed to address the research problem being investigated. A rationale for the study as well as the justification of the study was provided in this chapter. The next chapter will identify the knowledge gap in the literature and establish the need for this study.

CHAPTER 2

LITERATURE REVIEW

2.1. Introduction

The literature review is a report of published studies found in the body of knowledge related on a particular topic (Boote & Beile, 2005). The primary purpose of a literature review is to contextualise the research, to justify the research problem, to illustrate how the subject has been studied before, and to highlight the gaps. The chapter focuses on reviewing the literature on the adoption of big data analytics in South Africa and the rest of the world. Particularly, the chapter focuses on the adoption of big data analytics within the context of medical aid/ insurance, and healthcare. Today, big data analytics is seen as a valuable technology and companies are starting to benefit from its adoption, although it comes with some challenges. This chapter highlights the importance of big data analytics, and provides empirical evidence that justifies the use of constructs used in this study as well as delineates the knowledge gaps in the literature.

2.2. Big data- A review

It is evident from the literature that the term big data was coined in the 1970s but has just been included in research publications in 2008 (Ularu, Puican, Apostu, & Velicanu, 2012). In 1970, seven departments in the US conducted a joint project called BOMEX (Barbados Oceanographic and Meteorological Experiment), and the term big data was found in that project to describe the large volume of data produced (Halevi & Moed, 2012; Borkar, Carey & Li, 2012).

Big data is a terminology used to explain large and complex datasets that are difficult to store and process using traditional database and traditional processing applications (Oguntimilehin & Ademola, 2014). Big data technology is seen as a new type of technology and architecture that can provide value from large datasets (Villars, Olofson & Eastwood, 2011).

Laney (2001) was the first one to come up with the 3Vs (Volume, Velocity, Variety) characteristics of big data in 2001. Gurus and experts in the IT industry have argued about the characteristics of big data; as it is characterised by the 3Vs by some experts, as 4Vs by others and as 6Vs by certain experts. In this section the researcher explores the significance of big data from the literature.

Nowadays the size of data is enormous and does not fit the normal storage system. In the past, data was generated and created by humans but now data is also generated by networks, machines and the interaction of humans using systems such as social Media (Normandeau, 2013). Many other factors contribute to the increase of the volume of data, the increase of sensors, machine to machine interactions which generate a lot of data, and online transactions (SAS, 2012).

Volume indicates the quantity of data collected by the industry (Ularu *et al*, .2012; Bhoola *et al*, 2014; Normandeau, 2013). Velocity is all about the speed of the data. Data is streaming in very high speed and the need to analyse it in real time has become the requirement. The amount of data available has changed the way we look at data. Velocity deals with the time data is being processed (Ularu *et al*., 2012; SAS, 2012). Knowing how to ensure and manage the velocity of data is/will be a challenge to many organisations. Variety deals with the multiple formats of data. Data are in a structured and unstructured format, and data come in different content such as text notes, photos, videos, audio, and monitoring devices which causes a lot of trouble to organisations' storage systems (SAS, 2012; Bhoola *et al*., 2014). The variety of data is still a challenge for many organisations. Veracity refers to the confidence an organisation has on its data (Normandeau, 2013). Many organisations want data that can answer the business problem at hand.

Value deals with the aspect that ensures the information or evidence obtained from the data analysis is relevant to the business context and business problem (Normandeau, 2013; Géczy, 2014) . Does it provide more useful information? Does it improve the fidelity of the information? Does it improve the timeliness of the response? These are the questions many organisations would ask when tackling the value of big data (Villars *et al*., 2011). Volatility deals with the validity of the data, how long data is valid, and for how long an organisation should store it (Normandeau, 2013).

2.2.1. Big data sources

Big data has different sources; the literature reveals that most authors have grouped it into six categories: social networks, media, archives/historical data, business applications/public web, machine log data, and sensor data.

Companies can capture every mouse click on their websites to analyse and predict customers buying behaviors and can influence choices by recommending appropriate products. Medical aid organisations can analyse their websites using a mouse click to get valuable information. Social media also generates tremendous amount of data with the likes, tweets, and comments (Watson, 2014). Medical aid organisations can benefit from their social networks by analysing the likes, retweets, hashtags and users' conversations.

Villars *et al* (2011) have argued that the digitisation of the industry has helped grow the amount of data available, therefore becoming a source of big data. Since industries are trying to digitise their content, the volume of large datasets has incredibly increased.

The media industry has migrated to digital recording, production, digital delivery which provides them with large amounts of rich content and user viewing behaviours (Villars *et al*., 2011). The healthcare industry is also moving towards images, electronic medical records, which will help in public health monitoring and epidemiological research programs (Oguntimilehin & Ademola, 2014; Villars *et al*., 2011). Through big data analytics, the cost of gene sequencing has decreased and that facilitates the acquisition of gene sequencing which can generate tens of terabytes of information. This will definitely help in the genetic variations and potential treatment (Raghupathi & Raghupathi, 2014). This might help the healthcare industry to provide better treatment to patients and improve their health condition. The availability of huge amounts of data in healthcare has prompted the researcher to focus on the medical aid industry as this industry has the potential to generate a lot of data.

Cameras are not just for video surveillance but have the potential to produce data that can be used for behavioural patterns analysis (Oguntimilehin & Ademola, 2014). Transportation, retail, logistics, utilities, and telecommunications (GPS transceivers, smart meters, call data records, RFID tag readers) are providing the industry with a huge amount of data that can be used to optimise operations and improve operational business intelligence to realise immediate business opportunities and benefits (Oguntimilehin & Ademola, 2014; Villars *et al*., 2011). Social media such as Facebook, YouTube, and Twitter are also sources of data. A number of businesses are using social content such as likes, location sharing, and opinions to analyse consumers' behaviour and preferences (Oguntimilehin & Ademola, 2014). The volume of transactions that can be collected and analysed can double or triple in size due to the consolidation of global trading environments (Villars *et al*., 2011). Medical aid organisations can use social media content to analyse how its clients are discussing certain topics related to health issues, schemes choices, and schemes issues.

2.2.2. Big data analytics

Big data has no value without any analysis therefore companies or organisations have to analyse any data stored in their databases to get value to solve business problems at hand and to improve decision making. Haas, Maglio, Selinger & Tan, (2011) have argued that analytics can be defined as a complete business problem solving and as a decision making process.

Depending on the authors, analytic techniques can be grouped into three to five main categories: Watson (2014) has identified three main techniques namely: descriptive analytics, predictive analytics, exploratory or discovery analytics while other authors (Haas *et al*, 2011; Deloitte, 2014) have added some other categories such as prescriptive and cognitive analytics.

Descriptive analytics is the first and the simplest of the analytics. In this category, much of the analysis looks at what happened and draws conclusions (Watson, 2014). Most of the medical aid organisations are already using this type of analytics. In predictive analytics, much of the analysis is to find out what might occur in the future (Maltby, 2011; Mosavi & Vaezipour, 2013). Medical aid organisations are starting to realise that the predictive analytics is the type to use in order to minimise the business risk. Prescriptive analytics determines and predicts new ways to function (Haas *et al*, 2011). In exploratory or discovery analytics, although many consider it as predictive analytics, exploratory or discovery analytics is more about discovering relationships in “big” data that were not previously found. Finding these relationships provide additional opportunities for companies with huge amounts of data (Perer & Shneiderman, 2008; Watson, 2014). In a white paper published by Deloitte in 2014, cognitive analytics is defined as a combination of analytics and cognitive technologies humans use to make effective and efficient decisions.

2.2.3. Related Technologies

Techniques of big data analytics

There are various analytic techniques in the industry that can be used when undertaking big data projects. The type of analytic technique to use depends on the type of data being analysed, the problem the organisation is trying to solve, and the technology available (Maltby, 2011).

The association rule learning technique helps to find relationships among variables. The technique is used by some of the big companies like Netflix and Amazon (Chen, Mao & Liu, 2014; Maltby, 2012); while Picciano (2012) describes data mining as the technique of searching and scrutinising a data file for information. Cluster analysis is the technique of grouping similar objects into smaller groups, then trying to find about the similarities of these objects (Maltby, 2012; Manyika, Chui, Brown, Bughin, Dobbs, Roxburgh & Byers, 2011). Another technique is crowdsourcing which consists of collecting data from a large group of people using a web2.0 tool (Maltby, 2012). According to Troester (2012), companies including medical aid organisations should not only consider collecting data from Apps, social cloud but should consider also collecting data from connected devices to make the most of big data. The most recent technique is machine learning where computers are able to act without being explicitly programmed. Computers are able to recognise intricate patterns and then generate report for decision making (Manyika *et al*, 2011; Maltby, 2012). The US department of Homeland Security has used the machine learning technique to analyse cell phones, emails, and credit card purchase histories in an attempt to find patterns leading to any security attack or threat (Miller, 2012).

A large percentage of generated data is in text format such emails, webpage content, internet searches, business documents, and social media. Text mining is considered as a multi-disciplinary technique which involves information retrieval, statistics, and computing linguistics (Chen *et al*., 2014). Text analysis should be used to extract useful information (Maltby, 2011; Melville, Burke & Hirst, 2009). Image analytics which includes images and image sequences (video) is a technique which consists of extracting meaningful information from images and videos using algorithmic extraction and logical analysis systems (Fritz & Andrew, 2012).

Big data and cloud computing

The emergence of cloud computing has provided the storage capacity and processing to big data. Simultaneously, big data has accelerated the progress of cloud computing. Although cloud computing and big data use similar technologies, there are two aspects that distinguish them: - cloud computing is meant to transform the IT architecture; while big data is meant to influence business decision making. The target customers for the two technologies also differ. Cloud computing targets chief information officers (CIO) as it provides advanced IT solutions. Meanwhile, big data targets chief executive officers as it improves decision making (Chen *et al*., 2014). Cloud computing is the technology solution that supports big data. According to Kissinger, president of EMC the application of big data should be based on cloud computing. Cloud computing provides services such as software as a platform, platform as a service or infrastructure as a service (IaaS). SaaS is a possible option for organisations that have limited financial and human resources (Watson, 2014). The analytics part of big data relies mainly on the software services (Hilbert, 2013).

Big data and Internet of Things (IoT)

Internet of things (IoT) paradigm is seen as the data collected via network systems from sensors embedded into various devices and machines. The sensors are deployed in different fields and may collect different type of data, such as geographical data, environmental data, healthcare data, logistic data, astronomical data etc. Although IoT generates data for big data, currently, IoT data does not represent the majority of big data but by 2030, the world will have around one trillion sensors and IoT data will represent the most important component of big data (Chen *et al*., 2014).

Some authors have identified the benefits of the IoT as a component of big data analytics at four levels: society level, industry level, organisational level and individual level. At society level, IoT through the use of big data analytics has the capability to improve the transparency of the governments, and to reduce cost within government services (Sunil Datt, 2011; Knutsen, 2014). According to Glenn (2014), IoT as a component of big data analytics will help humanity become more compassionate and responsible, as people will see humanity as a whole. At the industry level, IoT as a component of big data analytics will transform the healthcare industry (Sunil Datt, 2011; Shrestha, 2014), education, retailing, manufacturing, construction (Sarkar, Lovett, Bertuccelli, vrabie, Krucinski & Mijanovic, 2013) and emergency services such as disaster management (Tucker, 2013). For instance, the early detection of problem in manufacturing materials such as machinery could lead to savings by providing early solutions. At the organisational level, it can improve efficiency, visibility, one to one marketing, cost reduction and productivity (Yonck, 2013). At the individual level IoT through the use of big data analytics, would benefit individuals in such a way that the remote monitoring of residences, and car service reminders become more effective and easy to use. It will also facilitate employment through the information shared using ubiquitous technology (Fowler, Pitta &Leventhal, 2013).

Data center

Nowadays, a data center is used as a platform for storage, data acquisition, managing, and organising data. For the enterprise to use big data effectively, it needs a powerful data center that supports the processing of big data. The enterprises should consider taking the development of a data center seriously. Since the big data analytics endows more functions to a data center, a data center should not only be seen by the management as hardware facilities but should add the capacity of processing, organisation, and analysis. It should also develop and provide solutions from big data (Chen *et al*., 2014). In addition, there is a solution to outsource the data center services. Four main companies are providing effective data warehousing products such as, Oracle, SAP, Microsoft, and IBM (Watson, 2014).

2.3. Big data analytics in the related industries

Data and information have been classified as the basis in the industry of insurance (Smallwood & Breading, 2012; IBM, 2012). The insurance industry is grounded on information, analysis, and relationships. With the explosion of data available and the availability of more technology and innovation able to analyse these data, the insurance industry is increasing their capacity to analyse and get more value from the large data set called big data. The capability to analyse these large datasets, to understand and evaluate risks is another benefit the insurance industry is gaining (Bhoola *et al*., 2014). Insurance industries are overwhelmed with the quantity of data from various sources such as: social media, sensors, and telematics. These new capabilities of analysis allow insurance organisations to gain new strategic and operational insights, as well as evidence for their businesses (Smallwood & Breading, 2012). The age of big data is enforcing the insurance industry to refocus on analytics (Josefowicz & Diana, 2012).

The term analytics involves approaches and tools that are used to get meaningful information or insights from datasets (Josefowicz & Diana, 2012), and many businesses are using these techniques to get answers to their business problems, as well as to get new insight to shape the business model.

Nowadays, effective analysis of large datasets cannot be done without the help of technology, and technological platforms such as Hadoop are taking the industry by storm in providing them with the possibilities to analyse large amounts of dataset available to health insurance. Hadoop is defined as a programming framework used for processing and storing large datasets in a computing distributed environment (White, 2012).

According to the Health Insurance Association of America, health insurance is defined as the coverage that provides for the payments of benefits because of sickness or injury, including insurance for losses from accidents, medical expense, disability, or accidental death and dismemberment. There are mainly two types of health insurance, the private health insurance and the public health insurance (Wilper, Woolhandler, Lasser, McCormick, Bor & Himmeltein, 2009).

Healthcare is considered as a field with a lot of untapped potential for big data analytics (Maltby, 2011). Big data analytics can potentially improve the whole healthcare value chain (Piai & Claps, 2013). In support to that, Belle, Thiagarajan, Sovoroushmehr, Navidi, Beard & Najarian (2015) state that big data analytics will impact the practice of healthcare in the near future. In the United States, big data analytics via the Pillbox project had reduced healthcare costs up to $500 million per year (Song & Ryu, 2015). The aim of the Pillbox project was to help in the identification of unknown pills. The project combined the images of pills with other information to help users to visually search for and identify oral solid dosage of medication.

Heterogeneous medical datasets have become available in healthcare (payers, providers, pharmaceuticals) in recent years. The availability of these large datasets can be an opportunity for improving healthcare service delivery, and at the same time present challenges in the analysis of these datasets (Piai & Claps, 2013). Moreover, Ryu & Song (2014) indicate that big data analytics is an opportunity to analyse, understand, predict, and monitor the context or problems in healthcare. These large datasets (Big data) have to be analysed to provide new and useful information.

Healthcare worldwide dealt with 500 petabytes of data in the past five years, and it is estimated to reach 25 000 petabytes by 2020 (Piai & Claps, 2013). Big data analytics has the capability to revolutionise the entire healthcare system value chain, from drug discovery to personalisation of care for patients; to industrialisation of patient’s medical record for enhanced medical results (Piai & Claps, 2013). The analysis of data has been taken to a new level in healthcare due to the rise and inclusion of social data analytics, even though the analysis of data is not new to science or healthcare (Ryu & Song, 2014). Healthcare has been moving from facts towards becoming data driven (Fitzgerald, 2015). In support, Chawla & David (2013) state that healthcare has moved from disease centred model towards a patient centred model. Medical diagnosis should not be based anymore on clinical based medicine, rather be based on evidence based medicine. In order to identify medical problems in patients, healthcare systems should analyse the medical records of patients, pharmaceuticals records, and insurance records to find patterns and problems accurately in patients rather than basing the analysis on one single doctor (Miller, 2012). Instead of the doctor guessing which drugs work for a particular patient, healthcare systems should be smarter using evidence based medicine (Miller, 2012). In support, Gujarathi & Costa (2014) state that personalised medicine can significantly improve the effectiveness and efficacy of health management at the individual level.

Benefits and opportunities of big data analytics for Healthcare stakeholders

This section identifies healthcare stakeholders and explores the potential benefits of big data analytics for these stakeholders. The body of literature has identified some stakeholders for healthcare as such: researchers, healthcare providers, healthcare payers/insurance, public health and patients (Piai & Claps, 2013; Ryu & Song, 2014).

Big data analytics is helping research in life science and personalised medicine. Healthcare research organisations are being supported by big data analytics in terms of optimising operations and strategies (Piai & Claps, 2013). Life science researchers have found out that big data analytics has the potential to improve clinical trial design and result analysis. The Innovative Medicine Initiative (IMI) is undertaking many projects using big data analytics. The projects consist of developing a toolbox (biomarkers, toxicology tests, and clinical trials protocols) which will prevent the failure or lack of efficacy of new medicines. The toolbox will also help in translating the outcomes of the research into methods which will enhance the practice in the industry (Ryu & Song, 2014; Piai & Claps, 2013). In personalised medicine, big data analytics helps in the examination of relationships between genetic variation, predisposition to specific diseases, and how patients respond to certain medicines. The results will allow hospitals to preventively detect and diagnose any disease before the symptoms are developed by patients (Piai & Claps, 2013).

With the potential to quickly analyse patients' information, healthcare providers are able to apply correctly the recent discoveries of medical research. As a result, healthcare providers will be able to provide personalised evidence based care services, to improve chronic disease management. Big data analytics will enable healthcare providers to leverage efficiently the information from remote patient monitoring systems, monitor patient adherence to prescriptions enabling patients to get better treatment in future, and reduce the potential of any complications in future (Piai & Claps, 2013).

Studies have found out that there are broad variations in healthcare practices, products, and costs across diverse providers, patients, and geographies. The advantageousness of big data analytics are starting to become obvious to healthcare authorities (payers) and healthcare funds (payers) across Europe. Payers should be able to measure the efficiency of several medical interventions through big data analytics. Big data analytics can help providers to identify and categorise the population that present the possibility to develop chronic diseases, so that they are able to design appropriate schemes. With the help of big data analytics, healthcare payers will be able to identify fraud more effectively, by implementing an automated system which will be able to overlook the reimbursement system anomalies. Payers in Europe are trying to use big data analytics to control and improve the so called "Optimal treatment pathways" (Piai & Claps, 2013; Ryu & Song, 2014).

Big data analytics can help the public health system to process data from national health and other social services more effectively, as well as help in detecting patterns and health trends. By doing so, health care providers should be able to analyse new facets and discover new correlations (Piai & Claps, 2013).

Big data analytics will enable the healthcare to get valuable insights and information. Thus with such information, patients will have knowledge of behaviour and treatments that are more effective as well as what is required of them in terms of health behaviours. Patients will profit from big data analytics outcomes in healthcare such that the prevention of chronic diseases will be effective, since the monitoring of patient life style and sensed data will be collected and analysed (Song & Ryu, 2015).

2.4. Benefits of big data analytics in medical aid industry

Big data has revolutionised several applications in different industries. Which range from business, web tech companies, universities, to the medical field (Zan & Yanfei, 2015). The applications of big data analytics vary depending on the industry. This study focuses on probable applications pertaining to the medical aid industry.

Risk assessment

Today, the relationships between insurance companies and customers are mostly virtual and decentralised and that makes it difficult for companies to assess risk effectively (Miller, 2012). However, big data analytics can help companies to effectively and efficiently assess and quantify risk by developing a behavioural model based on customers' profiles data crossed referenced with other data, which is relevant to specific products (Miller, 2012; Tomar & Agarwal, 2013).

Organisations should also be able to access data from previous treatment and current treatment including data from pharmacies, then compare the causes, symptoms, and analyse the data to identify patients with high risk. With such knowledge, medical aid organisations can design appropriate schemes, and reduce the cost due to hospital admissions (Durairaj & Ranjani, 2013; Shah & Pathak, 2014).

Customer relationship and Product personalisation

Customer relationship management is the interaction between the business and its customers. The rise of big data has prompted companies, governments and organisations to easily collect, analyse, predict, and to design efficient responses to customers' needs. Big data analytics can help to define the preferences, to determine usage patterns, and the previous, current and future needs of customers to make CRM more effective and well-organized. Big data analytics can also help to predict new products that customers will likely appreciate (Koh & Tan, 2011; Tomar & Agarwal, 2013). Customers' data based on demographics, account information, and health information can help aid insurers to tailor personalised schemes (Miller, 2012).

Fraud detection and claim management

Many companies are moving from claim-centric fraud detection technique to person-centric fraud technique. The person- centric approach consists of the integration of information from all the providers involved in the claim process (Bharal & Halfon, 2013). Big data analytics has taken the detection of fraudulent claims to another dimension. Big data analytics can improve investigations, as well as prevent crime efficiently (Hipgrave, 2013). Deloitte (2013) has developed a framework model to help insurance/medical aid organisations to detect fraudulent claims more effectively.

The framework consists of four steps such as fraud model, similarity model, segmentation model, and severity model. These steps are:

Fraud model: Collecting claim notes from the third party and data from social media, then analysing them to find patterns can improve the early detection of fraudulent claims.

Similarity model: The advanced text analytics technique can help medical aid organisations to identify similarities in claims which will allow them to easily research and establish best practices.

Segmentation model: The aim here is to classify claims into categories and assign the claims to the right adjuster.

Severity model: the aim here is to identify the cost of the claim, the higher the claim the more expensive the claim will be.

Smart health

Preventive care in daily life has become the solution to medical cost due to the aging of patients and the increase of certain diseases (Suzuki, Tanaka, Minami, Yamada & Miyata, 2013). With the increase of the amount of data and the capabilities of analysing the large datasets through big data analytics, the industry has introduced a new way to preventive care called smart health. Some organisations have designed and developed some sensors devices, wearable devices to monitor patients, analyse patient's health data, and prevent any risk.

The number of people aged 65 and above is expected to reach around 1 billion by 2030 worldwide (Teng, Zhang, Poon & Bonato, 2008); from the economic and social point of view, the aging of the population is a triumph of medicine over disease but comes with challenges in maintaining aging people's health because they are more fragile to certain diseases and need more care.

Some of the typical cases for smart health are to support and monitor old people's health, to prevent disease by knowing one's status, and to monitor diet progress process (Suzuki *et al.*, 2013). The recent developments in body area network (BAN) have made it possible for medical aid organisations to design an effective scheme which will allow them to monitor, analyse, and prevent any risk. These sensors and wearable devices will be the main source of data collection (Jakkula, Cook & Jain, 2007).

Medical aid organisations can design a scheme called smart home. The scheme will consist of sensors and wearable devices in a network environment to effectively monitor and prevent some diseases affecting aged people. These sensors and wearable devices can detect the temperature of the environment, and analyse data to monitor pulse, blood pressure, check progress of diet, and send information to a system that analyses data effectively. In addition, the devices could provide feedback to the patient or physician if there is any risk by alerting them with a text message sent to their phones or relatives' phones; or predict the health of the patient after analysing effectively and efficiently the data collected from the devices. The aim is to make a smart home whereby the health of a patient is monitored closely.

2.5. Adoption of big data analytics in industries

According to the CEO of Cloudwick Mani Chabra, adopting and integrating big data can take a year, and the process is divided in three stages. The first stage is the implementation of the platform, the second is building the data pipelines, and finally when the data is available, the organisation can analyse, transform, and visualize the data. On the other hand, Parashar (2013) has developed a big data framework to facilitate the adoption within an organisation. The framework consists of five steps: data discovery, analytics discovery, tools and technology discovery, infrastructure discovery and implementation. Most authors have similar steps but use different terminology.

Global estimation of the adoption of big data analytics

The estimated adoption of big data analytics for large organisations worldwide is 14% in 2012, 20% in 2013, 24% in 2014, 26% in 2015, 28% in 2016, and 29% in 2017 (Bhoola *et al*., 2014). IDGenterprise published in 2014 the result of a research survey exploring big data analytics and gaining a better understanding of how organisations adopt, utilise, and invest in big data analytics, and has found that seventy percent of organisations have started or are planning to start big data projects for large organisations versus fifty-five percent of small and medium businesses. Datameer (2015) found that 37.8% of enterprises in North America are currently investing in big data analytics and 18.5 % are planning to invest within a year. In Europe, Middle East, and Africa 26.8% are currently investing in big data analytics, while 17.5% are planning to invest in the coming years, in Asia/Pacific. In support, the Economist has stated that the adoption of big data analytics in Asia/Pacific is slower than the industry would have expected. A total of, 25.6% of enterprises are currently investing in big data analytics and 27.3% are planning to invest within a year, in Latin America. Furthermore, 17.8% are currently investing in big data analytics, while 11.1% are planning to invest in big data analytics within a year.

According to e-skills UK report (2013), 14 % of organisations with 100 or more employees have already adopted big data analytics, while 7% are in the process of implementing big data analytics. It was estimated that by the end of 2013 around 4600 organisations/businesses would have implemented big data analytics in the United Kingdom. The adoption rate of big data analytics in the UK will double between 2012 and 2017. According to a survey conducted by ITnewsAfrica in 2013, 38% of companies in South Africa had achieved a competitive advantage due to big data analytics, and 23% of companies had no plan to invest in big data analytics.

Organisations are deploying big data analytics projects because organisations want to improve the quality of decision making process, planning and forecasting, improve the speed of decision making, develop new products/services and revenue streams (Savitz, 2012; IDGenterprise, 2013).

According to Manyika *et al*., (2011), the public sector will not gain as much as the other sectors from big data analytics because the storage system of the public sector is not advanced as the storage system of other sectors. The value of big data analytics in Europe for public sectors is estimated around 250 billion euros regardless of the amount of data collected (Manyika *et al*., 2011). The public sector has started using web analytics, web 2.0 and social media analytics for their campaign advertising, policy discussion, voter mobilisation, and donations (Chen, Chiang, & Storey, 2012).

The private sector is constituted with a variety of industries and the private sector is handling enormous amounts of data as it stands to gain the most from big data analytics (Maltby, 2011). Any organisations dealing with any type of customers can benefit from big data analytics (Russom, 2011). From customer base segmentation to targeted marketing, to improving products, and decision making, the private sector benefits from big data analytics. Companies like Amazon, Wal-Mart, and Harrach effectively use big data analytics and are reaping the benefits (Manyika *et al*., 2011). The adoption of big data analytics by certain companies is impacted by the other industry parties (Riggins & Wamba, 2015). For in instance, the adoption of big data analytics by medical aid organisations will be also be impacted by the adoption of big data analytics by the pharmaceutical industry, governments, and hospitals as these industries are interrelated.

Big data analytics is going to revolutionise the future of higher education (Siemens & Long, 2011). The use of technology by education is increasing each year (Maltby, 2011). According to Picciano (2012), 30 % of worldwide students had enrolled in at least one online course in 2010, and many students have enrolled in blended courses (a course that includes face to face teaching and online teaching). Education is trending towards using more and more technology. Picciano (2012) and Siemens and Long (2011), listed nine areas which can benefit from big data analytics: recruitment and admissions, student performance monitoring, financial planning, donor tracking, help at- risk students, administrative decision making, analysing and understanding challenges, as well as understanding the hard and soft value of faculty activities.

A school in the USA, Arizona used big data analytics to monitor the performance of its students. They analysed the login information on their courses' websites, number of clicks, number of pages visited, the time spent on the page, what the students were posting on the website to quickly find out which students struggled, which assisted the faculty to predict which student struggled and provide help (Picciano, 2012).

2.6. Determinants of big data analytics adoption

It has been argued from the literature that determinants of an adoption of IT innovation can be either internal or external. In this study, the researcher subdivided the determinants into two categories: external and internal.

2.6.1. Internal factors

Many researchers have identified certain internal factors that may influence the adoption of IT innovation. However, the study focuses on the internal factors which are relevant to the adoption of big data analytics. These factors can be classified as internal IT capabilities, availability of financial resources (price of big data), and organisations' characteristics. According to The Economist, 91% of companies in Asia/Pacific see internal issues as impediments to the adoption of big data analytics; issues vary from lack of suitable software, information silos, lack of in-house skills, lack of willingness to share data, and no buy-in from management (management support).

