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A DECISION SUPPORT FRAMEWORK FOR SELECTING BIG DATA ANALYTICS TOOLS IN AN ORGANISATION

by

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DECLARATION

I, **Tonata Magano Nakashololo**, declare that the contents of this dissertation/thesis represent my own unaided work, and that the dissertation/thesis has not been previously submitted for academic examination towards any qualification, Furthermore, it represents my own opinions and not necessarily those of Cape Peninsula University of Technology.

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ABSTRACT

The objectives of this study were to gain an understanding into the factors that influence the selection of big data analytics tools in organisations, and to formulate criteria that can guide the selection of big data analytics tools in an organization. Based on the understanding of the factors and criteria, a decision support framework was proposed, to assist in the selection of big data analytics tools in an organisation. In achieving the aim and objectives of this study, a case study approach was employed, and developing countries was selected for the case of study. The qualitative methods and interpretive approach were used. Document analysis and semi-structured interviews were used to collect data. Actor-network theory was used to underpin the study. The approaches and methods were considered most appropriate in acquiring a deeper understanding of how organisations select, use and adopt big data analytics tools.

In the analysis, the moments of translation from the perspective of actor-network theory were employed to focus on the actors, networks that influence the selection of big data analytics tools in organisations. From the analysis, it was discovered that there are five factors that influence the selection of big data analytics tools in an organisation, namely: Requirements, Approach: Top-down vs Bottom-up, Stakeholder Role, BDA Usefulness, and Organisational Structure. Subsequently, criteria that guide the selection of big data analytics were formulated and noted to be: Scalability, Functionality, Non-functionality, Technology, Ownership, Model, and Skill. Based on these findings a decision support framework for the selection of big data analytics tools in an organisation was proposed.

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CHAPTER 1
INTRODUCTION

1.1. Introduction

Big Data Analytics focus on the processing of data which can be transformed into valuable business information by making use of computational methods to reveal trends and patterns amongst datasets (Zakir, Seymour & Berg, 2015). Similarly, Chen, Chiang, and Storey (2012) describe big data analytics as analytical tools for unusually large and complex datasets from numerous sources. Additionally, Nwanga, Onwuka, Aibinu, and Ubadike (2015) describe big data analytics as a term that comprises techniques and approaches for gathering and analysing datasets for intuitive and efficient decision making. It is evident from the descriptions presented that a common theme is repeated; that big data analytics involves the use of tools and techniques through which datasets are managed for improved efficiency and effectiveness (LaValle, Lesser, Shockley, Hopkins & Kruschwitz, 2011). However, in dealing with big data and analytics, organisations need to focus on both unstructured and structured data. This introduces a challenge in the handling of unstructured and structured data and helps to generate certain realities (Akter & Wamba, 2016).

Big data and analytics have become core to how many organisations deliver value to customers. Wang (2018) suggests that a new value chain results from analytics of big data. The process often starts from the extraction of information to generate knowledge, which ultimately helps to create intelligence used to inform decisions that contribute to organisational competitive advantage. Organisations are employing big data analytics to draw insights for commercial interests such as e-commerce and social media monitoring, as well as for public interest, such as e-government service delivery (Fan & Jin, 2015). However, the adoption of big data analytics in organisations comes with its own challenges. Matsebula and Mnkandla (2016) state that there are four factors that influence the adoption of big data analytics: (1) the endorsement of the idea of big data analytics by the senior management (2) an organisational culture that responds well to change; (3) a technical environment (architecture, infrastructure and expert skills) that can efficiently analyse volumes of data; and (4) the establishment of organizational policies and best practices that comply with local laws on data protection.

Wang , Chen, Hong, and Kang (2018) suggest that big data analytics can be grouped into three categories: (1) descriptive; (2) predictive; and (3) prescriptive analytics. For organisations to gain valuable insights, the analytics process requires the use of one or more various technologies. According to Chen, Chiang, and Storey (2012), the technologies for big data analytics include but are not limited to clustering, classification, regression, anomaly detection, neural networks, heuristic search, and data mining.

Both Assunção, Calheiros, Bianchi, Netto and Buyya (2015) and Maru (2018) suggest that big data analytics bring business opportunities to organisations, but taking the big data analytics route requires significant effort on both the part of the organisations and the chief information officers (CIOs). The effort commences at the planning, into the designing stage, including resource allocation and technology utilization. Despite the immense promises that the big data analytics bring, challenges still exist in how many organisations and their CIOs make decisions on which tools and methods best suit the organisational needs. Assunção et al. (2015) assert that the varying analytical nature of the tools, it forces some organisations to spend significant effort in choosing tools that can fulfil their individual needs. As such, there exists a gap in decision support for organisations in the selection of big data analytical tools.

1.2. Research Problem

Big data analytics is at the centre of digital transformation, which many organisations are increasingly relying on for competitiveness and sustainability (Wang & Wang, 2020). Currently, different types of big data analytics tools exist, including predictive, prescriptive and descriptive tools. In many organisations, challenges exist in the use of these tools, which emanates from selecting the wrong or inappropriate tools. The problem is that it is a challenge for some organisations to select and use appropriate tools that are able to deliver valuable insights for their business processes and IT strategies (Chen, Lin & Wu, 2020). As a result, some of the organisations either select multiple or none of the tools. The implications of such a decision leads to risks, such as a failure to reap returns from investment and add to complexities of IT solutions in the technical environment. Some of these risks translate to difficulties in the management of IT solutions, competitiveness, and sustainability of an organisation. Decision support frameworks improve the quality of decision making as they depend on thorough knowledge bases (Musaad et al., 2020). However, if these knowledge bases contain inappropriate data and information, it presents a risk to the decision-making process (Sutton et al., 2020). In the context of big data analytics tools selection, there exists a lack of DSFs to aid the selection decisions for big data analytics tools in organisations. Thus, organisations require a framework to support decision making in the selection of big data analytics tools for their specific processes and business needs, to avoid a continuation of these challenges.

1.3. Aim, Objectives and Research Questions

Based on the research problem stated above. The aim is to propose a decision support framework as a solution to address the challenges that organisations encounter in their attempts at selecting big data analytics tools for business and IT purposes.

1.3.1. Research Objectives

From the aim, the objectives of the study were articulated as follow:

i. To examine and understand the factors that influence the selection of big data analytics tools in an organisation. Without such understanding, it would be difficult or impossible to propose a solution.
ii. To formulate a set of criteria that can be used to guide the selection of big data analytics tools in an organisation.

These objectives help to achieve the aim of the research. The objectives were achieved through the research questions.

1.3.2. Research questions

The research questions were formulated based on the objectives as presented above:

Main Research Question:

i. How can a decision support framework be proposed to address the challenges that are encountered in selecting big data analytics tools in an organisation?

Sub Questions:

i. What are the factors that influence the selection of big data analytics tools in an organization?
ii. What are the criteria that can be used to guide the selection of big data analytics tools in an organisation?

1.4. Literature Review

A review of literature was conducted, with focus on the objectives of the study, which include the areas of information systems and technology, big data analytics, big data analytical methods, and decision support frameworks:

1.4.1. Information systems and technologies

Information systems and technologies (IS/IT) artefacts are used to support and enable the processing of data for an organisation’s purposes. Ullah and Lai (2013) assert that IS/IT are used to manipulate, store, and manage datasets in an organisation. Häckel, Lindermeir, Moser and Pfosser (2017) define IS/IT as the application of digital computer and communication technologies that can be used for various purposes.

The implementation of IS/IT artefacts in organisations is often aimed at achieving business goals and strategies (Oijako & Greenwood, 2007). However, the entire process of is not always as simple as sometimes claimed. Legris, Ingham and Collerette (2003) explained that the process of implementing IS/IT artefacts involves stages that begin with the acquisition of software or hardware, post-development activities – configuration, testing, installation, adaption, and the introduction of the system - and subsequently getting the acquired resources working properly in an operational environment. When properly implemented, IS/IT supports organisational process design and enables organisations to offer products and services for increased competitive advantage (Dumas, Van der Aalst & Ter Hofstede, 2005).

Organisations make investments in IS/IT in order to increase their competitive advantage. Oijako and Greenwood (2007) state that IS/IT provide organisations with improved competitiveness and flexibility which can have a major impact on business relationships. Additionally, IS&T remains a resource for organisations to utilise when striving for excellence. Wang and Ramiller (2009) assert that IS/IT artefacts are often used as an enabler of transformation and competency that empowers businesses to succeed.

1.4.2. Big Data Analytics

Over the years, big data analytics has increasingly gained attention. This is primarily due to the rise of the digital economy that has driven growth in the demand for data storage and analytics (Zakir, Seymour & Berg, 2015). Furthermore, we see an increase in the volumes of data being collected putting pressure on information technology departments of organisations to derive meaningful information from data sets. The large volumes of data being generated and collected may be structured, unstructured or semi-structured in nature, which require analytics or computational techniques to extract valuable information from such data sets (Guleria & Sood, 2017; Maru, 2018).

Big data analytics utilises analytical methods to inspect, transform, and model data to extract value (Hu, Wen, Chua & Li, 2014; Kaisler, Armour & Espinosa, 2016). Along the same line of argument, Gandomi and Haider (2015) suggest that the process through which value can be gained from big data may be viewed from two main perspectives: management and analytics. Management can be viewed as the process through which data are gathered and stored, including the preparation for analysis; and analytics involves the approach and the techniques that are employed to gain knowledge and intelligence from existing datasets (Gandomi & Haider, 2015).

Big data analytics helps organisations' drive to new market opportunities, take practical actions, and provide a way for enhanced strategic decision making, which fosters competitive advantage (Zakir, Seymour & Berg, 2015). Therefore, we can see that big data analytics brings about major benefits to organisations.

Some of the challenges exhibited by big data analytics include the type of analysis to be conducted on the data and the issues associated with the storage options that need to accommodate big data, as well as the server and network infrastructure demands required for big data analytics (Labrinidis & Jagadish, 2012; Katal, Wazid & Goudar, 2013). Additionally, Cai and Zhu (2015) mention the issue of managing data that are produced from different sources as an inherent challenge for big data analytics.

1.4.3. Big Data Analytics Methods

In order to derive actionable insights from big data, analytics need to be applied to make sense from the data sets for improved usefulness. Sivarajah et al. (2017) assert that through the selection of analytical methods, intelligence can be mined from data sets. There are three most common big data analytical methods: Descriptive, Predictive and Prescriptive (Wang et al., 2018). Watson (2014) states that it is important to distinguish between the three analytical methods, as the differences have an effect on the technologies and architectures used for big data analytics. Additionally, Sivarajah, Kamal, Irani and Weerakkody (2017) state that big data analytical methods can also be regarded as a "sub-process within the overall process of insight extraction from big data".

- Descriptive analytics is a technique that is used to tell the story of what has occurred (Watson, 2014). It involves summarising and describing knowledge patterns through the use of statistical methods. This includes the analysis of datasets in order to define the current state of an environment and to create reports that model past behaviour (Sivarajah et al., 2017). Banerjee, Bandyopadhya and Acharya (2013) define descriptive analytics as the use of dashboard applications to better understand business data for organisational objectives.

- Predictive analytics focuses on statistical and forecasting and modelling, towards defining future state and possibilities (Joseph & Johnson, 2013; Waller & Fawcett, 2013). In essence, it suggests what will occur in the future through the analysis of past performance. Evans and Lindner (2012) state that this kind of analytics is done by probing historical data, discovering patterns, and then inferring these patterns forward in time.

- Prescriptive analytics focuses on establishing the cause-effect from datasets within contests of business processes. Essentially, prescriptive analytics allows organisations to optimise their business process models through results from datasets and models (Bihani & Patil, 2014; Sivarajah et al., 2017). Evans and Lindner (2012) and Watson (2014) state that prescriptive analytics suggest what to do by utilising optimisation to find the best options that capitalise on business objectives.

Regardless of the different big data analytical methods, the process of big data analytics still remains labour intensive. The reason for this is that most current analytics tools are either proprietary or open source, which sometimes imposes a great deal of effort on organisations in the process of customising tools in order to meet their needs (Assunção et al. (2015). In essence, this presents a challenge for organisations in selecting and using the most appropriate big data analytics tools that meet their needs, and this requires a decision support framework.

1.4.4. Decision Support Frameworks

Decision support frameworks (DSFs) are aspects of IS/IT artefacts that assist in the decision-making processes in the activities of an organisation (Alyoubi, 2015). Also, the DSS is a collaborative and flexible IS/IT artefact that supports unstructured or semi-structured problems (Turban, Aronson & Liang, 2005). The DSS offers assistance in decision-making situations by supporting organisations in various scenarios (Power & Sharda, 2007).

DSSs have been used in IS/IT in varying use cases. For example, in software development, an area that is characterised by numerous goals and limitations, and a huge amount of uncertainty, the success of a software development initiative depends on having the "right knowledge at the right time." (Ruhe, 2003:143). Another example is that the DSS assists in systems development for the engineering of decision support (Ruhe, 2003). A decision support framework that analyses varying software components needed for a software application in order to help a user make a cost-effective decision(s) was introduced by Srivastava (2004). Similarly, decision support frameworks that aid decision making in software reengineering and selecting enterprise software have been in use for many years (Şen et al., 2009; Kamaludeen, Sulaiman & Cheah, 2011).

The use of DSSs is seen to be beneficial for organisations that are looking for support to problems. Chan, Song, Sarker and Plumlee (2017) assert that the decisions that come as a result of DSSs usage are made more speedily and accurately than unassisted decisions.

Decision support framework research in relation to big data analytics is seen to place focus on using big data to help organisations make better decisions. Horita et al. (2017) presents a model-based framework that connects organisational decision making with big data. Also, Kościelniak and Puto (2015) explore stages of organisational decision-making support based on big data analytics.

Decision support frameworks have been created to assist in many areas such as software development projects, as well as selection of software. There has also been research into the use of big data analytics tools to support organisation decision making (Kościelniak & Puto, 2015; Horita et al, 2017). However, there is a lack of alignment with decision support in big data analytics projects (Kamaludeen, Sulaiman & Cheah, 2011). As such, the objective of this study is to explore this area further by developing a decision support framework that examines big data analytics tool(s) needed for a big data analytics project to help with making worthwhile decisions. The objective is therefore underpinned by a theory.

1.4.5. Actor-Network Theory

Actor-Network Theory (ANT) is a socio-technical theory that focuses on actors and networks and the interaction and relationship between the actors and networks (Callon, 1986). ANT sees reality as organised by heterogeneous groupings of people, technology and objects (Doolin & Lowe, 2002; Tatnall, 2005). It is the relationships amongst these elements that make up reality; these relationships are posited as a network of non-human and human actors (Wissink, 2013). Hanseth, Aanestad, and Berg (2004) state that ANT draws on the notion of a socio-technical system where technical and social aspects are interconnected, and the degree to which these aspects work together is important in determining how the system as a whole works. Therefore, the theoretical construct of ANT is dependent on the mapping out of complex networks and relationships amongst human and non-human actors (Pollack, Costello & Sankaran, 2013).

The social (relationships of stakeholders) and IS/IT entities establish themselves as agents that form a network of groupings through the definition of actors, obliging them to take on particular roles (Hanseth et al., 2004). Conceptually, the use of an ANT-informed approach to information systems research can be valuable in understanding the intricacy and volatility of reality, which helps in theorising the way different realities are experienced by diverse actors (Tatnall, 2005).

According to Wissink (2013), ANT does not deny the variances between human and non-human actors but simultaneously emphasises that the study of associations amongst them have to be treated symmetrically. The process of accepting and producing these associations in ANT is called ‘translations’, which, according to Iyamu and Mgudlwa (2018), allows for various stages of analysis. ANT is often used to gain an understanding of how networks were created and come into existence, through actors’ interests and enrolments (Cresswell, Worth & Sheikh, 2010). In ANT, moments of translation consist of problematisation, interessement, enrolment, and mobilisation as depicted in Figure 1.4.5.1

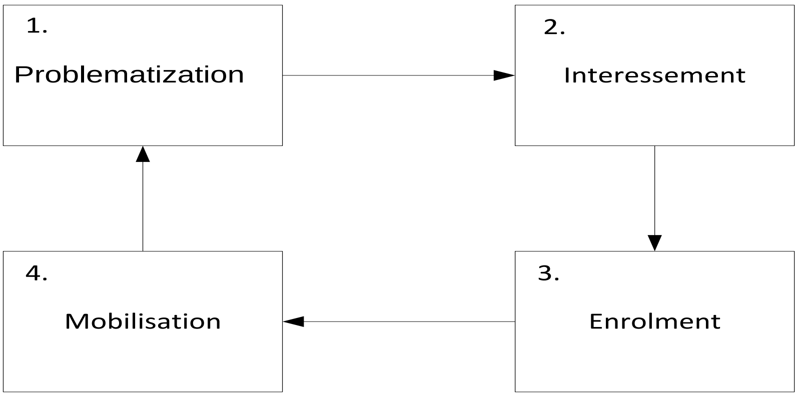

Figure 2.4.5.1: Four moments of translation (Callon, 1986)

Callon (1986) states that a network is built through a four-step process known as moments of translation as illustrated in Figure 1. The process begins with problematisation, whereby the primary actor seeks to identify the problem and what actors are involved in the network. In building the network, interest (interessment) from other actors regarding the roles they could take on within the network evolves. Enrolment occurs when a network is made and actors realise their defined roles. During the final step, the proposed solution is shared with interest groups and gains a wider acceptance by means of mobilisation by the actors.