Internal IT capabilities

This section can be divided into in-house IT skills and availability of IT infrastructure

In-house IT skills

According to IDC, the availability of people with big data IT skills and deep analytics skills will directly impact the big data market. In the long term, shortage of big data skills will turn most organisations to cloud platforms. Furthermore, Yang, Huang, Li, Liu & Hu (2017) support that big data is initiating the adoption of cloud computing in many enterprises. In a survey research conducted in Asia/pacific by the economist, 40% of respondents identified lack of skills as one of the barriers of the adoption of big data analytics. In another research survey conducted by e-skills in the United Kingdom, 90% of companies that implemented big data analytics said that having the required skills for big data analytics in the organisations would have a great impact in the setting up, running and benefits of big data analytics. People with different type of skills are needed during big data analytics projects such as statisticians, BI analysts, business analysts, and data scientists (Hilbert, 2013; Watson, 2014).

Availability of IT infrastructure

The body of knowledge identifies IT infrastructures as an influential factor of the adoption of big data analytics. Software, data warehouse, hardware, and a strong network system have been identified as part of the IT infrastructure. Most companies already have infrastructures for their business intelligence, which suit the analysis of structure data but do not suit unstructured data.

Bhoola *et al*., (2014) advocate that traditional IT infrastructure in an organisation can be a challenge in the development of big data processes and extraction processes. In a survey report conducted by the economist in Asia/Pacific, 42% of companies consider the lack of suitable software as one of the impediments to the adoption of big data analytics. The remedy to this internal impediment might be an external provider. However, according to e-skills UK, 81% of enterprises in UK run big data projects using their own infrastructure. Organisations need a strong big data analytics infrastructure. Generally, IT people understand the importance of big data infrastructure while business people within the organisation do not fully understand the importance (Watson, 2014). Suitable database, analysis tools are an impetus towards big data analytics adoption.

Price of big data

Big data analytics has the potential to provide useful information to companies but comes with some challenges including the cost related to the development of big data analytics projects (Miller, 2012). According to a Forrester research report, hardware costs only 18.8 % of company IT budgets and the rest of the budget is used in buying software and developing applications. The development and implementation of big data analytics in a company requires new storage systems, new analytics software, new analytical skills, and applications which require extra cost (Savitz, 2012). The cost associated with the acquisition of new infrastructure can affect the adoption of big data analytics.

The cost of big data is not only about the cost of storage but involves the cost of software and skills. Actually the cost of storage has decreased to the extent that many organisations can afford, the cost of a terabyte is around 70$ (Avanade, 2012). The most difficult challenge with big data analytics is acquiring people with high quality analytical skills. According to estimations, the United States is facing a shortage of people with deep analytical skills. The USA needs around 160.000 experts in analysis and about 1.5 million managers and analysts to manage big data analytics. The time associated with big data is costly to companies, as well as accessing the data to its effective use. If it takes long to access the data and use it, the costs may be high and the information retrieved from that data rendered useless (Maltby, 2011).

Firm size

E-skills UK conducted a survey with the aim of finding out if small enterprises have adopted big data analytics. The survey reveals that the proportion of SMEs running big data projects is minimal, and that the adoption of big data analytics is correlated with the size of the company. Larger companies are more likely to adopt and run big data analytics projects than small enterprises. This finding is supported by another survey finding conducted by the economist in Asia/Pacific; which reveals that, larger organisations in Asia/Pacific are better and well advanced in the adoption of big data analytics. There is a direct correlation between the size of organisation and the adoption of big data analytics.

Support from top management

Watson (2012) has identified seven factors that are needed by organisations in order for them to become successful in analytics. One of the factors identified is strong committed sponsorship. In order for organisations to successfully adopt and use big data analytics, the top management should be fully committed in supporting these projects. Schroeck, Sbockley, Smart, Dolores & Tufano (2012) state that at the beginning of the adoption of big data analytics, the CIO might be the main sponsor of the project but as the business opportunities are clearly identified and the big data infrastructures have been identified and acquired, the sponsorship should shift from the CIO to CMO, CFO, or CEO. Watson (2014) states that if the big data project is within a department then the sponsorship should remain within the department but if it is a strategic big data analytics project then the top executive should be the main sponsor.

2.6.2. External factors

Competition and industry pressure

Grandon and Pearson (2004) define external pressure as the direct or indirect influence exerted on a company by competitors, government, customers, the industry, or other firms to adopt an innovation. Al Qirim (2005) and Looi (2005) have concluded that competition and industry pressure can influence the adoption of an IT innovation. To the researcher's best knowledge, there is no literature advocating that social influence such as competition, industry pressure and customers do not influence the adoption of big data analytics. Thus, there is a need to test the variable.

Data privacy and governance

Big data analytics consists of collecting, extracting, analysing, trying to find patterns and relationships in the data collected, and all these processes can lead to a violation of privacy (Bryant, Katz & Lazowska, 2008). The ever increasing number of new personal data from tracking devices, sensors, social network/media, internet-of-things (IoT) devices make the violation of privacy possible (Swan, 2013). Therefore, regulations and rules should be put in place to ensure that customers' personal data are being used wisely in a protective way; that will lead customers to allow organisations, and governments to use their personal data. If regulations in a country do not allow organisations to easily use and share data due to privacy reasons, the adoption and utilisation of big data analytics can become difficult. Users are concerned by the inappropriate use of their personal data (Agarwal & Dhar, 2014). The development and implementation of big data analytics should consider creating safeguards to prevent abuse of privacy. Preventive measures should also be taken to protect sensitive data when a third party is handling customers' personal data (Chen *et al.*, 2014). Privacy and security are closely tied therefore customers' personal data, and patients data should be secured so that hackers are not able to access the data. Chen *et al*. (2012) say many big companies were expected to spend 32 billion dollars on computer security.

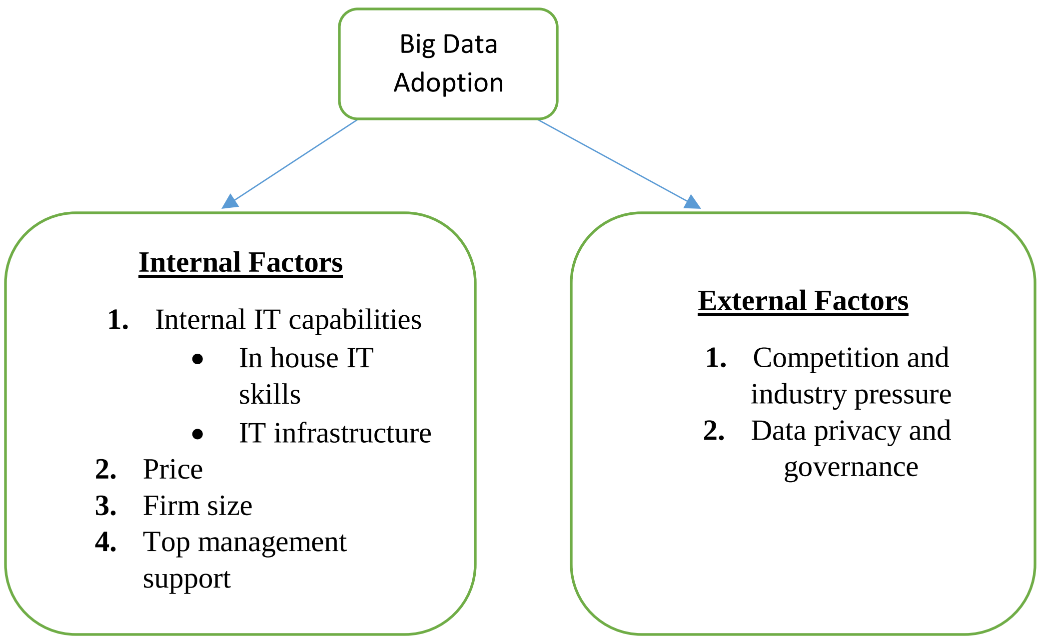

Figure2.1. Determinants of adoption of big data

2.7. Challenges in big data analytics process

As most organisations worldwide are ready to model and adopt big data as an essential element of the information management and analytics infrastructure, organisations should also be ready to face big data challenges. The whole process of big data analytics brings some technical and business challenges (Salian, 2015). The common challenges identified by IT practitioners, business sponsors and researchers are data extraction, data incorporation and aggregation.

Data extraction and cleaning

Data collected will not be ready for analysis directly, therefore there will be a need to analyse them. The different format of the data collected are not usually suitable for analysis, therefore there will be a need to make them suitable for analysis. Cleaning the data is an important part of big data analytics. The time spent in cleaning the data is more important than the time spent performing statistical analysis on the data (Salian, 2015). Big data analytics will have value only if the right data are being analysed. According to Salian (2015) data cleaning is a main challenge in big data analytics process. The solution to this problem relies on having a strong data governance or to have information management processes in place. This will lead to extracting the required information from the raw data (Labrinidis & Jagadish, 2012).

Data integration and Aggregation

Integrating data from different sources then combining it into meaningful and valuable information is another challenge to big data analytics (Salian, 2015). Furthermore, doing the integration in a fast way and at reasonable costs is another challenge at this stage (Lavastorm, 2013).

2.8. Theoretical Framework

Researchers have been writing about the adoption of a new innovation/technology. Many models and theories have been developed to understand the process of adoption of innovations by companies and users. The adoption of innovation is a process that comprises steps. Some of the models discuss the acceptance, the early adoption, the behaviour, the awareness and the full adoption. This study defines adoption as the acceptance for implementation. Some of the popular theories/models have been evaluated for the purpose of this study. These are discussed below:

2.8.1. Technology Acceptance Model

The technology acceptance model was established by Davis in order to explore the acceptance of technology by users. It is used to explain why users accept or reject information technology (Davis, Bagozzi & Warshaw, 1989). TAM do not really fit into the context of this study as it measures the acceptance of an already fully implemented technology.

2.8.2. Unified Theory of Acceptance and Use of Technology

The Unified Theory of Acceptance and Use of technology mixes eight models that were used in research to describe the usage behaviour and technology acceptance (Venkatesh, Morris, Davis & Davis, 2003). These are the 8 dominant theories/models: The Theory of Planned Behaviour (TPB); The Theory of Reasoned Action (TRA); The Technology Acceptance Model (TAM); The Model of Personal Computer Utilisation (MPCU); The Motivation Model (MM), The Diffusion of Innovation theory (DOI); The Social Cognitive Theory (SCT); a theory combining the Technology Acceptance Model; and the Theory of Planned Behaviour (C-TPB-TAM).

According to UTAUT1, the four main variables of the UTAUT model are the key determinants of the intention to use a technology (Venkatesh *et al*., 2003) . Although this study included most of the constructs from UTAUT, UTAUT did not fully fit this study as it does not provide enough constructs to measure the perception on adoption of big data analytics as intended in this study.

2.8.3. Diffusion of Innovation theory

The diffusion of innovation is a "decision making process that occurs through a series of communication channels over a period of time" (Rogers, 2003:5). According to Rogers, the term innovation refers to new technology. For this proposed study, the term technology will be used instead of innovation.

The adoption of any innovation is determined by five factors such as relative advantage, compatibility, simplicity or complexity, trialability, observability which are called as the five perceived characteristics of a technology and these characteristics are proven to be very influential to the decision making process in the adoption process (Robinson, 2009; Sahin, 2006; Rogers, 2003). DOI describes and explains the adoption process of innovations but fail to fit this study as DOI does not provide enough constructs to measure the perception on the adoption as it is intended in this study.

2.8.4. Theory of Planned Behaviour

This theory predicts the intention of individuals to engage in behaviour at different times and place. In this theory, behaviour is a key factor triggered by individual's intention. The behaviour intention is influenced by three main determinants: attitude toward behaviour, perceived behavioural control and subjective norms (Ajzen, 1991). TPB does not fit this study as it does not measure the acceptance for implementation of a technology which is the purpose of this study.

2.8.5. Conceptual Framework

In this proposed study, the researcher will be using a conceptual framework made of some of the constructs selected from the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2);

a construct from the technology acceptance model and the perceived characteristic of innovation from Diffusion of Innovation to explore the employees perception on the adoption of big data analytics by selected medical aid organisations in Durban.

Performance expectancy is referred to as the degree to which a user believes that the use of a system will increase his/her job performance. For the purpose of this study, this construct will be named perceived Performance Expectancy. Social influence is referred to as the extent to which individuals are influenced to use a new technology/innovation by influential people; for the purpose of this study, this construct will be called perceived social influence. Facilitating conditions is referred to as the availability of technical and organisational infrastructure to sustain the usage of a new innovation/system (technology) (Venkatesh, Y.L.Thong, & Xu, 2012). Price value is referred to as the cost of technology being used by the consumer or the cost of the technology a consumer is willing to invest. In this study, perceived price value is defined as the perception of cost of innovation as seen by the users. The main constructs of UTAUT are moderated by four variables: age, gender, experience, and voluntariness of use but for the purpose of this study, these four moderating variables (age, gender, experience and voluntariness of use) will not be used. The literature does not provide enough evidence of the importance of these four moderating variables in the adoption of big data analytics. According to Armida (2008), most studies using UTAUT did not use the moderating variables.

For the proposed study, the researcher will be using four constructs of UTAUT 2 (Perceived Performance expectancy, perceived social influence, facilitating conditions, and perceived price value) to explore the employees' perception on the attitudes towards the adoption of big data analytics by selected medical aid organisations. The constructs chosen were seen as having an impact on the employees' perception on the attitudes towards the adoption of big data analytics.

Relative advantage is seen as the degree to which a technology seems to provide better outcomes or services to the consumers or users. The more an innovation or technology seems to provide relative advantage the more chances it has to be adopted (Tornatzky & Klein,1982; Limthongchai & Speece, 2013; Damanpour & Schneider, 2009).

Compatibility is seen as the degree to which a new technology seems to be consistent and compatible with the past experience, values, and requirements of probable adopters (Tornatzky & Klein,1982; Limthongchai & Speece, 2013; Damanpour & Schneider, 2009).

Complexity of an innovation is seen as complicated to use and understand. Innovation/new technology that are easier to comprehend and use are likely to be adopted than technology that are difficult to comprehend (Tornatzky & Klein,1982; Limthongchai & Speece, 2013; Damanpour & Schneider, 2009).

Trialability is the degree to which a new technology/innovation can be tried before full implementation or adoption. The faster an innovation is tried the more likely it is to be adopted (Tornatzky & Klein,1982; Limthongchai & Speece, 2013; Damanpour & Schneider, 2009).

Observability is the degree to which the impact of a new technology is noticeable to others. The more others see the impact of a new technology the more likely it is to be adopted (Tornatzky & Klein,1982; Limthongchai & Speece, 2013; Damanpour & Schneider, 2009).

As mentioned in the literature, big data analytics comes with many challenges and one of them is privacy/security. For the purpose of this study, privacy/security was selected as a construct to influence the adoption and use of big data analytics. Privacy/security is seen as the degree to which user's information is used in a secure manner. The more information is used confidentially the more users can permit organisations to use it. Organisations can use users' information but also preserve patient privacy.

Attitude towards adoption can be seen as positive or negative feelings or beliefs a person has towards something; in this case towards big data analytics (Ajzen &Fishbein, 1975). In this study, attitude is considered as the dependable variable.

In this study, three of the perceived characteristics of innovations (compatibility, relative advantage, complexity) are used to explore the attitudes towards the adoption of big data analytics. Compatibility, relative advantage, and complexity are seen as potential factors that can determine the adoption of big data analytics and have an influence on the employees' attitudes towards the adoption of big data analytics. Rogers states that 49% to 87 % of the adoption of a new technology can be attributed to these factors. Figure 2.2 below illustrates the constructs that can be the potential determinants in the attitudes towards the adoption of big data analytics.

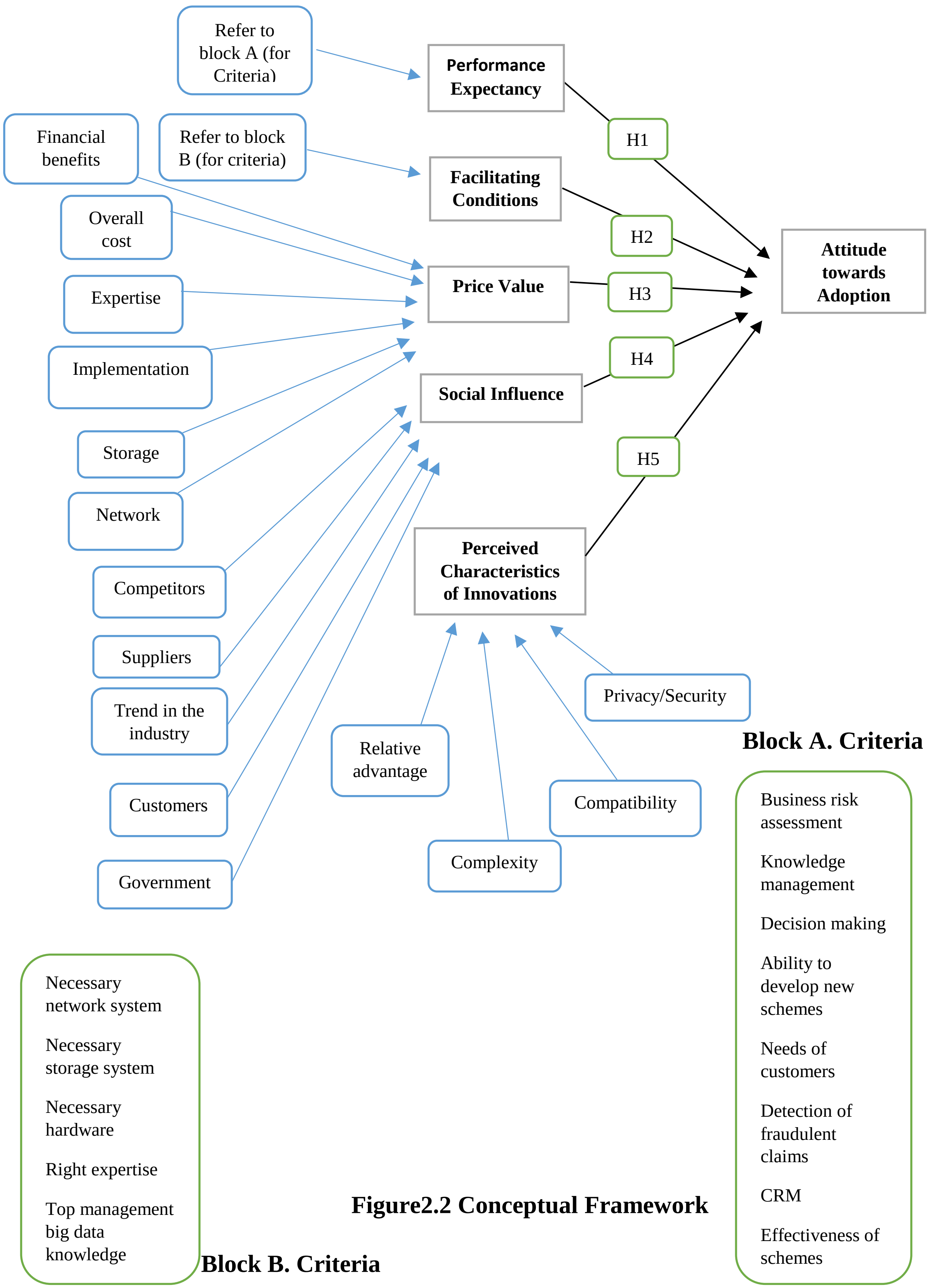

Figure2.2 Conceptual Framework

Hypotheses development and assumptions

H1: For the purpose of this study, the perceived performance expectancy is selected to be one of the constructs that can influence the attitudes towards the adoption of big data analytics. The perceived performance expectancy will have an influence on the attitudes towards the adoption of big data analytics; it will be expected to improve the performance of the company. Employees and executives will only have positive attitudes towards the adoption of big data analytics if they believe that big data will improve the company's performance.

H2: the availability of technological infrastructure will likely contribute to the intention to adopt big data analytics since big data analytics is a complex technology. The perceived facilitating conditions (resources) will influence the attitude towards the adoption of big data analytics.

H3: The perceived price value of big data analytics will influence the attitude towards the "adoption of big data analytics". If the price is perceived not to be affordable, then it is likely to have a negative influence on the attitudes towards the adoption of big data analytics and vice versa.

H4: The influence from industry, suppliers, government, and customers will influence the attitudes towards the adoption of big data analytics.

H5: the perceived characteristic of an innovation will greatly influence the adoption process of new innovation. The characteristics will influence the employees' attitudes towards the adoption of big data analytics. Companies will most likely want to know if they would get any relative advantage by adopting big data analytics. The more employees see that by adopting big data analytics, the company will get a competitive advantage, and that big data analytics is compatible with the actual company's business process or IT infrastructure; the more likely they are to have a positive attitude towards the adoption of big data analytics.

2.9. Summary

This chapter made every effort to identify the knowledge gap and establish the need for this research. A detailed discussion on big data analytics, benefits of big data analytics, and adoption of big data analytics were provided. The aim was to discuss the gaps in the body of knowledge. The chapter further provided a discussion on the benefit of big data analytics in the healthcare sector (medical aid sector) and across other industries. The determinants of big data analytics adoption were also discussed in this chapter. Moreover, the constructs for the adopted conceptual framework were identified from the internal and external determinants. The next chapter (Chapter3) discusses the methodology used to conduct this research project.

CHAPTER 3

RESEARCH METHODOLGY

3.1. Introduction

Research is generally based on some basic philosophical assumptions about a given research problem (Barnett, 2005). Research is considered as a voyage of discovery. The research methodology is defined as the study of strategies of enquiry by which knowledge is gained (Meert, Briller, Myers, Thurston & Kabel, 2009). The research methodology moves from the basic assumptions to research design, and data collection. This chapter describes in depth the research design and methodology employed in this research project to answer the research questions.

1. What is the perception of performance expectancy among the employees towards the adoption of big data analytics in selected medical aid organisations in Durban?
2. What are the perceived facilitating conditions influencing the adoption of big data analytics by selected medical aid organisations in Durban?
3. How does the employees' perception on price value influence the adoption of big data analytics in selected medical aid organisations in Durban?
4. How does the employees' perception of social factors influence the adoption of big data analytics in selected medical aid organisations in Durban?
5. What are the perceived characteristics of innovation influencing the employees' attitude towards the adoption of big data analytics by selected medical aid organisations in Durban?
6. How does the employees' attitude towards big data analytics influence its adoption by selected medical aid organisations in Durban?

The chapter explains the research instruments used, the population of the study, sampling methodology, data analysis method, the validity and reliability of the research instruments, and issues of ethical clearance are addressed.

3.2. Research Paradigm

Kuhn (1976) explains research paradigm as a set of beliefs, understanding, and covenant between researchers about how to address and understand problems. Five main research paradigms have emerged from the literature (Feingold, 1990; Scotland, 2012).

Positivists considered, as realists believe that there is a single truth (reality). Interpretivists also considered, as constructivists believe that there is no one truth or reality and that reality is generally created in a group of individuals. Pragmatists believe that the reality is something that can be constantly renegotiated. Subjectivism suggests that the reality is the reflection of what we perceive to be. Critical believers advocate that social entities are under continuous internal influence. This study has opted for a positivist paradigm, as it is believed that reality can be measured through reliability and validity tools.

3.3. Research design

Research design is defined as an overall strategy employed in a research study to effectively address the research problem. It is a skeleton of the measurement, collection and data analysis of data (Creswell, 1994).

3.3.1. Nature of the Study

The literature has identified three main types of study in research such as descriptive study which is referred to as a research that describes the characteristics of variables rather than testing relationships between variables (Polit, Beck, Hungler & Bartholomeyczik, 2004; Sekaran & Bougie, 2010); and exploratory which is conducted to gain new insights, to discover news ideas, and increase knowledge of the phenomenon (Burns & Grove, 2001). Explanatory study also known as casual research is conducted to explain and understand the cause and effect relationships (Abid & Naifar, 2006).

This study attempts to explore the employees' perception on the adoption of big data analytics by selected medical aid organisations in Durban. Since big data analytics is still new in the industry, and the researcher was willing to get new insights and more knowledge about the phenomenon, the research philosophy selected is suitable for this study. The exploratory design allows the research methodology to be flexible. Since this is an exploratory study, conclusive evidence is not provided. The findings serve as a ground for further research to investigate big data analytics in depth.

3.3.2. Research strategy

A research strategy is a general plan that helps the researcher to address research questions in an organised way (Saunders, 2011).

In survey research strategy, the researcher selects people from a population to administer a standardised questionnaire (face to face or online questionnaire) to the respondents (Fowler & Leventhal, 2013). In case study strategy, the researcher investigates in depth one or few similar problems in other organisations (Saunders, 2011). Pilot studies, the researcher uses sampling but does not apply rigorous standards (Van Teijlingen & Hundley, 2002). In action research, participants scrutinise their own educational practice thoroughly and carefully, using the techniques of research (Brydon, Greenwood & Maguire, 2003). In an archival research strategy, the researcher seeks and extracts evidence from archival records such as manuscripts, documents, records or other materials (Mohr & Ventresca, 2002).

In this study, the researcher opted for survey research strategy as the aim was to get data from the two companies, analyse, then compare for any significant difference between the data from the two companies.

3.4. Research Approach

Most researchers have agreed that the research methodology revolves around quantitative and qualitative approaches (Creswell, 1994; Leedy & Ormrod, 2005; Kumar & Phromathed, 2005). A quantitative approach is seen as a more structured and quantifiable approach (Kumar & Phromathed, 2005). This approach is suitable for researchers who plan to quantify the variation in a phenomenon, problem, or situation. Furthermore, statistical analyses are used in the quantitative approach (Allison, 2002). The qualitative approach falls under the category of interpretivist paradigm. The qualitative approach is suitable for a research project describing a situation, phenomenon, or problem. In this approach, the analysis is not meant to quantify the variations in the situation, phenomenon being investigated but find the difference in the situation, or phenomenon (Kumar & Phromathed, 2005). In this approach the emphasis is on the words rather than quantifying the data (Bryman, 2001).

For the purpose of this study, the quantitative approach was chosen as it enables the researcher to relate independent and dependent variables in order to determine causality within the framework.

3.5. Research Site

The research sites for this research project were two selected medical aid organisations based in Durban in KwaZulu-Natal/South Africa.

3.6. Target population

The target population for this study was drawn from two selected medical aid organisations in Durban. Organisation A had 27 and organisation B, 36 employees. The sample population for this study is 59.

3.7. Sample

A sample is referred to as a small group of the whole population designated to participate in the study; while the sample size is the effective number of people selected to take part in a study (Yin, 1994). Two main sampling methods have emerged in the research industry: probability sampling and non- probability sampling. In probability sampling everyone has an the same chance to be chosen to represent the sample (Latham & Locke, 2007); while in non-probability sampling, the researcher selects some participants that he/she thinks are helpful to the research project (Thomas & Brubaker, 2000).

There are four probability sampling techniques.

In simple random sampling, all the medical aid organisations have an equal chance to be selected and to participate in a proposed study (Cooper, Schinder & Sun, 2003).

In systematic random sampling also known as proportional sampling, the target population is divided into subgroups, and then the researcher selects random samples from each subgroup (Csikszentmihalyi & Larson, 2014).

In stratified random sampling, the researcher is interested in particular strata (groups) within the population (Teddlie & Yu, 2007).

In cluster sampling, the researcher selects a group of study units (clusters) instead of selecting study units individually (Malilay, Flanders & Brogan, 1996).

There are three non- probability sampling techniques identified by the researcher:

In quota sampling technique, the selection of the sample is based on certain variables determined by the researcher (Moser, 1952).

In purposive sampling technique, the sample selected to represent the population is solely determined by the expertise of the researcher (Teddlie & Yu, 2007).

Convenience sampling includes accessibility, availability, readiness and willingness to participate as factors that determine the selection of the sample to represent the population (Teddlie & Yu, 2007).

In this study, the researcher opted for a non-probability sampling and the purposive sampling technique, as they were suitable for this study. The sample selected was determined by the researcher.

3.8. Sampling design for the study

Gay (1996) has provided a guideline for selecting a population sample. The whole population should be selected if the population size is less than 100 individuals. A total of 50% of the population should be selected if the whole population is about 500; and At least 400 participants are required if the whole population is more than 5000. The decision on sampling design was made following the guideline provided by Gay (1996).

Primary data is information collected from an instrument such as questionnaires, interviews or from observations to address the research problems and research objectives (Leedy & Ormrod, 2005). The advantage of primary data is that the information collected is current, and the researcher gets a more realistic view of the problem being investigated. The study opted for primary data as there was no secondary data that would have addressed the research questions.

3.9. Data collection

Data collection is a process of gathering information from one source or many sources (Sandelowski, 2000). Research data is categorised as primary data or secondary data.

3.10. Questionnaire design

The questions used in the questionnaire were drawn from the constructs identified in this study. The questions were then adjusted to fit the context of the study. The rest of the questions were developed to answer the remaining research questions. To answer the six research questions, the questionnaire (see Appendix B) is divided into seven sections. The researcher also provided an explanation of key terminologies to the respondents to familiarise them with the study.