1.5. Research Design, Methodology and Ethics

This section presents the methodology that was employed in carrying out the research. This includes the philosophical assumptions, research approach, research methods, research design, data collection and data analysis, as discussed below:

1.5.1. Philosophical Assumption

Philosophical assumptions are the different types of philosophies that guide research. There are two common types of philosophies in information systems studies, namely; ontology and epistemology.

Ontology focuses on the state of realism upon which a theory can be developed within a social system (Iyamu & Mgudlwa, 2018). Also, ontological assumptions is about how the researcher consciously understands the phenomenon being studied (Burrell & Morgan, 2017). It can also be said that ontology relates to the "nature of reality and its characteristics" (Cresswell, 2013:19). To simply put it, ontology is what constitutes reality; what is considered true (Bernard & Bernard, 2013). Within the context of philosophical assumption of reality, researchers are required to take a position about the current state of the phenomena being studied (Scotland, 2012).

Epistemology is what can be known in relation to the aims of a research. The philosophy is concerned with providing a grounding for determining the knowledge that is possible and how a researcher can ensure that this knowledge is both acceptable and valid (Bernard & Bernard, 2013). The epistemological assumption is essentially how knowledge can be "created, acquired and communicated" (Scotland, 2012: 9). The assumption guides a researcher's understanding of reality and how to communicate that reality to others (Orlikowski & Baroudi, 1991).

In the context of this study, on the one hand, the ontological assumption is that big data analytics tools and their challenges do exist in various environments. On the other hand, epistemologically, the assumption is that a solution can be developed to resolve the challenges of big data analytics tools, through examining and gaining an understanding of the influencing factors and criteria. Thus, the interpretivist approach was selected as the philosophical stance in this study.

1.5.2. Research Approach

In research, approaches are often employed towards achieving the goal and objectives. In information systems research, two research approaches are common, namely; deductive and inductive:

Deductive reasoning follows a direction from generalisations to a specific case (Andreewsky & Bourcier, 2000). The approach focuses on how generalisations can be applied to specific scenarios (Hyde, 2000). The deductive approach is often considered to be the most suitable in cases whereby the researcher is testing theories which begin from established theories or generalisations (Hyde, 2000).

The inductive approach seems to be on the opposite side of the deductive in that its focus is from a specific instance or an assortment of observations to generalisations (Kovács & Spens, 2005; Danermark, Ekström & Karlsson, 2019). The approach is a theory-constructing process that seeks to form generalisations about a phenomenon (Hyde, 2000).

As stated in section 3 above, the aim of this study is to develop a decision support framework that can assist organisations in their selection of big data analytics tools. The study was conducted by looking at two organisational perspectives. The outcome, which is the framework, can be used by any organisation, thereby generalising it. Inductive reasoning was employed, based on the aim of the study.

1.5.3. Research Method

Research methods guide the entire process of the study (Remenyi et al., 2003). There are two types of research methods: qualitative methods and quantitative methods. Also, the two methods can be combined, which is called the mixed methods.

The quantitative methods focus on the general characteristics of a population and overlook the details about individual elements under investigation (Hyde, 2000). Neuman and Robson (2012) suggest that the quantitative research method is used when a researcher begins with a theory and aims to test the validity of the theory. Essentially, one can say that quantitative research involves deductive reasoning. Additionally, quantitative research designs may include experimental studies where the control of variables is required (Bryman, 2006).

The qualitative methods focus on the quality of data, to gain an understanding about social phenomena (Lewis, 2015). The Methods allow the researcher to conduct an in-depth study where data collection is not restricted to fixed categories (Hyde, 2000). Conboy, Fitzgerald and Mathiassen, (2012) state that qualitative research comprises a range of methods that seeks to explain and interpret the meaning of phenomena in the social world. Furthermore, based on the philosophical assumptions of the study, qualitative research can either be of a positivist, interpretive, or critical nature (Merriam, 2015).

This study has interpreted and uncovered an in-depth meaning of factors from a social context perspective, in order to develop a framework that can be used to guide the selection of big data analytics tools in an organisation. As such, in order to achieve the aim of the study, a qualitative interpretivist research methodology was employed.

1.5.4. Research Design

Research design is a plan within which a research is carried out. There are various types of design, which include case study, ethnography, and survey (Neuman & Robson, 2012). In addition, there is design science, which is also used in IS research (Hevner, Alan, March, Park & Ram, 2004). The ethnography, design science and survey types of design were explored but were not used in this study. The case study method was selected based on the aim and objectives of the study as stated in section 3 above..

1.5.4.1. Case Study Research

Case study research involves an investigation of a social phenomenon within a real-life context (Bassey, 2003; Hays, 2004). The objective of case study research is to study information systems in an organisation (Myers, 1997). A researcher conducts an in-depth examination of cases over a period of time with comprehensive and mixed data. These cases are carefully selected to show a problem and study it (Neuman & Robson, 2012). Additionally, because of its flexible design, good planning for a case study is vital. Several issues need to be addressed in the planning of a case study. These include; the objective of the case study, the frame of reference, how to collect data and where to find the data (Runeson & Höst, 2009).

The South African environment was used as the case in the study. This is primarily because the researcher would holistically like to cover a large space in the study, rather than one or two organisations. Also, big data analytics is an emerging type of technology and approach in many developing countries, including South Africa. This means that many of these countries are struggling to deploy the analytics tools. Thus, it is difficult to find organisations that have deployed and are practising or making use of the tools. However, documentation and academic literature are used in a study of this nature.

1.5.5. Data Collection

Within the qualitative methods, there are different types of data collection techniques: interview, documentation, and observation (Denzin, Lincoln & Giardina, 2006). In achieving the objectives of this study, the documentation and systematic analysis of peer-reviewed literature were employed.

The document analysis technique was employed as a means of data collection for this study. This means that documents that relate to the study were collected and analysed. The document analysis technique is aimed at studying documents to provide an understanding of their content and find their meaning (Altheide et al., 2008). Documents, in this context, refer to peer-reviewed articles, software documentation, reports, and books. The selection of the technique was guided by the research objectives, which are to examine and understand the factors and criteria that influence and guide the selection of big data analytics tools in an organisation. Bowen (2009) states that the document analysis technique can provide rich amounts of information from different sources and document types.

Peer-reviewed articles focusing on the South African context published between 2009 and 2019 were used as documents within this study. However, documents within other contexts were also used as supporting documentation. The rationale behind selecting documents within a 10-year period is to have a reasonable historical spread and consistency of meaning within the data.

1.5.6. Data Analysis

Data analysis is the process involved in the engagement with data and the clarification of their meaning (Barbour, 2013; Bazeley, 2019). It is about using critical thinking to interpret data which is, more often than not, informed by social and cultural experiences (Bazeley, 2019). Miles, Huberman and Saldana (2014) state that this interpretation makes use of a set of analytic strategies to transform data into a comprehensible representation of the subject of a study.

The interpretivist approach was employed in the data analysis. The analysis was guided through the moments of translation, from the perspective of ANT as a lens. ANT is discussed in section 4.5. The analysis focuses on three main areas in achieving the aim of the study:

i. Establish the actors and networks that exist; how the networks were formed; the roles of the various networks; and how the networks come together to influence the selection of big data analytics tools in an organisation.
ii. Through the moments of translation, examine the interaction and roles of actors, and how their actions influence the selection of big data analytics tools in an organisation.

iii. Through the moments of translation, examine the relationship and heterogeneity of actors and networks in the formulation of criteria that guide the selection of big data analytics tools in an organisation.

1.6. Ethics

Ethical issues that were considered include the Respect for Intellectual Property by honouring patents and copyrights and acknowledging all contributions to the research. Confidentiality, through the protection of confidential documents and information supplied by subjects in the study. Another consideration in the research was to seek permission from the organisation in order to make use of documents about their business and activities. Ethical clearance was obtained from the university in order to carry out the study. The data was kept confidential to only the student and her supervisor.

1.7. Outcome, Contribution and Significance

The main outcome achieved from this study is a decision support framework that can be used for selecting big data analytics tools. The framework is intended to benefit IS/IT specialists in organisations, IS/IT vendors and consultants, and data analytics and product owners, in that the framework will guide them on how to select and use big data analytics tools in an organisation.

Thus, the contributions of this study are both theoretical and practical. Theoretical in that it added to existing literature, through which it contributes to the body of knowledge. The practical contribution comes from the development of the framework to guide the selection of big data analytics tools in an organisation.

Additionally, it is significant that this study is intended to benefit organisations, in that it can be used to guide the decision-making process of selecting big data analytics tools to gain competitive advantage within organisations.

1.8. Structure of the thesis

The thesis is structured into six chapters. In addition, it includes an abstract, the acknowledgement and the ethical consideration sections. The chapters are briefly described as follows:

CHAPTER 1: Introduction – this chapter introduces the entire thesis by providing a short and concise discussion of each of the chapters.

CHAPTER 2: Literature Review – through a detailed discussion, the chapter presents the gap which the study tries to address. This was done by conducting a review of literature in the keys, such as IS/IT, big data analytics, and decision support.

CHAPTER 3: Research Methodology – this chapter discussed the research methodology employed in the study.

CHAPTER 4: Case Overview – the outline of the case used in this research was presented here.

CHAPTER 5: Data Analysis and Results – this chapter presents the analysis of the data and the findings.

CHAPTER 6: Conclusions and Recommendations – this chapter provides the conclusion of the study.

1.9. Summary

The aim of the study was to create a decision support framework for selecting big data analytics tools in an organisation. The chapter clearly states the objectives and questions. It clarifies the contributions of the study, based on which the outcomes are measured. The ethical issues that were considered are also discussed in this chapter. To ensure a better understanding of the flow of the thesis, the structure is presented.

CHAPTER 2

LITERATURE REVIEW

2.1. Introduction

Literature review encapsulates and assesses literature about a specific topic (Knopf, 2006). A literature review aims to establish the context of the topic being studied, identify associations amongst processes and practices, and provide a rationale for the importance of the problem (Randolph, 2009). Therefore, this review concentrated on the aim of the study, which was to propose a decision support framework for the selection of big data analytics tools in organisations.

This chapter provides a review of existing literature related to the study. The areas of study within the literature review include Information Systems and Technologies, Big Data Analytics (BDA), Big Data Analytics Methods and Decision Support Frameworks. A review was done on Actor-Network Theory (ANT), which was used to underpin the study.

2.2. Information Systems and Technologies

Information systems are technologies that are created and utilised by organisations. Allen (2000) states that the rise of innovations in information technology brings unity in information systems research. Information technology is defined as computerised tools that individuals and organisations use to aid information processing needs, whereas information systems store and process information to fulfil a particular organisational need (Oliveira & Martins, 2011). Furthermore, information systems represent more than just the use of information technology (Allen & Kim, 2005). Information systems combine interrelated components that process, retrieve, collect and supply information that aids in organisational decision-making and coordination (Nowduri, 2012). O'Brien and Marakas (2014) mention that information systems are a combination of hardware, software, networks, people, data, and processes that allow for the storage, retrieval and transformation of information within an organisation.

Additionally, information systems assist organisations in analysing and visualising complex problems and facilitating the development of new products (Al-Mamary, Shamsuddin & Aziati, 2014). Similarly, Rainer, Prince, Splettstoesser-Hogeterp, Sanchez-Rodriguez and Ebrahimi (2020) state that organisations utilise technological innovations of information systems to decipher business problems and attain competitive advantage. There are different applications of information systems within an organisational context, Al-Yaseen, Al-Jaghoub and Al-Shorbaji (2010) state that the different types of information systems can be categorised as enterprise collaboration systems, data processing systems, decision support systems and management information systems.

According to Prescott (2013), organisations depend on the procurement and management of suitable information systems. Furthermore, Abdekhoda, Ahmadi, Dehnad, and Hosseini (2014) state that the arrangement of technologies, people, and data provides solutions that allow organisations to expand their operations and support decision making. Additionally, Shin (2006) suggests that a number of organisations use information systems to meet their business needs and improve their effectiveness.

2.3. Big Data Analytics

With the fast-paced advancements and innovations in the technological world, most data is being generated from digital media (Jensen, Lowry, Burgoon, & Nunamaker Jr, 2010). According to Lycett (2013), the size of the data generated and stored in digital media exceeds five (5) exabytes.

With organisational processes becoming catalysts for change and competitive advantage, many organisations are gradually making use of big data analytics to generate valuable insights. This is attributed to the fact that organisations are increasingly gaining more understanding of the value of data (Davenport, 2006; Abbasi, Sarker, & Chiang, 2016). Additionally, information technology departments are assigned the responsibility of managing and assimilating data. Subsequently, Goes (2014) states that the rise of big data has intensified the significance of the role that information technology departments play within an organisation aiming to take advantage of big data analytics.

A crucial component of big data analytics is the characteristics that define big data. The characteristics of big data are volume, velocity, variety, veracity, value and complexity, which can be seen in figure 2.1 below (Mohammadpoor& Torabi, 2020).

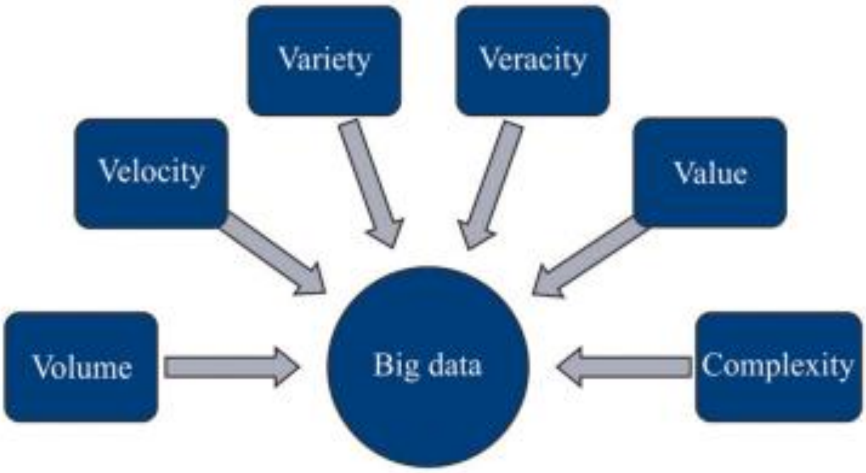

Figure 2.1: Big Data Characteristics

Volume refers to the amount of data being produced and stored. Velocity refers to the rapidity of data generation, processing and transmission (Tsai, Lai, Chao & Vasilakos, 2015; (Mohammadpoor & Torabi, 2020).Variety refers to the different types of data being stored and analysed. Data is generated in various formats such as text, social media data, web clickstreams, audio, video or image, structured, unstructured and semi-structured. Veracity refers to the usefulness of the data in analysis. "*It is about distinguishing between clean and dirty data. This is very important as the dirty data can significantly affect the velocity and accuracy of data analysis*" (Mohammadpoor & Torabi, 20202). Value refers to the return on investment for big data initiatives (Kapil, Agrawal & Khan, 2016). Complexity refers to the intricacies of the problem for which the data is collected. Subsequently, big data characteristics form the basis upon which IT departments opt to utilise distributed infrastructure that can handle large amounts of data generated in various formats (McAfee, Brynjolfsson, Davenport, Patil & Barton, 2012; Abbasi, Sarker, & Chiang, 2016).

Big Data Analytics (BDA) facilitates the capturing of valuable insights from data. Organisations are generating data of unprecedented volumes, complexity and variety, and gaining meaningful insights from this data has become crucial (Zakir, Seymour & Berg, 2015). Furthermore, BDA is intricately important in realising the value of big data to enhance organisational performance (Tsai et al, 2015).

A classic example of BDA initiatives employed in healthcare include the initiative for fighting the flu. This initiative makes use of flu reports collected weekly by the CDC. The reports include information of the illness, treatments given and the result of the treatments given. Big data analytics is used to organise and examine the data to provide healthcare practitioners with insights into the spread of the illness, patient locations, and appropriate treatments (Nambiar, Bhardwaj, Sethi & Vargheese, 2013).