Table 3.1. Structure of the Questionnaire

Section	Name	Questions
A	General Information	1 - 6
B	Perceived Price value	7.1 – 7.6
C	Perceived Performance expectancy	8.1 – 8.11
D	Perceived Social influence	9.1- 9.5
E	Perceived Facilitating condition	10.1- 10.6
F	Perceived characteristic of Innovation	11.1- 11.15
G	Attitude towards the adoption	12.1 – 12.4

Section A: General information

In this section, the aim was to get necessary information about the respondents and the company. In this section, the questionnaire captures the role of the respondents in the organisation, - the time the respondent has been working for the organisation, the size of the organisation, and the location of organisation.

Section B: Perceived Price Value

In this section, the researcher used questions to measure perception of price value on the adoption of big data analytics. The perception on the cost of hardware, network system, and the cost expertise were measured. The purpose of this section is to address research objective 3.

Section C: Perceived Performance Expectancy

In this section, the researcher used questions to measure the perceived performance expectancy. The aim was to examine the employees' perception on expected improved performance of the company. The aim of this section is to address the research objective 1. The perception of the employees on the business risk assessment, knowledge management, decision making, customer relationship management, and detection of fraudulent medical claims were measured.

Section D: Perceived Social Influence

In this section, the researcher used questions to measure the perceived social influence. The aim was to get the employees perception on the social influence (competitors, the industry, the government). This section was designed to address the research objective 4.

Section E: Perceived Facilitating Condition

In this section, questions were used to measure the facilitating conditions influencing the attitudes towards the adoption of big data analytics by selected medical aid organisations. The network system, the hardware and the right expertise for big data analytics were examined. This section addresses the research objective 2.

Section F: Perceived characteristic of innovation

In this section, the researcher tried to find out what are the perceived characteristics of innovations influencing the adoption of big data analytics by selected medical aid organisations. Items were used to examine relative advantage, complexity, and privacy/security. The purpose of this section was to address research objective 5.

Section G: Attitudes towards the adoption

This section, makes an attempt to find out the employees attitudes towards the adoption of big data analytics.

3.11. Measures

Measures used in this study were from similar studies about the adoption of an innovation. A five Likert scale was used in this study, varying from strongly agree, agree, neutral, disagree to strongly disagree.

3.12. Procedure

Data collection started in July 2016 and ended in October 2016, the researcher travelled to Durban to hand deliver the questionnaires to the respondents. The researcher had a meeting with the branch managers to seek authorisation to talk and hand deliver the questionnaires to the employees. A request was made to the respondents to complete the questionnaires the same day but most of them asked for more time. It was arranged with most of the respondents that the researcher would collect the completed questionnaires every Monday and Friday. Some of the respondents took more than 14 days to complete the questionnaire, the reason being they were too busy. Before handing the questionnaires to each respondent, the researcher had to explain the purpose of the study, the structure of the questionnaires and key concepts of the study. Five questionnaires were emailed to respondents because some respondents were not available when the researcher handed out the questionnaires. A total of, 57 questionnaires out of 59 were collected from two selected medical aid organisations in Durban.

3.12.1. Inclusion and exclusion criteria

Inclusion criteria: permanent employees working for the two selected medical aid organisations in Durban. Open medical aid organisations willing to participate were also included. Medical aid organisations that have at least basic I.T infrastructure were included.

Exclusion criteria: Open medical aid organisations (medical aid organisations open to any citizen in South Africa) that were not available and not willing to participate in the study were excluded. The selected medical aid organisations are referred to in the study as company A and company B as they requested to be anonymous. Part time employees were excluded from this research project. Medical aid organisations which were well advanced in the usage of big data were also excluded.

3.13. Data analysis

The version 23 of the "Statistical Package for Social Science (SPSS)" was selected and used for analysis. Items from the questionnaire were translated into meaningful variables. The aim of the research instrument is to measure the research hypotheses or research objectives (Coghlan & Brannick, 2014). Then responses from the research instruments were coded then entered into SPSS. Descriptive and inferential statistics were used for this study

3.13.1. Validity and Reliability

Validity and reliability are used in research to measure and improve the quality of the research instrument (Guion, 2002).

3.13.2. Validity

Validity is the extent to which a measure reflects what it is supposed to measure (Roberts, Priest & Traynor, 2006). There are various types of validity tests (Leedy & Ormrod, 2010):

In the face validity, the measure appears to be assessing the intended construct being tested. This type of validity is not recognised as a scientific type of validity. The content validity is the estimation of how much the measure represents every single element of a construct. The construct validity deals with the ability of the measure to actually assess what it is intended to measure. The criterion validity predicts future or current performance. The judgement by a panel of experts, experts' views and judgements are used to measure the instrument.

The researcher used the content validity technique and the judgment by a panel of experts. The researcher designed the questionnaire, and administered it to one lecturer at the University of KwaZulu-Natal for assessment to test if the questions measure the constructs being tested. The questionnaire was then sent to the statistician to assure that the questionnaire was able to measure the intended objectives. Furthermore, the researcher conducted a pilot study before sending out the questionnaire to the actual respondents. The aim of the pilot study was to ensure that respondents could understand the content of the questionnaire and were able to answer. After getting the feedback from the pilot study, the questionnaire was modified accordingly and finalised.

3.13.3. Reliability

Reliability is defined as the sturdiness, consistency, and trustworthiness of the tool being used for a study (Roberts *et al.*, 2006).

Interrater reliability assesses the level of agreement of different judges or raters in their assessment decisions. Internal consistency reliability is used to assess the degree to which diverse test items that analyses similar construct produce the same results. In Test–test reliability type, the researcher administers the same test to the same group of people over a period.

The researcher used Cronbach's alpha coefficient which is a technique of internal consistency reliability to measure the reliability, and consistency of the items of the instrument being used. The Cronbach's alpha coefficients of each research question are presented in chapter 4.

3.14. Ethical considerations

Firstly, a letter was obtained from the supervisor to ask permission from the organisations to obtain consent to their participation in the study. Gate keeper's letters were obtained from the organisations, then the ethical clearance form was filled and submitted to the research office of the University of KwaZulu-Natal.

There are four main ethical principles in a research project (Beauchamp & Childress, 2001):

1. Autonomy is referred to as the freedom given to a participant to participate or not in the study without any fear and having the necessary knowledge about the research project being conducted. To ensure autonomy: participants had the choice to willingly participate or not: An explanation of the research project and key concepts of the study were given to the participants willing to participate: a letter of consent was given to those who accepted to participate indicating that they understood and agreed to participate.
2. Non-maleficence refers to the prevention of any type of harm be it physical or psychological that might occur to the research participants, the Ethical Clearance Committee of the University of KwaZulu-Natal addressed any maleficence issue by providing an ethical clearance to the proposed study.
3. Beneficence is the significance of the study to the participants and society. This study promotes the adoption of big data analytics. Medical aid organisations will profit from big data analytics as it has the potential to have better schemes, better services, reduced fraudulent claims, and better understanding of customers, delighted customers therefore increase revenue.
4. Justice refers to the equality of all participants in the study. All participants were equally treated during this research project and participated voluntarily in the study.

The researcher obtained ethical clearance approval (refer to Appendix C) from the research office of the University of KwaZulu- Natal before conducting the research to comply with the ethical requirement of the university.

3.15. Summary

The research opted for an exploratory research design and a survey research strategy. The instrument used was the questionnaire, and was hand delivered to employees of two selected medical aid organisations in Durban. The questionnaire was designed by the researcher, and assessed by a lecturer from the University of KwaZulu-Natal. The questionnaire was then sent to a statistician for assessment again, and modified accordingly. Data was collected from employees of two selected medical aid organisations. The chapter also discussed the ethical considerations as well as the type of data analysis method chosen for this study. The results of the analysis are presented in chapter 4.

CHAPTER 4

DATA ANALYSIS

4.1. Introduction

Data analysis is the process of applying statistical techniques to describe, clarify, summarise, outline, and evaluate data. This chapter presents the analysis of data collected. The Statistical Package for Social Software (SPSS) was used to analyse data. Data were coded using Microsoft Excel then transferred to SPSS for analysis. Descriptive and inferential statistics (Wilcoxon signed ranks test, regression analysis, one t-test and varimax) were used and are presented in this chapter. Data was analysed to address the research objectives:

1. To determine the perceived performance expectancy that is influencing the adoption of big data analytics by selected medical aid organisations in Durban.
2. To determine the perceived facilitating conditions that is influencing the adoption of big data analytics by selected medical aid organisations in Durban.
3. To understand how the perception of price value is influencing the adoption of big data analytics in selected medical aid organisations in Durban.
4. To understand how the perceived social factors is influencing the adoption of big data analytics in selected medical aid organisations in Durban.
5. To determine the perceived characteristics of innovation influencing the adoption of big data analytics by selected medical aid organisations in Durban.
6. To understand the attitudes of the employees towards the adoption of big data analytics.

4.2. Response rate

A total of 59 questionnaires were handed to the respondents, while the researcher expected to collect 59 questionnaires, 57 questionnaires were collected which represents 96.6% of the response rate. Six questionnaires were not fully completed by respondents as they neither disclosed their age nor gender.

4.3. Statistical Analysis

In this chapter, for the convenience of the readers, only some of the tables and graphs are presented. The rest of the tables and graphs are provided in Appendix A.

4.3.1. Descriptive Statistics

Descriptive statistics provide simple summaries about the sample and observations that have been made. It describes and presents the key features of the data collected in a meaningful and simple way (Fialho & Zyngier, 2014). Means and standard deviations were used where applicable and frequencies are represented in tables or graphs. In this chapter, only a few descriptive statistics graphs, tables, and charts are used.

4.3.2. Inferential Statistics

Inferential statistics help to assess the strength of the relationships between the independent variables and the dependent variables (Lowry, 2014).

The tests used in this study are as follows: Wilcoxon Signed Ranks test is a non-parametric test used to test whether the average value is significantly different from a value of three (the central score). This is applied to Likert scale questions. It is also used in the comparison of the distributions of two variables. Regression analysis is linear regression that calculates the coefficients of the linear equation, involving one or more independent variables that best predict the value of the dependent variable. One sample t-test is used to test whether a mean score is significantly different from a scalar value (Colman & Pulford, 2006; Cai, Wei & Wilcox, 2000).

4.3.3. Reliability Analysis

Joppe (2000) defines reliability as the extent to which results obtained from a research project can be replicated under a similar methodology. In order to measure the reliability, Cronbach's coefficient is used and the Cronbach's alpha value superior to 0.7 for a combined measure is declared reliable (Bland & Altman, 1997).

Table 4.1. Reliability statistic of constructs

Variables	Number of Items	Cronbach's alpha
Performance Expectancy	11	.985

Facilitating condition	6	.882
Price Value	6	.924
Social Influence	5	.924
Perceived Characteristic of innovation	15	.961

As it is shown in Table 4.1, the reliability of all constructs is successful. The Cronbach's alpha value was superior to 0.7.

4.4. Results of data analysis

4.4.1. Section A: General information

This section does not address any research questions as there was not any research question on general information of respondents, this section simply provides general information about the sample. It provides a background information about respondents' information about age, gender, position in the company, number of employees, time in the company, and location of the company.

The combined results (Figure 4.1) show that the majority of respondents were females (57.9%), and the age of the majority of respondents was between 26 and 40 (63.2 %). Only 8.8 % of the respondents were less than 25 years old and 24.6 % of the respondents were over 40. Out of 57 respondents (N=57), 6 respondents did not disclose their age.

Majority of respondents (47.4%) have been working for these companies for between 6 to 10 years, 29.8 % of respondents have been working there for between 1 to 5 years, 10.5 % of respondents have been working there for less than a year, and 10.5 % have been working there for more than 11 years (Figure 4.2).

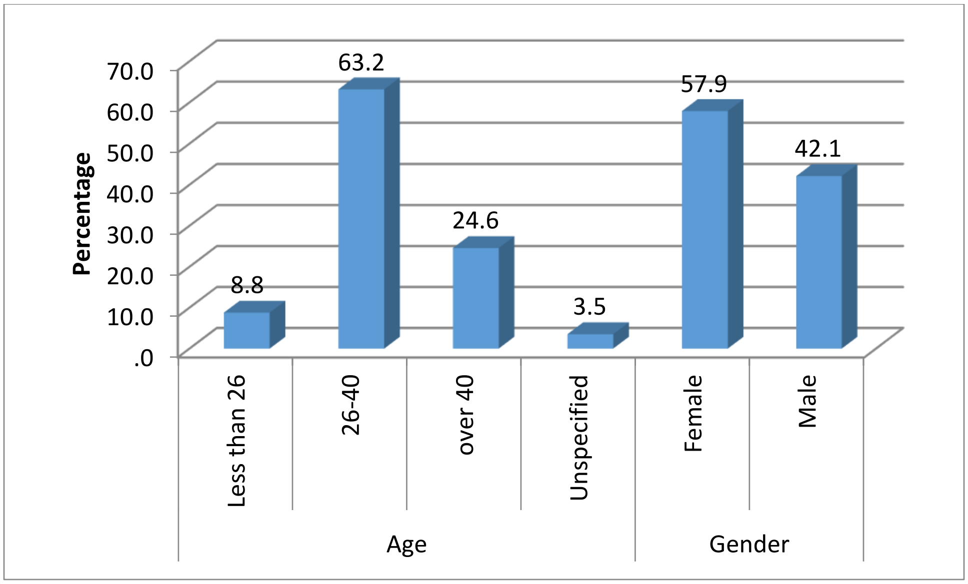

Figure 4.1. Respondents' age and gender

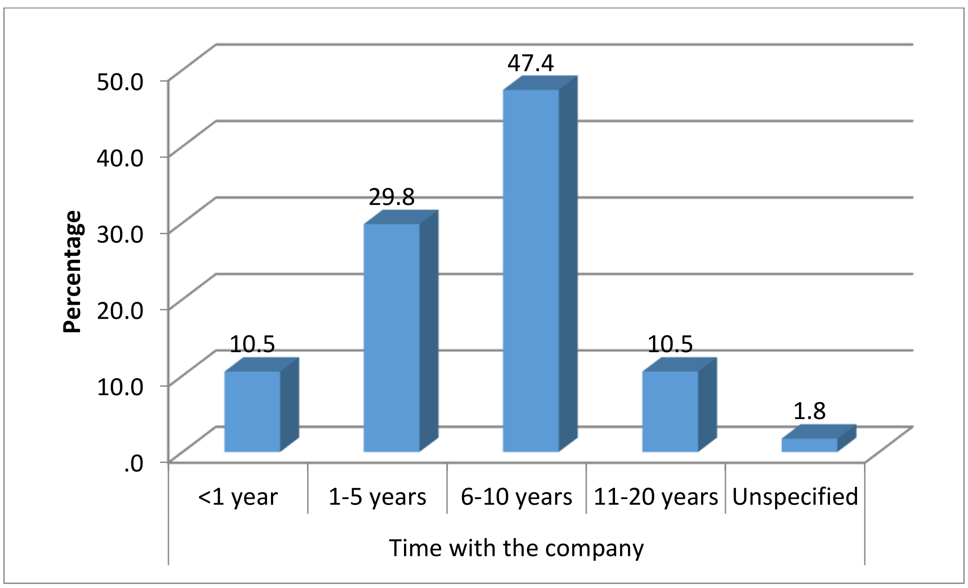

Figure 4.2: Time with the company

Table 4.2 and table 4.3 show that there is no "significant difference between the two companies in terms" of age and gender. In company A, 65.2% of respondents are between 26- 40 years old and in company B, 65.6% of the respondents are between 26-40 years old; 60.0% of respondents in company A are females while 56.3% of respondents in company B are female.

Table 4.2. Employees Age (A &B)

			1 Age			Total
			Less than 26	26-40	over 40	
Company	Company A	Count	2	15	6	23
		% within Company	8.7%	65.2%	26.1%	100.0%
		% within 1 Age	40.0%	41.7%	42.9%	41.8%
	Company B	Count	3	21	8	32
		% within Company	9.4%	65.6%	25.0%	100.0%
		% within 1 Age	60.0%	58.3%	57.1%	58.2%
Total		Count	5	36	14	55
		% within Company	9.1%	65.5%	25.5%	100.0%
		% within 1 Age	100.0%	100.0%	100.0%	100.0%

Table 4.3. Employees Gender (A & B)

			2 Gender		Total
			Female	Male	
Company	Company A	Count	15	10	25
		% within Company	60.0%	40.0%	100.0%
		% within 2 Gender	45.5%	41.7%	43.9%
	Company B	Count	18	14	32
		% within Company	56.3%	43.8%	100.0%
		% within 2 Gender	54.5%	58.3%	56.1%
Total		Count	33	24	57
		% within Company	57.9%	42.1%	100.0%
		% within 2 Gender	100.0%	100.0%	100.0%

Table 4.4. Employees Role (A & B)

			3 Role					Total
			Branch manager	Manager	CFO	IT professional	Other	
Company	Company A	Count	1	2	0	8	12	23
		% within Company	4.3%	8.7%	.0%	34.8%	52.2%	100.0%
		% within 3 Role	50.0%	50.0%	.0%	44.4%	42.9%	43.4%
	Company B	Count	1	2	1	10	16	30
		% within Company	3.3%	6.7%	3.3%	33.3%	53.3%	100.0%
		% within 3 Role	50.0%	50.0%	100.0%	55.6%	57.1%	56.6%
Total		Count	2	4	1	18	28	53
		% within Company	3.8%	7.5%	1.9%	34.0%	52.8%	100.0%
		% within 3 Role	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Table 4.5. Employees Time in the company (A & B)

			6 Time				Total
			<1 year	1-5 years	6-10 years	11-20 years	
Company	Company A	Count	4	6	13	1	24
		% within Company	16.7%	25.0%	54.2%	4.2%	100.0%
		% within 6 Time	66.7%	35.3%	48.1%	16.7%	42.9%
	Company B	Count	2	11	14	5	32
		% within Company	6.3%	34.4%	43.8%	15.6%	100.0%
		% within 6 Time	33.3%	64.7%	51.9%	83.3%	57.1%
Total		Count	6	17	27	6	56
		% within Company	10.7%	30.4%	48.2%	10.7%	100.0%
		% within 6 Time	100.0%	100.0%	100.0%	100.0%	100.0%

Table 4.5 shows that only 16.7% worked for company A for less than a year, while 25.0% worked for between 1-5 years. In addition, 54.2% have worked for between 6-10 years and only 4.2% have

worked for more than 10 years, while 6.3% have worked for less than a year for company B. 34.4% have worked for between 1-5 years, 43.8% have worked between 6-10 years and 15.6% have worked for more than 10 years.

4.4.2. Section B: Perceived price value

The objective of this section is to understand how the perception of price value influences the employees' attitude towards the adoption of big data analytics in selected medical aid organisations in Durban. Six sub questions were formulated. The respondents' views of each sub question are presented below, the composite measure of the construct is presented at the end.

Q.1. The overall cost of big data analytics is affordable

Table 4.6. The overall cost of big data analytics is affordable.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	21	36.8	38.2	38.2
	Neutral	27	47.4	49.1	87.3
	Agree	5	8.8	9.1	96.4
	Strongly agree	2	3.5	3.6	100.0
	Total	55	96.5	100.0	
Missing	System	2	3.5		
Total		57	100.0		

12.7% (agree + strongly) of the respondents reported that the overall cost of big data analytics is affordable, while 38.2% of the respondents reported that the overall cost of big data analytics is not affordable; 49.1% of the respondents did not have an opinion or were neutral about this question as depicted in Table 4.6. The result shows that there is significant disagreement that the overall cost of big data analysis is affordable ($M=2.78$, $SD = .762$), $t\ (54) = -2.123$, $p=.038$; this tells us that employees think that the overall cost of big data is not affordable.

Q.2. The cost of expertise for big data analytics is affordable

Table 4.7. The cost of expertise for big data analytics is affordable

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	30	52.6	52.6	52.6
	Neutral	18	31.6	31.6	84.2
	Agree	8	14.0	14.0	98.2
	Strongly agree	1	1.8	1.8	100.0
	Total	57	100.0	100.0	

15.8% (agree + strongly) of the respondents reported that the cost of expertise for big data analytics is affordable, while 52.6% of the respondents reported that the cost of expertise for big data analytics is not affordable; 31.6% of the respondents did not have an opinion or were neutral about this question as depicted in Table 4.7. The result shows that there is significant disagreement that ($M=2.65$, $SD = .790$), $t\ (56) = -3.352$, $p=.001$: the cost of expertise for big data analysis is affordable. This result tells us that employees think that the cost of expertise for big data is not affordable.

Q.3. The cost of implementation of big data analytics is affordable

Table 4.8. The cost of implementation of big data analytics is affordable

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	29	50.9	50.9	50.9
	Neutral	20	35.1	35.1	86.0
	Agree	7	12.3	12.3	98.2
	Strongly agree	1	1.8	1.8	100.0
	Total	57	100.0	100.0	

14.1% (agree + strongly agree) of the respondents reported that the cost of implementation of big data analytics is affordable, while 50.9% of the respondents reported that the cost of implementation of big data analytics is not affordable; 35.1% did not have an opinion or were neutral about this question as depicted in Table 4.8. The result shows that there is significant disagreement that (M=2.65 SD=.767), t (56) = -3.452, p=.001; the cost of implementation for big data analysis is affordable; this tells us that employees think that the cost of implementation of big data is not affordable.

Q.4. The storage system required for big data analytics is affordable

Table 4.9. The storage system required for big data analytics is affordable

		Frequency	Percent	Valid Percent	Cumulative Percent”
Valid	Disagree	20	35.1	35.1	35.1
	Neutral	21	36.8	36.8	71.9
	Agree	15	26.3	26.3	98.2
	Strongly agree	1	1.8	1.8	100.0
	Total	57	100.0	100.0	

28.1% (agree + strongly agree) of the respondents reported that the storage system required for big data analytics is affordable, while 35.1% of respondents reported that the storage system required for big data analytics is not affordable; 36.8% of respondents were neutral or did not have an opinion about this question as depicted in Table 4.9. The result shows that there is significant disagreement that the cost of storage system required for big data analysis is affordable (M=2.95 SD=.833), t (56) = -477, p=.635; this shows that employees think the cost of storage system required for big data analytics is not affordable.

Q.5. The cost of big data network technologies is affordable

Table 4.10. The cost of big data network technologies is affordable

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	21	36.8	36.8	36.8
	Neutral	24	42.1	42.1	78.9
	Agree	11	19.3	19.3	98.2
	Strongly agree	1	1.8	1.8	100.0
	Total	57	100.0	100.0	

21.1 % (agree + strongly agree) of the respondents reported that the cost of big data network technologies is affordable, while 36.8% of the respondents reported that the cost of big data network technologies is not affordable; 42.1% of respondents were neutral about this question as depicted in Table 4.10. The result shows that there is significant disagreement that the cost of big data network technologies is affordable (M=2.86 SD=.789), t (56) = -1.343, p=.185; this shows that employees think the cost of big data network technologies is not affordable.

Q.6. Big data analytics can provide financial benefits

Table 4.11. Big data analytics can provide financial benefits

		"Frequency"	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	16	28.1	28.1	28.1
	Neutral	26	45.6	45.6	73.7
	Agree	13	22.8	22.8	96.5
	Strongly agree	2	3.5	3.5	100.0
	Total	57	100.0	100.0	

26.3% (agree + strongly agree) of the respondents reported that big data analytics can provide financial benefits, while 28.1% of the respondents reported that big data analytics cannot provide financial benefits; and 45.6% of the respondents did not have an opinion about this question as depicted in Table 4.11. The result shows that there is significant disagreement that big data analytics can provide financial benefits (M=3.02 SD=.813), t (56) =.163, p=.871. This shows that employees think big data analytics cannot provide financial benefits.

A one-sample t-test to the composite measures was performed to test for significant agreement or disagreement about this construct. The results show that perceived price value is a significant disagreement as depicted in Table A.21 (t (56) = -2.055, p=.045) (see Appendix A).

H3: The perceived price value of big data analytics will influence the attitude towards the adoption of big data analytics. If the price is perceived to be not affordable then it is likely to have a negative influence on the attitudes towards the adoption of big data analytics and vice versa.

A regression analysis was performed to test for the influence of the independent Price Value on the dependent variable Attitudes. The independent variable PRICE VALUE accounts for 14.6% (R^2 = .146) of the variance in attitude (ATT), F (1, 55) = 9.388, p=.003. PRICE VALUE is a significant predictor of ATTITUDE (β = .489, p=.003). As depicted in Table A.22, Table A.23, and Table A.24 (see Appendix A).

The results of the comparison analysis between the two companies will be presented below.

For each of the Likert scale questions, an independent sample t-test was applied to compare scores across company average.

Table 4.12. Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
7.1. The overall cost of big data analytics is affordable.	Equal variances assumed	2.859	.097	-.903	53	.371	-.187	.207	-.601	.228
	Equal variances not assumed			-.941	49.223	.351	-.187	.198	-.585	.212
7.2.The cost of expertise for big data analytics is affordable	Equal variances assumed	4.159	.046	-2.559	55	.013	-.515	.201	-.918	-.112
	Equal variances not assumed			-2.691	53.494	.009	-.515	.191	-.899	-.131
7.3.The cost of implementation of big data analytics is affordable	Equal variances assumed	3.274	.076	-1.858	55	.069	-.373	.201	-.774	.029
	Equal variances not assumed			-1.946	54.060	.057	-.373	.191	-.756	.011
7.4.The storage system required for big data analytics is affordable	Equal variances assumed	1.443	.235	1.064	55	.292	.236	.222	-.209	.681

	Equal variances not assumed			1.084	54.459	.283	.236	.218	-.201	.673

7.5. The cost of big data network technologies is affordable	Equal variances assumed	2.024	.161	-.165	55	.870	-.035	.213	-.461	.391
	Equal variances not assumed			-.170	54.986	.866	-.035	.206	-.449	.379
7.6. Big data analytics can provide financial benefits	Equal variances assumed	.267	.607	2.230	55	.030	.468	.210	.047	.888
	Equal variances not assumed			2.260	53.874	.028	.468	.207	.053	.882

There is a significant difference between companies in the agreement that the cost of expertise for big data analytics is affordable (t (53.494) = -2.691, p=.009). Company B shows a higher agreement (M=2.88, SD = .841) than company A (M=2.36, SD = .569).

A regression analysis for each company was performed separately to test for the influence of the independent variable on the dependent variable- ATT. The independent variables are included one at a time. The results for company A and company B show that: The perceived PV is not a significant predictor in company A and PV is a significant predictor in company B as depicted in table 4.13 and table 4.14.

Table 4.13.Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.815	1.027		2.741	.012
	PV	.408	.365	.227	1.120	.274

a. Company = Company A

b. Dependent Variable: ATT

Table 4.14.Coefficients[a,b]

Model		"Unstandardized Coefficients"		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.115	.513		4.126	.000
	PV	.525	.174	.484	3.027	.005

a. Company = Company B

b. Dependent Variable: ATT

4.4.3. Section C: Perceived Performance Expectancy

The objective of this section is to determine the perceived performance expectancy that is influencing the employees' attitude towards the adoption of big data analytics by selected medical aid organisations in Durban. Eleven sub questions were asked to the respondents. The respondents' views of each sub question are presented below then a composite measure of the construct is presented at the end.

Q.1. I would expect that the adoption of big data analytics would result in the improvement of business risk assessment.

Table4.15. Business risk assessment

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	8	14.0	14.0	14.0
	Neutral	11	19.3	19.3	33.3
	Agree	30	52.6	52.6	86.0
	Strongly agree	8	14.0	14.0	100.0
	Total	57	100.0	100.0	

66.6% (Agree + strongly agree) of the respondents think that the adoption of big data analytics would improve business risk assessment, 14 % disagree that the adoption of big data analytics would improve business risk assessment and 19.3% were neutral as depicted in table 4.15. The result shows that there is a significant agreement that respondents would expect that the adoption of big data analytics would result in the improvement of the business risk assessment (M= 3.67, SD=.893), t (56) =5.636, p<.0005; this shows that employees have a positive perception on the adoption of big data analytics in the improvement of business risk assessment.

Q.2. I would expect the adoption of big data analytics would result in the improvement of Knowledge management.