According to Hu and Vasilakos (2016), the taxonomy of big data analytics can be classified into three (3) classes: 1) Big Data Architecture, 2) Big Data Intelligence, and 3) Big Data Security.

Despite the potential of BDA, it poses some challenges in data processing, storage, management and acquisition (Zaman, Pazouki, Norman, Younessi, & Coleman, 2017). Sun (2018) mentions data transfer, security, data quality, data integration, data ownership and data protection as the challenges involved in big data analytics.

2.4. Big Data Analytics Methods

According to Sun, Sun and Strang (2018), big data analytics is an evolving technology related to multidisciplinary information systems (IS), decision science and machine learning (ML) for big data. Additionally, BDA is the process of organising and analysing big data to uncover patterns and intelligence (Rajaraman, 2016). The main components of big data analytics are descriptive analytics, predictive analytics and prescriptive analytics (Minelli, Chambers & Dhiraj, 2013; Sun, Zou & Strang, 2015; Sun, Sun & Strang, 2018).

Descriptive analytics is defined as the most rudimentary form of analytics, which looks at both real-time and historical data (Ukhalkar, Phursule, Gadekar & Sable, 2020). It is known to be the starting point for other types of analytics. Kantardzic (2011) states that organisations make use of descriptive analytics in order to determine new patterns, clarify the characteristics and associations amongst data, and provide discourse on organisational issues such as "*what happened, and when, as well as what is happening*" (Sun, Sun & Strang, 2018:3). Furthermore, Ukhalkar et al. (2020) assert that descriptive analytics is the starting point for business big data analytics. Descriptive analytics commonly includes two (2) steps: 1) Preparation and analysis of historical data; and 2) identifying patterns for business reporting. Examples of descriptive analytics include business intelligence tools.

Predictive analytics utilises historical data to predict trends. It makes use of algorithms to recognise patterns from past data. Zakir, Seymour and Berg (2015) assert that predictive analytics is an analytical method that utilises machine learning for data analysis and prediction formulation. Many organisations use predictive analytics to enhance future marketing campaigns. As mentioned previously, descriptive analytics is the starting point for business analytics. Upon completing descriptive analytics, past data can be combined with machine learning algorithms to formulate predictions about future trends (Delen & Demirkan, 2013; Kannan, Sivasubramanian, Kaliappan, Vimal & Suresh, 2019). It is important to note that the predictions that come from predictive analytics are possibilities of what could or could not occur. However, through BDA techniques, the precision of the predictions can be assessed. Soltanpoor and Sellis (2016) assert that predictive analytics is utilised 1) to make predictions about future trends and 2) to analyse associations in data that would not be detectable through regular data analysis. Bertolucci (2013) notes the following tasks to be involved in predictive analytics: 1) Classification – refers to the use of decision trees for predicting categories; 2) Clustering – refers to a process of uncovering natural groups; 3) Association – refers to the process of discovering items that happen together; 4) Divergence Detection – refers to discovering deviations; and 5) Estimation and Time Series – involves predicting unremitting values. Furthermore, Coronel and Morris (2016) state that predictive analytics aims to enhance system performance through the use of intelligent technological solutions to discover associations within big data to forecast future events.

Prescriptive analytics addresses business questions such as what should we do? Why should it be done? And what will occur with the best outcome? Van Rijmenam (2019) states that prescriptive analytics encourages organisations to deliberate on predictive analytics within a specific business context to enhance decision-making. Prescriptive analytics offers "*projected outcomes for potential actions*" (Ukhalkar et al, 2020:2671). Deka (2014) states that prescriptive analytics aids in the organisation's analytical maturity and is noted to be the concluding phase in business analytics. Furthermore, Rao, Mitra, Bhatt and Goswami (2019) notes that prescriptive analytics has two (2) features: 1) to evaluate and determine novel ways of operation, 2) to target business objectives.

Organisations in various industries have invested or are looking to invest greatly in BDA initiatives. Gupta and George (2016) suggest that investments in BDA do not automatically produce competitive advantage, instead organisations are required to make appropriate investments that match their business needs to reap returns on investments. Additionally, Hao, Zhang and Song (2019) assert that due to the presence of big data and the business need to use data for decision-making, investments in BDA capabilities required. However, there is still a lack of understanding and guidance in making appropriate decisions in selecting the BDA tools needed for BDA initiatives (Assunção et al, 2015; Hao, Zhang & Song, 2019; Jha, Agi & Ngai, 2020). This presents a challenge for organisations in selecting and adopting BDA tools that will meet their business needs, which necessitates a decision support framework.

2.5. Decision Support Framework

Decision support frameworks (DSF) provide direction on how to tackle and address problems to produce outcomes. Additionally, a DSF enables decision-making in multifaceted situations that often include various decision-makers with contradictory views (Chitaka, von Blottnitz & Cohen, 2018). Hayen (2006) states that a DSF aims to support managerial decision-making, assist managers in making informed judgments and enhance the effectiveness of decision-making. According to Greenes, Bates, Kawamoto, Middleton, Osheroff, and Shahar (2018), DSSs are complemented by suitable processes and technology that are applicable to the decision circumstances at hand.

The benefits of DSSs include capabilities to provide a categorisation of features that can be utilised in decision support situations to identify decisions that are associated with the bearings that are being assessed. (Mingers & Rosenhead, 2001; Greenes et al, 2018).

According to Azapagic and Perdan (2005), generic DSSs are organised into two (2) stages: problem structuring and problem analysis.

- Problem structuring involves procedures that aim at developing an understanding of the decision circumstances. Petrie, Cohen and Stewart (2007) describe it as an extensively planned process that includes engagement with relevant stakeholders. Similarly, problem structuring is an expansive and purposeful process that involves direct interactions amongst stakeholders (Schwartz, Cook, Pressey, Pullin, Runge, Salafsky & Williamson, 2018).

- Problem Analysis includes the acquisition of data on the capabilities of the choices in all the criteria (Olewnik & Lewis, 2006). Additionally, Belton and Stewart (2002) state that problem analysis involves the assessment of all the alternatives being deliberated on, and deciding to what degree these fulfil decision objectives. After this, a preferred alternative is selected and analysed to guarantee that the decision is robust (Hajkowicz, 2007; Schwartz et al, 2018). According to Greco, Figueira and Ehrgott (2016) multiple criteria decision analysis (MCDA) is usually employed for problem analysis, as it facilitates the evaluation of decisions described by opposing criteria.

Organisations face challenges and opportunities with selecting BDA vendors, tools and services (Rodríguez-Mazahua, Rodríguez-Enríquez, Sánchez-Cervantes, Cervantes, García-Alcaraz, & Alor-Hernández, 2016; Venkatesh, Ali, Nithiyanandam, & Rajesh, 2019). Horita et al (2017) state that deciding appropriate BDA systems is not a minor task and needs proper planning. Ayaburi, Maasberg and Lee (2020) agree that a DSF for design choices should be proposed to provide decision-makers with sensible design choices.

Research conducted by Agarwal, Narayanan, Sinha, Gupta, Eswaran and Mukherjee (2018) presents a DSF with a decision engine for classifying appropriate BDA deployment and implementation choices from NoSQL storage solutions namely, Apache Cassandra and MongoDB and the Hadoop Distributed File System. Similarly, Ayaburi, Maasberg and Lee (2020) proposed a DSF that provides decision makers insights into the selection of vendor-specific cloud-based big data services. Regardless of the existence of these DSSs within big data analytics, there is still a lack of a DSF that addresses the selection of BDA tools at an organisational level as opposed to a specific technology stack.

As such, this research aims to investigate this area further by proposing a DSF that assists in the selecting BDA tools within organisations. The aim of this research is thus reinforced by theory.

2.6. Actor-Network Theory

Actor-network theory (ANT) observes the action of actors who create connected aspects and elements of heterogeneous networks (Latour, 1996). According to Walsham (1997), ANT states that social reality contains a mixture of objects, human and non-human actors, and was created for analysing circumstances where disassociating these elements is challenging. For example, how can one distinguish between the portion of a software application which is a non-living object and which is the outcome of human interactions? Essentially, it is challenging to distinguish a software application’s technical elements from the influence applied by the socio-cultural background of the development team (Doolin & Lowe, 2002; Tatnall, 2005). ANT is concerned with examining the processes of power being created in the formulation, conservation and change of networks that contain non-human and human actors (Dolwick, 2009). These networks comprise organisations, machines, and people (Munro, 2009).

According to Latour (2005) ANT discovers how networks are formed and preserved, how they participate with other networks, and how they gain robustness. Additionally, ANT looks at how actors (non-human or human) recruit other actors into a network, and how roles and responsibly are conferred to these actors. Some of the key concepts of ANT are actors, networks and translation. Actors are both non-human and human beings, they are elements to which activity is established by others that is, it is something that adjusts a situation in social reality by making definite difference (McLean & Hassard, 2004), for example idea, plant, person, etc. Networks are a group of actors or actions that make provision for an activity, which allows for researchers to follow and note at firsthand. Translation involves the creation of associations between actors by "*translation their interest to be aligned with the actor-network*" (Walsham, 1997:468). Additionally, it is when one actor acts as the spokesperson for the other actors and achieves in enrolling them into a set of actions. In ANT, the moments of translation include problematisation, interessement, enrolment, and mobilisation as showed in figure 2.2 below.

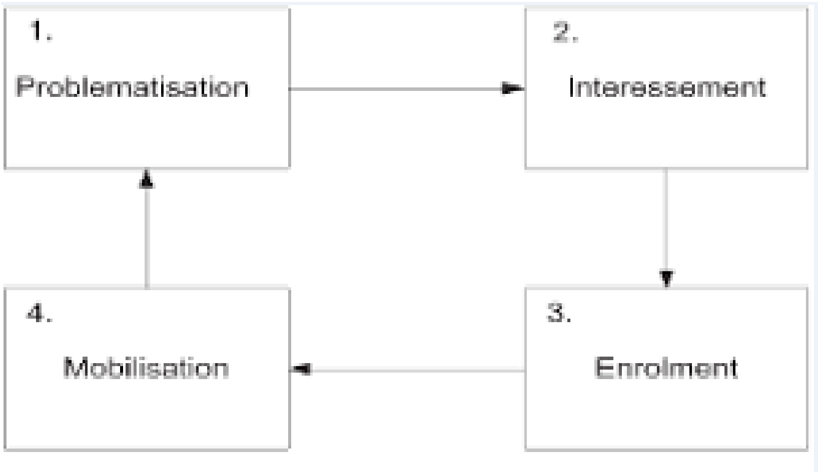

Figure 2.2: Moments of Translation (Callon, 1986)

Problematisation involves the interpretation of a problem within social reality, in which aspects of the problem, the actors involved and solutions to be proposed are classified (Horowitz, 2012). Whereas interessement makes an effort to stabilise the elements discovered in the problematisation stage, actors are able to agree or not agree with these elements and identities (Horowitz, 2012; Heeks & Stanforth, 2015). In the enrolment stage, the roles and responsibilities are made definite with a series of power struggles consisting of negations that may occur (Cordella & Shaikh, 2003; Twum-Darko & Harker, 2017). Mobilisation involves the use of various methods to make the project noticeable, this action is carried out by the spokesperson (Elbanna, 2009).

2.6.1. Actor-Network Theory and Information Systems Research

There have been approaches created that aim at examining humans and their interaction with technology, one such approaches is the Socio-Technical Systems (STS) viewpoint (Mitchell & Nault, 2003). A socio-technical system is defined as a system whereby the social and technical dimensions connected (Baxter & Sommerville, 2011). The level to which these dimensions form and accompany each other is vital in understanding the workings of the systems. De Bruijn and Herder (2009) states that ANT draws on the STS viewpoint, by focusing on entities and their influence on social dimensions. ANT considers social reality as being made up of networks, and these networks include actors - ideas, humans, things (Cordella & Shaikh, 2003; McLean & Hassard, 2004; Bencherki, 2017). The central activity in ANT is to draw out the associations amongst network elements, by investigating how networks are formed, how actors are enrolled into a network, "*how parts of a network form a whole network*", and outline the relationships occur (Cresswell, Worth & Sheikh, 2010:2).

Cresswell, Worth and Sheikh (2010) state that ANT can be used by researchers that accept and aim to understand the complexities of reality such as Information System selection and adoption. It assists to theorise the different realities being experienced by a diverse set of actors to provide a more distinction depiction of the associations between actors, which is vital if one takes note of the evolving world of information systems (Mpazanje, Sewchurran & Brown, 2013).

2.7. Summary

Information systems embody correlated components such as technology, people and processes. Organisations make use of information systems interpret business problems, examples of different applications of information systems include data processing systems and decision support frameworks. In order to gain competitive, organisations are making investments into information systems to increase operations and aid decision making processes.

Big data is characterised by the volume, velocity, variety, veracity, value and complexity of the data. Big Data Analytics involves processes to analyse big data to generate valuable insights. Organisations are increasingly noticing the benefits of the use of BDA to understand data assets to enrich operations. Big data analytics does pose a few challenges such as transfer of data between data sources with particular communication bandwidth.

There are three (3) main methods and components of big data analytics, namely descriptive analytics, predictive analytics, and prescriptive analytics. Organisations make use of BDA tools through the collection, storage and analyses of big data in order discover and visualise insights to meet business needs. In order to reap the return on investments for BDA initiatives, organisation need to understand their BDA capabilities and decisions.

Organisations are making use of decision support frameworks to organise and decipher difficult subjects and uncover their relationships. DSSs consist of two stages, namely problem structuring and problem analysis. The application of DSF in big data analytics has been investigated in the areas of choosing amongst cloud-based big data systems.

Lastly, ANT is a socio-technical theory that consists of elements such as actors, networks and translation. ANT examines the actions of actors, how networks are formed, how networks participate with each other. ANT is used in information systems to understand intricacies of social reality, such as system selection and implementation. The next chapter will discuss the research methodology used in the study.

CHAPTER 3

RESEARCH METHODOLOGY

3.1. Introduction

In this chapter, the methodology used in carrying out the research is discussed. The methodology consists of philosophy, approaches, methods, and techniques. The aspects of the methodology were selected based on the objectives of the study as presented in chapter 1 and revisited in this chapter. This chapter is divided into seven main sections as follows: 1) Research Philosophy; 2) Research Approach; 3) Research Methods; 4) Research Design; 5) Data Collection; 6) Data Analysis and 7) Ethical Considerations.

3.2. Overview

Research Methodology is a general research plan which outlines how a research will be conducted. This includes the philosophical assumptions that shape the point of view of the research questions and reinforce the selection of research methods (Creswell, 2018; Melnikovas, 2018). Research Methodology is a fundamental part of a study, as it helps to safeguard the unity amongst the chosen methods, design, and philosophy (Saunders, Lewis & Thornhill, 2016; Melnikovas, 2018). Figure 3.1 below depicts a research onion that can be applied in a study. The research onion includes research philosophies, approaches, designs and methods used in conducting a research. This chapter discusses the methods, approaches and techniques that are applied in this study.

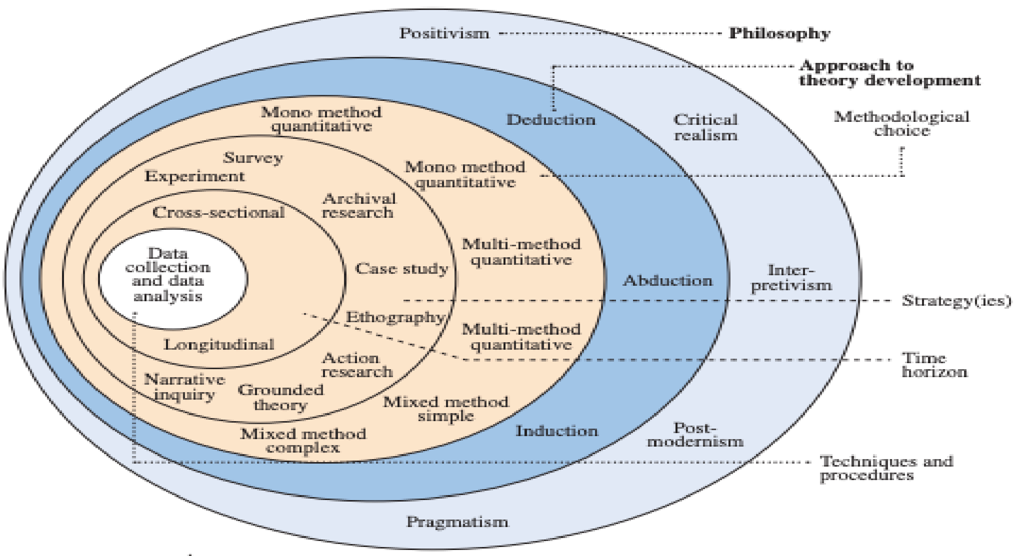

Figure 3.1 - Research Onion (Melnikovas, 2018)

Research methodology is vital in a study as it helps to structure the research and develop a clear step-by-step path that can be used to conduct the study and communicate findings. Research methodology also allows for the critical evaluation of a study's reliability and validity.