Table 4.16. Knowledge management

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	7	12.3	12.3	12.3
	Neutral	11	19.3	19.3	31.6
	Agree	32	56.1	56.1	87.7
	Strongly agree	7	12.3	12.3	100.0
	Total	57	100.0	100.0	

As depicted in table 4.16, 68.4% (agree+ strongly agree) of the respondents think that the adoption of big data analytics would improve knowledge management, while 12.3% disagree that the adoption of big data analytics would improve knowledge management; 19.3% were neutral about this question. The result shows that there is a significant agreement that respondents would expect that the adoption of big data analytics would result in the improvement of knowledge management (M=3.68, SD= .848), t (56) =6.088, p<.0005; this indicates that employees have a positive perception on the adoption of big data analytics in improving knowledge management.

Q.3. I would expect the adoption of big data analytics would result in the improvement of decision making.

Table 4.17. Decision making

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	6	10.5	10.5	10.5
	Neutral	6	10.5	10.5	21.1
	Agree	34	59.6	59.6	80.7
	“Strongly agree”	11	19.3	19.3	100.0
	Total	57	100.0	100.0	

As depicted in table 4.17, 78.9 % (agree + strongly agree) of the respondents think that the adoption of big data analytics would improve decision making, while 10.5% disagree that the adoption of big data analytics would improve decision making; 10.5 % were neutral about this question.

The result shows that there is a significant agreement that respondents would expect that the “adoption of big data analytics” would result in the improvement of knowledge management (M= 3.88, SD=847), t (56) =7.822, p<.0005; this indicates that employees have a positive perception on “the adoption of big data analytics” in improving decision making.

Q.4. I would expect the adoption of big data analytics would result in the improvement of the ability to develop new schemes.

Table 4.18. The ability to develop new schemes

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	6	10.5	10.5	10.5
	Neutral	8	14.0	14.0	24.6
	Agree	32	56.1	56.1	80.7
	Strongly agree	11	19.3	19.3	100.0
	Total	57	100.0	100.0	

As depicted in table 4.18, 75.4% (agree + strongly agree) of the respondents think that the adoption of big data analytics would improve the ability to develop new schemes, while 10.5% disagree that the adoption of big data analytics would improve the ability to develop new schemes; 14.0% were neutral about this question. The result shows that there is a significant agreement that respondents would expect that the adoption of big data analytics would result in the improvement of the ability to develop new schemes ($M=3.84$, $SD=.862$), $t(56)=7.378$, $p<.0005$; This shows that employees have a positive perception on the adoption of big data analytics in improving the ability to develop new schemes.

Q.5. I would expect the adoption of big data analytics would result in the improvement in understanding the needs of customers.

Table 4.19. Understanding the needs of customers

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	6	10.5	10.5	10.5
	Neutral	6	10.5	10.5	21.1
	Agree	33	57.9	57.9	78.9
	Strongly agree	12	21.1	21.1	100.0
	Total	57	100.0	100.0	

79% (agree + strongly agree) of the respondents think that the adoption of big data analytics would improve the understanding of the needs of customers, while 10.5% of the respondents disagree that the adoption of big data analytics would result in the improvement in understanding the needs of customers; 10.5% of the respondents were neutral about this question as depicted in table 4.19. The result shows there is a significant agreement that respondents would expect the adoption of big data analytics would result in the improvement in understanding the needs of customers ($M=3.89$, $SD=.859$), $t(56)=7.859$, $p<0005$. This indicates that employees have a positive perception on the adoption of big data analytics in the understanding the needs of customers.

Q.6. I would expect the adoption of big data analytics would result in the improvement in the detection of fraudulent medical claims.

Table 4.20. The detection of fraudulent medical claims

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	6	10.5	10.5	10.5
	Neutral	6	10.5	10.5	21.1
	Agree	32	56.1	56.1	77.2
	Strongly agree	13	22.8	22.8	100.0
	Total	57	100.0	100.0	

78.9% (agree + strongly agree) of the respondents think that the adoption of big data analytics would results in the improvement in the detection of fraudulent medical claims, while 10.5% of respondents disagree that the adoption of big data analytics would result in the improvement in the detection of fraudulent medical claims; 10.5% of the respondents were neutral about this question as depicted in table 4.20. The result shows that there is a significant agreement that respondents would expect the "adoption of big data analytics" would result in the improvement in the detection of fraudulent medical claims ($M=3.91$, $SD=.872$), $t(56)=7.900$, $p<0005$. This shows that employees have a positive perception on the adoption of big data analytics in improving the detection of fraudulent claims.

Q.7. I would expect the adoption of big data analytics would result in the improvement of customer relationship management.

Table 4.21. Customer relationship management

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	6	10.5	10.5	10.5
	Neutral	6	10.5	10.5	21.1
	Agree	35	61.4	61.4	82.5
	Strongly agree	10	17.5	17.5	100.0
	Total	57	100.0	100.0	

78.9% (agree + strongly agree) of the respondents think that the adoption of big data analytics would result in the improvement of customer relationship management, while 10.5% of the respondents disagree; 10.5% were neutral about this question as depicted in table 4.21. The result shows that there is a significant agreement that respondents would expect the adoption of big data analytics would result in the improvement in customer relationship management (M=3.86 SD=.833), t (56) =7.789, p<0005; this tells us that employees have a positive perception on the adoption of big data analytics in improving customer relationship management.

Q.8. I would expect the adoption of big data analytics would result in the improvement in effectiveness of existing schemes.

Table 4.22. The effectiveness of existing schemes

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	6	10.5	10.5	10.5
	Neutral	11	19.3	19.3	29.8
	Agree	34	59.6	59.6	89.5
	Strongly agree	6	10.5	10.5	100.0
	Total	57	100.0	100.0	

70.1% (agree + strongly) of the respondents think that the adoption of big data analytics would result in the improvement in effectiveness of existing schemes, while 10.5% of the respondents disagree that the adoption of big data analytics would result in the improvement in effectiveness of existing schemes; 19.3 % were neutral about this question as depicted in table 4.22. The result shows that there is a significant agreement that respondents would expect that the adoption of big data analytics would result in the improvement in effectiveness of existing schemes (M=3.70 SD=.801), t (56) =6.614, p<0005. This indicates that employees have a positive perception on the adoption of big data analytics in improving effectiveness of existing schemes.

Q.9. I would expect the adoption of big data analytics would result in the improvement of competitive advantage.

Table 4.23. Competitive advantage

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	6	10.5	10.5	10.5
	Neutral	12	21.1	21.1	31.6
	Agree	34	59.6	59.6	91.2
	Strongly agree	5	8.8	8.8	100.0
	Total	57	100.0	100.0	

68.4% (agree + strongly) of the respondents think that the adoption of big data analytics would result in the improvement of competitive advantage, while 10.5% of respondents disagree that the adoption of big data analytics would result in the improvement of competitive advantage; 21.1% were neutral about this question as depicted in table 4.23. The result shows that there is a significant agreement that respondents would expect the adoption of big data analytics would result in the improvement of competitive advantage (M=3.67 SD=.787), t (56) =6.397, p<0005. This indicates that employees have a positive perception on the adoption of big data analytics in improving competitive advantage.

Q.10. I would expect the adoption of big data analytics would result in the improvement in the identification of new trends.

Table 4.24. The identification of new trends

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	6	10.5	10.5	10.5
	Neutral	7	12.3	12.3	22.8
	Agree	35	61.4	61.4	84.2
	Strongly agree	9	15.8	15.8	100.0
	Total	57	100.0	100.0	

77.2% (agree + strongly agree) of the respondents think that the adoption of big data analytics would result in the improvement in the identification of new trends, while 10.5% of the respondents disagree that the adoption of big data analytics would result in the improvement in the identification of new trends; 12.3% were neutral about this question as depicted in table 4.24. The result shows that there is a significant agreement that respondents would expect the adoption of big data analytics would result in the improvement of the identification of new trends (M=3.82 SD=.826), t (56) =7.533, p<0005; this tells us that employees have a positive perception on the adoption of big data analytics in improving competitive advantage.

Q.11. I would expect the adoption of big data analytics would result in the improvement of the overall performance of the organisation.

Table 4.25. The overall performance of the organisation

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	6	10.5	10.5	10.5
	Neutral	14	24.6	24.6	35.1
	Agree	31	54.4	54.4	89.5
	Strongly agree	6	10.5	10.5	100.0
	Total	57	100.0	100.0	

As depicted in table 4.25, 64.9% (agree + strongly agree) of the respondents agreed that the adoption of big data analytics would result in the improvement of the overall performance of the organisation, while 10.5% disagree that the adoption of big data analytics would result in the improvement of the overall performance of the organisation. In addition, 24.6% were neutral about this question. The result (M=3.65 SD=.813), t (56) =6.031, p<0005, (Table A.3 in Appendix A) shows that there is a significant agreement that respondents would expect that the adoption of big data analytics would result in the improvement of the overall performance of the organisation. This shows that employees have a positive perception on the adoption of big data analytics in improving overall performance of the organisation.

A one-sample t-test to the composite measures was performed to test for significant agreement or disagreement about this construct. The results, t (56) = 7.519, p<.0005, show that Perceived Performance Expectancy revealed to be a significant agreement as depicted in table A.21 (see Appendix A).

H1: The perceived performance expectancy will have an influence on the attitudes towards the adoption of big data analytics, it will be expected to improve the performance of the company. Employees and executives will only have a positive attitude towards the adoption of big data analytics if they believe that big data will improve the company's performance.

Regression analysis was performed to test for the influence of the independent variable on the dependent variable- ATT and the results reveal that:

The independent variable Perceived Performance Expectancy accounts for 74.7% ($R^2 = .747$) of the variance in attitude (ATT), F (1, 55) = 162.750, p<.0005. PERFORMANCE EXPECTANCY is a significant strong predictor of ATTITUDE (β =.957, p<.0005) as depicted in table A.26, table A.27, and table A.28 (see Appendix A).

The results of the comparison analysis between the two companies A and B will be presented below.

For each of the Likert scale questions, an independent sample t-test was applied to compare scores across company average.

Table 4.26. Group Statistics

	Company	N	Mean	Std. Deviation	Std. Error Mean
8.1. Business risk assessment	Company A	25	3.80	.764	.153
	Company B	32	3.56	.982	.174
8.2.Knowledge management	Company A	25	3.64	.700	.140
	Company B	32	3.72	.958	.169
8.3. Decision making	Company A	25	3.88	.781	.156
	Company B	32	3.88	.907	.160
8.4.The ability to develop new schemes	Company A	25	3.88	.781	.156
	Company B	32	3.81	.931	.165
8.5.Understanding the needs of customers	Company A	25	3.84	.746	.149
	Company B	32	3.94	.948	.168
8.6.The detection of fraudulent medical claims	Company A	25	3.96	.841	.168
	Company B	32	3.88	.907	.160
8.7.Customer relationship management	Company A	25	3.80	.707	.141
	Company B	32	3.91	.928	.164
8.8.The effectiveness of existing schemes	Company A	25	3.64	.700	.140
	Company B	32	3.75	.880	.156
8.9.Competitive advantage	Company A	25	3.56	.651	.130
	Company B	32	3.75	.880	.156
8.10.The identification of new trends	Company A	25	3.84	.746	.149
	Company B	32	3.81	.896	.158
8.11.The overall performance of the organisation	Company A	25	3.60	.764	.153
	Company B	32	3.69	.859	.152

Table 4.26 shows there is no significant difference between the two companies about the Likert scale questions.

A regression analysis for each company was performed to test for the influence of the independent variable on the dependent variable- ATT and the results for company A and company B show that:

Perceived Performance Expectancy is a significant predictor in each company (Company A and Company B) as shown in Table 4.27 and Table 4.28.

Table 4.27. Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.293	.401		-.730	.473
	PE	1.126	.105	.913	10.734	.000

a. Company = Company A

b. Dependent Variable: ATT

Table 4.28. Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.252	.347		.724	.474
	PE	.886	.089	.875	9.914	.000

a. Company = Company B

b. Dependent Variable: ATT

4.4.4. Section D: Perceived Social Influence

The objective of this question is to understand how the perceived social factors influence the employees' attitude towards the adoption of big data analytics in selected medical aid organisations in Durban. In order to address this research objective, five sub questions were formulated

Q.1. A proportion of competitors in the medical aid industry have adopted big data analytics

Table 4.29. A proportion of competitors in the medical aid industry have adopted big data analytics

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly disagree	2	3.5	3.5	3.5
	Disagree	27	47.4	47.4	50.9
	Neutral	24	42.1	42.1	93.0
	Agree	4	7.0	7.0	100.0
	Total	57	100.0	100.0	

7.0% of the respondents reported that a proportion of competitors in the medical aid industry have adopted big data analytics, while 50.9% (disagree + strongly disagree) reported that a proportion of competitors in the medical aid industry have adopted big data analytics; 42.1% of the respondents neither agreed nor disagreed as depicted in table 4.29. The result shows that there is significant disagreement that a proportion of competitors in the medical aid industry have adopted big data analytics ($M=2.53$ $SD=.684$), $t(56) = -5.227$, $p<.0005$. This shows that employees think a proportion of competitors in the medical aid industry have not adopted big data analytics.

Q.2. Suppliers think that medical aid companies should adopt big data analytics

Table 4.30. Suppliers think that medical aid companies should adopt big data analytics

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly disagree	3	5.3	5.3	5.3
	Disagree	35	61.4	61.4	66.7
	Neutral	15	26.3	26.3	93.0
	Agree	4	7.0	7.0	100.0
	Total	57	100.0	100.0	

7% of respondents reported that suppliers think medical aid companies should adopt big data analytics, while 66.7% of respondents reported that suppliers do not think medical aid companies should adopt big data analytics; 26.3% of respondents were neutral about this question as depicted in table 4.30. The result shows that there is significant disagreement that suppliers think medical aid companies should adopt big data analytics (M=2.35 SD=.694), t (56) = -7.060, p<.0005. This indicates that suppliers do not think that medical aid companies should adopt big data analytics.

Q.3. It is a trend in the medical aid industry to adopt big data analytics

Table 4.31. It is a trend in the medical aid industry to adopt big data analytics

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly disagree	2	3.5	3.5	3.5
	Disagree	29	50.9	50.9	54.4
	Neutral	23	40.4	40.4	94.7
	Agree	3	5.3	5.3	100.0
	Total	57	100.0	100.0	

5.3% of respondents reported that it is a trend in the medical aid industry to adopt big data analytics, while 54.4% (disagree + strongly disagree) of the respondents reported that it is not a trend in the medical aid industry to adopt big data analytics; 40.4% were neutral about this question as depicted in table 4.31. The result shows that there is significant disagreement that it is a trend in the medical aid industry (M=2.47 SD=.658), t (56) = -6.043, p<.0005. This shows that employees think it is not a trend in the medical aid industry to adopt big data analytics.

Q.4. The government is encouraging medical aid companies to adopt big data analytics

Table 4.32. The government is encouraging medical aid companies to adopt big data analytics

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly disagree	5	8.8	8.8	8.8
	Disagree	31	54.4	54.4	63.2
	Neutral	18	31.6	31.6	94.7
	Agree	3	5.3	5.3	100.0
	Total	57	100.0	100.0	

5.3% of the respondents reported that the government is encouraging medical aid companies to adopt big data analytics, while 63.2% of the respondents reported that the government is not encouraging medical aid companies to adopt big data analytics; 31.6% of the respondents did not have an opinion about this question as depicted in table 4.32. The result shows that there is significant disagreement that the government is encouraging medical aid companies to adopt big data analytics (M=2.33 SD=.715), t (56) = -7.035, p<.005. This tells us the government is not encouraging medical aid companies to adopt big data analytics.

Q.5. Customers would like medical aid companies to adopt big data analytics because it results in better services and schemes.

Table 4.33. Customers would like medical aid companies to adopt big data analytics because it results in better services and schemes.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly disagree	16	28.1	28.1	28.1
	Disagree	25	43.9	43.9	71.9
	Neutral	13	22.8	22.8	94.7
	Agree	3	5.3	5.3	100.0
	Total	57	100.0	100.0	

5.3% of the respondents reported that customers would like medical aid companies to adopt big data analytics because it results in better services and schemes, while 72% (disagree + strongly disagree) of the respondents reported that customers would like medical aid companies to adopt big data analytics because it results in better services and schemes. Furthermore, 22.8% of the respondents were neutral about this question as depicted in table 4.33. The result shows that there is significant disagreement that customers would like medical aid companies to adopt big data analytics because it results in better services and schemes (M=2.05 SD=.854), t (56) = - 8.375, p<.0005. This shows that employees think customers are not requesting medical aid companies to adopt big data analytics.

A one-sample t-test to the composite measures was performed to test for significant agreement or disagreement about this construct. The results, t (56) = -7.770, p<.005, show social factors revealed to be a significant disagreement as depicted in Table A.21 (see Appendix A).

H4: The influence from industry, suppliers, government, customers will influence the attitudes towards the adoption of big data analytics.

A regression analysis was performed to test for the influence of Perceived Social Influence on the dependent variable –ATT and the result revealed that:

The independent variables Perceived Social Influence accounts for 1, 6% ($R^2 = .016$) of the variance in attitude (ATT), F (1, 55) =.909, p<.0005. Perceived Social Influence is NOT a significant predictor of ATTITUDE (β =.174, p=.345) as depicted in table A.29, table A.30, table A.31 (see Appendix A).

The results of the comparison analysis between the two companies will be presented below.

For each of the Likert scale questions, an independent sample t-test was applied to compare scores across company average.

As depicted in table 4.44, question 9.3 has a significant agreement for the company A, while for company B, it shows a significant disagreement.

Table 4.34. Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
9.1.A proportion of competitors in the medical aid industry have adopted big data analytics	Equal variances assumed	2.493	.120	1.516	55	.135	.274	.181	-.088	.636
	Equal variances not assumed			1.574	54.842	.121	.274	.174	-.075	.622
9.2.Suppliers think that medical aid companies should adopt big data analytics	Equal variances assumed	.018	.893	.469	55	.641	.088	.187	-.286	.461
	Equal variances not assumed			.477	54.245	.635	.088	.184	-.280	.455
9.3.It is a trend in the medical aid industry to adopt big data analytics	Equal variances assumed	.505	.480	2.161	55	.035	.368	.170	.027	.708
	Equal variances not assumed			2.220	54.941	.031	.368	.166	.036	.699
9.4.The government is encouraging medical aid companies to adopt big data analytics	Equal variances assumed	.018	.893	1.379	55	.174	.261	.189	-.118	.641

Table 4.34 (Contd…)

	Equal variances not assumed			1.403	54.312	.166	.261	.186	-.112	.635
9.5. Customers would like medical aid companies to adopt big data analytics because it results in better services and schemes.	Equal variances assumed	2.091	.154	-.721	55	.474	-.165	.229	-.624	.294
	Equal variances not assumed			-.706	47.070	.484	-.165	.234	-.635	.305

A regression analysis for each company was performed to test for the influence of the independent variable on the dependent variable- ATT. The independent variables are included one at a time. The result for company A and company B show that: The perceived SI is not a significant predictor for both companies, as depicted in Table 4.35 and 4.36.

Table 4.35. Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.603	.788		4.575	.000
	SI	.142	.315	.093	.450	.657

a. Company = Company A

b. Dependent Variable: ATT

Table 4.36. Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.287	.546		6.017	.000
	SI	.142	.230	.112	.616	.543

a. Company = Company B

b. Dependent Variable: ATT

4.4.5. Section E: Perceived Facilitating Conditions

The objectives of this question is to determine the perceived facilitating conditions that influence the employees' attitude towards the adoption of big data analytics by selected medical aid organisations in Durban. The construct was broken down into six sub questions. The aim was to get the respondent's view about facilitating conditions.

Q.1. the company has the necessary network system to adopt big data analytics

Table 4.37. The company has the necessary network system to adopt big data analytics

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly disagree	1	1.8	1.8	1.8
	Disagree	9	15.8	16.1	17.9
	Neutral	14	24.6	25.0	42.9
	Agree	32	56.1	57.1	100.0
	Total	56	98.2	100.0	
Missing	System	1	1.8		
Total		57	100.0		

57.1 % (agree) of the respondents agreed that the company has the necessary network system to adopt big data analytics; 17.9 (disagree + strongly disagree) of the respondents disagreed that the company does not have the necessary network system to adopt big data analytics; and 25.0 % were neutral or were not sure about this question as depicted in table 4.37. The result shows that there is a significant agreement that respondents believe the organisation has the necessary network system to adopt big data analytics (M=3.38 SD=.822), t (55) = - 3.416, p=.001. This shows that the employees think that the company has the necessary network system to accommodate the adoption of big data analytics.

Q.2. the company has the necessary storage system required for big data analytics

Table 4.38.The company has the necessary storage system required for big data analytics

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	8	14.0	14.0	14.0
	Neutral	13	22.8	22.8	36.8
	Agree	36	63.2	63.2	100.0
	Total	57	100.0	100.0	

63.2% (agree) of the respondents reported that the company has the necessary storage system required for big data analytics; 14% of respondents disagreed that the company does not have the necessary storage system for big data analytics; and 22.8 % were neutral or did not have an opinion about this question as depicted in table 4.38. The result shows that there is a significant agreement that respondents believe the organisation has the necessary network system to adopt big data analytics (M=3.49 SD=.735), t (56) = -5.046, p<.0005. This indicates that the employees think the company has the storage system required for the adoption of big data analytics.

Q.3. The company has the necessary hardware required for big data analytics

Table 4.39. The company has the necessary hardware required for big data analytics

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	9	15.8	15.8	15.8
	Neutral	19	33.3	33.3	49.1
	Agree	29	50.9	50.9	100.0
	Total	57	100.0	100.0	

50.9% (agree) of the respondents reported that the company has the necessary hardware required for big data analytics, while 15.8% of the respondents reported that the company does not have the necessary hardware required for big data analytics; 33.3% were neutral or did not have any opinion as depicted in table 4.39. The result shows that there is a significant agreement that respondents believe the organisation has the necessary hardware required for the adoption of big data analytics (M=3.35 SD=.744), t (56) = 3.561, p=.001. This indicates that the employees think the company has the hardware required for the adoption of big data analytics.

Q.4. The Company has the right expertise required for big data analytics

Table 4.40. The company has the right expertise required for big data analytics

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	17	29.8	29.8	29.8
	Neutral	11	19.3	19.3	49.1
	Agree	29	50.9	50.9	100.0
	Total	57	100.0	100.0	

50.9% (agree) of the respondents reported that the company has the right expertise required for big data analytics, while 29.8% of the respondents reported that the company has the right expertise required for big data analytics; 19.3% of the respondents did not have an opinion or were neutral as depicted in table 4.40. The result shows that there is a significant agreement that respondents believe the organisation has the necessary hardware required for the adoption of big data analytics (M=3.21 SD=.881), t (56) = 1.804, p=.077. This indicates respondents think that the company has, somehow the right skills required for big data analytics adoption.

Q.5. The top management team has the necessary knowledge about big data analytics

Table 4.41. The top management team has the necessary knowledge about big data analytics

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly disagree	6	10.5	10.5	10.5
	Disagree	17	29.8	29.8	40.4
	Neutral	10	17.5	17.5	57.9
	Agree	24	42.1	42.1	100.0
	Total	57	100.0	100.0	

42.1% (agree) of the respondents reported that the top management has the necessary knowledge about big data analytics, while 40.3% (disagree + strongly disagree) reported that the top management does not have the necessary knowledge about big data analytics; 17.5% of the respondents were neutral about this question as depicted in table 4.41. The result shows that there is a disagreement that respondents believe the top management has the necessary knowledge about big data analytics, t (56) = -.617, p=.540. Respondents were divided about this question and there was disagreement among employees that the top management has the necessary knowledge about big data analytics.

Q.6. The company has a requirement to share data between departments within the company

Table 4.42. The company has a requirement to share data between departments within the company

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly disagree	1	1.8	1.8	1.8
	Disagree	7	12.3	12.3	14.0
	Neutral	11	19.3	19.3	33.3
	Agree	38	66.7	66.7	100.0
	Total	57	100.0	100.0	

66.7% (agree) of respondents reported that there is a requirement to share data between departments within the company, while 14.1% of the respondents disagreed; 19.3% of the respondents did not have an opinion or were neutral about this question as depicted in table 4.42. The result, t (56) = 4.912, p<.0005, shows that there is a significant agreement that respondents believe the organisation has the requirement to share data between departments within the company.

A one-sample t-test to the composite measure was performed to test for significant agreement or disagreement about this construct. The result, t (56) = 3.483, p=.001, shows that Facilitating condition is a significant agreement as depicted in table A.21 (see Appendix A).

H2: the availability of technological infrastructure will likely contribute to the intention to adopt big data analytics since big data analytics is a complex technology. The perceived facilitating conditions (resources) will influence the attitude towards the adoption of big data analytics.

A regression analysis was performed to test for the influence of the independent variable on the dependent variable-ATT and the result revealed that:

The independent variable Facilitating condition accounts for 60, 3% ($R^2 = .603$) of the variance in attitude (ATT), F (1, 55) = 83.549, p<.0005. FACILITATING CONDITION is a significant strong predictor of ATTITUDE (β =1.006, p<.0005) as depicted in table A.32, table A.33, and table A.34 (see Appendix A).

The results of the comparison analysis between the two companies will be presented below.

For each of the Likert scale questions, an independent sample t-test was applied to compare scores across company average. As depicted in table 4.43, the results reveal that: there is a significant difference between companies in the agreement that the top management team has the necessary knowledge about big data analytics ($t(55) = -3.000$, $p=.004$). Company A shows a significant disagreement while company B shows a significant agreement. In addition, question 10.4 shows that the result is different between the two companies.

Table 4.43. Group Statistics

	Company	N	Mean	Std. Deviation	Std. Error Mean
10.1.The company has the necessary network system to adopt big data analytics	Company A	25	3.36	.810	.162
	Company B	31	3.39	.844	.152
10.2.The company has the necessary storage system required for big data analytics	Company A	25	3.64	.638	.128
	Company B	32	3.38	.793	.140
10.3.The company has the necessary hardware required for big data analytics	Company A	25	3.36	.700	.140
	Company B	32	3.34	.787	.139
10.4. The company has the right expertise required for big data analytics	Company A	25	2.84	.898	.180
	Company B	32	3.50	.762	.135
10.5.The top management team has the necessary knowledge about big data analytics	Company A	25	2.24	1.012	.202
	Company B	32	3.44	.801	.142
10.6.The company has a requirement to share data between departments within the company	Company A	25	3.52	.823	.165
	Company B	32	3.50	.762	.135

A regression analysis for each company was performed to test for the influence of the independent variable on the dependent variable- ATT. The independent variables are included one at a time. The result for company A and company B show that: The perceived FC appears to be a significant predictor in each company (Company A and Company B) as depicted in Table 4.44 and 4.45.

Table 4.44. Coefficients[a,b]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.510	.732		.696	.494
	FC	1.089	.229	.705	4.761	.000

a. Company = Company A

b. Dependent Variable: ATT

Table 4.45. Coefficients[a,b]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.172	.273		-.632	.532
	FC	1.104	.078	.933	14.177	.000

a. Company = Company B

b. Dependent Variable: ATT

4.4.6. Section F: Perceived characteristic of Innovation

The objective of this research question is to determine the perceived characteristics of innovation influencing the employees' attitude towards the adoption of big data analytics by selected medical aid organisations in Durban. Eleven sub questions were asked. Results of the eleven questions are presented.

Q.1. I think the adoption of big data analytics is aligned with the company's business process

Table 4.46. I think the adoption of big data analytics is aligned with the company's business process

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	7	12.3	12.3	12.3
	Neutral	9	15.8	15.8	28.1
	Agree	34	59.6	59.6	87.7
	Strongly agree	7	12.3	12.3	100.0
	Total	57	100.0	100.0	

71.9 % (agree + strongly agree) of the respondents reported that the adoption of big data analytics is aligned with the company's business process, while 12.3% of respondents reported that the adoption of big data analytics is not aligned with the company's business process; 12.3% of the respondents were neutral about this question as depicted in table 4.46. The result (M=3.72 SD=.840), t (56) = 6.465, p<.0005, shows that there is significant agreement that employees think the adoption of big data analytics is aligned with the company's business process.

Q.2. I think the adoption of big data analytics is in harmony with the company's value

Table 4.47. I think the adoption of big data analytics is in harmony with the company's value

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	7	12.3	12.3	12.3
	Neutral	11	19.3	19.3	31.6
	Agree	32	56.1	56.1	87.7
	Strongly agree	7	12.3	12.3	100.0
	Total	57	100.0	100.0	

68.4% (agree + strongly agree) of the respondents reported that the adoption of big data analytics is in harmony with the company's value, while 12.3% of the respondents reported that the adoption of big data analytics is not in harmony with the company's value; 19.3% of the respondents were neutral about this question as depicted in table 4.47. The result (M=3.72 SD=.840), t (56) = 6.465, p<.0005, shows that there is significant agreement that the adoption of big data analytics is in harmony with the company's value.