3.3. Research Philosophy

Research philosophy is a theoretical framework used by researchers to gather, study and interpret data collected in a research (Palagolla, 2016). Remenyi, Pather and Klopper (2011) state that it is the basis of a study, which guides the selection of a research design, data collection and analysis. A philosophical assumption establishes the thought processes used for coming to conclusions. These assumptions are vital to establish before proceeding with a research study, as the research philosophy provides the foundation for adopting the appropriate methods and strategies to carry out a study (Mesel, 2013; Palagolla, 2016). The two main philosophical assumptions used to develop research methodologies are ontology and epistemology (Remenyi et al, 2011; Mesel, 2013).

3.3.1. Ontology

Ontology is a concept that examines the existence and associations between different social structures, actors, and cultural norms (Snape & Spencer, 2003; Richards, 2009). Furthermore, ontology is the study of the "*nature of existence and structure of reality or what it is possible to know about the world*" (Al-Saadi, 2014:1). Additionally, the ontological assumption is what we make about the nature and existence of reality. Killam (2013) describes the ontological perspective as one in which a researcher ponders whether reality exists, independently of their perceptions of it. As such, decisions for the research methodology employed comes as a result of the ontological perspective. This is determined by whether the researcher perceives as "*external, independent reality or an experienced, constructed reality based on social or individual human conception*" (Jackson, 2013: 52).

In the context of this study, ontologically, we know that BDA tools and their challenges exist in various environments. Gulgec, Shahidi, Matarazzo and Pakzad (2017) state that one of the main challenges with using BDA tools is the processing and transmission of big data that can keep abreast with the velocity at which organisations generate data from various sources. We know that BDA tools are selected for use in various environments. Marshall, Mueck and Shockley (2015) mention that many organisations understand the potential of big data analytics tools to assist in predictive analytics of customer needs and behavior and make use of these tools to support innovation. Thus, the ontological stance seeks to explore what is not known about the selection and use of BDA tools in various environments.

3.3.2. Epistemology

Epistemology provides insight into the nature of knowledge. Scotland (2012) states that the epistemological assumption concerns "*how knowledge can be created, acquired and communicated*". Essentially, epistemology is what can be known about a certain reality. Furthermore, Jackson (2013) states that epistemology is the logical study of knowledge and how that knowledge came to be true. A researcher's epistemological stance is vital to the decision of research approach and methods, as how a researcher seeks and develops new knowledge relies on the approaches and methods employed (Scotland, 2012; Jackson, 2013). This justifies for how a study brings about new knowledge. An ontological stance that puts knowledge through an interpretation means that epistemologically, the knowledge is uncovered through meaning and explanation (Bahari, 2010; Jackson, 2013).

In this study, epistemologically, the assumption is that a decision support framework can be developed to address the challenges with BDA tools selection.

Interpretivism

Interpretivism states that reality does not exist independently from our knowledge of it (Bahari, 2010; Goertz & Mahoney, 2012; Jackson, 2013; Al-Saadi, 2014). Scotland (2012:12) states that "*knowledge and meaningful reality are constructed in and out of interaction between humans and their world and are developed and transmitted in a social context*". Essentially, what this is saying is that reality is only understood from the participants' viewpoint in that social context. Interpretivism is not objective as the findings are influenced by a researcher's perspective and the understanding that the researcher understands that the social world is seen from their and the participants' viewpoints (Goertz & Mahoney, 2012; Klakegg, 2016). In interpretivism, "knowledge is seen as personal, subjective and unique" (Al-Saadi, 2014: 7). Klakegg (2016) states that interpretivist epistemology is one of ontological subjectivism.

Objectivism

Objectivism states that reality exists independently from our understanding of it, and that it can be observed in a direct and clear-cut way (Jackson, 2013). Social phenomena and its meaning are unable to change. Furthermore, reality is determined in measurable terms rather than the researcher's experience (Jackson, 2013; Al-Saadi, 2014). Additionally, objectivism aims to determine casual associations that explain social phenomena (Ratner, 2002). The process involves the development of hypotheses from the view of the researcher, as objectivists maintain that "*there are independent causes that lead to the observed effects, and hypotheses are either verified or refuted by the observed effects*" (Holden & Lynch, 2004: 407).

Based on the objectives of this study, objectivism was found not to be suitable for the following reasons: (1) this study was not determined by any attributes regarding BDA tools in an organisation; (2) the study had no set criteria for evaluating the selection of BDA tools in an organisation.

Subjectivism

This study follows a subjective ontological stance. Subjectivism is concerned with the idea that social reality is a product of the interactions with it (Bahari, 2010; Lemke, 2017). Furthermore, Lemke (2017) states that subjectivism refers to a belief in which social phenomena are constructed from the discernment of reality. Subjectivists concentrate on the explanation and interpretation of social phenomena as opposed to its measurement (Nissen, 2015). Essentially, researchers who take a subjective stance maintain that it is an inquiry into the meaning participants attach to a phenomenon rather than causality. The goal of subjectivist research is to interpret and understand a problem in a particular environment.

It is accepting that multiple realities exist, and that reality is subjective as seen by the participants in a study. In this study it is known that BDA tools are being selected and used in various organisational settings, and that challenges exist in the selection of these tools in organisations.

3.4. Research Approach

In research, there are three main approaches employed to achieve research objectives; namely, deductive, inductive and abductive approaches. The approach chosen for a research is based on the philosophical assumption.

3.4.1. Deductive approach

The deductive approach involves beginning from a theory, and obtaining and testing hypotheses (Woiceshyn & Daellenbach, 2018). Essentially, deductive reasoning begins from a theoretical base upon which multiple hypotheses can be deduced. Hyde (2000) states that a researcher that employs deductive reasoning uses an existing theory and identifies aspects of refinement upon which hypotheses are derived and data is collected. Furthermore, Soiferman (2010) posits that using deductive reasoning in a study is usually to test theories by searching for evidence to either refute or support the hypotheses.

The deductive approach was found to be not suitable in this study as the study does not aim to do an experiment of various BDA tools in an attempt to verify or refute their selection.

3.4.2. Inductive approach

Inductive research approach utilises inductive reasoning which advances from specific observations to broader generalisations. By using inductive reasoning, the research begins with particular statements and proceeds to identify patterns and themes in data (Burney & Saleem, 2008). This process allows a researcher to form a hypothesis that can be explored. Subsequently, the outcome of such an exploratory exercise is to lead to general conclusions. Furthermore, Hyde (2000) states that inductive reasoning allows researchers to gather information to detect the theme which leads to the development of theories.

This study aims to develop a decision support framework to assist organisations in selecting BDA tools; that is, to gather data from specific sources and create a decision support framework that can be used by various entities. Therefore, the inductive approach was employed.

3.5. Research Methods

Quantitative and Qualitative are the main research methods frequently followed in IS research. In addition, both methods can be combined to form the mixed method. The following section describes these methods.

3.5.1. Quantitative methods

Quantitative research methods involve conducting research with facets of reality that can be quantified or measured. Chan (2000) states that the use of quantitative methods seeks to gain precise measurements that will allow for statistical analysis. It proposes to measure the associations between variables. The focal point is on objectivity, meaning that data is collected in a systematic and objective way (Ponelis, 2015). Quantitative methods are specifically suited for studies that are collecting measurable inferences from sets of data.

In the context of this study, the quantitative method was found to not be suitable as the objective of the study was not to make any quantifiable inferences about the selection of big data analytics tools, but rather (1) to understand the factors that influence the selection of tools in organisations; (2) to formulate criteria that can guide the selection of BDA tools in organisations.

3.5.2. Qualitative methods

Qualitative research explores the process of allocating meaning. It considers that there exist multiple realities based on the establishment of an ever-changing reality (Lázaro & Marcos, 2006). It constructs a comprehensive understanding of data. Similarly, Ponelis (2015) states that the qualitative method in information systems research aims to probe phenomena through data from various sources, such as documents, interviews, and observations. Furthermore, qualitative research assists in gaining extensive insights into compounded information systems practices. The study aimed to develop a decision support framework for selecting BDA tools in organisations by examining factors that influence their selection and through the formulation of criteria that can be used to guide the process. Therefore, the qualitative research method was employed in this study.

3.6. Research Design

Research design provides a plan that governs the procedures for data collection and analysis in a way that is relevant to the study (Leech & Onwuegbuzie, 2009). It is a tactical framework that connects the research question and the implementation of the research. (Leech & Onwuegbuzie, 2009; Creswell, Hanson, Clark Plano & Morales, 2007). The research design ensures that the study achieves its objectives with the available resources (Ridder, 2017). There are several qualitative approaches to research design, including grounded theory, phenomenology, action research, and case study research (Creswell et al., 2007).

3.6.1. Case study

Merriam and Tisdell (2015) state that case studies can be used in an assortment of contexts, for example, organisations within information communications technology and small communities in developing countries. Additionally, a case study as a research design is distinctly alluring for examining and understanding processes that can help improve practices in information systems. Pickard (2013) states that the purpose of employing a case study design is to provide a comprehensive description and investigation of a unit within a specific context in an attempt to provide insights into reality. Furthermore, the use of a case study research design has strengths in displaying mutual understanding among research subjects (Ponelis, 2015).

Developing countries ere chosen as a case study to gain a deeper understanding of how BDA tools are selected and used in organisations. The cases consisted of one organisation within the financial sector, peer-reviewed articles, and white papers in the financial sectors and healthcare facilities. The peer-reviewed articles and white papers were classified based on the scope and year of publication. The scope covered included BDA tools/techniques and decision support frameworks.

How BDA tools are selected and used in organisations varies, including the strategies for implementation. The study adopted the case study research design, together with the qualitative research method.

3.7. Data Collection

Data collection is the process of using tools and techniques to collect information about a phenomenon (Gill, Stewart, Treasure & Chadwick, 2008). Qualitative data collection is not numeric and mainly focuses on gaining information about insights and meaning; as such, the type of data collected needs to be nuanced and rich (Barrett & Twycross, 2018). A number of methods and techniques are used for qualitative data collection, including textual documents, interviews, observations, and focus groups (Gill et al, 2008).

3.7.1 Interviews

Interviews are employed to gather data from participants. In a research, the researcher poses questions to the participants and reports their responses. Interviews may occur virtually, telephonically, or face-to-face. The purpose of conducting an interview is to collect information about a specific phenomenon or subject area from the view of the participants (Alshenqeeti, 2014). There are different types of interviews: structured, semi-structured, and unstructured (Alshenqeeti, 2014; Kallio, Pietilä, Johnson & Kangasniemi, 2016). Structured interviews use a standardized list of questions, whereby the interviewer sequentially follows through the list of questions (Gill et al, 2008; Kallio et al, 2016). Semi-structured interviews make use of a list of predetermined questions and allow the interviewer to ask questions that may arise from the conversation. As such, semi-structured interviews contain elements of both structured and unstructured interviews (Kallio et al, 2016).

Typically, interviews are regarded as a primary data source as information is collected directly from the source (Gill et al., 2008). However, in this study, the interviews used are regarded as a secondary source of data as another researcher conducted the interviews. The rationale for making use of these interviews is because the criteria and subject area for the study matched the objectives, which were to examine the factors that influence the selection of BDA tools in an organisation and to formulate criteria that will guide the selection of BDA tools in an organisation.

The interviews were conducted at a financial institution in Cape Town, South Africa. The participants include IT and Business employees who have working knowledge of selecting and using BDA tools.

3.7.2 Documentation

The documentation technique for data collection consists of probing and assessing documents through the examination of data in order to extract meaning and gain comprehension. Bowen (2009) states that documents incorporate text that can be utilised by the researcher to perform a systematic evaluation. Documents can include books, peer-reviewed articles, software manuals, and meeting agenda. The purpose of using the documentation technique is to determine, review, and unify the data contained within the documents (Mills, Bonner & Francis, 2006). The logic behind using documents lies in the value that textual data brings to case study research and the effectiveness as an autonomous method for qualitative research. Corbin and Strauss (2014) state that the documentation technique is especially suited for qualitative studies that aim to produce plentiful descriptions of phenomena.

Documents accessed and obtained were from peer-reviewed journals and organisational white papers. Information about the documents obtained for the study are presented Table 3.1. Each document is assigned code as shown in the table. The code is purposely for identification and referencing.

Table 3.1 - Data Collection and Coding

Healthcare Facility	Code	Financial Institution	Code
A Big Data Approach for Querying Data in EHR Systems - *Cassavia, Ciampi, De Pietro & Masciari (2016)*	H01	The Role of Big Data, Data Science and Data Analytics in Financial Engineering - *Chakravaram, Rao, Srinivas, & Ratnakaram (2019)*	FIN01
A Predictive Analytics Toolbox for Medical Applications - *Valenzuela, Rozenblit & Hamilton (2014)*	H02	A review of credit scoring research in the age of Big Data – *Onay & Öztürk (2018)*	FIN02
Big Data in Health Informatics Architecture - *Onyejekwe (2014)*	H03	A Big Data Financial Information Management Architecture for Global Banking - *Munar, Chiner & Sales (2014)*	FIN03
A Case Study of HealthCare Platform using Big Data Analytics and Machine Learning - *Islam, Liu, Wang, Zhou, Yu & Wu (2019)*	H04	How FinTech is shaping Financial Services – *PwC, Global FinTech Report March (2016)*	FIN04

Healthcare Facility	Code	Financial Institution	Code
Big Data in Healthcare: Are we getting useful insights from this avalanche of data? – *Adenuga, Muniru, Sadiq, Adenuga & Solihudeen (2019)*	H05	Suitability of Big Data Analytics in Indian Banking Sector to Increase Revenue and Profitability - *Srivastava, Singh, Sanwar & Tyagi (2017)*	FIN05
Hadoop-Based Intelligent Care System (HICS): Analytical Approach for Big Data in IoT - *Rathore, Paul, Ahmad, Anisetti & Jeon (2017)*	H06	Creating value from data – *PWC, February (2019)*	FIN06
Big Data solutions in Healthcare: Problems and perspectives – *Mathew & Pillai (2015)*	H07	The motivation of big data technology adoption in Saudi banks – *Almoqren & Altayar (2016)*	FIN07
Big Data In Health Care: Using Analytics To Identify And Manage High-Risk And High-Cost Patients - *Bates, Saria, Ohno-Machado, Shah & Escobar (2014)*	H08	Digitalisation and Big Data Mining in Banking - *Hassani, Huang & Silva (2018)*	FIN08
Determinants of Big Data Adoption and Success - *Al-Qirim, Tarhini & Rouibah (2017)*	H09	The value of big data: how analytics differentiates winners – *Wegener & Sinha (2013)*	FIN09
Concurrence of big data analytics and healthcare: A systematic review **-** *Mehta & Pandit (2018)*	H10	Big Data Analytics Enabled Smart Financial Services: Opportunities and Challenges – *Ravi & Kamaruddin (2017)*	FIN10
An integrated big data analytics-enabled transformation model: Application to health care**. -** *Wang, Kung, Wang & Cegielski, (2018)*	H11	Big data's role in expanding access to financial services in China - *Kshetri (2016)*	FIN11

3.8. Data Analysis

Data Analysis is the process of interaction amongst raw data, and the process and methods used to interpret and organise the data, and the findings (Caudie, 2004). It is "*making sense of relevant data gathered from sources such as interviews and documents*", and subsequently unveiling what the data uncovers (Caudie, 2004:417). Qualitative data analysis entails organising the collected data in a way that is relevant to the study. Qualitative data analysis is determined by the researcher's interpretations of the data, guided by a theory (Thomas, 2003). Researchers embark on an analytical process that involves turning raw data into comprehensible and perceptive analysis by using different approaches and theories (Liamputtong, 2009). The analysis of the data was guided by actor-network theory.

Actor-Network Theory was used as a lens to guide the data analysis as follows:

i. Determining the actors and networks that exist in the selection of BDA tools
ii. Determining how networks are formed
iii. Establishing the roles of various networks and how they come together to influence the selection of BDA tools
iv. Using the moments of translation to determine the communication and roles of actors, and how their actions influence the selection of BDA tools
v. Using moments of translation to study the association amongst actors and networks in the creation of criteria that assist in selecting BDA tools

3.9. Ethical Consideration

Ethical considerations are the moral standards that govern how researchers carry out and document studies (Rani & Sharma, 2012). They are the guidelines for ethically undertaking a study. Arifin (2018: 30) states that the "protection of human subjects through the application of appropriate ethical principles is important." Ethical considerations are important as they require the researcher to protect the dignity of participants and report competently and honestly on the information researched (Akaranga & Makau, 2016).