Q.3. I think the adoption of big data analytics fits right into the company's work practices.

Table 4.48. I think the adoption of big data analytics fits right into the company's work practices

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	7	12.3	12.3	12.3
	Neutral	8	14.0	14.0	26.3
	Agree	38	66.7	66.7	93.0
	Strongly agree	4	7.0	7.0	100.0
	Total	57	100.0	100.0	

73.7% (agree + strongly) of the respondents reported that the adoption of big data analytics fits right into the company's work practices, while 12.3% of the respondents reported that the adoption of big data analytics does not fit right into the company's work practices; 14.0% of the respondents were neutral about this question as depicted in table 4.48. The result (M=3.68 SD=.783), t (56) =6.599, p<0005, shows that there is significant agreement that the adoption of big data analytics fits right into the company's work practices.

Q.4. I think the adoption of big data analytics fits right into the actual organisation's technological infrastructure.

Table 4.49. I think the adoption of big data analytics fits right into the actual organization's technological infrastructure

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	8	14.0	14.0	14.0
	Neutral	8	14.0	14.0	28.1
	Agree	36	63.2	63.2	91.2
	Strongly agree	5	8.8	8.8	100.0
	Total	57	100.0	100.0	

72% (agree + strongly agree) of the respondents reported that the adoption of big data analytics fits right into the actual organisation's technological infrastructure, while 14.0% of the respondents reported that the adoption of big data analytics does not fit right into the actual organisation's technological infrastructure; 14.0% of the respondents were neutral about this question as depicted in table 4.49. The result (M= SD=), t (56) =6.057; p<.0005, shows that there is significant agreement that the adoption of big data analytics fits right into the actual company's technological infrastructure.

Q.5. I think big data analytics is flexible to interact with.

Table 4.50. I think big data analytics is flexible to interact with

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	16	28.1	28.1	28.1
	Neutral	26	45.6	45.6	73.7
	Agree	15	26.3	26.3	100.0
	Total	57	100.0	100.0	

26.3% of the respondents reported that big data analytics is flexible to interact with, while 28.1% of the respondents reported that big data analytics is not flexible to interact with; 45.6% of the respondents did not have any opinion about this question as depicted in table 4.50. The result (M=2.98 SD=.744), t (56) = -.178, p=.859, shows that there is significant disagreement that big data analytics is flexible to interact with.

Q.6. I think big data analytics is easy to implement.

Table 4.51. I think big data analytics is easy to implement

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	19	33.3	33.3	33.3
	Neutral	23	40.4	40.4	73.7
	Agree	15	26.3	26.3	100.0
	Total	57	100.0	100.0	

26.3% of the respondents reported that big data analytics is easy to implement, while 33.3% of the respondents reported that big data analytics is not easy to implement; 40.4% of the respondents were neutral about this question as depicted in table 4.51. The result (M=2.93 SD=.776), t (56) = -.683, p=.498, shows that there is significant disagreement among the employees that big data analytics is easy to implement.

Q.7. I think it is easy to train employees on big data analytics.

Table 4. 52. I think it is easy to train employees on big data analytics

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	18	31.6	32.1	32.1
	Neutral	27	47.4	48.2	80.4
	Agree	11	19.3	19.6	100.0
	Total	56	98.2	100.0	
Missing	System	1	1.8		
Total		57	100.0		

19.6% of the respondents reported that it is easy to train employees on big data analytics, while 32.1% of the respondents reported that it is not easy to train employees on big data analytics; 48.2% of the respondents did not have any opinion about this question as depicted in table 4.52.

The result (M=2.88 SD=.715), t (55) = -1.308, p=.196, shows that there is significant disagreement among the employees that big data analytics is easy to train employees on big data analytics.

Q.8. I think big data analytics is easy to maintain.

Table 4.53. I think big data analytics is easy to maintain

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	19	33.3	33.3	33.3
	Neutral	25	43.9	43.9	77.2
	Agree	12	21.1	21.1	98.2
	Strongly agree	1	1.8	1.8	100.0
	Total	57	100.0	100.0	

22.9% (agree + strongly agree) of the respondents reported that big data analytics is easy to maintain, while 33.3% of the respondents reported that big data analytics is not easy to maintain; 43.9% of the respondents did not have any opinion about this question as depicted on table 4.53. The result (M=2.91 SD=.786), t (56) = -.843, p= .403, shows that there is significant disagreement that big data analytics is easy to maintain.

Q.9. I think the law permits companies to use data from their customers.

Table 4.54. I think the law permits companies to use data from their customers

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	13	22.8	23.2	23.2
	Neutral	26	45.6	46.4	69.6
	Agree	16	28.1	28.6	98.2
	Strongly agree	1	1.8	1.8	100.0
	Total	56	98.2	100.0	
Missing	System	1	1.8		
Total		57	100.0		

30.4% (agree + strongly agree) of the respondents reported that they think the law permits companies to use data from their customers while 23.2% of the respondents reported that they think the law does not permit companies to use data from their customers; 46.4% of the respondents did not have any opinion about this question as depicted in table 4.54. The result (M=3.09 SD=.769), t (55) = .868, p=.389, shows that there is a significant disagreement that employees think big data analytics is not easy to maintain.

Q.10. I think the company can rightly access data from third parties (suppliers).

Table 4.55. I think the company can rightly access data from third parties(suppliers)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	16	28.1	28.1	28.1
	Neutral	25	43.9	43.9	71.9
	Agree	14	24.6	24.6	96.5
	Strongly agree	2	3.5	3.5	100.0
	Total	57	100.0	100.0	

28.1 % (agree + strongly agree) of the respondents reported that they think the company can rightly access data from third parties (suppliers), while 28.1% of the respondents reported that they don't think the company can rightly access data from third parties (suppliers); 43.9% of the respondents did not have any opinion about this question as depicted in table 4.55. The result (M=3.04 SD=.823), t (56) =.322, p=.749, shows that there is a significant disagreement that the company can rightly access data from third parties.

Q.11. I think information security within the company is assured.

Table 4.56. I think information security within the company is assured

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	8	14.0	14.0	14.0
	Neutral	6	10.5	10.5	24.6
	Agree	27	47.4	47.4	71.9
	Strongly agree	16	28.1	28.1	100.0
	Total	57	100.0	100.0	

75.5% (agree + strongly agree) of the respondents reported that they think information security within the company is assured, while 14.0% of the respondents reported that they don't think the information security within the company is assured; 10.5% of the respondents didn't have any opinion about this question as depicted in table 4.56. The result (M=3.89 SD=.976), t (56) =6.920, p<.0005, shows that there is significant agreement that employees think information security within the company is assured.

Q.12. I think big data analytics allows an organisation to use its data more effectively.

Table 4.57. I think big data analytics allows an organization to use its data more effectively

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	8	14.0	14.0	14.0
	Neutral	6	10.5	10.5	24.6
	Agree	33	57.9	57.9	82.5
	Strongly agree	10	17.5	17.5	100.0
	Total	57	100.0	100.0	

75.4 % (agree + strongly agree) of the respondents reported that they think big data analytics allows an organisation to use its data more effectively, while 14.0% of the respondents reported that they do not think that big data analytics allows an organisation to use its data effectively; 10.5% of the respondents did not have any opinion about this question as depicted in table 4.57. The result (M=3.79 SD=.901), t (56) =6.614, p<.0005, shows that there is significant agreement that big data analytics allows an organisation to use its data more effectively.

Q.13. I think big data analytics helps a company to customise products(schemes)

Table 4.58. I think big data analytics helps a company to customise products (schemes)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	7	12.3	12.3	12.3
	Neutral	10	17.5	17.5	29.8
	Agree	36	63.2	63.2	93.0
	Strongly agree	4	7.0	7.0	100.0
	Total	57	100.0	100.0	

70.2% (agree + strongly agree) of the respondents reported that they think big data analytics helps a company to customise products (schemes), while 12.3% of the respondents reported that they do not think big data analytics helps a company to customise products (schemes); 17.5% of the respondents did not have any opinion about this question as depicted in table 4.58. The result (M=3.65 SD=.790), t (56) =6.201, p<.0005, shows that there is significant agreement that employees think big data analytics can help a company to customise products (schemes).

Q.14. I believe big data analytics increases customer base.

Table 4.59. I believe big data analytics increases customer base

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	8	14.0	14.0	14.0
	Neutral	17	29.8	29.8	43.9
	Agree	26	45.6	45.6	89.5
	Strongly agree	6	10.5	10.5	100.0
	Total	57	100.0	100.0	

56.1% (agree + strongly agree) of the respondents reported that they believe big data analytics increases customer base, while 14.0% of the respondents reported that they do not believe big data analytics increases customers base; 29.8% of the respondents were neutral as depicted in table 4.59. The result (M=3.53 SD=.868), t (56) =4.577, p<.0005, shows that there is significant agreement that employees think big data analytics increases the customer base.

Q.15. I think big data analytics helps an organisation gain competitive advantage.

Table 4.60. I think big data analytics helps an organization gain competitive advantage

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	8	14.0	14.0	14.0
	Neutral	11	19.3	19.3	33.3
	Agree	33	57.9	57.9	91.2
	Strongly agree	5	8.8	8.8	100.0
	Total	57	100.0	100.0	

66.7% (agree + strongly agree) of the respondents reported that big data analytics helps an organisation gain competitive advantage while 14.0% of the respondents reported that they do not think big data analytics helps an organisation gain competitive advantage; 19.3% of the

respondents did not have any opinion about this question as depicted in table 4.60. The result (M=3.61 SD=.840), t (56) =5.519, p<.0005, shows that there is significant agreement among the employees that big data analytics helps an organisation gain competitive advantage.
It is the objective of this study to determine the characteristics of innovation. Therefore, factor analysis with varimax rotation was applied in order to identify underlying factors in this data.

The results of this construct showed (table 4.61) a clear distinction between sub questions 11.1 - 11.4; 11.11 – 11.15 and 11.5 – 11.10. For the analysis purpose, sub questions 11.1 – 11.4; 11.11 – 11.15 is named COI_INT and sub questions 11.5 – 11.10 is named COI_EXT.

Table 4.61. Rotated Factor Matrix[a]

	Factor	
	1	2
11.1.I think the adoption of big data analytics is aligned with the company's business process	.898	
11.2. I think the adoption of big data analytics is in harmony with the company's value	.855	
11.3. I think the adoption of big data analytics fits right into the company's work practices	.878	
11.4. I think the adoption of big data analytics fits right into the actual organisation's technological infrastructure	.897	
11.5. I think big data analytics is flexible to interact with		.876
11.6. I think big data analytics is easy to implement		.907
11.7.I think it is easy to train employees on big data analytics		.918
11.8. I think big data analytics is easy to maintain		.885
11.9. I think the law permits companies to use data from their customers		.770
11.10.I think the company can rightly access data from third parties(suppliers)		.792
11.11.I think information security within the company is assured	.928	
11.12.I think big data analytics allows an organisation to use its data more effectively	.936	
11.13.I think big data analytics helps a company to customize products (schemes)	.846	
11.14. I believe big data analytics increases the customer base	.756	
11.15.I think big data analytics helps an organisation to gain competitive advantage	.866	

Extraction Method: Principal Axis Factoring.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 3 iterations.

The two factors (COI_INT and COI_EXT) are tested for reliability.

Table 4.62. Reliability Statistics

Cronbach's Alpha	N of Items
.976	9

Table 4.63. Reliability Statistics

Cronbach's Alpha	N of Items
.959	6

The results show that the reliability, Cronbach's alpha of these two factors are excellent (see table 4.62 and table 4.63).

A one-sample t-test to the composite measures was performed to test for significant agreement or disagreement about this construct. The results t (56) = 6.671, p<.0005, show that COI_INT is a significant agreement, while COI_EXT t (56) = -.284, p=.777 is neither a significant agreement nor disagreement as depicted in table A.21 (see Appendix A).

H5: the perceived characteristic of an innovation will greatly influence the adoption process of new innovation. The characteristics of big data analytics will influence the employees' attitudes towards the adoption of big data analytics. Companies will likely want to know by adopting big data analytics, are we going to get any relative advantage. The more the employees see that by adopting big data analytics, the company will get a competitive advantage, and big data analytics is compatible with the actual company's business process or IT infrastructure, the more likely they will have a positive attitude towards the adoption of big data analytics.

A regression analysis was performed to test the influence of the two independent variables on the dependent variable- ATT and the finding reveals that:

The independent variables CHARACTERISTIC OF INNOVATION_INT accounts for 85.3% ($R^2 = .853$) of the variance in attitude (ATT), F (1, 55) = 318.857, p<.0005. COI_INT is a significant strong predictor of ATTITUDE (β =1.023, p<.0005), while the independent variables CHARACTERISTIC OF INNOVATION_EXT accounts for 31, 9% ($R^2 = .319$) of the variance in attitude (ATT), F (1, 55) = 25.765, p<.0005. COI_EXT is a significant strong predictor of ATTITUDE (β =701, p<.0005) as depicted in tables A.35; A.36; A.37; A.38; A.39; and table A.40 (see Appendix A).

The results of the comparison analysis between the two companies will be presented below.

For each of the Likert scale questions, an independent sample t-test was applied to compare scores across company average.

Table 4.64. Group Statistics

	Company	N	Mean	Std. Deviation	Std. Error Mean
11.1.I think the adoption of big data analytics is aligned with the company's business process	Company A	25	3.84	.800	.160
	Company B	32	3.63	.871	.154
11.2. I think the adoption of big data analytics is in harmony with the company's value	Company A	25	3.76	.831	.166
	Company B	32	3.63	.871	.154
11.3. I think the adoption of big data analytics fits right into the company's work practices	Company A	25	3.84	.746	.149
	Company B	32	3.56	.801	.142
11.4. I think the adoption of big data analytics fits right into the actual organisation's technological infrastructure	Company A	25	3.80	.764	.153
	Company B	32	3.56	.878	.155
11.5. I think big data analytics is flexible to interact with	Company A	25	3.04	.611	.122
	Company B	32	2.94	.840	.148
11.6. I think big data analytics is easy to implement	Company A	25	2.92	.702	.140
	Company B	32	2.94	.840	.148
11.7.I think it is easy to train employees on big data analytics	Company A	24	2.75	.608	.124
	Company B	32	2.97	.782	.138
11.8. I think big data analytics is easy to maintain	Company A	25	2.80	.707	.141
	Company B	32	3.00	.842	.149
11.9. I think the law permits companies to use data from their customers	Company A	24	3.04	.751	.153
	Company B	32	3.13	.793	.140
11.10.I think the company can rightly access data from third parties(suppliers)	Company A	25	3.00	.866	.173
	Company B	32	3.06	.801	.142
11.11.I think information security within the company is assured	Company A	25	4.04	.889	.178
	Company B	32	3.78	1.039	.184
11.12.I think big data analytics allows an organisation to use its data more effectively	Company A	25	3.96	.841	.168
	Company B	32	3.66	.937	.166

Table 4.64 (Contd…)

11.13.I think big data analytics helps a company to customize products (schemes)	Company A	25	3.68	.690	.138
	Company B	32	3.63	.871	.154
11.14. I believe big data analytics increases the customer base	Company A	25	3.48	.770	.154
	Company B	32	3.56	.948	.168
11.15.I think big data analytics helps an organisation to gain competitive advantage	Company A	25	3.72	.737	.147
	Company B	32	3.53	.915	.162

As depicted in the Table 4.64, the result reveals that there is no significant difference between the two companies concerning these questions.

A regression analysis for each company was performed separately to test for the influence of the independent variable on the dependent variable- ATT and the result for company A and company B show that: COI_INT is not a significant predictor of either companies as depicted in the table 4.65 and table 4.66.

Table 4.65. Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.019	.434		.044	.965
	COI_INT	1.037	.113	.887	9.197	.000

a. Company = Company A

b. Dependent Variable: ATT

Table 4.66. Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.005	.221		.024	.981
	COI_INT	.997	.060	.950	16.733	.000

a. Company = Company B

b. Dependent Variable: ATT

The results reveal that COI_ EXT is not a significant predictor for both companies as depicted in Table 4.67 and 4.68.

Table 4.67. Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.942	.762		2.549	.018
	COI_EXT	.685	.255	.489	2.686	.013

a. Company = Company A

b. Dependent Variable: ATT

Table 4. 68. Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.421	.488		2.908	.007
	COI_EXT	.728	.157	.645	4.625	.000

a. Company = Company B

b. Dependent Variable: ATT

4.4.7. Section G: The dependent variable Attitude towards the adoption

The objective of this section was to understand the attitudes of the employees towards the adoption of big data analytics.

The reliability of this section was also done and showed that the dependable variable is reliable.

As depicted in Table 4.69, the dependent variable ATT is reliable.

Table 4.69. Reliability Statistics

Cronbach's Alpha	N of Items
.968	4

The dependent variable-ATT was broken down into four sub questions.

Q.1. I believe it is a good idea to adopt big data analytics.

Table 4.70. believe it is a good idea to adopt big data analytics

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	7	12.3	12.3	12.3
	Neutral	12	21.1	21.1	33.3
	Agree	29	50.9	50.9	84.2
	Strongly agree	9	15.8	15.8	100.0
	Total	57	100.0	100.0	

66.7% (agree + strongly agree) of the respondents reported that they believe it is a good idea to adopt big data analytics, while 12.3% of the respondents reported that they believe it is not a good idea to adopt big data analytics; 21.1% of the respondents did not have any opinion about this question.

Q.2. I believe that big data analytics will allow the company to access more accurate information.

Table 4.71. believe that big data analytics will allow the company to access more accurate information

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	8	14.0	14.0	14.0
	Neutral	5	8.8	8.8	22.8
	Agree	31	54.4	54.4	77.2
	Strongly agree	13	22.8	22.8	100.0
	Total	57	100.0	100.0	

77.2% (agree + strongly agree) of the respondents reported that they believe that big data analytics will allow the company to access more accurate information, while 14.0% of the respondents do not believe that big data analytics will allow the company to access more accurate information. In addition, 8.8% of the respondents were neutral about this question.

Q.3. the adoption of big data analytics by the company would be a positive decision.

Table 4.72. The adoption of big data analytics by the company would be a positive decision

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	8	14.0	14.0	14.0
	Neutral	11	19.3	19.3	33.3
	Agree	28	49.1	49.1	82.5
	Strongly agree	10	17.5	17.5	100.0
	Total	57	100.0	100.0	

66.6% (agree + strongly agree) of the respondents reported that the adoption of big data analytics by the company would be a positive decision, while 14.0% of the respondents did not believe that the adoption of big data analytics would be a positive decision; 19.3% of the respondents did not have any opinion about this decision.

Q.4. I believe that big data analytics will enhance the company's decision making.

Table 4.73. I believe that big data analytics will enhance the company's decision making

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	8	14.0	14.0	14.0
	Neutral	6	10.5	10.5	24.6
	Agree	34	59.6	59.6	84.2
	Strongly agree	9	15.8	15.8	100.0
	Total	57	100.0	100.0	

75.4% of the respondents reported that they believe big data analytics will enhance the company's decision making, while 14.0% of the respondents did not believe that big data analytics will enhance the company's decision making; 10.5% of the respondents did not have any opinion about this question.

A one-sample t-test to the composite measures was performed to test for significance of agreement or disagreement about this construct. The results, $t(56) = 6.605$, $p<.005$, show that Attitudes towards the adoption of big data analytics is a significant agreement as depicted in table A.21 (see appendix A).

Although the size of the population is small, Peter *et al*., (2015) support that it is possible to use only five respondents per independent variable to include all the independent variables all together in order to test the importance of each independent variable on the dependent variable.

Table 4.74. Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.943[a]	.889	.876	.30539	1.791

a. Predictors: (Constant), COI_EXT, SI, PE, PV, FC, COI_INT

b. Dependent Variable: ATT

Table 4.75. ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	37.457	6	6.243	66.937	.000[a]
	Residual	4.663	50	.093		
	Total	42.121	56			

a. Predictors: (Constant), COI_EXT, SI, PE, PV, FC, COI_INT

b. Dependent Variable: ATT

Table 4.76. Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-.317	.253		-1.254	.216		
	PV	-.225	.082	-.176	-2.763	.008	.547	1.828
	PE	.350	.122	.316	2.880	.006	.184	5.446
	SI	.093	.074	.068	1.246	.218	.748	1.337
	FC	.034	.120	.026	.284	.778	.258	3.876
	COI_INT	.692	.131	.625	5.287	.000	.158	6.319
	COI_EXT	.168	.078	.135	2.162	.035	.566	1.768

As depicted in table 4.76, facilitating condition p=.778 is the least important as a predictor to the dependent variable Attitudes towards the adoption. When Independent variables are put together, Price value p=.008, shows a negative influence on Attitudes towards the adoption. Performance expectancy (PE) p= .008, is the second most important as a predictor to the dependent variable ATT, while Social Influence p=.218, is the second least important as a predictor. COI_EXT p= .035, is the third important as a predictor and COI_INT p<.0005 is the most important as a predictor.

The table 4.77 reveals that when looking at the constructs, there is no significant difference between the results of the two companies.

Table 4.77. Group Statistics

	Company	N	Mean	Std. Deviation	Std. Error Mean
PV	Company A	25	2.7800	.45826	.09165
	Company B	32	2.8438	.81423	.14394
PE	Company A	25	3.7673	.66705	.13341
	Company B	32	3.7898	.87363	.15444
SI	Company A	25	2.4400	.54160	.10832
	Company B	32	2.2750	.69792	.12338
FC	Company A	25	3.1600	.53246	.10649
	Company B	32	3.4250	.74709	.13207
COI_INT	Company A	25	3.7911	.70369	.14074
	Company B	32	3.6146	.84289	.14900
COI_EXT	Company A	25	2.9333	.58729	.11746
	Company B	32	3.0052	.78344	.13849
ATT	Company A	25	3.9500	.82285	.16457
	Company B	32	3.6094	.88431	.15633

Table 4.78. Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
12.1.I believe it is a good idea to adopt big data analytics	Equal variances assumed	.501	.482	1.997	55	.051	.460	.230	-.002	.922
	Equal variances not assumed			1.984	50.320	.053	.460	.232	-.006	.926
12.2.I believe that big data analytics will allow the company to access more accurate information	Equal variances assumed	1.702	.197	.714	55	.478	.179	.250	-.323	.681
	Equal variances not assumed			.730	54.730	.469	.179	.245	-.312	.670
12.3.The adoption of big data analytics by the company would be a positive decision	Equal variances assumed	2.036	.159	1.596	55	.116	.389	.244	-.099	.877
	Equal variances not assumed			1.615	53.708	.112	.389	.241	-.094	.871
12.4. I believe that big data analytics will enhance the company's decision making	Equal variances assumed	1.416	.239	1.428	55	.159	.335	.235	-.135	.805
	Equal variances not assumed			1.442	53.345	.155	.335	.232	-.131	.801

4.5. Summary

The aim of this chapter was to present the research analysis. Thus, this chapter presented the analysis related to the sections from the questionnaire. Results from seven sections were presented in this chapter. The tests used in this study were discussed. The descriptive study was presented then the inferential study was presented. The comparison analysis of the two companies were also presented to find out whether there is any significant difference.

All the constructs proved to be reliable and can be used for further analysis. Perceived price value, perceived performance expectancy, perceived facilitating conditions and perceived characteristics of innovation proved to be significant predictors to the dependent variable ATT- attitudes towards the adoption of big data analytics. The data presented in chapter4 will be discussed in depth in the next chapter (Chapter 5).

CHAPTER 5

FINDINGS, DISCUSSIONS, AND RECOMMENDATIONS

5.1. Introduction

This chapter discusses the results presented in chapter four. The findings will be interpreted in relation to the guiding research questions as well as the hypotheses developed in this study. A conclusion of the study will be provided to summarise the study, and recommendations will be made based on the discussion of the findings.

5.2. Addressing Research Questions

The key findings of this study are discussed and summarised then are interpreted accordingly. The findings are positioned in the existing body of knowledge and an attempt to compare the findings with the existing body of knowledge (if available) is made.

5.2.1. Research Question 1

What is the perception of performance expectancy among the employees on the adoption of big data analytics in selected medical aid organisations in Durban?

Perceived performance expectancy was analysed through the criteria (Table 5.1):

Table 5.1. Perceived performance expectancy criteria

CRITERIA	QUESTION NUMBER
Business risk assessment	8.1
Knowledge management	8.2
Decision making	8.3
Ability to develop new schemes	8.4
Ability to understand the need of customers	8.5

Detection of fraudulent medical claims	8.6
Customer relationship management	8.7
The effectiveness of existing schemes	8.8
Competitive advantage	8.9
The identification of new schemes	8.10
The overall performance of the company	8.11

The study found that perceived performance expectancy has a positive influence on the attitude towards the adoption of big data analytics. This indicates that employees would expect the adoption of big data analytics to improve the performance of the company in general. Employees expect that the adoption of big data analytics would result in the improvement of business risk assessment, knowledge management, decision making, the ability for medical aid organisations to develop new schemes, and the ability to understand the needs of customers as depicted in the Tables 4.15, 4.16, 4.17, 4.18, 4.19, 4.20, 4.21, 4.21, 4.22 and 4.23. Employees think that the adoption of big data analytics would improve the detection of fraudulent medical claims and this finding is aligned with Manyika *et al*., (2011) study which claims that companies are expecting and are reaping great benefits from big data analytics. Since information is the cornerstone of the insurance companies (Bhoola *et al.*, 2014), employees think that the adoption of big data analytics would improve decision making by having better information flow. The construct shows a significant agreement and proved to be a strong predictor of the attitude towards the adoption of big data analytics as depicted in section 4.4.3 in the previous chapter. It was clearly indicated that the perception of performance expectancy has a positive influence on the attitude towards the adoption of big data analytics by selected medical aid organisations as depicted in tables A.26, A.27 and A.28 (see Appendix A). The thought of improving the key areas of the company by big data analytics has a positive influence on their attitudes towards the adoption of big data analytics. Russom (2011) stated that organisations dealing with any type of customers will benefit from big data analytics, the findings of this study supports this claim by showing that employees expect that the adoption of big data analytics will improve performance of the company. Perceived performance expectancy is seen as the belief that a user or a company's use of a system will translate into an improvement of his/her job, or the company's performance. The findings show that employees have a strong belief that the adoption of big data analytics will improve the performance of selected medical aid organisations in Durban. The results indicate that the influence of perception of performance expectancy among the employees in the attitude towards the adoption of big data analytics is significant. Perceived performance expectancy proved to be the second most important independent variable. The comparative analysis between the two companies A and B shows that there are no significant differences in the likert scale answers from the employees of the two companies as depicted in the table 4.26. The analysis of the construct between the two companies shows that there is no significant difference as well. The separate regression analysis of each company reveals that the perceived performance expectancy is a significant predictor of the attitudes towards the adoption in each company as depicted in Table 4.27 and Table 4.28.

The results of this research question on the perception of performance expectancy shows that performance expectancy is a significant agreement and a strong predictor of the dependent variable, attitude towards the adoption of big data analytics.

5.2.2. Research Question 2

What are the perceived facilitating conditions influencing the adoption of big data analytics by selected medical aid organisations in Durban?

The perceived facilitating conditions were measured using the criteria (Table 5.2):

Table 5.2. Perceived facilitating conditions criteria

CRITERIA	QUESTION NUMBER
The necessary network system required for big data analytics	10.1
The necessary storage system required for big data analytics	10.2
The necessary hardware required for big data analytics	10.3

The right expertise required for big data analytics	10.4
The top management team having the necessary knowledge about big data analytics	10.5
The company having a requirement to share data between departments within the company.	10.6

The results indicate that some employees agree and others disagree with the criteria used to measure the perceived facilitating conditions. According to the economist (2013), majority of companies in Asia/pacific believe that the lack of suitable software, suitable hardware can influence negatively the adoption of big data analytics by companies. The majority of employees believe that the company has the necessary network system to adopt big data analytics. It was evident (Table 4.38) that the employees think that the selected medical aid organisations have the necessary storage system and hardware required for big data analytics as shown in table 4.39; while employees were divided about the top management having the necessary knowledge about big data analytics as depicted in table 4.41. The employees believe that the companies have the right expertise required for big data analytics as shown in section 4.4.5. This result is in contrast with the result in section B where employees believe that the cost of expertise is not affordable. The comparative analysis (Table 4.43) revealed that for company A, employees believe the top management team does not have the necessary knowledge about big data analytics; while for company B, the result shows that the employees believe the top management has the necessary knowledge about big data analytics. It has been argued that top management is key to any adoption of technology (Watson, 2012; Gagnon & Toulouse, 1996; Cooper & Zmud, 1990). Thus the study made an attempt to get the perception of employees on whether the top management have necessary knowledge about big data analytics. In a research survey conducted by the Economist (2013) in Asia/pacific, it was found that not being able to share data by different departments within the company can influence the adoption of big data analytics. Thus the present study had to get the view of employees on that matter, and table 4.42 shows that the employees strongly agreed there is a requirement to share data between departments within the company. The composite measure of this construct shows a significant agreement. The likert scale question about the company having the right expertise required for big data analytics proved different from the two companies (Table 4.43). The combined regression analysis was done to test the influence of perceived facilitating conditions on the dependent variable attitude towards the adoption of big data analytics. It shows that perceived facilitating conditions is a strong predictor of the ATT. Thus, thinking that the company has the necessary facilitating conditions is linked with a positive attitude towards the adoption of big data analytics. Although perceived facilitating conditions proved to be a strong predictor of attitude, it appears to be the least important independent variable as depicted in table 4.76. The regression analysis on each company separately reveals that the perceived facilitating condition is also a significant predictor of the dependable variable ATT in each company.