Ethical considerations with regard to Intellectual Property had to be honoured by acknowledging contributions to the study. Institutions of higher learning have a research code of ethics that aims to protect all parties involved in a research. Therefore, the researcher had to abide by the CPUT University Research Code of Ethics by taking the code of ethics into account during the data collection and data analysis processes.

Some of the considerations and ways in which they were adhered to during the research are as follows:

1. Access to academic journals was granted by student number.
2. Access to documentation (peer-reviewed articles) was obtained from academic journals the university subscribes to.
3. The authors of the materials used were clearly acknowledged through referencing.
4. Ethical clearance was obtained from CPUT to conduct the study.

3.10. Summary

In this chapter, the researcher discussed the research methodology chosen and employed in the study. The discussion included research philosophy, approach, methods, design, data collection, data analysis, and ethical considerations.

As mentioned above, the research methods employed are associated with qualitative research studies. This includes subjectivism, interpretivism, and the inductive research approach. Additionally, secondary data from interviews and documentation were collected. The Actor-Network Theory was used as a lens for data analysis. Finally, the ethical considerations that were applied to guide the study were discussed.

The next chapter is an overview of the case used in the study.

CHAPTER 4
CASE OVERVIEW

4.1. Introduction

This chapter describes the details of the case study selected. The objective of the case study in the context of the use of information systems specifically big data analytics tools within financial services and healthcare institutions. An in-depth examination and analysis of big data analytics over time were carefully selected to illustrate the problem and investigate it. The documentation and interviews used in this case study were selected based on the following criteria: 1) are the cases in line with the objectives of the study?, 2) what are the frames of reference?, and 3) where can these cases be found?

4.2. Data collection and analysis overview

A systematic approach for data collection and analysis was followed in carrying out this study as depicted in Figure 4.1. The aim and objectives of this study guided these approaches. In phase 1, the environment in which to collect the data was chosen based on the objectives of the study. That is financial institutions and healthcare facilities within developing countries. A detailed description can be found in section 4.4. In phase 2, two types of data (big data analytics and decision support frameworks) were collected within the environment of the study as further explained in section 4.5.

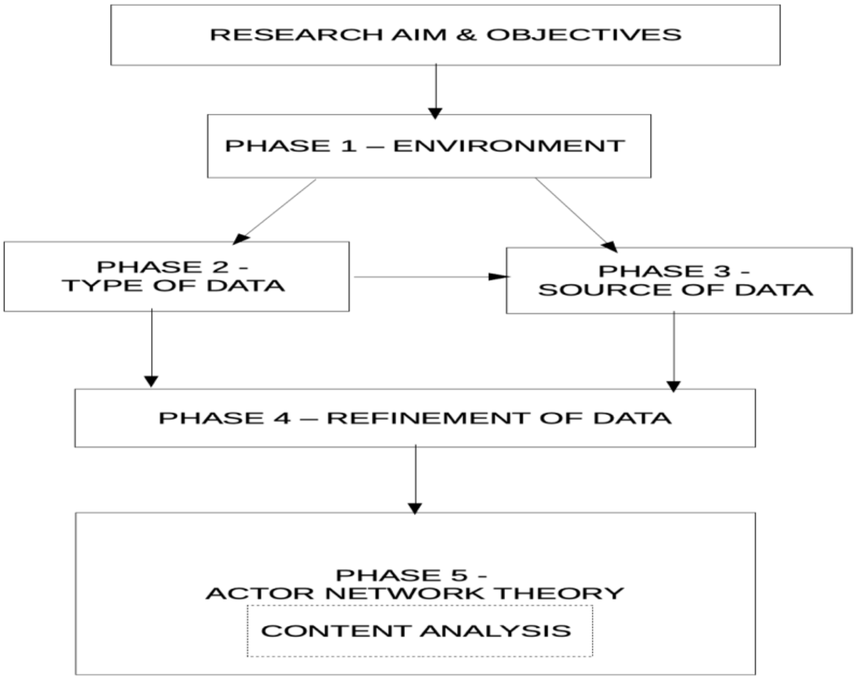

Figure 4.1: Data collection and analysis overview

Criteria were formulated that was used as guide through sourcing of the data from peer-reviewed articles and white papers as discussed in section 4.6. The criteria used was the area of focus (type of data) and the year of document publication. After the data was collected, it was refined and coded by grouping it into environment of concern. Section 4.7 illustrates the refinement through table 4.3. Lastly, the analysis of the data was done by conducting a content analysis guided by the moments of translation from the perspective of the actor network theory, which is further explained in section 4.8.

4.3. Qualitative method

Information systems qualitative research in this study aims to investigate the selection and adoption of big data analytics tools through qualitative data from archival material such as peer-reviewed articles and white papers. An in-depth description of the criteria for the peer-reviewed articles and white papers can be found in section 4.5 of this chapter.

To investigate and uncover the phenomena for this study which is the factors that influence the selection of big data analytics tools in organisations, data in the areas of big data analytics and decision support frameworks was collected. Furthermore, the areas of focus were broken down in sub-areas to assist in uncovering the phenomena of study in more detail. The sub-areas for further investigation are big data analytics, the theory of how decision support frameworks come into existence within organisations and the practical use of decision support frameworks within organisations in facilitated business decision-making processes.

The qualitative research method was employed in this study to understand the meaning and perspective of big data analytics tool selection. It conducts an analysis of documents and texts to learn more about dispersed knowledge. Furthermore, because qualitative research involves a systematic collection of data as stated by Hammarberg, Kirkman and de Lacey (2016). This study makes use of structure for the collection of data by firstly establishing the environment for the study (Phase 1), secondly the areas of focus to cover (Phase 2) and lastly where to source the data (Phase 3). Additionally, the organisation of the data for analysis has been arranged in a structural format that separates the data into the different environments of study

The subjective reasoning of the research was employed in the analysis of the data, through the content analysis which is guided by the Actor Network Theory as mentioned in Phase 5.

4.4. PHASE 1 – Environment

As shown in Figure 4.2, the data collection and its analysis overview focused on identified environment (P1). Developing countries was chosen as the environment of study. The environment was divided into main areas, financial institutions and healthcare facilities as depicted in Figure 4.3.

Even though developing countries was chosen as the environment, no specific financial institution or healthcare facility was used in the study. This is primarily because it impossible to find organisations that have successfully deployed and implemented big data analytics at the time of this study. This challenge could be attributed to novelty of big data analytics technology in developing countries. However, academic literature and professional whitepapers (documents) were available enough to carry out this study.

Financial institutions and Healthcare facilities were used as the environment for this study. The rationale for this, was to ultimately carry out a comparison of big data analytics in a South African context within two major sectors that are reported to have made strides with the use of big data analytics.

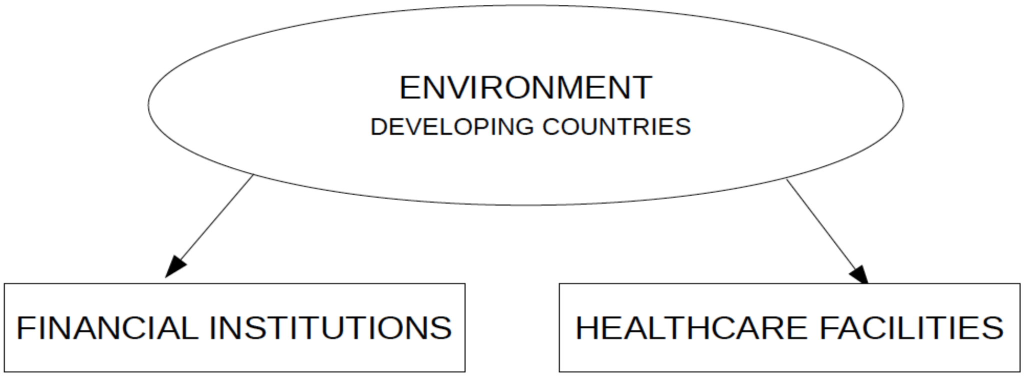

Figure 4.2: Environment

Financial Institutions

Big data analytics has been found to foster significance in financial institutions because of the value it brings in unlocked patterns in money movements that assist in detecting criminal activity as well as understanding of customer behavior (Srivastava and Gopalkrishnan, 2015). Furthermore, financial institutions are reaping the benefits of big data analytics to develop models that can be used in business process efficiency ranging from regulatory compliance, financial crime management to sentiment analysis (Trelewicz, 2017).

Financial institutions are facing growing data processing demands, in which big data analytics could provide significant benefits (Munar, Chiner and Sales, 2014). The financial institutions that include but are not limited to investments, insurance and banking require rigorous data administration, analysis, and reporting capabilities.

Healthcare Facilities

Health data is dramatically growing and will continue to grow in the years to come (Dimitrov, 2016). The benefits of digitising, merging and efficiently using big data sees healthcare organisations uncover insights that help in the early detection of diseases, patient care management and health care fraud detection (Raghupathi & Raghupathi, 2014).

The rapid growth in big data analytics has been noted to play a vital role in the advancement of healthcare. Belle, Thiagarajan, Soroushmehr, Navidi, Beard and Najarian (2015) states that big data analytics tools can be used to manage, integrate and analyse large volumes of structured and unstructured data being produced by healthcare information systems. Similarly, big data analytics has been used in supporting the process of disease exploration and patient care delivery.

4.5. PHASE 2 – TYPE OF DATA

Based on the objectives of the study, there were two areas of focus in the collection of data as shown in Figure 4.3. The areas are big data analytics and information systems, as depicted in Tables 4.1 and 4.2.

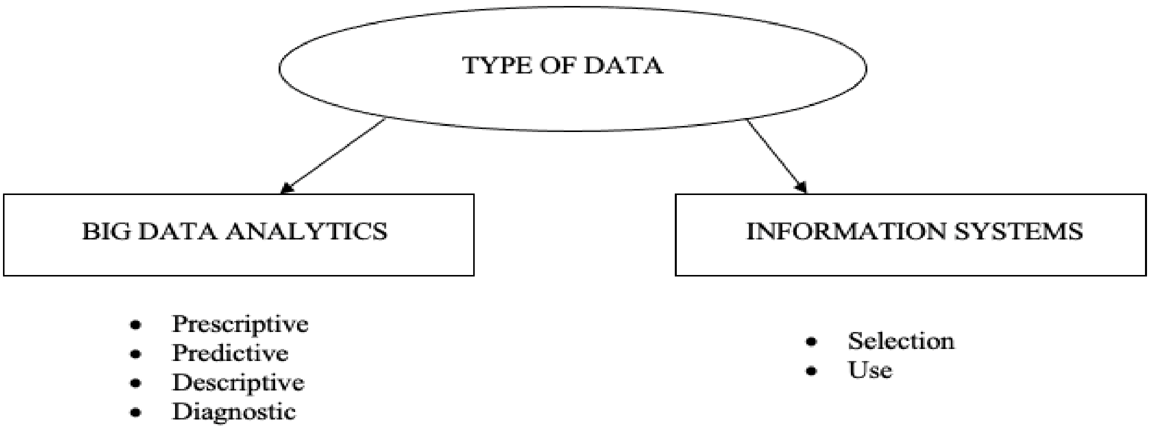

Figure 4.3: Type of Data

As shown in Table 4.1, the big data analytics consist of Prescriptive analytics, Predictive analytics, Descriptive analytics, and Diagnostic analytics. These four analytics approaches were selected for the study primarily because of the following reasons:

1. Several articles that deal with data analytics focus primarily the four types of analytics, deeming them most popular. This is illustrated by Banerjee, Bandyopadhya and Acharya (2013) stating that data analytics can be predictive, prescriptive, diagnostic and descriptive. Similarly, Nayebi, Ruhe, Mota and Mufti (2015) mentions prescriptive, descriptive, diagnostic and predictive analytics within their study.

Big Data Analytics	Description	Focus
Prescriptive Analytics	Prescriptive analytics describes the options of action that may be taken in order to optimise business processes, by linking varying decisions with predicted outcomes (Bertsimas & Kallus, 2020).	1. Benefits – Focus is placed on deriving the advantages of using each type of analytics within Healthcare facilities and Financial Institutions. 2. Value – The importance and usefulness of each type big data analytics for healthcare big data and financial big data is uncovered. 3. Adoption – The acquisition and use of big data analytics types within Healthcare and Financial Institutions. 4. Selection – Make informed and guided decisions in choosing of types of big data analytics tools for healthcare facilities and financial institutions.
Predictive Analytics	Predictive analytics probes past and present data to provide a forecast about the future. Essentially, it analyses data to give insight into what will happen (Waller & Fawcett, 2013). For example, predictions on product sales for an upcoming month.	
Descriptive Analytics	Baesens, Van Vlasselaer and Verbeke (2015) note descriptive analytics as the simplest form of analytics because it uses data collected to synopsise what has happened. It assists in understand past performance through unravelling what has happen and what is currently happening.	
Diagnostic Analytics	Diagnostic analytics is uses exploratory analysis of data to discover the causes of patterns and insights. It goes beyond describing data by providing insights into why did certain things occurred (Banerjee, Bandyopadhya & Acharya, 2013).	

Table 4.5: Big Data Analytics

As shown in Table 4.2, the information systems focus areas consist of Selection and Use. These two focus areas were selected for the study primarily because of the following reasons:

Table 4.6: Decision Support Frameworks

Focus area	Description
Information Systems – Selection	Information systems such as decision support frameworks assist in overcoming barriers to decision making that can be caused by lack of experience and placing no consideration to alternatives (Farshidi, Jansen, de Jong & Brinkkemper, 2018). Aslam, Ahmad, Saba, Almazyad, Rehman, Anjum and Khan (2017) states that DSS aid decision-makers with multi-criteria

	decision-making problems, such as big data analytics tool selection.
Information Systems - Use	The use of information systems in solving multi-criteria decision-making problems consists of a decision model that has knowledge of the criteria for selection, the alternatives and the relationships amongst them.

4.6. PHASE 3 – SOURCE OF DATA

Qualitative research acknowledges three main sources of empirical data: observation, interviewing, and documents (Bachiochi & Weiner (2002). As mentioned, this study made use of documents (peer-reviewed articles and white papers) and secondary interviews as a source of data. Bauer, Bicquelet and Suerdem (2014) states that that documents are usually produced separately from the current researcher in a “naturalistic environment”.

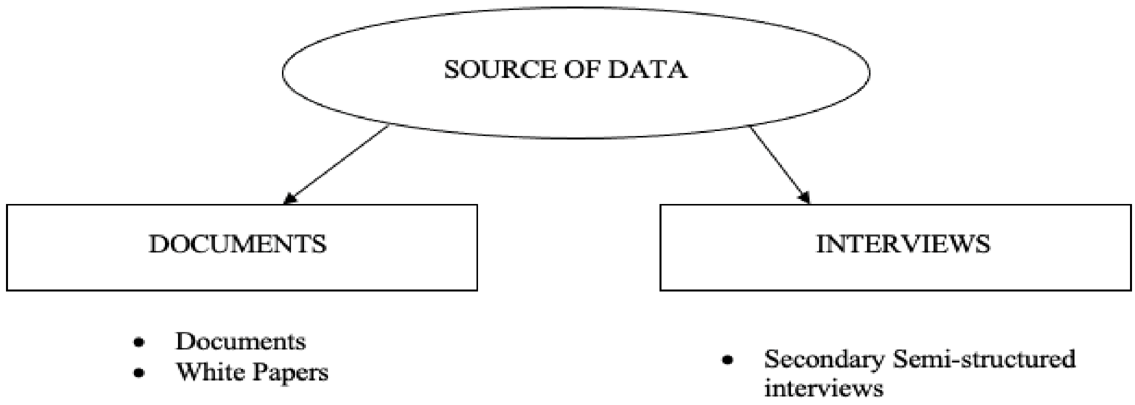

Figure 4.4: Source of Data

The use of documents unlocks sources of information where data in other respects may be hard to collect because of researcher constraints and challenges (Miller & Alvarado, 2005). The selection and analysis of documents is not independent from the ideals of social actors and as such are produced by researchers who transfer a way of thinking (Bauer, Bicquelet & Suerdem, 2014).

The study was carried out within the environment of a developed countries through the sourcing of documents in the areas of big data analytics and the selection and use of big data analytics tools, as mentioned in Phase 1. However, documentation within other environments (developed countries) were also used as supplementary documentation. The academic literature and documentation sourced followed the criteria as mentioned below:

1. Published between the years of 2009 and 2019. Selecting documents within this 10-year timeframe provided the study with a sound historical range and consistency of meaning of the phenomenon (Nakashololo & Iyamu, 2019).
2. The areas of focus include Big data analytics and Information Systems as this is based on the objectives of the study.

The data collected came from two main sources, namely documents (Peer-reviewed articles and White papers) and interviews as shown in Figure 4.4

a) Peer-reviewed Articles

The peer-reviewed articles (as data) were collected based on Tables 4.1 and 4.2. Different databases were used in search for the articles. This includes Emerald, SpringerLink, IEEE Xplore Digital Library and Proquest Computing.

These databases were selected for the following reasons:

1. The databases host majority of IS/IT journals.
2. The university (CPUT) subscribes to the databases. This makes access easier and possible in the process of collecting the data (accessing the articles).

b) White Papers

A white paper is described as a report that aids in solving of problem. The aim of a white paper is to educate the reader to bring to light a new and different perspective. However, Willerton (2013) state that there are different types of white papers. Evaluator's guide - provides information detailing the functionality and features of a product. Position paper - advocates for and explains are particular trend or technology. Business benefits - provides information on why a customer would require a certain product. Competitive review - differentiates a product by positioning it amongst competitors.

The white papers that formed part of the data were collected from company websites of companies within developing countries which were in the Healthcare and Financial Services.

The data collected was a total of 22 documents; 11 documents within healthcare facilities; and 11 documents within financial institutions as described in chapter 3.

Additionally, semi-structured interviews from a financial intuition within South African was used as secondary data.

4.7. PHASE 4 – REFINEMENT OF DATA

The refinement of data was a process to cleanse the raw data collected. It involved selection, categorisation, coding and summarising of the raw data in the context of the study. Selection involved choosing data that either covered big data analytics in healthcare facilities or financial institutions. A code was assigned to each document and interview transcript in order to make it easier to reference in data analysis. Data summary involved going through each document and interview transcript to uncover points of relevance in the context of the study. The refinement of data for documentation was documented. Information about the documents are shown in Table 4.3. Only the student and supervision have access to the document for confidentiality purposes.

Table 4.7: Data collection and coding structure - Documents

Healthcare facility	Code	Financial institution	Code
First set of health-related documentation.	H01	First set of finance-related documentation.	FIN01
Second set of health-related documentation.	H02	Second set of finance-related documentation.	FIN02

4.8. PHASE 5 – Analysis of the data

The analysis of the data was conducted by doing content analysis that was guided by the moments of translation through the perspective of Actor Network Theory (ANT). The research objectives were used to guide the analysis of data and keep from deviating from the point of the study, as depicted in Figure 4.5. The objectives of the study informed the content analysis of the data. As mentioned, content analysis was guided by ANT, firstly actors and networks were described. Secondly, the moments of translation were used to further analyse the data.

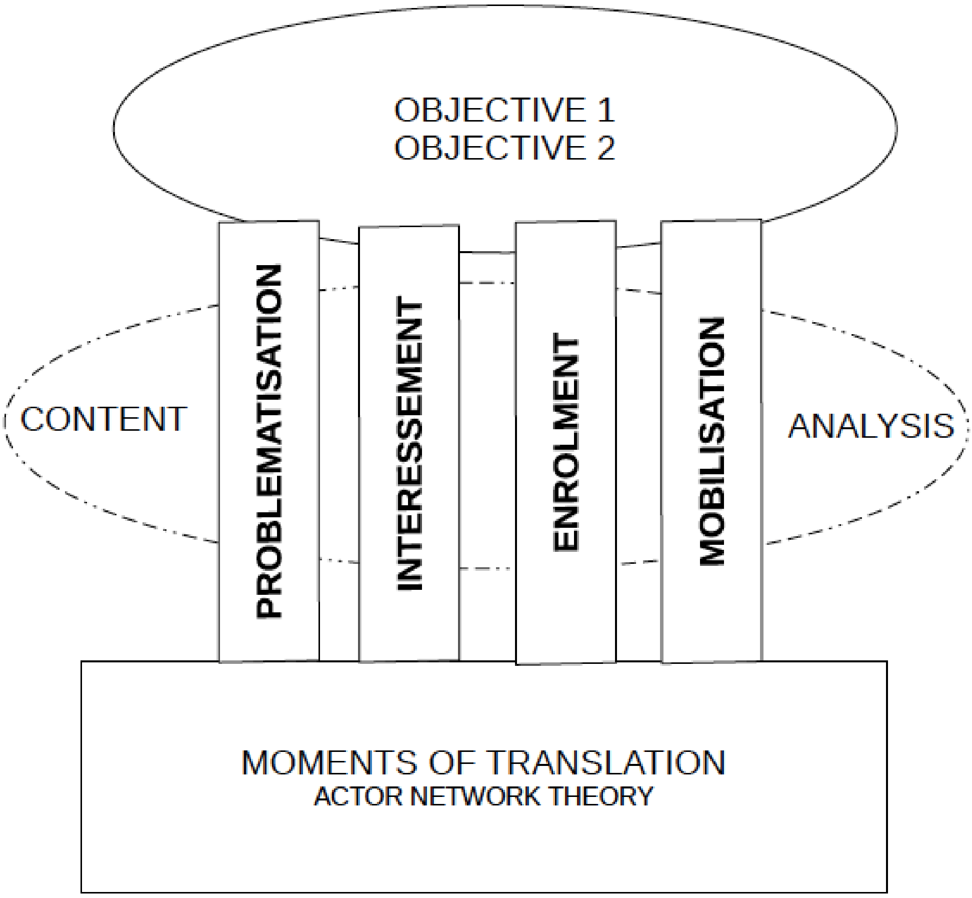

Figure 4.5: Analysis of Data

4.9. Content Analysis

Erlingsson and Brysiewicz (2017) states that the objective of qualitative content analysis is to thoroughly convert a large amount of text into a highly systematised summary of information. The analysis of raw data for documents to form categories is a process of "further abstraction of data at each step of analysis: from the literal content to latent meaning", as can be seen in Figure 5. Furthermore, Erlingsson and Brysiewicz (2017) note that content analysis is a reflective process that requires the researcher to code and categorise meaning then return to the raw data. Additionally, Smith (200) defines content analysis as a research technique used to make valid deductions through the coding and interpretation of data by logical evaluation.

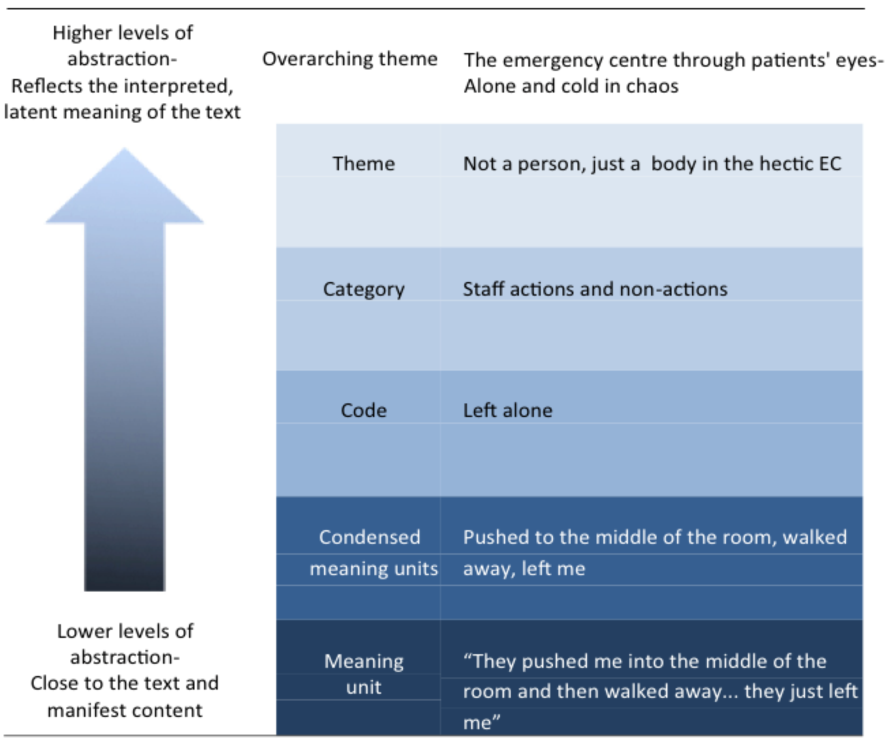

Figure 4.6 Examples of Analysis (Erlingsson & Brysiewicz, 2017)

In this study, the initial step was to read and re-read the documents collected to get a general understanding of what the text is saying. The researcher refined the text, by focusing on the environments of focus outlined in the Phase 4, and further condensed into the scope outlined. Each document collected was labelled with code, which was grouped based on scope and environmental context.

4.10. Actor-Network Theory

The application of ANT assisted to conceptualise how big data analytics in healthcare facilities and financial institutions is used and adopted by different actors, evolving into a more nuanced idea of the dynamic associations amongst actors. This is imperative because of the ever-changing area of finance and healthcare. Cresswell, Worth and Sheikh (2010) illustrated that ANT can be a useful tool in understanding the relationships amongst actors in IS/IT implementation.

Furthermore, ANT was used to help guard against superficial arguments in reference to the role of objects in shaping the use and adoption of big data analytics tools. The objects were seen to be playing an active role in a dynamic network. The use of ANT allowed for understanding the separation between material and human worlds, this is illustrated by analysing the role that big data analytics played in interposing social relationships within healthcare facilities and financial institutions.

The use of ANT made cognisant that multiple realities can coexist, with big data analytics tools being used in healthcare facilities and financial institutions in different contexts by different actors.

4.11. Summary

This chapter provides an overview of the environment that was selected in this study. In the above-mentioned sectioned, the environment of the study, type of data, source of data and analysis of data were discussed. Furthermore, the criteria and rationale for the selection was also discussed.

CHAPTER 5
DATA ANALYSIS AND RESULTS

5.1. Introduction

This chapter presents the analysis of data, based on the objectives of the study, which are stated in chapter 1 and revisited in chapter 3, as follows: to examine and understand the factors that influence the selection of big data analytics tools in an organisation, in order to formulate a set of criteria that can be used to guide the selection of big data analytics tools in an organisation. Based on the results revealed in this chapter, a decision support framework was created which can be used to guide the selection of big data analytics tools. The approach employed in the collection of data is discussed in chapter 3. The data and its format are covered in chapter 4.

This chapter is divided into six main sections. The first section introduces the chapter. The second and third sections present the overview and the data analysis, respectively. As mentioned frequently, particularly in chapters 3 and 4, the analysis of the data is guided by the actor-network theory (ANT). The findings from the data analysis are discussed in the fourth section. Based on the discussion, a set of criteria was developed and presented in the fifth section. The criteria are intended to be used as a guide in selecting big data analytics tools in both financial institutions and healthcare facilities. A conclusion on the chapter is drawn in the last section.

5.2. Overview of data analysis

As discussed in chapter 3, qualitative data was collected, which was informed by the objectives of the study. The data used in the analysis is documented and explained in chapter 4, as tabulated in Table 3.1. For ease of referencing, a format was adopted as follows: Type (Financial institution or Healthcare facility) of data; Order of number of documents in the table; Page number in the document. For example, H02:22 means H - health related data; 02 – the second document as tabulated; P – page number in that document.

As shown in Figure 4.1, the moments of translation was employed as a lens, from the perspective of ANT. The theory is extensively discussed in chapter 2, and its use in this study is covered in chapter 3.

The theory (ANT) was selected to conduct the data analysis in this study in order to determine the actors and networks that exist, how the networks were created, and how the networks fuse together to influence the selection and use of big data analytics tools in organisations. It was used also to assess the interaction of actors and their actions in influencing the selection of big data analytics tools in organisations, and to examine the association of actors and networks in criteria formulation that assists in the selection of big data analytics tools in organisations.

5.3. Data analysis

As briefly explained above and detailed in chapter 3, the content analysis approach was employed in the analysis of the qualitative data. This was guided, using the moments of translation from the perspective of ANT. The use of ANT as a lens for analysis, with particular focus on financial institutions and healthcare facilities in developing countries, is explained in chapters 3 and 4 The choice of the financial and health sectors was primarily because they seem to be the fastest growing industries in Africa where this study was conducted. Two different sectors were combined. This was purposely to ascertain and enact the level of generalisation in the use of certain criteria for the selection of big data analytics (BDA) across organisations.

In achieving the aim of the study, which is to propose a decision support framework as a solution to address the challenges in the selection of big data analytics tools in organisations, the analysis was conducted in accordance with the research objectives as presented in chapter 1, and revisited in chapter 3, as follows: (1) to examine and understand the factors that influence the selection of big data analytics tools in an organisation; and (2) to formulate a set of criteria that can be used to guide the selection of big data analytics tools in an organisation.

5.3.1 The factors that influence the selection of big data analytics tools in an organisation

The analysis begins with identifying the actors, their roles, and responsibilities. This takes cognisance of the fact that in ANT, actors are both humans and non-humans (Callon, 1986). This is followed by identifying and understanding the networks that exist, how the networks exist and how they influence the selection and use of big data analytics took place within organisations in developing countries. Thereafter, the four moments of translation are employed to examine how and why things happen in the ways that they do in the selection and use of BDA tools. These are done through an understanding of the interactions and negotiations that happen among actors in their various associations or groupings within organisations.

Actors

Human and non-human actors are involved in the selection, implementation, and use of BDA tools in both financial institutions and healthcare facilities. Someh, Davern, Breidbach and Shanks (2019) explain that the capacity and capabilities of people that are involved in BDA are crucial to its selection and effective implementation within organisations.

Within the financial institutions, the humans that are involved in the selection, implementation, and use of big data analytics include data analysts, database engineers, systems engineers, IT managers, compliance officers, and business managers. These individuals have different roles and responsibilities in the selection and use of BDA tools within their organisations. For example, the IT managers are tasked with selecting, configuring and implementing analytics solutions through an understanding of business needs and objectives. The data analysts make use of BDA tools implemented by the IT managers in carrying out analytics tasks towards fulfilling business needs. The database engineers and systems engineers handle the infrastructure and architectural considerations for implementing a BDA architecture. The regulatory compliance officials play a significant role in the selection, implementation, and use of BDA tools, mostly in financial organisations. It is evidently revealed in the data that:

> *"Governance systems regarding social and economic life must fully comprehend the workings of advanced analytics and algorithms behind BDA" (FIN02: 2).*

The non-human actors in the selection and/or use of big data analytics were divided into: technical and non-technical. The technical include artefacts, designs and methods, such as algorithms, architecture, and a financial technological model. The financial technological model refers to:

> *"The banking technological model: rich and complex workflows, massive volumes, enormous variety of data structures that must be combined together and stringent requirements of reliability, consistency (every single record counts), data back-up and persistency "(FIN03: 385).*

The non-technical include business models, business strategy, processes, and human resources.

Similar to the financial institutions, within the healthcare facilities, the actors are both humans and non-humans. However, the human actors slightly differ from those that are involved in the activities of financial institutions. The actors include healthcare practitioners, patients, executive management, and government representatives, such as the minister of health. Similar to the financial institutions, actors' roles and responsibilities are distinctively different from one another. Healthcare practitioners, notably doctors, nurses, and specialists provide healthcare services, such as diagnoses, prognoses, surgeries, and general patient care. The actors make use of insights gained from the use of BDA to improve quality of service delivery.

Patients are directly influenced by the use of BDA tools, as the information obtained from BDA activities is used to provide better services. The executive management of healthcare facilities are made up of a board of directors, facility directors and facility managers. They are involved in making decisions on the effectiveness of the use of BDA tools in operational efficiency, as well as engaging the IT specialists in the selection, implementation and use of BDA tools.

The human actors involved in the selection and use of big data analytics in Claremont Finance include data engineers, platform engineers, and market and business analysts. These actors have varying roles and responsibilities in the selection and use of BDA within their organisation. Market analysts make use of information gained from BDA initiatives to inform business decisions. One of the participants explains as follows:

> *"We use big data analytics to inform investment decision., That is a primary reason and it is an overlying or overarching decision for the organisation. It is an overarching reason because we are an investment management firm and the decisions that we make are for investment cases and the decisions have to be supported by solid evidence that the likelihood of the investment giving a return is higher and the risk of losing the value of that investment is lower" (FIN_INT01: 8 – 12).*

The data engineers make use of Extract, Transform and Load (ETL) tools connected to core systems. Essentially, the data engineers extract the data from the core system, transform it into a format that is usable for analysis and load it into their database platforms for analytics services such as reporting and visualization. Participant 2 is cited to have said:

> *"We have core systems; in other words, their normal functionality is to do that so we have a trading system that will go and pull that data in. We utilise that for compliance and business. We have, over the past year-and-a-half,*

an ETL. We use Pentaho. Pentaho has been our ETL for quite a number of years and we are exploring it as a bi reporting system. Again it is capable of handling big data Hadoop and that, but we don't have a use case for big data as yet " (FIN_INT02: 3 - 8).