The results of this research question on the perception of facilitating conditions shows that facilitating condition is a significant agreement and a very strong predictor of the dependent variable.

5.2.3. Research Question 3

How does the employees' perception on price value influence the adoption of big data analytics in selected medical aid organisations in Durban?

The perceived Price Value was measured using the criteria (Table 5.3):

Table 5.3. Perceive price value criteria

CRITERIA	**QUESTION NUMBER**
The overall cost of big data analytics	7.1
The cost of expertise	7.2
The cost of implementation	7.3
The cost of storage system	7.4
The cost of big data network	7.5
Financial benefit of big data analytics	7.6

The results shows us that there is a general significant disagreement about this construct and the construct is a strong predictor of the attitude towards the adoption of big data analytics. This shows that the employees believe that big data analytics is not affordable as depicted in table 4.6. Employees believe that the price of big data analytics implementation is not affordable (Table 4.8), the finding coincides with Katina and Miller (2013) who mentioned that the cost associated with the development/implementation of big data analytics projects could be a challenge. The combined finding of this study reveals that employees believe the cost of expertise for big data analytics is not affordable (Table 4.7). This finding is in agreement with e-skills (2013) research survey which revealed the cost related to finding right skills for big data analytics is high. Nowadays, with the availability of open sources, companies can overcome the high cost of big data analytics. The negative perception on the price of big data analytics can be changed by informing companies and employees of the price of open sources which is much cheaper now. The comparative analysis showed that there is a significant difference between companies about their perception on the cost of expertise for big data analytics, company B shows a higher agreement than company B (Table 4.12). A regression analysis was done to test the influence of the independent variables PV on the dependable variable ATT; the result shows that Price Value is a significant predictor of Attitude. Interestingly when independent variables are put together to measure their influence on the attitude towards the adoption of big data analytics, it shows that respondents thinking it is not affordable is still linked with a more positive attitude towards the adoption of big data analytics. A regression analysis on each company separately shows that perceived price value is not a significant predictor of ATT in company A; while it is a significant predictor of the ATT in company B (Table 4.13 and Table 4.14). The perceived price value proved to be the third most important independent variable.

The results of this research question on the perception of price value shows that the composite measure of price value showed to be is a significant disagreement (employees have a negative perception) but at the same time a significant predictor of the dependent variable.

5.2.4. Research Question 4

How does the employees' perception of social factors influence the adoption of big data analytics in selected medical aid organisations in Durban?

The perceived social factors (influence) were examined using the criteria (Table 5.4):

Table 5.4. Perceived social factors criteria

CRITERIA	QUESTION NUMBER
Competitors influence	9.1
Suppliers influence	9.2
Big data analytics trending in the industry	9.3
Government influence	9.4
Customers influence	9.5

Looi (2005) claims that competition and industry pressure can influence the adoption of an IT innovation, thus it was necessary for this study to find out which social and how social factors are influencing the attitude towards the adoption of big data analytics. The results in section 4.4.5 show us that there is a significant disagreement about this construct social influence (social factors). As depicted in the table 4.29, Employees think that a proportion of competitors have not adopted big data analytics. This indicates that they do not see competitors pressurizing their companies to adopt big data analytics. As depicted in table 4.33, they also think suppliers are not pressurizing them to adopt big data analytics or big data analytics being a trend in the medical industry. However the Table 4.33 shows that company A agree that big data analytics is a trend in the industry, while company B disagree. The results also show us that employees believe that the government is not encouraging medical aid companies to adopt big data analytics, and customers are not pressurizing them to adopt big data analytics (Table 4.32 and Table 4.33). Employees disagree that customers would like medical aid companies to adopt big data analytics. The result shows that employees have a negative perception on social influence, and the independent variable social influence is not a significant predictor of attitude towards the adoption of big data analytics. Even the regression analysis done separately for the two companies revealed that the perceived social influence is not a significant predictor for either companies. Employees believe that social factors such as competitors adopting big data analytics, customers, suppliers, and government are not influencing their attitude towards the adoption of big data analytics, but the comparative analysis showed that there is a significant difference between the two companies. When asked if the employees believe that the adoption of big data analytics is a trend in the medical aid industry, the company A shows a significant agreement, while the company B shows a significant disagreement (Table 4.36 and Table 4.34). The perceived social influence appeared to be the fifth most important independent variable.

The results of this research question on the perception of social influence (factors) shows that employees have a negative perception about the independent variable social influence and it is not a significant predictor of the dependent variable.

5.2.5. Research Question 5

What are the perceived characteristics of innovation influencing the employees' attitudes towards the adoption of big data analytics in selected medical aid organisations in Durban?

The perceived characteristic of innovation were examined using the criteria (Table 5.5):

Table 5.5. Perceived characteristic of innovation criteria (COI)

CRITERIA	QUESTION NUMBER
Compatibility	11.1; 11.2;11.3;11.4
Complexity	11.4;11.5;11.6;11.7;11.8
Privacy/security	11.9;11.10;11.12
Relative advantage	11.13;11.4;11.15

Bhoola *et al*., (2014) advocate that the company's traditional IT infrastructure can be a challenge to big data analytics development. A company which does not have a proper IT infrastructure to implement a big data project will struggle. As depicted in tables 4.49; 4.46; 4.47; and 4.48, the results of this study reveal that employees think the adoption of big data analytics is aligned with the company IT infrastructure, business process, value, and company's work practice. Xia and Lee (2005) stated that many information systems projects fail due to the complexity. Thus, it was important to assess the employees' perception on the complexity of the adoption of big data analytics, and the results revealed that employees think big data analytics is a complex project.

The one- sample t-test was applied to the composite measures and the results show that COI_INT (compatibility, relative advantage) is a significant agreement and the most important predictor as depicted in Table 4.76. The regression analysis reveals that COI_INT (compatibility, relative advantage) are strong predictors and are positively influencing the attitude towards the adoption of big data analytics. One possible explanation for this can be that employees believe and expect adoption of big data analytics to provide an advantage to the company by improving the performance of the company. The finding coincides with the study conducted by Park (2009) which concluded that perceived usefulness (self-efficacy, relative advantage) is one of the motivational factors affecting the attitude. The one- sample t-test to this composite measure COI_EXT (complexity, privacy/security) reveals neither a significant agreement nor significant disagreement and the third most important predictor. A possible explanation can be that employees are not sure about the complexity and the privacy factor of big data analytics. As depicted in table 4.64, the comparative analysis shows no significant difference on the likert scales questions, and the regression analysis on each company reveals that COI_INT and COI_EXT proved not to be significant predictors (Tables 4.65; 4.66; 4.67; 4.48).

The results of this research question on the perceived characteristic of innovation show that the perceived characteristic was divided into two parts; COI_INT revealed to be a significant agreement and a strong predictor of the attitude while COI_EXT revealed neither a significant agreement nor a significant disagreement and strong predictor of the attitude.

5.2.6. Research question 6

How does the employees' attitude towards big data analytics influence its adoption by selected medical aid organisations in Durban?

Generally the employees have a positive attitude towards the adoption of big data analytics. The employees' attitudes influence positively the adoption of big data analytics as depicted in Table A.21 (see Appendix A). As depicted in Table 4.70, employees believe that the adoption of big data analytics is a good idea. They also believe that the adoption of big data analytics will allow the company to access more accurate data (Table 4.71); that the adoption of big data analytics would be a position decision (Table 4.72); and that big data analytics will enhance the company's decision making (Table 4.73). The comparative analysis on the likert scale questions reveals that there is no significant difference between company A and company B.

The positive attitude of employees towards the adoption might be explained by the fact that employees believe that the adoption of big data analytics by the companies will improve the performance of the companies in terms of improving the decision, creating more business opportunities, and improving the products (schemes).

5.3. Addressing hypothesises

5.3.1. Hypothesis 1

H1: The perceived performance expectancy will have an influence on the attitudes towards the adoption of big data analytics

The outcome of this study in section 4.4.3 indicates that perceived performance expectancy is a strong predictor of the dependent variable. Therefore, the hypothesis 1 is accepted. The study reveals that perceived performance influences the attitude towards the adoption of big data analytics as depicted in table A.26, A.27, and A.28 (see Appendix A).

5.3.2. Hypothesis 2

H2: The perceived facilitating conditions (resources) will influence the attitude towards the adoption of big data analytics.

The result of this study as presented in section 4.4.5 indicates that perceived facilitating conditions is a significant strong predictor of the dependent variable. Therefore, the hypothesis is accepted. The study reveals that perceived facilitating conditions influence the employees' attitudes towards the adoption of big data analytics as depicted in tables A.32, A.33 and A.34 (see Appendix A).

5.3.3. Hypothesis 3

H3: The perceived price value of big data analytics will influence the attitude towards the adoption of big data analytics.

The result of this study as presented in section 4.4.2 indicates that perceived price value is a significant predictor of the dependent variable. Therefore, the hypothesis is accepted. The study reveals that perceived price value influences the employees' attitude towards the adoption of big data analytics as depicted in tables A.22, A.23, and A.24 (see Appendix A)

5.3.4. Hypothesis 4

H4: The influence from industry, suppliers, government, customers will have an influence on the attitudes towards the adoption of big data analytics.

The result of this study as presented in section 4.4.4 indicates that perceived social influence is not a significant predictor of the dependent variable. Therefore, the hypothesis is rejected. The study reveals that perceived social influence does not influence the employees' attitude towards the adoption of big data analytics as depicted in tables A.29, A.30, and A.31 (see Appendix A).

5.3.5. Hypothesis 5

H5: The characteristics of big data analytics will influence the employees' attitudes towards the adoption of big data analytics.

As presented in section 4.4.6, the analysis of the construct (perceived characteristic of innovation) as shown in Table 4.61, indicates that there is a clear distinction between the sub questions of this construct. They were grouped and labelled as characteristic of innovation _internal (COI_INT) and characteristic of innovation _ external (COI_EXT). The results indicate that both COI_INT and COI_EXT are significant strong predictors of the dependent variable as depicted in tables A.35, A.36, A.37, A.38, A.39, and A.40 (see Appendix). Therefore the hypothesis is accepted. The findings reveal that the perceived characteristic of innovations influences the attitude towards the adoption of big data analytics.

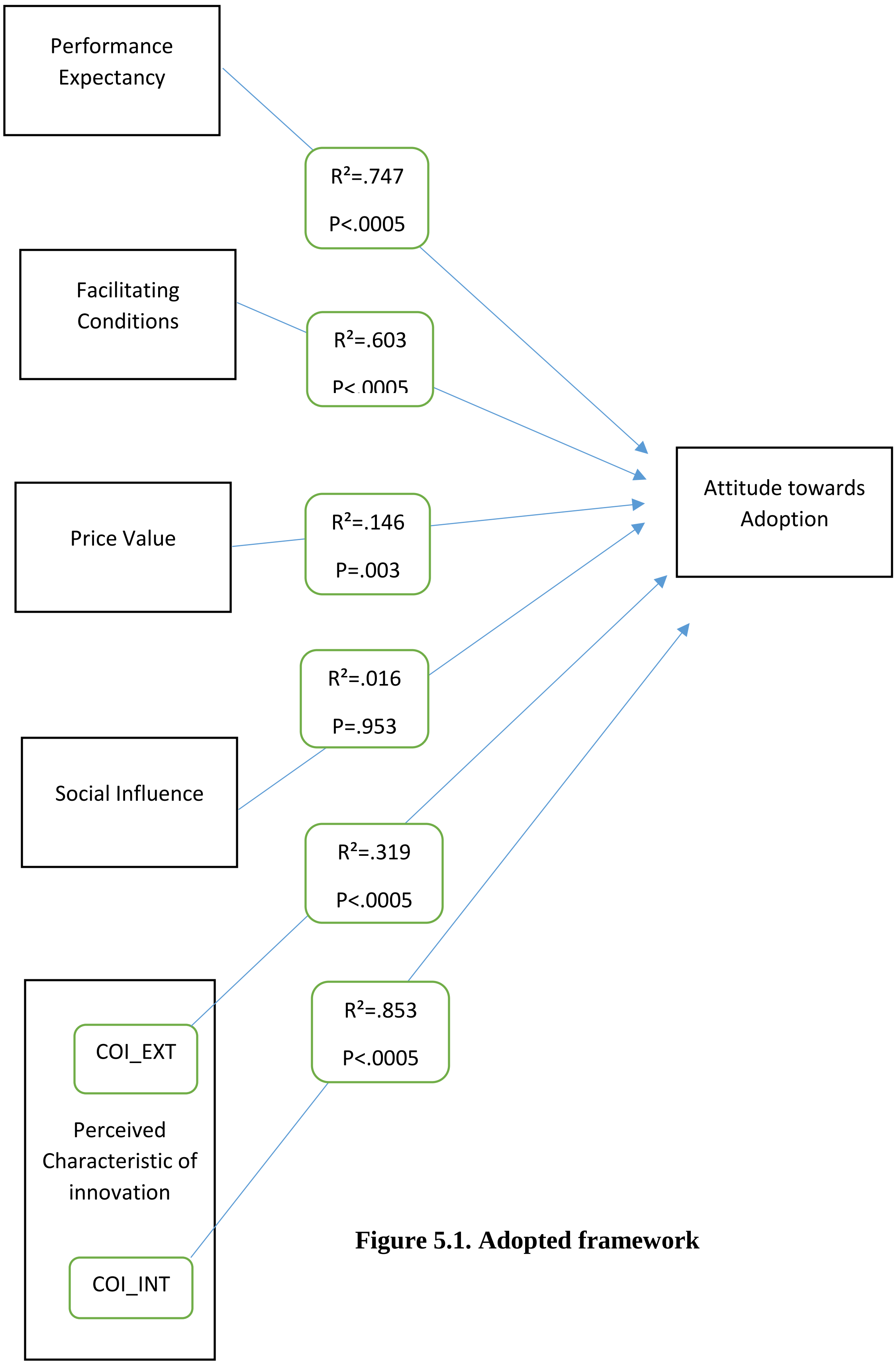

Figure 5.1. Adopted framework

5.4. Limitations to the study

Due to the inclusion and exclusion criteria (refer chapter 3), only two selected medical aid organisations participated in this study. Therefore, more fully representative research is needed to assess whether the findings can be generalised to the entire medical aid industry. Furthermore, the validity of constructs was not successful due to the small number of respondents. Therefore, a larger population may yield better results.

5.5. Recommendations

Researchers argue about the value of big data analytics in diverse sectors. The following recommendations emerged from this study to support the adoption of big data analytics:

5.5.1. Government

As depicted in table 4.32, the study reveals that there is room for improvement in terms of the government encouraging companies to adopt big data analytics by implementing flexible policies to allow companies to use more freely data from customers. As depicted in table 4.54, the employees think that law and regulations in the country do not allow companies to rightly access data from customers. It has been argued that the adoption of big data analytics by medical aid organisations can effectively and efficiently improve the healthcare sector which will have an impact on the population of South Africa. Thus, government should encourage medical aid organisations to adopt and use big data analytics. The study also reveals that employees have the perception that big data analytics is not affordable in terms of cost of expertise (table 4.7), yet still have a positive attitude towards the adoption. Thus, the government should help by encouraging universities to train more students in having the required skills for big data analytics that will reduce the cost associated with acquiring people with required skills, which may be high currently.

5.5.2. Medical Aid Organisation

As depicted in table 4.70, the study reveals that employees have a positive attitude towards the adoption of big data analytics. Thus medical aid organisations in South Africa should invest more in this new technology which can lead them to have more accurate information and knowledge therefore leading to better business decision making. Although, employees perceive big data analytics as not affordable, the study reveals interestingly that having a perception that big data analytics is not affordable is still linked to a more positive attitude towards the adoption of big data analytics. The adoption of big data analytics will improve the performance as indicated in the literature; results show that employees have that perception. Therefore medical aid organisations should invest in the adoption of big data analytics.

5.5.3. Universities in South Africa

Although the aim of the study was not to assess the analytical skills in the companies, the literature reveals that there is a shortage of people with strong analytical skills required for big data analytics worldwide (e-skillsUK, 2013). Thus universities should invest to train more students in that field, there are great opportunities for employments in the field. Furthermore, today students are the future employees perhaps for medical aid organisations, therefore with basic analytical background, the employees' perception on the adoption of big data analytics will improve.

5.6. Suggestions for future research

The reliability of the model used in this study proved to be excellent but could not test the validity due to the size of the population. Thus a larger population is required to test the validity of the constructs of this model. Moreover, the study used only quantitative method, perhaps a mixed method might provide better insight and add a different dimension to the study. Further research surveys are required to find out to what extent big data analytics is adopted by medical aid organisations in South Africa.

5.7. Summary

The purpose of this research study was to explore the perception of employees on the adoption of big data analytics by medical aid organisations in Durban. Specifically, factors (constructs) that might influence the attitudes towards the adoption of big data analytics. To this end, five perceived factors that might influence the employees' perception on the adoption of big data analytics were examined: - perceived performance expectancy, - perceive price value, - perceived social influence, - perceived facilitating conditions, - perceived characteristic of Innovation. The employees' attitude towards the adoption of big data analytics were examined as well. These perceived factors (constructs) were selected from the literature to constitute a conceptual framework. In this study, the adoption was defined as acceptance for implementation of big data analytics by selected medical aid organisations.

The study reveals that generally the employees have a positive perception on the adoption of big data analytics by selected medical aid organisations. The study also reveals that all variables were influencing the attitudes towards the adoption of big data analytics except perceived social influence. The study revealed that performance expectancy, perceived characteristic of innovation, and facilitating conditions were positively influencing the employees' attitude towards the adoption of big data analytics. Meanwhile, employees have the perception that the price of big data analytics is not affordable but the analysis revealed that although the negative perception about price value is true, it is still linked to a positive attitude towards the adoption of big data analytics. The comparative analysis revealed some significant difference on the likert scale questions between the two companies A and B. When looking at the constructs, the comparative analysis revealed that there is no significant difference between the two companies. Employees think that the adoption of big data analytics would improve the performance of the company in terms of improving the decision-making, the ability to develop new schemes, business risk assessment, the identification of new trends, the detection of fraudulent medical claims, and management decision making.

Findings also revealed that employees do not think that big data analytics is affordable; they have a negative perception on the price of the implementation of big data analytics projects. However, this perception on Price value is wrong, as the open sources have reduced the price of big data technologies. Employees also think that social factors such as influence from competitors, influence from government, and influence from customers are not influencing their attitude towards the adoption of big data analytics. Generally, employees think that the companies have the necessary hardware, software and network systems for the adoption of big data analytics. However, they were divided about the top management having the necessary knowledge about big data analytics.

This research study found that employees think that the adoption of big data analytics would be compatible with the company's business process, company's work practice, and company's IT infrastructure. It also revealed that employees think that the adoption of big data analytics would provide relative advantage to the company. However, employees think that big data analytics is a complex technology and that the privacy of data can still be a problem.

The characteristic of innovation (Compatibility, relative advantage) appeared to be the most important independent variable, which influences the dependent variable attitude towards the adoption of big data analytics, and facilitating conditions appeared to be the least important.

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APPENDICES

Appendix A: Data Analysis

Price Value

Table A.1. One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
7.1. The overall cost of big data analytics is affordable.	55	2.78	.762	.103
7.2.The cost of expertise for big data analytics is affordable	57	2.65	.790	.105
7.3.The cost of implementation of big data analytics is affordable	57	2.65	.767	.102
7.4.The storage system required for big data analytics is affordable	57	2.95	.833	.110
7.5. The cost of big data network technologies is affordable	57	2.86	.789	.105
7.6. Big data analytics can provide financial benefits	57	3.02	.813	.108

Table A.2. One-Sample Test

	Test Value = 3					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
7.1. The overall cost of big data analytics is affordable.	-2.123	54	.038	-.218	-.42	-.01
7.2.The cost of expertise for big data analytics is affordable	-3.352	56	.001	-.351	-.56	-.14
7.3.The cost of implementation of big data analytics is affordable	-3.452	56	.001	-.351	-.55	-.15
7.4.The storage system required for big data analytics is affordable	-.477	56	.635	-.053	-.27	.17
7.5. The cost of big data network technologies is affordable	-1.343	56	.185	-.140	-.35	.07
7.6. Big data analytics can provide financial benefits	.163	56	.871	.018	-.20	.23

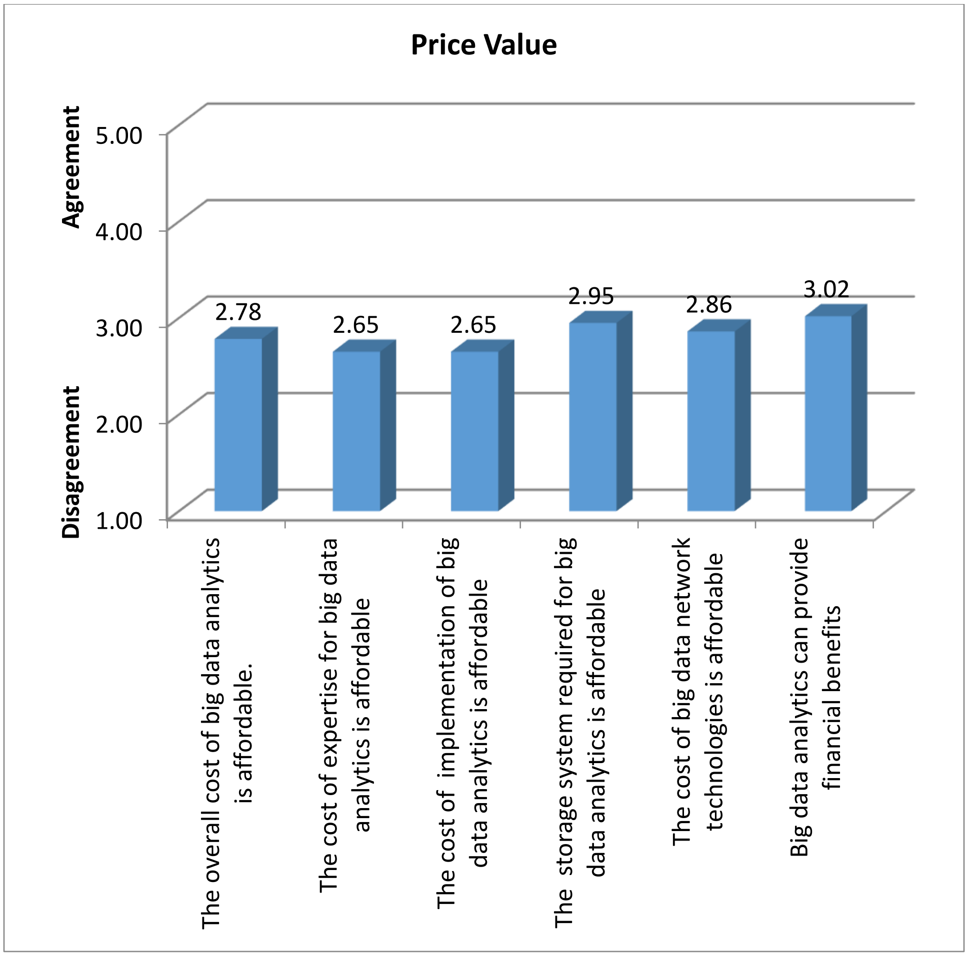

Figure A.1. Sig Price Value

Performance Expectancy

Table A.3. One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
8.1. Business risk assessment	57	3.67	.893	.118
8.2.Knowledge management	57	3.68	.848	.112
8.3. Decision making	57	3.88	.847	.112
8.4.The ability to develop new schemes	57	3.84	.862	.114
8.5.Understanding the needs of customers	57	3.89	.859	.114
8.6.The detection of fraudulent medical claims	57	3.91	.872	.115
8.7.Customer relationship management	57	3.86	.833	.110
8.8.The effectiveness of existing schemes	57	3.70	.801	.106
8.9.Competitive advantage	57	3.67	.787	.104
8.10.The identification of new trends	57	3.82	.826	.109
8.11.The overall performance of the organisation	57	3.65	.813	.108

Table A.4. One-Sample Test

	Test Value = 3					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
8.1. Business risk assessment	5.636	56	.000	.667	.43	.90
8.2.Knowledge management	6.088	56	.000	.684	.46	.91
8.3. Decision making	7.822	56	.000	.877	.65	1.10
8.4.The ability to develop new schemes	7.378	56	.000	.842	.61	1.07
8.5.Understanding the needs of customers	7.859	56	.000	.895	.67	1.12
8.6.The detection of fraudulent medical claims	7.900	56	.000	.912	.68	1.14
8.7.Customer relationship management	7.789	56	.000	.860	.64	1.08
8.8.The effectiveness of existing schemes	6.614	56	.000	.702	.49	.91
8.9.Competitive advantage	6.397	56	.000	.667	.46	.88
8.10.The identification of new trends	7.533	56	.000	.825	.61	1.04
8.11.The overall performance of the organisation	6.031	56	.000	.649	.43	.86

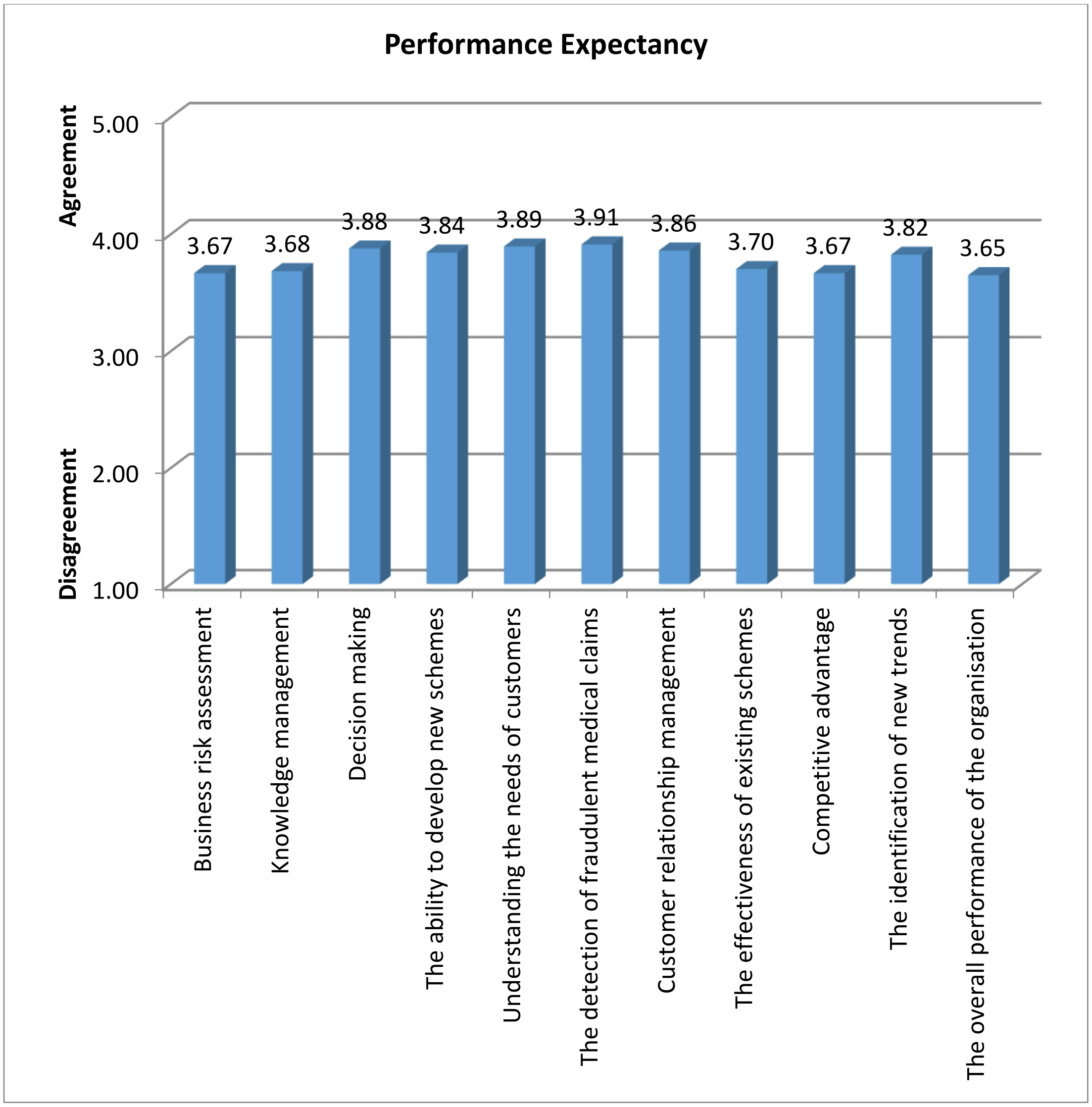

Figure A.2. Sig Performance Expectancy

Table A.5. One-Sample Test

	Test Value = 3					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
9.1.A proportion of competitors in the medical aid industry have adopted big data analytics	-5.227	56	.000	-.474	-.66	-.29
9.2.Suppliers think that medical aid companies should adopt big data analytics	-7.060	56	.000	-.649	-.83	-.46
9.3.It is a trend in the medical aid industry to adopt big data analytics	-6.043	56	.000	-.526	-.70	-.35
9.4.The government is encouraging medical aid companies to adopt big data analytics	-7.035	56	.000	-.667	-.86	-.48
9.5. Customers would like medical aid companies to adopt big data analytics because it results in better services and schemes.	-8.375	56	.000	-.947	-1.17	-.72