Additionally, the platform engineers perform the administration and configuration of ETL and BDA tools within the organisation.

The non-human actors in the selection and/or use of BDA for healthcare facilities are divided into two categories: technical and non-technical. The technical actors include infrastructure, architecture, and technologies. Infrastructure for BDA comprises virtual and physical media for the storing of data, tools for collecting data and the networks that are used in the transfer and communication of analytics. The architecture used in facilitating big data analytics is notably a three-tier architecture that is comprised of a user-interface tier, middleware, and a data storage tier. In one of the studies, the architecture is described as follows:

"Implementing three-tier architecture with client tier providing access to system, middle tier for defining the rules and processing for dealing with heterogenous data in health care" (H07: 4).

The non-human technical actors within Claremont Finance are identified as vendor supportability and technical capabilities the BDA tools offer.

"We looked at things like the supportability; who supports it in terms of the vendor. We asked questions like, is there support in Cape Town, is there support in Africa, is there support in South Africa?" (FIN_INT01: 24 – 26)

"the ability to have adaptors and to be able to connect into any type of data (FIN_INT02: 7). It is able to do analytics, visualisation, and reporting; so, we have two requirements within that aspect" (FIN_INT02: 27 - 28).

Additionally, the usability of the BDA tools is also identified as a technical actor:

"So, there is quite a lot of things that go with that and then we looked at the usability of the tool; say, is it going to need more training for us?" (FIN_INT01: 29 – 30).

"Usability is something we definitely have to look at" (FIN_INT02: 21)

Furthermore, the development roadmap of the BDA tools outlined by the vendor is another important technical actor that influences the selection and use of BDA tools.

> *"We also looked at the roadmap of the tool where we looked at the development; are there improvements that would probably be coming with that? And we look at the strength of the vendor. Is the vendor likely to develop the tool further?" (FIN_INT01: 27 – 29)*

Some technologies used for big data analytics are Hadoop, Apache Spark, Machine Learning, Artificial Intelligence, Stream Computing and Data Warehousing. Furthermore, the non-technical actors were identified as standards, processes and skills.

The non-human non-technical actors that had an influence on the selection and use of big data analytics included the capabilities and skillset of technical staff.

> *"The first requirements now are around the organisation building a capability in-house for the company to be able to build a capability of the foundation of big data analytics" (FIN_INT01: 14 – 16).*

The pricing and dependability of the BDA tools, which is how cost-effective and reliable the BDA tools is:

> *"We did an evaluation of those tools against our objectives. Some of the factors used in the evaluation included pricing…" (FIN_INT01: 4 – 5).*

Adoption, which is defined in this context as getting the buy-in of business and management on the usefulness of the tools. Additionally, feasibility is another factor of influence which Claremont Finance defines as whether or not BDA tools are easy to implement.

> *"Because we are not experienced enough within that space, with all projects you are going to look at the feasibility; the feasibility of it is saying once you have experience it's faster and easier to implement something new because you have a better knowledge" (FIN_INT02: 42 – 45).*

Each of these actors in the financial institutions or healthcare facilities form part of a group or groups, which ANT refers to as a network. Each group (or network) often has a specific focus or objective, and has the capability of making a difference in the environment.

Actor-network

Within organisations, roles and responsibilities are assigned and executed accordingly, and ultimately decisions are made. The selection, use, and implementation of BDA within both financial institutions and healthcare facilities exhibited a group or groups of networks. Within a network, there were networks which often replicated themselves. This is referred to as a heterogenous network in ANT.

Within financial institutions, the networks were divided into two: The IT and business departments (or units). From the IT department perspective, the networks involved in the selection, use, and implementation of BDA tools were the IT management, project implementers, the project maintenance team, and the data analytics team.

The IT management consisted of various departmental managers within IT, such as the IT Infrastructure manager, the Data and Analytics manager, and the Technical Support manager. Project implementers and the project maintenance team included actors that implemented and maintained the data infrastructure, which was made up of the systems engineers and database engineers. The data analytics team consisted of the data analysts. These networks were in collaboration as mentioned below:

> *"The ability to exploit the potential value of data is contingent upon having the right technical infrastructure and management processes, as well as the right talent" (FIN06: 9).*

Similarly, within Claremont Finance, the networks are divided into Back-office operations (IT) and Investment and Business operations (Business). The IT unit included platform engineers and data engineers. The business unit consisted of market and business analysts.
The business department consisted of risk managers and compliance officers. Similarly, the networks that existed in the IT department and the actors within the business department had various roles and responsibilities that were assigned to them by the focal actors (the Data and Analytics manager). A network consisting of both business and IT was consciously formed because collaborative efforts and responsibilities are needed to implement BDA tools. The same IT management team was part of the executive comment of the IT department. This means that the IT management was a heterogenous network within the organisation.

Within healthcare facilities, various networks were identified. These networks were identified through roles, responsibilities, and the execution of activities.

> *"Healthcare decision makers and stakeholders can now apply the outcome of BDA obtained from big data to provide recommendations that can help their respective organisations solve problems related to differences in healthcare quality and escalating healthcare expenditure" (H05: 197).*

The networks were divided into four categories, namely; healthcare practitioners, regulatory, IT, and healthcare service receivers. This was based on the main functions of the health sector. Most importantly, this was to gain a better understanding of the specific tasks of the networks, and how they provide services. According to one of them:

> *"To fully realise the benefits brought forth by BDA, a need exists to shift the focus from technology tools to examine and present the managerial, economic, and strategic impacts of BDA and explore the effective path of how BDA can be leveraged to deliver business value for healthcare organisations." (H11: 64)*

Healthcare practitioners consist of nurses, pharmacists, specialists, and doctors. Within this main network, sub-networks were formed amongst healthcare practitioners with similar roles and responsibilities. The regulatory network was made up of government representatives and the executive management that influence decisions for implementation of BDA tools through realised benefits of use. According to an executive with a *government agency in the healthcare sector*:

> *"the use of BDA will improve both preventive care and the management of population health" (H03: 2).*

There has never been doubt in this view. The challenges many African countries struggle to address are how the BDA is selected and used. Healthcare service receivers consist of various types of patients; from those needing basic or general care to those with chronic conditions. Similar to that of the healthcare practitioners, there were heterogeneity of patients' networks, which were based on health conditions. The networks were either consciously or unconsciously formed, as the patients received care over a period of time. The formation of the networks can assist health practitioners and IT specialists in selecting the most appropriate BDA tools in fostering services. This means that IT as a network (unit) needs to collaborate more with the unit (network) that it enabled in order to gain a better understanding of their needs and requirements.

In the selection and use of BDA tools in healthcare facilities, collaborative efforts amongst team members from different networks was being achieved, and can be improved. One of the employees shared his views as follows:

> *"Proper implementation could enhance healthcare decision making and bring about productive outcomes. Also, a proper selection of tools to do analytics on health care data can provide promising results" (H05: 198).*

Some team members from the regulatory network, IT, and healthcare practitioners were assigned roles and responsibilities for either, in the selection or use of BDA tools.

The actors and networks were inextricable in the selection and use of BDA in both healthcare facilities and financial institutions. This is primarily because group or groups (network/s) could not be constituted with actors, and no actor could work in isolation, without colleagues, facility, and patients. In the process of selecting and using BDA tools for health services, interactions and negotiations happen within the networks, which ultimately require translations of events, activities and services.

Moments of Translation

The moments of translation in ANT is used to understand actors' roles and responsibilities, including how activities or events were negotiated and carried out in the selection and use of the BDA in both financial and health institutions in developing countries, with particular focus on the African continent. The moments of translation was particularly useful in understanding the stages (initiation to practice) that were involved in the selection and use of BDA in both financial and health institutions.

Table 4.1 presents a summary of the BDA tools selection from both financial and health institutions' perspectives, using the moments of translation. Although the summary is a combined view of financial and health institutions, the detailed analysis that follows is separated.

Table 5.8: Selection of BDA: moments of translation

Problematisation	Interessessment
The selection and use of BDA tools are guided by requirements, which are problematised through two different stages in an organisation. Firstly, business requirements are formulated. Secondly, the technical requirements are articulated. These processes (or stages) apply to both the financial and health institutions in many countries in Africa. In addition, there are different focal actors for the stages.	Various actors, health practitioners, IT specialists, patients, society, and the government are always interested in the services that are provided and received in the health sectors of many developing countries. This includes the tools (including BDA) that are used in providing the services. Some of the interested stakeholders in the financial institutions include financial service providers, regulators (professional bodies and government), clients, and business partners.
Mobilisation	**Enrolment**
Owing to the strict and sensitive nature of the environments, financial and health institutions, spokespersons are often not voluntary. Spokespersons are appointed, or seek consent of the authorities before representations. The spokespersons represent the interest of the institutions in communicating their objectives, outcomes, activities, and processes to the general stakeholders and the public.	From both health and financial institutions' perspectives, not all the interested actors and networks participate in the actual operations, which is in this case, the selection and use of the BDA for services. The participation and non-participation of the actors are influenced by different factors. Some of them are known, and others are unknown. These factors are of both technical and non-technical nature.

Moments of Translation: Problematisation

In both financial institutions and health facilities, problematisation occurs in the process of selecting and using the BDA tools.

Financial institution

The need for BDA tools in Claremont Finance (CF) and other financial services was realised by executives who noted the benefits of their use towards increased profitability, helping to gain competitive advantage, and minimising business risks in real-time. This could be a motivating factor for the senior management in CF and other financial institutions in many developing countries. One of the the employees in CF explains as follows:

> *"We use BDA to inform investment decisions. That is a primary reason and it is an overlying or overarching decision for the organization. It is an overarching reason because we are an investment management firm and the decisions that we make are for investment cases and the decisions*

have to be supported by solid evidence that the likelihood of the investment giving a return is higher and the risk of losing the value of that investment is lower" (FIN_INT01: 8 – 12).

"the use of BDA brings about benefits in areas such as operational efficiency; improvements in Cyber Security; and it improves customer services by easily drawing outside intelligence from the processed results of big data" (FIN01: 47).

This implies a top-down approach, which means that the decision makers imposed a solution on the IT specialists and other employees in the IT and business units. Furthermore, areas in which big data analytics could prove to be beneficial are noted to be credit management, supporting investment decisions, fraud detection and marketing. The decision making for the selection, use, and implementation of BDA tools within both financial institutions involved the IT/Technical department heads and their teams. One of the managers explains as follows:

"We understood it. We had knowledge of how it operates, and how we could connect it. It has multiple connectors so to the point it can crunch any type of data, it can be an API, it can be a file or database connection, and it can be unstructured and raw data. We do not utilise it for all of those but that's what its usability is. We first use it for integration purposes" (FIN_INT02: 20 – 23).

"In order to take advantage of BDA, banks need to upgrade their traditional technological approach and start implementing new technologies and processes." (FIN05: 3)

The structure of many financial institutions in Africa allows the business managers within the legal, marketing, and credit departments to present a business case to the CIO. The business case is expected to focus on leveraging the BDA tools with financial data in order for managers and employees to gain better insights and make effective business decisions.

"Moreover, the development and popularisation of e-banking and mobile banking add to the exponential growth of real time banking information. These continuous developments and the rapidly increasing availability of big data make mastering relevant big data analytics tools one of the most crucial tasks for the banking sector" (FIN08: 1).

The goal is to ultimately grow the business, minimise customer churn and maximise profits whilst providing exciting product offering to customers. It is within this goal that the CIO discussed the potential benefits of the BDA tools with the IT department heads. Based on how the discussion went, the IT department heads agreed to the benefits that can be realised through the use of BDA tools. Also in agreement was that the benefits can only be realised through the selection and use of the appropriate tool(s).

Based on the many benefits of the BDA, tools are increasingly developed. This makes it extremely difficult for many organisations, in terms of knowing what is appropriate for their organisations' objectives. Some employees in CF shared their views and experiences as follow:

> *"the reason why there is a multitude of tools out there, there's no tool that does it all" (FIN_INT01: 11 – 12).*

> *"…that is, out there, there are so many tools that are very good at promoting themselves. If you do not have requirements in place you will be lost and you end up using wrong tools" (FIN_INT02: 13 - 16).*

Thus, defining the problem of having a range of BDA tools to choose from for use and implement, that could be assisted through the introduction of decision-support for the selection of BDA tools.

Healthcare Facility

In healthcare, particularly public facilities, the procurement of BDA tools is often centralised in accordance with government's policies, which include regulations that define commercial suppliers. This limits the involvement of hospitals' management and end-users (users of computer systems) in defining the requirements for selecting BDA tools. This type of limitation affects the selection of BDA tools, which ultimately shapes how the tools are used for services in the environments.

Organisational structure and management (Health service, IT, and project managers) in some healthcare facilities propose the use of BDA tools, to better understand health-related big data that are used to carry out services on a daily basis. From the IT unit's perspective, the IT Support HOD discusses the benefits of implementing and using BDA tools with his/her team members. Together, the team solicits advice from various commercial suppliers of BDA tools in order to decide upon which tools to select and use. In response, the commercial suppliers present various products of the BDA to the team. The numerous presentations on BDA sometimes confuse some members of the IT team, which makes it difficult for them to decide on a tool.

Moments of Translation: Interessessment

Even though stakeholders are in the same vein interested in the selection and use of BDA tools for services in financial and health institutions, the types of interest are not always the same for different reasons.

Financial Institution

The use of BDA has shown appeal to various actors within financial institutions and healthcare facilities. The interest of various actors was either of a voluntary or mandatory nature.

Within healthcare facilities, the actors included healthcare providers, management, and patients. These actors had different roles and responsibilities in the selection and use of BDA tools. Furthermore, some actors directly influenced the selection and use of BDA tools whilst others had a more indirect influence. For example, patients that received healthcare were directly influenced by the use of BDA tools as the tools were used in analysing patient data.

In financial institutions, the actors that took an interest in the selection and implementation of BDA tools included data analysts, database engineers, systems engineers, and the IT management. The compliance officers and business managers took an interest in the use of BDA tools.

The actors within healthcare facilities and financial institutions had varied interests in both the selection, implementation, and use of BDA tools. The interest was influenced by a range of factors. The interest of government representatives stemmed from the need to improve patient care and healthcare facility management through the use of technological innovations, such as BDA. Their interest in applying BDA to healthcare, saw them engaging with healthcare facility executive management to realise the benefits of use.

They made the decisions on the use of big data analytics tools within healthcare facilities from the executive management's viewpoint. Essentially, they assessed the need for BDA tools, the benefits of use, and engaged specialists in selecting the appropriate tools. It is noted that the executive management is most likely to adopt the use of BDA in their healthcare facilities to bring about a better management of patient care and ensure the productivity of the organisation. Although the executive management believes in the benefits of using BDA, they see that in the implementation of new standards, the mechanism of operation may hinder the adoption as this may require additional financial investment for the training of staff. One of the documents stated that:

> *"Lack of skillsets; lack of tools required to carry out BDA strategies; new workflows and incentives must be designed to prioritise data-driven decision making; disruptions of conventional methods may hinder the adoption of big data analytics" (H09:90).*

IT specialists included data architects, engineers and analysts. Their interest in the selection of BDA tools was triggered by the executive management needing technical expertise in the selection of appropriate tools. Furthermore, the factors that influenced the selection of BDA tools by the IT specialists included the healthcare data structure and the technical environment which would house the BDA tools.

From the financial institutions' perspective, the business management's interest in the use of BDA tools came from research initiatives carried out that highlight the effectiveness and benefits of use for BDA tools in the financial services sector. Interest from the IT managers was influenced by the business management's buy-in and by the varied number of tools available for use that serve different purposes.

The interest of the IT staff stemmed from management proposals and the need for a standardised approach to selecting tools to serve different business objectives within the financial institution. Additionally, compliance officers' interest in the selection and use of BDA tools was triggered by the importance of applying correct governance structures in the implementation of technological innovations within the financial institution.

Moments of Translation: Enrolment

From both financial and health institutions' perspectives, the participation of actors is structured differently. This could be associated with the sensitive nature of the environments.

Financial institution

Enterprises could afford integrating phases or paralleling them in order to increase value and competitiveness. This could be possible if the appropriate tools are selected and deployed. This draws on the importance of the human actors that are involved or enrolled in the process.