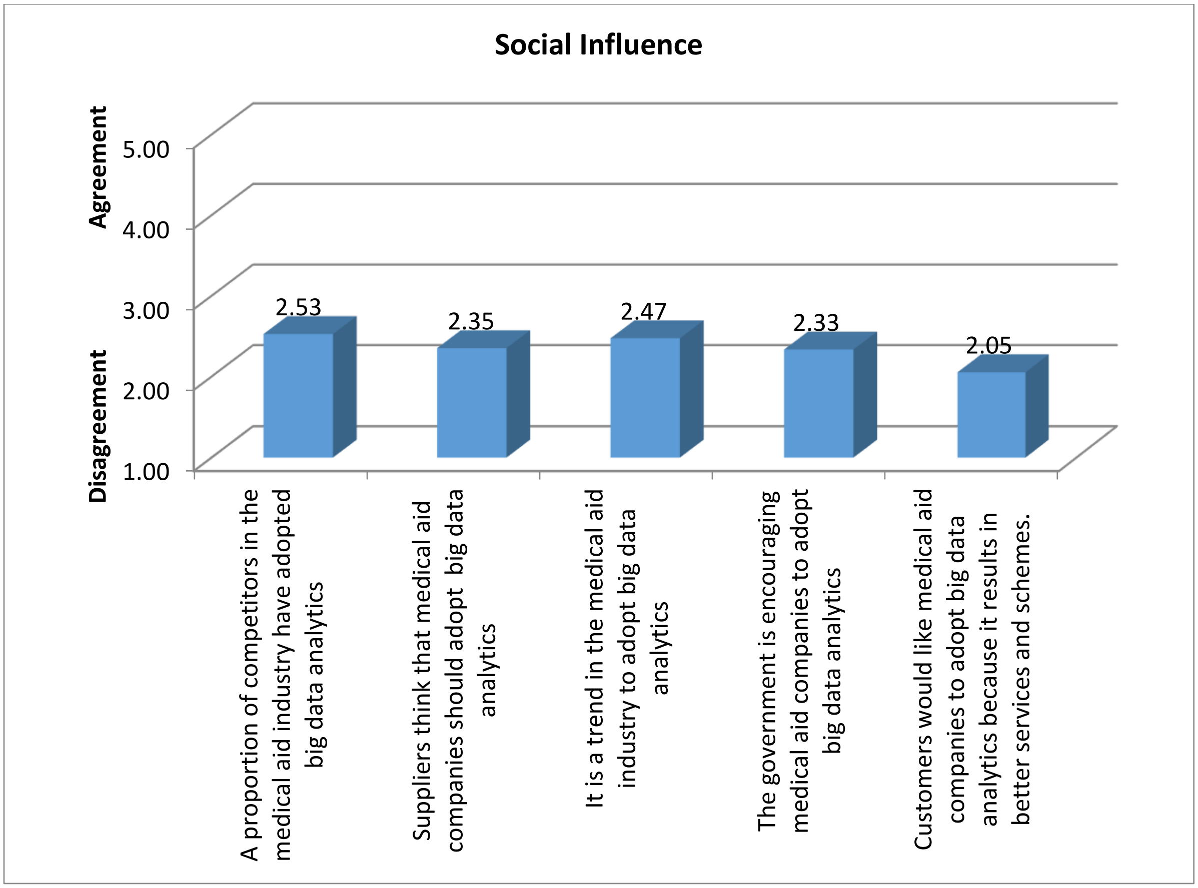

Figure A.3. Sig Social Influence

Facilitating Conditions

Table A.6. One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
10.1.The company has the necessary network system to adopt big data analytics	56	3.38	.822	.110
10.2.The company has the necessary storage system required for big data analytics	57	3.49	.735	.097
10.3.The company has the necessary hardware required for big data analytics	57	3.35	.744	.099
10.4. The company has the right expertise required for big data analytics	57	3.21	.881	.117
10.5.The top management team has the necessary knowledge about big data analytics	57	2.91	1.074	.142
10.6.The company has a requirement to share data between departments within the company	57	3.51	.782	.104

Table A.7. One-Sample Test

	Test Value = 3					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
10.1.The company has the necessary network system to adopt big data analytics	3.416	55	.001	.375	.15	.60
10.2.The company has the necessary storage system required for big data analytics	5.046	56	.000	.491	.30	.69
10.3.The company has the necessary hardware required for big data analytics	3.561	56	.001	.351	.15	.55
10.4. The company has the right expertise required for big data analytics	1.804	56	.077	.211	-.02	.44
10.5.The top management team has the necessary knowledge about big data analytics	-.617	56	.540	-.088	-.37	.20
10.6.The company has a requirement to share data between departments within the company	4.912	56	.000	.509	.30	.72

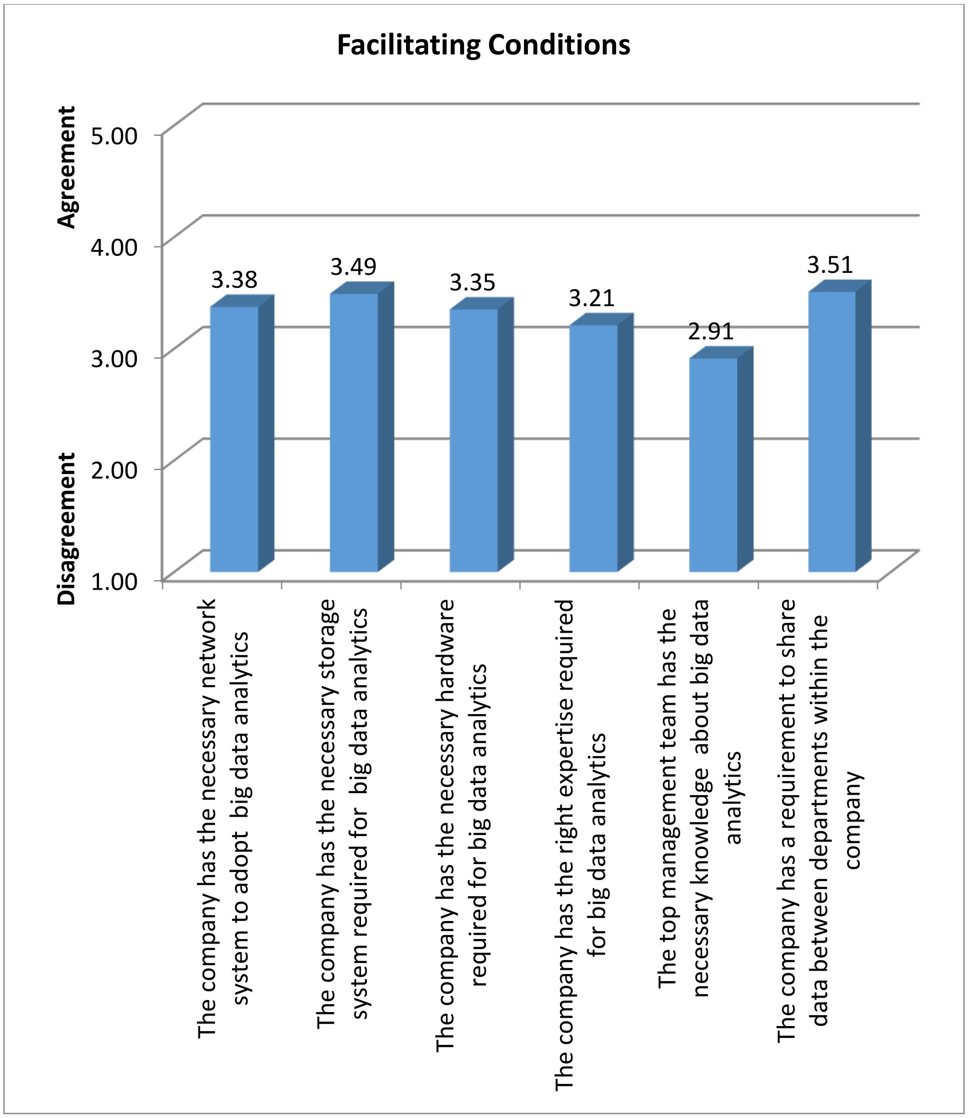

Figure A.4. Sig Facilitating Conditions

Perceived characteristics of Innovations

Table A.8. One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
11.1.I think the adoption of big data analytics is aligned with the company's business process	57	3.72	.840	.111
11.2. I think the adoption of big data analytics is in harmony with the company's value	57	3.68	.848	.112
11.3. I think the adoption of big data analytics fits right into the company's work practices	57	3.68	.783	.104
11.4. I think the adoption of big data analytics fits right into the actual organisation's technological infrastructure	57	3.67	.831	.110
11.5. I think big data analytics is flexible to interact with	57	2.98	.744	.099
11.6. I think big data analytics is easy to implement	57	2.93	.776	.103
11.7.I think it is easy to train employees on big data analytics	56	2.88	.715	.096
11.8. I think big data analytics is easy to maintain	57	2.91	.786	.104
11.9. I think the law permits companies to use data from their customers	56	3.09	.769	.103
11.10.I think the company can rightly access data from third parties(suppliers)	57	3.04	.823	.109

11.11.I think information security within the company is assured	57	3.89	.976	.129
11.12.I think big data analytics allows an organisation to use its data more effectively	57	3.79	.901	.119
11.13.I think big data analytics helps a company to customize products (schemes)	57	3.65	.790	.105
11.14. I believe big data analytics increases the customer base	57	3.53	.868	.115
11.15.I think big data analytics helps an organisation to gain competitive advantage	57	3.61	.840	.111

Table A.9. One-Sample Test

	Test Value = 3					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
11.1.I think the adoption of big data analytics is aligned with the company's business process	6.465	56	.000	.719	.50	.94
11.2. I think the adoption of big data analytics is in harmony with the company's value	6.088	56	.000	.684	.46	.91
11.3. I think the adoption of big data analytics fits right into the company's work practices	6.599	56	.000	.684	.48	.89
11.4. I think the adoption of big data analytics fits right into the actual organisation's technological infrastructure	6.057	56	.000	.667	.45	.89
11.5. I think big data analytics is flexible to interact with	-.178	56	.859	-.018	-.21	.18
11.6. I think big data analytics is easy to implement	-.683	56	.498	-.070	-.28	.14
11.7.I think it is easy to train employees on big data analytics	-1.308	55	.196	-.125	-.32	.07
11.8. I think big data analytics is easy to maintain	-.843	56	.403	-.088	-.30	.12
11.9. I think the law permits companies to use data from their customers	.868	55	.389	.089	-.12	.30

11.10.I think the company can rightly access data from third parties(suppliers)	.322	56	.749	.035	-.18	.25
11.11.I think information security within the company is assured	6.920	56	.000	.895	.64	1.15
11.12.I think big data analytics allows an organisation to use its data more effectively	6.614	56	.000	.789	.55	1.03
11.13.I think big data analytics helps a company to customize products (schemes)	6.201	56	.000	.649	.44	.86
11.14. I believe big data analytics increases the customer base	4.577	56	.000	.526	.30	.76
11.15.I think big data analytics helps an organisation to gain competitive advantage	5.519	56	.000	.614	.39	.84

Figure A.5. Sig Perceived Characteristics of Innovation

ATTITUDES towards Adoption

Table A.10. One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
12.1.I believe it is a good idea to adopt big data analytics	57	3.70	.886	.117
12.2.I believe that big data analytics will allow the company to access more accurate information	57	3.86	.934	.124
12.3.The adoption of big data analytics by the company would be a positive decision	57	3.70	.925	.123
12.4. I believe that big data analytics will enhance the company's decision making	57	3.77	.887	.117

Table A.11. One-Sample Test

	Test Value = 3					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
12.1.I believe it is a good idea to adopt big data analytics	5.982	56	.000	.702	.47	.94
12.2.I believe that big data analytics will allow the company to access more accurate information	6.947	56	.000	.860	.61	1.11
12.3.The adoption of big data analytics by the company would be a positive decision	5.727	56	.000	.702	.46	.95
12.4. I believe that big data analytics will enhance the company's decision making	6.572	56	.000	.772	.54	1.01

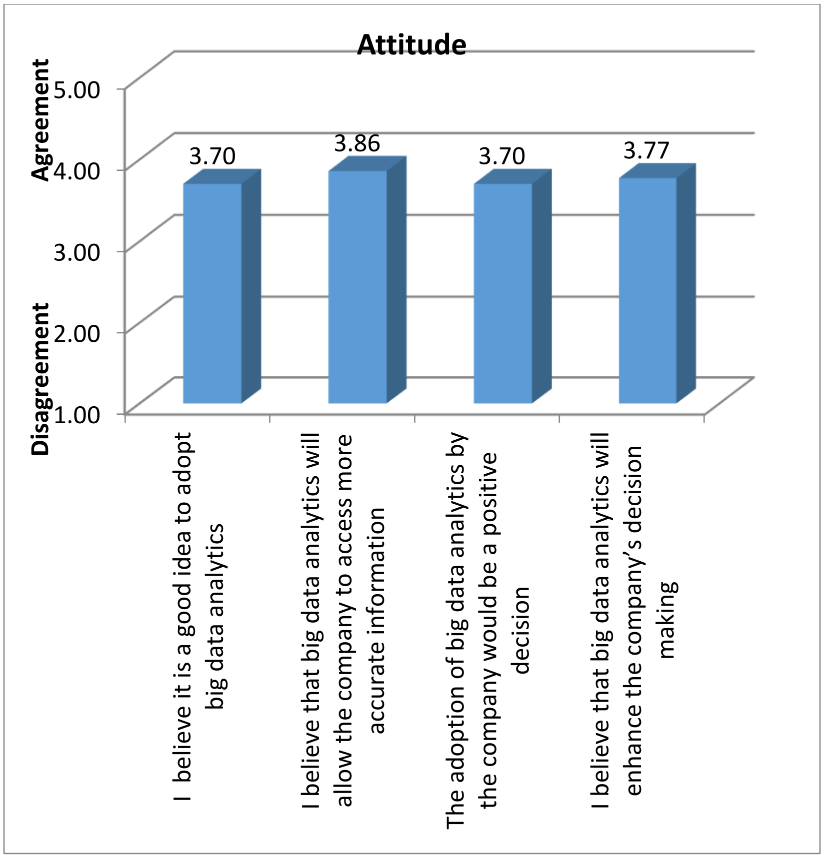

Figure A.6. Sig Attitudes towards the adoption

Bivariate analysis

Table A.12. Item Statistics

	Mean	Std. Deviation	N
8.1. Business risk assessment	3.67	.893	57
8.2.Knowledge management	3.68	.848	57
8.3. Decision making	3.88	.847	57
8.4.The ability to develop new schemes	3.84	.862	57
8.5.Understanding the needs of customers	3.89	.859	57
8.6.The detection of fraudulent medical claims	3.91	.872	57
8.7.Customer relationship management	3.86	.833	57
8.8.The effectiveness of existing schemes	3.70	.801	57
8.9.Competitive advantage	3.67	.787	57
8.10.The identification of new trends	3.82	.826	57
8.11.The overall performance of the organisation	3.65	.813	57

Table A.13. Item Statistics

	Mean	Std. Deviation	N
8.1. Business risk assessment	3.67	.893	57
8.2.Knowledge management	3.68	.848	57
8.3. Decision making	3.88	.847	57
8.4.The ability to develop new schemes	3.84	.862	57
8.5.Understanding the needs of customers	3.89	.859	57
8.6.The detection of fraudulent medical claims	3.91	.872	57
8.7.Customer relationship management	3.86	.833	57
8.8.The effectiveness of existing schemes	3.70	.801	57
8.9.Competitive advantage	3.67	.787	57
8.10.The identification of new trends	3.82	.826	57
8.11.The overall performance of the organisation	3.65	.813	57

Table A.14. Item Statistics

	Mean	Std. Deviation	N
9.1.A proportion of competitors in the medical aid industry have adopted big data analytics	2.53	.684	57
9.2.Suppliers think that medical aid companies should adopt big data analytics	2.35	.694	57
9.3.It is a trend in the medical aid industry to adopt big data analytics	2.47	.658	57
9.4.The government is encouraging medical aid companies to adopt big data analytics	2.33	.715	57
9.5. Customers would like medical aid companies to adopt big data analytics because it results in better services and schemes.	2.05	.854	57

Table A.15. Item Statistics

	Mean	Std. Deviation	N
10.1.The company has the necessary network system to adopt big data analytics	3.38	.822	56
10.2.The company has the necessary storage system required for big data analytics	3.48	.738	56
10.3.The company has the necessary hardware required for big data analytics	3.34	.745	56
10.4. The company has the right expertise required for big data analytics	3.20	.883	56
10.5.The top management team has the necessary knowledge about big data analytics	2.93	1.076	56
10.6.The company has a requirement to share data between departments within the company	3.50	.786	56

Table A.16. Item Statistics

	Mean	Std. Deviation	N
11.1.I think the adoption of big data analytics is aligned with the company's business process	3.73	.842	56
11.2. I think the adoption of big data analytics is in harmony with the company's value	3.68	.855	56
11.3. I think the adoption of big data analytics fits right into the company's work practices	3.68	.789	56
11.4. I think the adoption of big data analytics fits right into the actual organisation's technological infrastructure	3.66	.837	56
11.5. I think big data analytics is flexible to interact with	2.98	.751	56
11.6. I think big data analytics is easy to implement	2.91	.769	56
11.7.I think it is easy to train employees on big data analytics	2.88	.715	56
11.8. I think big data analytics is easy to maintain	2.89	.779	56
11.9. I think the law permits companies to use data from their customers	3.09	.769	56
11.10.I think the company can rightly access data from third parties(suppliers)	3.04	.830	56
11.11.I think information security within the company is assured	3.89	.985	56
11.12.I think big data analytics allows an organisation to use its data more effectively	3.79	.909	56
11.13.I think big data analytics helps a company to customize products (schemes)	3.64	.796	56
11.14. I believe big data analytics increases the customer base	3.52	.874	56
11.15.I think big data analytics helps an organisation to gain competitive advantage	3.61	.846	56

Table A.17. Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Sc	
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variar
1	9.825	65.498	65.498	9.655	64.369	64.369	7.336	48
2	2.903	19.354	84.851	2.738	18.250	82.619	5.057	33
3	.656	4.372	89.224					
4	.447	2.981	92.204					
5	.277	1.847	94.051					
6	.201	1.337	95.388					
7	.168	1.121	96.510					
8	.149	.996	97.505					
9	.099	.663	98.168					
10	.095	.633	98.801					
11	.055	.367	99.168					
12	.048	.318	99.486					
13	.033	.218	99.704					
14	.029	.191	99.895					
15	.016	.105	100.000					

Extraction Method: Principal Axis Factoring.

Table A.18. Reliability COI_INT and COI_EXT Item Statistics

	Mean	Std. Deviation	N
11.1.I think the adoption of big data analytics is aligned with the company's business process	3.72	.840	57
11.2. I think the adoption of big data analytics is in harmony with the company's value	3.68	.848	57
11.3. I think the adoption of big data analytics fits right into the company's work practices	3.68	.783	57
11.4. I think the adoption of big data analytics fits right into the actual organisation's technological infrastructure	3.67	.831	57
11.11.I think information security within the company is assured	3.89	.976	57
11.12.I think big data analytics allows an organisation to use its data more effectively	3.79	.901	57
11.13.I think big data analytics helps a company to customize products (schemes)	3.65	.790	57
11.14. I believe big data analytics increases the customer base	3.53	.868	57
11.15.I think big data analytics helps an organisation to gain competitive advantage	3.61	.840	57

Table A.19. Item Statistics

	Mean	Std. Deviation	N
12.1.I believe it is a good idea to adopt big data analytics	3.70	.886	57
12.2.I believe that big data analytics will allow the company to access more accurate information	3.86	.934	57
12.3.The adoption of big data analytics by the company would be a positive decision	3.70	.925	57
12.4. I believe that big data analytics will enhance the company's decision making	3.77	.887	57

Table A.20. One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
PV	57	2.8158	.67677	.08964
PE	57	3.7799	.78315	.10373
SI	57	2.3474	.63418	.08400
FC	57	3.3088	.66939	.08866
COI_INT	57	3.6920	.78315	.10373
COI_EXT	57	2.9737	.69920	.09261
ATT	57	3.7588	.86727	.11487

Table A.21. One-Sample Test

	Test Value = 3					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
PV	-2.055	56	.045	-.18421	-.3638	-.0046
PE	7.519	56	.000	.77990	.5721	.9877
SI	-7.770	56	.000	-.65263	-.8209	-.4844
FC	3.483	56	.001	.30877	.1312	.4864
COI_INT	6.671	56	.000	.69201	.4842	.8998
COI_EXT	-.284	56	.777	-.02632	-.2118	.1592
ATT	6.605	56	.000	.75877	.5287	.9889

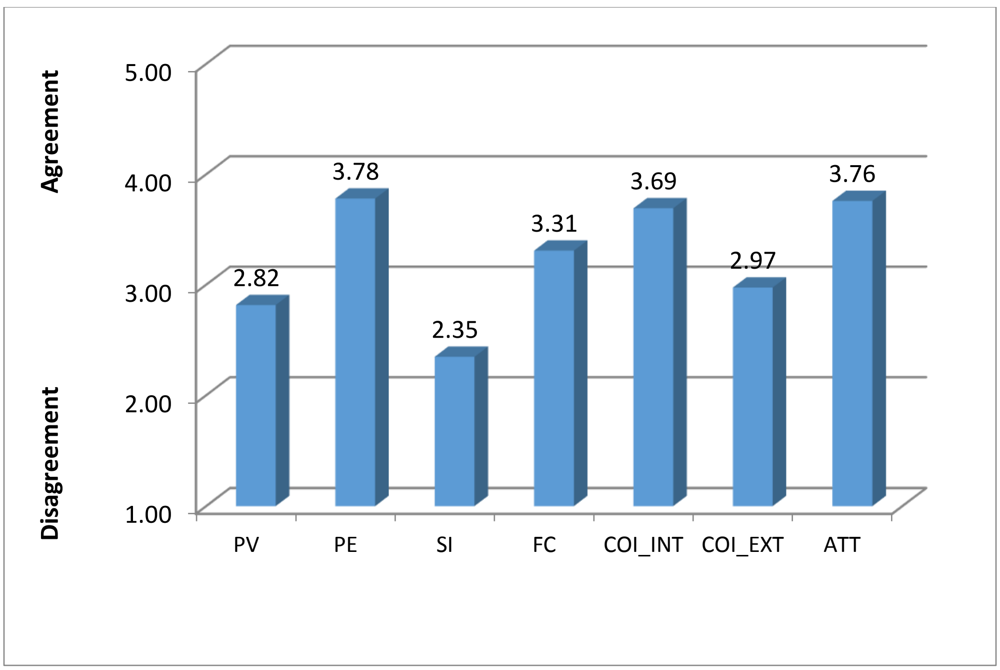

Figure A.7. Sig Composite measure of constructs.

Regression Analysis

PV

Table A.22. Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.382[a]	.146	.130	.80881	1.515

a. Predictors: (Constant), PV

b. Dependent Variable: ATT

Table A.23. ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6.141	1	6.141	9.388	.003[a]
	Residual	35.980	55	.654		
	Total	42.121	56			

a. Predictors: (Constant), PV

b. Dependent Variable: ATT

Table A.24. Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2.381	.462		5.151	.000		
	PV	.489	.160	.382	3.064	.003	1.000	1.000

a. Dependent Variable: ATT

Table A.25. Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.865[a]	.747	.743	.43981	1.551

a. Predictors: (Constant), PE

b. Dependent Variable: ATT

PE

Table A.26. Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.865[a]	.747	.743	.43981	1.551

a. Predictors: (Constant), PE

b. Dependent Variable: ATT

Table A.27. ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	31.482	1	31.482	162.750	.000[a]
	Residual	10.639	55	.193		
	Total	42.121	56			

a. Predictors: (Constant), PE

b. Dependent Variable: ATT

Table A.28. Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.140	.290		.483	.631		
	PE	.957	.075	.865	12.757	.000	1.000	1.000

a. Dependent Variable: ATT

SI

Table A.29. Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.127[a]	.016	-.002	.86798	1.509

a. Predictors: (Constant), SI

b. Dependent Variable: ATT

Table A.30. ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.684	1	.684	.909	.345[a]
	Residual	41.436	55	.753		
	Total	42.121	56			

a. Predictors: (Constant), SI

b. Dependent Variable: ATT

Table A. 31. Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	3.350	.444		7.536	.000		
	SI	.174	.183	.127	.953	.345	1.000	1.000

a. Dependent Variable: ATT

FC

Table A.32. Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.777[a]	.603	.596	.55137	1.068

a. Predictors: (Constant), FC

b. Dependent Variable: ATT

Table A.33. ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	25.400	1	25.400	83.549	.000[a]
	Residual	16.721	55	.304		
	Total	42.121	56			

a. Predictors: (Constant), FC

b. Dependent Variable: ATT

Table A.34. Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.430	.371		1.157	.252		
	FC	1.006	.110	.777	9.140	.000	1.000	1.000

a. Dependent Variable: ATT

COI_INT and COI_EXT

Table A.35. Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.565[a]	.319	.307	.72216	1.146

a. Predictors: (Constant), COI_EXT

b. Dependent Variable: ATT

Table A.36. ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13.437	1	13.437	25.765	.000[a]
	Residual	28.684	55	.522		
	Total	42.121	56			

a. Predictors: (Constant), COI_EXT

b. Dependent Variable: ATT

Table A.37. Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.675	.421		3.976	.000		
	COI_EXT	.701	.138	.565	5.076	.000	1.000	1.000

a. Dependent Variable: ATT

Table A.38. Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.924[a]	.853	.850	.33566	1.926

a. Predictors: (Constant), COI_INT

b. Dependent Variable: ATT

Table A.39. ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	35.924	1	35.924	318.857	.000[a]
	Residual	6.197	55	.113		
	Total	42.121	56			

a. Predictors: (Constant), COI_INT

b. Dependent Variable: ATT

Table A.40. Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-.017	.216		-.079	.937		
	COI_INT	1.023	.057	.924	17.857	.000	1.000	1.000

a. Dependent Variable: ATT

Table A.41. All constructs put all together

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.943[a]	.889	.876	.30539	1.791

a. Predictors: (Constant), COI_EXT, SI, PE, PV, FC, COI_INT

b. Dependent Variable: ATT

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	37.457	6	6.243	66.937	.000[a]
	Residual	4.663	50	.093		
	Total	42.121	56			

a. Predictors: (Constant), COI_EXT, SI, PE, PV, FC, COI_INT

b. Dependent Variable: ATT

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-.317	.253		-1.254	.216		
	PV	-.225	.082	-.176	-2.763	.008	.547	1.828
	PE	.350	.122	.316	2.880	.006	.184	5.446
	SI	.093	.074	.068	1.246	.218	.748	1.337
	FC	.034	.120	.026	.284	.778	.258	3.876

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.943[a]	.889	.876	.30539	1.791

a. Predictors: (Constant), COI_EXT, SI, PE, PV, FC, COI_INT

	COI_INT	.692	.131	.625	5.287	.000	.158	6.319
	COI_EXT	.168	.078	.135	2.162	.035	.566	1.768

a. Dependent Variable: ATT

Comparative analysis

Table A.42. Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
7.1. The overall cost of big data analytics is affordable.	Equal variances assumed	2.859	.097	-.903	53	.371	-.187	.207	-.601	.228
	Equal variances not assumed			-.941	49.223	.351	-.187	.198	-.585	.212
7.2.The cost of expertise for big data analytics is affordable	Equal variances assumed	4.159	.046	-2.559	55	.013	-.515	.201	-.918	-.112
	Equal variances not assumed			-2.691	53.494	.009	-.515	.191	-.899	-.131
7.3.The cost of implementation of big data analytics is affordable	Equal variances assumed	3.274	.076	-1.858	55	.069	-.373	.201	-.774	.029
	Equal variances not assumed			-1.946	54.060	.057	-.373	.191	-.756	.011
7.4.The storage system required for big data analytics is affordable	Equal variances assumed	1.443	.235	1.064	55	.292	.236	.222	-.209	.681
	Equal variances not assumed			1.084	54.459	.283	.236	.218	-.201	.673
7.5. The cost of big data network	Equal variances assumed	2.024	.161	-.165	55	.870	-.035	.213	-.461	.391

technologies is affordable	Equal variances not assumed			-.170	54.986	.866	-.035	.206	-.449	.379
7.6. Big data analytics can provide financial benefits	Equal variances assumed	.267	.607	2.230	55	.030	.468	.210	.047	.888
	Equal variances not assumed			2.260	53.874	.028	.468	.207	.053	.882

Table A. 43. Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
8.1. Business risk assessment	Equal variances assumed	4.471	.039	.996	55	.324	.238	.238	-.240	.715
	Equal variances not assumed			1.027	55.000	.309	.238	.231	-.226	.701
8.2.Knowledge management	Equal variances assumed	2.103	.153	-.345	55	.731	-.079	.228	-.536	.379
	Equal variances not assumed			-.358	54.792	.721	-.079	.220	-.519	.362
8.3. Decision making	Equal variances assumed	.542	.465	.022	55	.983	.005	.228	-.452	.462
	Equal variances not assumed			.022	54.433	.982	.005	.224	-.444	.454
8.4.The ability to develop new schemes	Equal variances assumed	1.548	.219	.291	55	.772	.068	.232	-.397	.532
	Equal variances not assumed			.297	54.687	.767	.068	.227	-.387	.522
8.5.Understanding the needs of customers	Equal variances assumed	.984	.326	-.422	55	.675	-.098	.231	-.561	.366

	Equal variances not assumed			-.434	54.993	.666	-.098	.224	-.547	.352
8.6.The detection of fraudulent medical claims	Equal variances assumed	.274	.603	.362	55	.718	.085	.235	-.385	.555
	Equal variances not assumed			.366	53.345	.716	.085	.232	-.381	.551
8.7.Customer relationship management	Equal variances assumed	1.092	.300	-.474	55	.637	-.106	.224	-.555	.343
	Equal variances not assumed			-.490	54.977	.626	-.106	.217	-.540	.328
8.8.The effectiveness of existing schemes	Equal variances assumed	.612	.438	-.511	55	.611	-.110	.215	-.541	.321
	Equal variances not assumed			-.526	54.972	.601	-.110	.209	-.529	.309
8.9.Competitive advantage	Equal variances assumed	.774	.383	-.903	55	.370	-.190	.210	-.612	.232
	Equal variances not assumed			-.937	54.865	.353	-.190	.203	-.596	.216
8.10.The identification of new trends	Equal variances assumed	1.083	.303	.124	55	.902	.028	.223	-.419	.474
	Equal variances not assumed			.126	54.743	.900	.028	.218	-.409	.464
8.11.The overall performance of the organisation	Equal variances assumed	.103	.750	-.400	55	.690	-.088	.219	-.526	.351

	Equal variances not assumed			-.406	54.026	.686	-.088	.215	-.519	.344

Table A.44. Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
10.1.The company has the necessary network system to adopt big data analytics	Equal variances assumed	.643	.426	-.122	54	.904	-.027	.223	-.474	.420
	Equal variances not assumed			-.122	52.317	.903	-.027	.222	-.472	.418
10.2.The company has the necessary storage system required for big data analytics	Equal variances assumed	3.919	.053	1.361	55	.179	.265	.195	-.125	.655
	Equal variances not assumed			1.398	54.940	.168	.265	.190	-.115	.645
10.3.The company has the necessary hardware required for big data analytics	Equal variances assumed	.886	.351	.081	55	.936	.016	.200	-.385	.418
	Equal variances not assumed			.082	54.027	.935	.016	.197	-.380	.412
10.4. The company has the right expertise required for big data analytics	Equal variances assumed	2.377	.129	-3.000	55	.004	-.660	.220	-1.101	-.219
	Equal variances not assumed			-2.940	47.061	.005	-.660	.225	-1.112	-.208

10.5.The top management team has the necessary knowledge about big data analytics	Equal variances assumed	.666	.418	-4.991	55	.000	-1.198	.240	-1.678	-.717
	Equal variances not assumed			-4.850	44.914	.000	-1.198	.247	-1.695	-.700
10.6.The company has a requirement to share data between departments within the company	Equal variances assumed	.001	.976	.095	55	.925	.020	.211	-.402	.442
	Equal variances not assumed			.094	49.679	.925	.020	.213	-.407	.447

Table A.45. Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
11.1.I think the adoption of big data analytics is aligned with the company's business process	Equal variances assumed	1.000	.322	.958	55	.342	.215	.224	-.235	.665
	Equal variances not assumed			.968	53.501	.337	.215	.222	-.230	.660
11.2. I think the adoption of big data analytics is in harmony with the company's value	Equal variances assumed	.180	.673	.593	55	.556	.135	.228	-.322	.592
	Equal variances not assumed			.596	52.778	.554	.135	.226	-.319	.589
11.3. I think the adoption of big data analytics fits right into the company's work practices	Equal variances assumed	1.681	.200	1.337	55	.187	.278	.207	-.138	.693
	Equal variances not assumed			1.349	53.246	.183	.278	.206	-.135	.690
11.4. I think the adoption of big data analytics fits right into the actual organisation's technological infrastructure	Equal variances assumed	1.894	.174	1.072	55	.288	.238	.222	-.206	.681
	Equal variances not assumed			1.091	54.310	.280	.238	.218	-.199	.674

11.5. I think big data analytics is flexible to interact with	Equal variances assumed	6.940	.011	.513	55	.610	.103	.200	-.298	.503
	Equal variances not assumed			.533	54.763	.596	.103	.192	-.283	.488
11.6. I think big data analytics is easy to implement	Equal variances assumed	2.421	.125	-.084	55	.934	-.018	.209	-.436	.401
	Equal variances not assumed			-.086	54.713	.932	-.018	.204	-.427	.392
11.7.I think it is easy to train employees on big data analytics	Equal variances assumed	.846	.362	-1.136	54	.261	-.219	.193	-.605	.167
	Equal variances not assumed			-1.177	53.911	.244	-.219	.186	-.591	.154
11.8. I think big data analytics is easy to maintain	Equal variances assumed	.140	.709	-.953	55	.345	-.200	.210	-.621	.221
	Equal variances not assumed			-.974	54.682	.334	-.200	.205	-.612	.212
11.9. I think the law permits companies to use data from their customers	Equal variances assumed	.144	.706	-.398	54	.692	-.083	.209	-.503	.336
	Equal variances not assumed			-.401	51.075	.690	-.083	.208	-.500	.334
11.10.I think the company can rightly access data from third parties(suppliers)	Equal variances assumed	.118	.733	-.282	55	.779	-.063	.222	-.506	.381
	Equal variances not assumed			-.279	49.625	.781	-.063	.224	-.512	.387

11.11.I think information security within the company is assured	Equal variances assumed	1.419	.239	.993	55	.325	.259	.261	-.264	.781
	Equal variances not assumed			1.012	54.505	.316	.259	.256	-.254	.771
11.12.I think big data analytics allows an organisation to use its data more effectively	Equal variances assumed	1.622	.208	1.270	55	.210	.304	.239	-.176	.783
	Equal variances not assumed			1.287	53.893	.204	.304	.236	-.169	.777
11.13.I think big data analytics helps a company to customize products (schemes)	Equal variances assumed	1.723	.195	.259	55	.797	.055	.213	-.371	.481
	Equal variances not assumed			.266	54.980	.791	.055	.207	-.359	.469
11.14. I believe big data analytics increases the customer base	Equal variances assumed	1.339	.252	-.353	55	.725	-.083	.234	-.551	.386
	Equal variances not assumed			-.362	54.897	.718	-.083	.228	-.539	.374
11.15.I think big data analytics helps an organisation to gain competitive advantage	Equal variances assumed	2.858	.097	.840	55	.405	.189	.225	-.262	.639
	Equal variances not assumed			.862	54.934	.392	.189	.219	-.250	.627

Table A. 46. Group Statistics

	Company	N	Mean	Std. Deviation	Std. Error Mean
12.1.I believe it is a good idea to adopt big data analytics	Company A	25	3.96	.889	.178
	Company B	32	3.50	.842	.149
12.2.I believe that big data analytics will allow the company to access more accurate information	Company A	25	3.96	.841	.168
	Company B	32	3.78	1.008	.178
12.3.The adoption of big data analytics by the company would be a positive decision	Company A	25	3.92	.862	.172
	Company B	32	3.53	.950	.168
12.4. I believe that big data analytics will enhance the company's decision making	Company A	25	3.96	.841	.168
	Company B	32	3.63	.907	.160

Table A.47. Regression Analysis A & B

Variables Entered/Removed[b,c]

Model	Variables Entered	Variables Removed	Method
1	PV[a]	.	Enter

a. All requested variables entered.

b. Company = Company A

c. Dependent Variable: ATT

Table A.48. Model Summaryb

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.227[a]	.052	.011	.81852

a. Predictors: (Constant), PV

b. Company = Company A

Table A.49. ANOVAb,c

Model	Sum of Squares	df	Mean Square	F	Sig.

Variables Entered/Removed[b,c]

Model	Variables Entered	Variables Removed	Method
1	PV[a]	.	Enter

a. All requested variables entered.

b. Company = Company A

1	Regression	.841	1	.841	1.255	.274[a]
	Residual	15.409	23	.670		
	Total	16.250	24			

a. Predictors: (Constant), PV

b. Company = Company A

c. Dependent Variable: ATT

Table A. 50. Coefficientsa,b

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	2.815	1.027		2.741	.012
	PV	.408	.365	.227	1.120	.274

a. Company = Company A

b. Dependent Variable: ATT

Variables Entered/Removedb,c

Model	Variables Entered	Variables Removed	Method
1	PV[a]	.	Enter

a. All requested variables entered.

b. Company = Company B

c. Dependent Variable: ATT

Model Summaryb

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.484[a]	.234	.208	.78677

a. Predictors: (Constant), PV

b. Company = Company B

Table A.51. ANOVA[b,c]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.672	1	5.672	9.163	.005[a]
	Residual	18.570	30	.619		
	Total	24.242	31			

a. Predictors: (Constant), PV

b. Company = Company B

c. Dependent Variable: ATT

Table A.52. Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.115	.513		4.126	.000
	PV	.525	.174	.484	3.027	.005

a. Company = Company B

b. Dependent Variable: ATT

PE

Company= Company A

Table A.53. Variables Entered/Removed[b,c]

Model	Variables Entered	Variables Removed	Method
1	PE[a]	.	Enter

a. All requested variables entered.

b. Company = Company A

c. Dependent Variable: ATT

Table A. 54. Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.913[a]	.834	.826	.34289

a. Predictors: (Constant), PE

b. Company = Company A

Table A.55. ANOVA[b,c]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13.546	1	13.546	115.209	.000[a]
	Residual	2.704	23	.118		
	Total	16.250	24			

a. Predictors: (Constant), PE

b. Company = Company A

c. Dependent Variable: ATT

Table A.56. Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.293	.401		-.730	.473
	PE	1.126	.105	.913	10.734	.000

a. Company = Company A

b. Dependent Variable: ATT

Company = Company B

Table A.57. Variables Entered/Removed[b,c]

Model	Variables Entered	Variables Removed	Method
1	PE[a]	.	Enter

a. All requested variables entered.

b. Company = Company B

c. Dependent Variable: ATT

Table A.58. Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.875[a]	.766	.758	.43469

a. Predictors: (Constant), PE

b. Company = Company B

Table A.59. ANOVA[b,c]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	18.573	1	18.573	98.294	.000[a]
	Residual	5.669	30	.189		
	Total	24.242	31			

a. Predictors: (Constant), PE

b. Company = Company B

c. Dependent Variable: ATT

Table A.60. Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.252	.347		.724	.474
	PE	.886	.089	.875	9.914	.000

a. Company = Company B

b. Dependent Variable: ATT

IV = SI

Company = Company A

Table A.60. Variables Entered/Removed[b,c]

Model	Variables Entered	Variables Removed	Method
1	SI[a]	.	Enter

a. All requested variables entered.

b. Company = Company A

c. Dependent Variable: ATT

Table A.61. Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.093[a]	.009	-.034	.83687

a. Predictors: (Constant), SI

b. Company = Company A

Table A.62. ANOVA[b,c]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.142	1	.142	.203	.657[a]
	Residual	16.108	23	.700		
	Total	16.250	24			

a. Predictors: (Constant), SI

b. Company = Company A

c. Dependent Variable: ATT

Table A.63. Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.603	.788		4.575	.000
	SI	.142	.315	.093	.450	.657

a. Company = Company A

b. Dependent Variable: ATT

Company = Company B

Table A.64. Variables Entered/Removed[b,c]

Model	Variables Entered	Variables Removed	Method
1	SI[a]	.	Enter

a. All requested variables entered.

b. Company = Company B

c. Dependent Variable: ATT

Table A. 65. Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.112[a]	.012	-.020	.89330

a. Predictors: (Constant), SI

b. Company = Company B

Table A.66. ANOVA[b,c]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.303	1	.303	.379	.543[a]
	Residual	23.940	30	.798		
	Total	24.242	31			

a. Predictors: (Constant), SI

b. Company = Company B

c. Dependent Variable: ATT

Table A.67. Coefficientsa,b

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.287	.546		6.017	.000
	SI	.142	.230	.112	.616	.543

a. Company = Company B

b. Dependent Variable: ATT

IV = FC

Company = Company A

Table A.68. Variables Entered/Removed[b,c]

Model	Variables Entered	Variables Removed	Method
1	FC[a]	.	Enter

a. All requested variables entered.

b. Company = Company A

c. Dependent Variable: ATT

Table A. 69. Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.705[a]	.496	.474	.59652

a. Predictors: (Constant), FC

b. Company = Company A

Table A.70. ANOVA[b,c]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8.066	1	8.066	22.667	.000[a]
	Residual	8.184	23	.356		
	Total	16.250	24			

a. Predictors: (Constant), FC

b. Company = Company A

c. Dependent Variable: ATT

Table A.71.Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.510	.732		.696	.494
	FC	1.089	.229	.705	4.761	.000

a. Company = Company A

b. Dependent Variable: ATT

Company = Company B

Table A.72. Variables Entered/Removed[b,c]

Model	Variables Entered	Variables Removed	Method
1	FC[a]	.	Enter

a. All requested variables entered.

b. Company = Company B

c. Dependent Variable: ATT

Table A.73. Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.933[a]	.870	.866	.32396

a. Predictors: (Constant), FC

b. Company = Company B

Table A.74. ANOVA[b,c]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	21.094	1	21.094	200.994	.000[a]
	Residual	3.148	30	.105		
	Total	24.242	31			

a. Predictors: (Constant), FC

b. Company = Company B

c. Dependent Variable: ATT

Table A.75. Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.172	.273		-.632	.532
	FC	1.104	.078	.933	14.177	.000

a. Company = Company B

b. Dependent Variable: ATT

IV = COI_INT

Company = Company A

Table A.76. Variables Entered/Removed[b,c]

Model	Variables Entered	Variables Removed	Method
1	COI_INT[a]	.	Enter

a. All requested variables entered.

b. Company = Company A

c. Dependent Variable: ATT

Table A.77. Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.887[a]	.786	.777	.38864

a. Predictors: (Constant), COI_INT

b. Company = Company A

Table A.78. ANOVA[b,c]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	12.776	1	12.776	84.589	.000[a]
	Residual	3.474	23	.151		
	Total	16.250	24			

a. Predictors: (Constant), COI_INT

b. Company = Company A

c. Dependent Variable: ATT

Table A.79. Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.019	.434		.044	.965
	COI_INT	1.037	.113	.887	9.197	.000

a. Company = Company A

b. Dependent Variable: ATT

Company = Company B

Table A.80. Variables Entered/Removed[b,c]

Model	Variables Entered	Variables Removed	Method
1	COI_INT[a]	.	Enter

a. All requested variables entered.

b. Company = Company B

c. Dependent Variable: ATT

Table A.81. Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.950[a]	.903	.900	.27965

a. Predictors: (Constant), COI_INT

b. Company = Company B

Table A.82. ANOVA[b,c]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	21.896	1	21.896	279.980	.000[a]
	Residual	2.346	30	.078		
	Total	24.242	31			

a. Predictors: (Constant), COI_INT

b. Company = Company B

c. Dependent Variable: ATT

Table A.84. Coefficients[a,b]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.005	.221		.024	.981
	COI_INT	.997	.060	.950	16.733	.000

a. Company = Company B

b. Dependent Variable: ATT

IV = COI_EXT

Company = Company A

Table A.85. Variables Entered/Removed[b,c]

Model	Variables Entered	Variables Removed	Method
1	COI_EXT[a]	.	Enter

a. All requested variables entered.

b. Company = Company A

c. Dependent Variable: ATT

Table A.86. Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.489[a]	.239	.206	.73339

a. Predictors: (Constant), COI_EXT

b. Company = Company A

Table A.87. ANOVA[b,c]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3.879	1	3.879	7.212	.013[a]
	Residual	12.371	23	.538		
	Total	16.250	24			

a. Predictors: (Constant), COI_EXT

b. Company = Company A

c. Dependent Variable: ATT

Table A.88. Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.942	.762		2.549	.018
	COI_EXT	.685	.255	.489	2.686	.013

a. Company = Company A

b. Dependent Variable: ATT

Company = Company B

Table A.89. Variables Entered/Removed[b,c]

Model	Variables Entered	Variables Removed	Method
1	COI_EXT[a]	.	Enter

a. All requested variables entered.

b. Company = Company B

c. Dependent Variable: ATT

Table A.90. Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.645[a]	.416	.397	.68680

a. Predictors: (Constant), COI_EXT

b. Company = Company B

Table A.91. ANOVA[b,c]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	10.092	1	10.092	21.394	.000[a]
	Residual	14.151	30	.472		
	Total	24.242	31			

a. Predictors: (Constant), COI_EXT

b. Company = Company B

c. Dependent Variable: ATT

Table A.92. Coefficientsa,b

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.421	.488		2.908	.007
	COI_EXT	.728	.157	.645	4.625	.000

a. Company = Company B

b. Dependent Variable: ATT

Appendix B: Questionnaire

UNIVERSITY OF KWAZULU-NATAL

School of Management, Information Technology & Governance,

Discipline of Information Systems and Technology

M Com Research Project

Researcher: Junior Vela Vela (0846141891/ 210535115@stu.ukzn.ac.za)

Supervisor: Dr Prabhakar Rontala Subramanian (0332605643/ Prabhakarr@ukzn.ac.za)

Research Office: Mariette Snyman (031 260 8350)

I am a Masters student in the school of Management, Information Technology& Governance, discipline of Information Systems & Technology at the University of KwaZulu-Natal. You are invited to participate in a research project entitled "**The employee's perception on the adoption of big data analytics by selected medical aid organisations in Durban**"

The aim of this study is to explore the perception of employees on the adoption of big data analytics by selected medical aid organisations in Durban".

Your participation in this project is voluntary. You may refuse to participate or withdraw from the project at any time with no negative consequence. There will be no monetary gain from participating in this research project. Confidentiality will be maintained by the researcher and the school of Management, I.T. & Governance and your responses will not be used for any purpose outside of this study.

If there are any questions or concerns about participating in this study, please contact the researcher or my supervisor via the numbers provided above.

Approximately (10) **minutes** is required to complete the questionnaire. I hope you will take the time to complete the questionnaire.

Yours faithfully

Junior Vela Vela

Researcher's Signature:

UNIVERSITY OF KWAZULU-NATAL

School of Management, Information Technology & Governance,

Discipline Information Systems and Technology

Researcher: Mr Junior Vela Vela (0846141891/ 210535115@stu.ukzn.ac.za)

Supervisor: Dr Prabhakar Rontala Subramanian (0332605643/ Prabhakarr@stu.ukzn.ac.za)

Research Office: Mariette Snyman (031 260 8350)

CONSENT

I ____ (full names of participant) hereby confirm that I understand the contents of this document and the nature of the research project, and I agree to participate in the research project. I also understand that I can withdraw from the project at any time.

____________________ ________________

Signature of Participant Date

- Please complete this voluntary questionnaire on the adoption and usage of big data analytics
- Please be forthright in your answers.
- Complete the questionnaire by pen and please do not revise your initial answers.
- Please indicate your response to the Question by completing the appropriate boxes.
- Please sign the letter of informed consent, giving the researcher permission to use the responses for this research project.

Questionnaire

Big data analytics refers to the process of collecting, organizing and analysing **large** sets of **structured data and unstructured data** (called **big data**) to discover patterns, new trends and other useful information to improve decision making.

Structured data: data that resides in a fixed field within a record of file (table); this includes data contained in relational databases.

Unstructured data: usually refers to data that doesn't reside in a traditional row-column database. This is can be text file, image file, video file, etc.…

By **adopting and using big data analytics**, medical aid organisations will be able to have better schemes, better services, can reduce fraudulent claims, and have a better understanding of customers, delight customers therefore increase revenue.

Section A: GENERAL INFORMATION

1. Your age:

25 or below	26 to 40	Above 40

2. Your gender :

Female	Male

3. Your role in the company (Select <u>ONE</u> option only)

Branch manager	Manager	Chief financial officer	IT Professional
Other specify			

4. The size of your company

a) Full time employees

Below 20	20 to 50	51 to 100	101 to 150	151 to 200	Above 200

b) Part time and contract employees

Below 20	20 to 50	51 to 100	Above 100

5. Your business is established

Nationwide	KwaZulu-Natal Only

6. How long have you been working for this company?

Less than a year	1 to 5 years	6 to 10years	11 to 20years	More than 20years

SECTION B. PERCEIVED PRICE VALUE

7. Indicate your level of agreement with the following statements

	Strongly disagree	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
7.1. The overall cost of big data analytics is affordable.					
7.2.The cost of expertise for big data analytics is affordable					
7.3.The cost of implementation of big data analytics is affordable					
7.4.The storage system required for big data analytics is affordable					
7.5. The cost of big data network technologies is affordable					
7.6. Big data analytics can provide financial benefits					

SECTION C. PERCEIVED PERFORMANCE EXPECTANCY

8. Indicate your agreement with the following statements on the perceived performance expectancy with the use of big data analytics:

I would expect that the adoption of big data analytics would result in an improvement in…	**Strongly disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
8.1. Business risk assessment					

8.2.Knowledge management					
8.3. Decision making					
8.4.The ability to develop new schemes					
8.5.Understanding the needs of customers					
8.6.The detection of fraudulent medical claims					
8.7.Customer relationship management					
8.8.The effectiveness of existing schemes					
8.9.Competitive advantage					
8.10.The identification of new trends					
8.11.The overall performance of the organization					

SECTION D. PERCEIVED SOCIAL INFLUENCE

9. **Indicate your agreement with the following statements regarding social influence in the adoption of big data analytics:**

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
9.1.A proportion of competitors in the medical aid industry have adopted big data analytics					
9.2.Suppliers think that medical aid companies should adopt big data analytics					

9.3.It is a trend in the medical aid industry to adopt big data analytics					
9.4.The government is encouraging medical aid companies to adopt big data analytics					
9.5. Customers would like medical aid companies to adopt big data analytics because it results in better services and schemes.					

SECTION E. PERCEIVED FACILITATING CONDITIONS

10. Indicate your agreement with the following statements

	Strongly disagree	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
10.1.The company has the necessary network system to adopt big data analytics					
10.2.The company has the necessary storage system required for big data analytics					
10.3.The company has the necessary hardware required for big data analytics					
10.4. The company has the right expertise required for big data analytics					
10.5.The top management team has the necessary knowledge about big data analytics					
10.6.The company has a requirement to share data between departments within the company					

SECTION F. PERCEIVED CHARACTERISTICS OF INNOVATION

11. Indicate your level of agreement with the following statements

Statements	**Strongly disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
11.1.I think the adoption of big data analytics is aligned with the company's business process					

11.2. I think the adoption of big data analytics is in harmony with the company's value					
11.3. I think the adoption of big data analytics fits right into the company's work practices					
11.4. I think the adoption of big data analytics fits right into the actual organisation's technological infrastructure					
11.5. I think big data analytics is flexible to interact with					
11.6. I think big data analytics is easy to implement					
11.7.I think it is easy to train employees on big data analytics					
11.8. I think big data analytics is easy to maintain					
11.9. I think the law permits companies to use data from their customers					
11.10.I think the company can rightly access data from third parties(suppliers)					
11.11.I think information security within the company is assured					
11.12.I think big data analytics allows an organisation to use its data more effectively					
11.13.I think big data analytics helps a company to customize products (schemes)					
11.14. I believe big data analytics increases the customer base					
11.15.I think big data analytics helps an organisation to gain competitive advantage					

SECTION G. ATTITUDE

12. Indicate your level of agreement with the following statements

	Strongly disagree	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
12.1.I believe it is a good idea to adopt big data analytics					
12.2.I believe that big data analytics will allow the company to access more accurate information					
12.3.The adoption of big data analytics by the company would be a positive decision					
12.4. I believe that big data analytics will enhance the company's decision making					

Appendix C: Ethical Clearance Approval

UNIVERSITY OF KWAZULU-NATAL™
INYUVESI YAKWAZULU-NATALI

10 January 2017

Mr Junior Vela Vela (210535115)
School of Management, IT & Governance
Pietermaritzburg

Dear Mr Vela Vela

Protocol reference number: HSS/1831/015M
Project title: The employees' perception on the adoption of big data analytics by selected medical aid organisations in Durban

Approval Notification – Amendment Application

This letter serves to notify you that your application received on 09 January 2017 regarding an amendment has now been approved as follows:

- Change in Title

Any alterations to the approved research protocol i.e. Questionnaire/Interview Schedule, Informed Consent Form; Title of the Project, Location of the Study must be reviewed and approved through an amendment /modification prior to its implementation. In case you have further queries, please quote the above reference number.

PLEASE NOTE: Research data should be securely stored in the discipline/department for a period of 5 years.

The ethical clearance certificate is only valid for period of 3 years from the date of original issue. Thereafter Recertification must be applied for on an annual basis.

Best wishes for the successful completion of your research protocol.

Yours faithfully

Dr Shenuka Singh (Chair)

/ms

cc Supervisor: Dr Prabhakar Rontala Subramaniam
cc Academic leader Research: Professor Brian McArthur
cc School administrator: Ms Debbie Cunynghame

Humanities & Social Sciences Research Ethics Committee
Dr Shenuka Singh (Chair)
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Appendix D: Letter from the Statistician

Gill Hendry B.Sc. (Hons), M.Sc. (Wits), PhD (UKZN)
Mathematical and Statistical Services

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17 January 2017

Re: Assistance with statistical analysis

Please be advised that I have assisted Junior Vela Vela (student number 210535115), who is presently studying for a Master of Commerce (IS&T), with the statistical analysis for his study.

Yours sincerely

Gill Hendry (Dr)

Appendix E: Letter from language editor

28 January 2017

TO WHOM IT MAY CONCERN

This is to confirm that I assisted Mr. Junior Vela Vela with the language editing of his dissertation **'The Employees' Perception on the Adoption of Big Data Analytics by Selected Medical Aid Organisations in Durban'**. I went through the entire draft making corrections and suggestions with respect predominantly to language usage and punctuation.

Mrs. Barbara L. Mutula-Kabange

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