The involvement of various human actors was initiated through a distinctive means in both healthcare facilities and financial institutions. The government representatives for healthcare engaged with the executive management of healthcare facilities and negotiated their participation in the selection and use of BDA tools with healthcare facilities. Executive meetings were conducted between the two stakeholder groups in order to get the interested parties to enroll in the network that will be responsible for carrying out the implementation of BDA tools.

Healthcare Facility

Furthermore, the healthcare facility's executive management engaged with the IT specialists to negotiate their involvement in the selection of BDA tools that will be appropriate to handle healthcare big data. Technical consultations were carried out in order to get the IT specialists enrolled in the network that will be responsible for selecting and implementing BDA tools. Consequently, the selection, implementation and use of BDA tools in healthcare facilities could not occur separately. Assortment teams and individuals, inclusive of government officials, healthcare management, as well as data engineers, architects, and analysts combined their skills to influence the selection, implementation and use of BDA tools.

From a financial institutions' perspective, the business managers engaged with IT managers and negotiated their participation in the selection, implementation, and use of BDA tools. Consultations and meetings were held as a basis for negotiation to occur and to entice those interested to enroll in the network of BDA tools selection and use. As both the business and IT management realised the benefits of BDA use and the significance of the selection of appropriate BDA tools in the financial sector, enrolling into this network was a success. Additionally, the IT managers reached out to their subordinates to negotiate their participation in this network. The IT managers used the power conferred on them by the organisation to attract their employees to participate and assume roles and responsibilities assigned to them during the selection and use of BDA tools.

Both IT specialists and IT managers in the healthcare facilities and financial institutions respectively, had to ensure that they enrolled proficient, committed, and skilled staff that would be able to fulfill the roles involved in the selection, implementation and use of BDA tools.

Moments of Translation: Mobilisation

The mobilisation of activities and processes, including the communication of outcomes and dissemination of information by actors are employed differently in the financial and health institutions. This could be associated with the nature of each institution's focus.

Financial institution

The undertaking to pursue the consultants and staff members was carried out along the structures and policies put in place by both the financial institutions and healthcare facilities, respectively.

Within financial institutions, the business owner/managers requested for analytical data to serve a specific business objective. The IT management evaluated the task components, the data structure environment, and the tools available to carry out BDA. The analysis done by the IT management was handed over to the data analysts and architects to assess the data architecture and infrastructure and draft a plan detailing the factors in the architectural environment that will affect the type(s) of BDA tools that will be used. The data engineers and systems engineers used the plan to select BDA tools for use within the financial institution.

Health Facility

In the healthcare facilities, the ministry of health officials requested for BDA use on patient data to improve healthcare provision and management. The executive management assessed this need within their healthcare facilities and engaged with the IT specialists to carry out the selection and implementation of BDA tools. The IT specialists evaluated the operational and technical environment and carried out consultations with the healthcare staff to gather user and data requirements which assisted them in creating a plan of action that was used for the selection and implementation of BDA tools.

Persuasion was an important aspect in the pursuit of the staff members and consultants in the selection, implementation, and use of BDA tools. As the introduction and implementation of a technological innovation is a collaborative venture, it required that all actors involved deliver on the roles and responsibilities assigned to them in order to select the appropriate BDA tools that would best serve the business/institutional objectives as outlined by the business owners/managers and the government.

As mentioned above, mobilisation happened through various channels, including meetings and technical and business consultations. The meetings were held with the management team, whereas the consultations often occurred between IT specialists and the business managers. The meetings were crucial in order for the management to outline the objectives of the exercise, make decisions, and supply progress reports, whereas the consultations served the need for IT to align the technical aspects with the business objectives through analysis.

5.4. Interpretation of the findings

From the analysis presented above, some factors were found to influence the selection of big data in both financial institutions and healthcare facilities in developing countries. The factors include requirements, top-down vs bottom-up approach, the role of stakeholders, the usefulness of BDA: IT vs Business, and organisational maturity. The factors are discussed below, primarily for appropriateness and within context.

Requirements

Various varieties, velocities, and volumes of data impose constantly changing requirements on the selection of big data analytics tools (Demchenko et al., 2013). These are both technical (IT) (Daki et al., 2017) and non-technical (business) requirements (Gardiner et al., 2018). The business requirements include business processes, strategies, policies, and human resources, which are aimed at response time, efficiency, and effectiveness and IT requirements include technical capabilities of BDA tools, the implementation standards and the technical architecture. Requirements play a key role in the selection and usefulness of the BDA tools.

In carrying out activities to select BDA tools, organisations rely on different networks such as end-users, software developers, business managers, and IT managers for the requirements in selecting the tools. It is the approach by which data engineers and IT specialists gather non-functional and/or functional requirements from end-users and business units to aid the selection of quality BDA tools for organisations' purposes. It is therefore important to gather explicit information about the proposed analytics environment and examine the organisational needs and practices. This is a critical process in ensuring appropriateness in selecting BDA tools for efficient and functional use within an organisation.

Top-down vs bottom-up approach

The selection of BDA tools for organisational purposes should be an inclusive process and approach (Hu & Zhang, 2018). However, it is not the case in many organisations. This brings about a lot of challenges that are of a conflicting nature, in the selection and use of BDA tools. Based on the analysis, the selection of BDA tools in organisations is currently done using two different approaches: namely, top-down and bottom-up. The top-down approach refers to the management imposing BDA solutions on employees within the IT and business units. Essentially, information system solutions to be introduced within an organisation are based on the approval and mandate given by a higher authority. Specific tasks and responsibilities are imposed upon the IT and business employees. Additionally, the top-down approach sees senior management according to the organisational structure initiated for the tasks needed to be carried out in the selection of BDA tools, after which team members such as data engineers and data analysts are informed of their roles and responsibilities in the BDA tools selection. The implications of this approach revolve around the fact that decision making is guided by the roles and responsibilities being clearly defined.

The bottom-up approach implies that BDA tools selection and use is influenced and imposed by the employees within the IT and business departments on the decision makers. It involves an organisation-wide collaboration whereby employees give their input on BDA tools solutions. Employees provide their input on how to achieve BDA tools selection based on their expertise and day-to-day needs. This allows for more realistic task breakdowns as there is a high employee engagement and reduced risk of project failure as the capacity of employees is examined at the outset.

The role of stakeholders

The stakeholders consist of different networks such as the senior management, software developers, IT managers, and the business unit. Each of these groups are experts in the roles that are assigned to them, and they take ownership. The role of each of these groups contributes to the selection, use, and management of the BDA tools within an organisation. One of the most critical networks is the business unit. The unit defines the business models, which is a fundamental role in the selection of BDA tools. This is primarily because the business model regulates the requirements in ensuring communication between various systems, and the transfer of big data (Daki et al., 2017).

Various stakeholders are involved in the selection and use of BDA within organisations. The role that each stakeholder plays requires an active and appropriate participation; this is due to the fact that their influence on BDA tools selection and use varies considerably. For example, the executive management includes people with skills and ownership responsibility to approve procurement requests for BDA tools. From a specialist perspective, the business and IT teams collaborate to elicit and formulate systems design specifications that inform the procurement decisions. The users make use of BDA tools and gain insights for analytics to meet business objectives. As such, each stakeholder’s role and influence have to be taken into consideration. This is the pinnacle of covert and overt power dynamics within the selection and procurement of BDA tools and depicts the cooperation between business, IT, vendors and users.

The usefulness of BDA: IT vs Business

Many organisations employ BDA because of the premise that the tools are useful (Iyamu, 2020). The usefulness of BDA can be explained from two perspectives: namely, IT and Business. From the IT perspective, some organisations employ BDA tools to foster innovation through analytics. This is achieved through the effective management of an organisation's information management and transformation cycle, which is the collection, storage and consolidation, and the use of data to produce valuable insights. In order to produce valuable insights, organisations require technical infrastructure that is able to process and manage large volumes of data. The technical architecture covers activities which IT is tasked with managing and includes networking infrastructure, database management systems, data integration capabilities, visualisation, reporting, and infrastructure management.

Essentially, the technical environment goes through a data management cycle which begins with obtaining and procuring big data architecture and various data access protocols, structuring and categorising data, employing algorithms and techniques to analyse the data and finally deriving valuable insights from analytics activities. Business, in this context, is considered to be the end-user of the insights gained from the use of BDA tools. As such, the business strategy needs to be taken into account in the selection of BDA tools for the development of an organisation-wide data and analytics environment. This is to allow for improved operational efficiency and to enrich end-user engagement and allow for the innovation of business models.

Organizational Structure

The explicit knowledge of an organisation lies on the structure, which makes it easier for decision making. Also, activities and processes are controlled and managed through the organisation's structures. Doherty, Champion and Wang (2010) argue that organisational structures influence strategy as well as the interaction that happens between employees.

The selection of BDA tools within organisations needs an examination of the organisational structure regarding the use of BDA. The importance is to identify and distinguish the way in which data is being used or not used within an organisation in order to create a properly designed plan for the selection and use of BDA tools. A number of factors can be used to assess the organisational maturity in relation to the selection of BDA tools. The skills and expertise of people within an organisation needto be examined to understand the level of skills in existence and those required to achieve an effective BDA. Additionally, the technical infrastructure installed and required, the extent to which an organisation engages in data management, the leadership and corporate culture in supporting and influencing the use of BDA tools for business processes, and the existence of effective data governance policies govern the usage and dissemination of data that will ensure access to valuable information.

5.4.1. Factors that influence the selection of BDA tools

From the findings, five factors were found to have influence on the selection of BDA tools within an organisation: requirements, top-down vs bottom-up approach, the role of stakeholders, BDA usefulness, and organisational structure. The factors are depicted in figure 5.1. The discussion below should be read with the figure in order to gain a better understanding of the factors that influence the selection of big data analytics tools in an organisation.

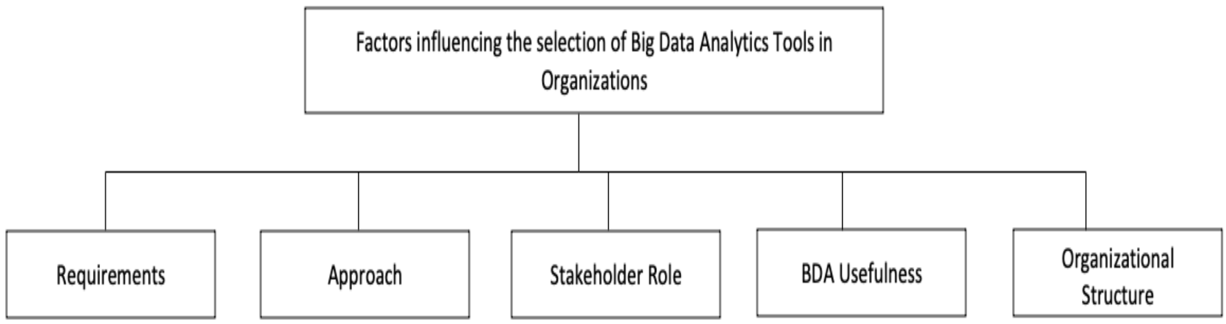

Figure 5.1: Factors that influence the selection of big data analytics tools

Requirements

Requirements define scope, object, subject, goals and objectives (Leffingwell, 2010). In defining the criteria for BDA tools, two types of requirements, business and IT are involved. The requirements can either be functional or non-functional, from both business and IT perspectives (Chen, Tan, Sun, Liu, Pang & Li, 2013). Functional requirements define and describe the objective and use (or usefulness) of the BDA tools in an environment (organisation). Essentially, these requirements cover aspects of an organisation's needs, such as business rules, system capabilities, and processes. The requirements deal with the functionality of BDA tools. This involves conducting an evaluation of organisational needs as well as BDA tools. The non-functional requirements define and describe the criteria that govern how software tools should work within an environment. Examples of non-functional requirements include reliability, usabilitiy, compliance, and supportability. Furthermore, an understanding of the systems currently in place within an organisation should be considered in order to allow for intergration possibilities.

Additionally, the technology weaved into BDA tools should be taken into consideration. This is to understand what kind of technology BDA tools offer, and what technology is needed by an organisation to achieve BDA initiaitives. Technology includes components and modules that allow for data storage, extraction, analytics and visualisation.

Top-down vs Bottom-up Approach

There are different approaches; top-down and bottom-up, in the selection of BDA tools in some finance and health institutions in many developing countries. These approaches sometimes conflict in their application in the selection of BDA tools in some organisations. As a result, it is critical to clarify ownership responsibility. Ownership within both top-down and bottom up approaches needs to be considered when selecting BDA tools. Ownership refers to the organisation's stakeholders who control, impose, and drive the implementation of BDA tools. From a top-down perspective, management has ownership, whereas from a bottom-up perspective the employees (users) have ownership. From the management perspective, it is about strategic intent, whereas the users' focus is more about operationalisation. These two approaches often conflict with each other in that stakeholders are only an interested party, which do not participate in the actual operations of the organisation. This is well distinguished by ANT's moments of translation. Within financial institutions, as mentioned previously in problematisation moments of translation, a top-down approach was seen. This meant that the decision makers (management) enforced a solution on the IT and business departments.

Risk is another element in the selection of criteria, which manifests from the top-down and bottom-up approaches' conflict. This has an impact on the operations, management and implementation of BDA tools in an environment. Thus, the management needs to take into consideration the type of risks and how they affect business operations in the selection and implementation of BDA tools. Employees such as IT staff who will implement BDA tools within an organisation need to adopt a risk culture that embeds risk elements within the decision-making process of selecting BDA tools. This has to be built into the governance of the IT processes and activities. Governance is an approach that can be used in the mobilisation of activities that are related to BDA tools in the organisation. Mobilisation occurs through various channels, with the aim of communicating relevant information to various stakeholders.

Stakeholder Role

Stakeholders include employees, the management, suppliers, vendors, competitors and consumers (Carroll, 2004). The role of stakeholders contains two criteria, namely: Support and Budget. Support is a multi-faceted criterion that refers to organisational stakeholders providing support based on their assigned roles and responsibilities. Management provides decision-making support in BDA tools selection. The IT staff provide technical support for implemented BDA tools, whereas the business staff provide business support for operational models used in line with and informed by the BDA tools. Budget refers to the amount of money available for making procurements. In a collaborative initiative to acquire BDA tools software, management is required to make procurement decisions on the software to purchase. These procurement decisions should be informed by the budget available.

BDA Usefulness

The usefulness of BDA tools crucially depends on the role of the networks (stakeholders). Müller and Schurr (2016) emphatically explain the criticality and essentiality of networks' roles in the deployment of solutions. The role of stakeholders for selecting BDA tools is comprised of three criteria, namely: Data Management, Scalability and Business Strategy. Data management refers to the cycle an organisation undergoes in acquiring and managing their BDA assets. Organisations need to consider BDA tools vendor viability when acquiring data assets. This viability should be guided by the functional and non-functional requirements.

Scalability refers to BDA tools' ability to not limit functionality and enable system extensions and enhancements. This is crucial as BDA tools need to be selected with organisational growth in mind, that will be able to adapt to technological changes and upgrades. Business strategy refers to policies and standards in place within an organisation that guide business operations and models. Organisations need to consider the policies and standards adopted and ensure that they align with the outcome of the use of BDA tools.

Organisational Structure

Organisational structure is the practice by which work flows through an organisation (Cosh, Fu & Hughes, 2012). The organisational structure defines the levels and units, including the roles and responsibilities in an organisation. In the formulation of criteria, there are two important components that should be associated with organisational structure, namely: Skills and Organizational culture. Skills refers to the competencies of the employees within an organisation. For the selection and use of BDA tools, an organisation needs competent staff with varied skillset to effectively implement and use BDA tools. These include professionals such as project managers, data engineers, data analysts and systems engineers. Otherwise, despite the appropriateness of the tools, it will be problematic. Thus, a set of criteria should guide the assembly of personnel (skills).

5.5.1. Criteria for selecting BDA tools

Each of the factors discussed above contains a set of components that assist with the selection of BDA tools. These components together with the factors are used as the criteria to guide the selection of BDA tools. Table 5.2 shows the factors and their associated components which make up the criteria to guide the selection.. Based on these factors, a decision support framework is developed.

Table 5.2: Criteria for selecting BDA tools

	Scalability	Functionality	Non-functionality	Technology	Ownership	Model	Skill
Requirements		✓	✓	✓			
Approach					✓	✓	
Stakeholder Role				✓			✓
BDA Usefulness		✓	✓	✓			✓
Organisational Structure	✓					✓	✓

5.5. Decision Support Framework

From the findings, five factors were found to have influence on the selection of BDA tools in organisations: requirements, approach, stakeholder role, BDA usefulness and organisational structure. Subsequently, a set of components used in conjunction with these factors was found and used to formulate a set of the criteria that guide the selection of BDA tools. Each factor consists of the criteria for the selection. To understand the framework, the discussion is carried out below.

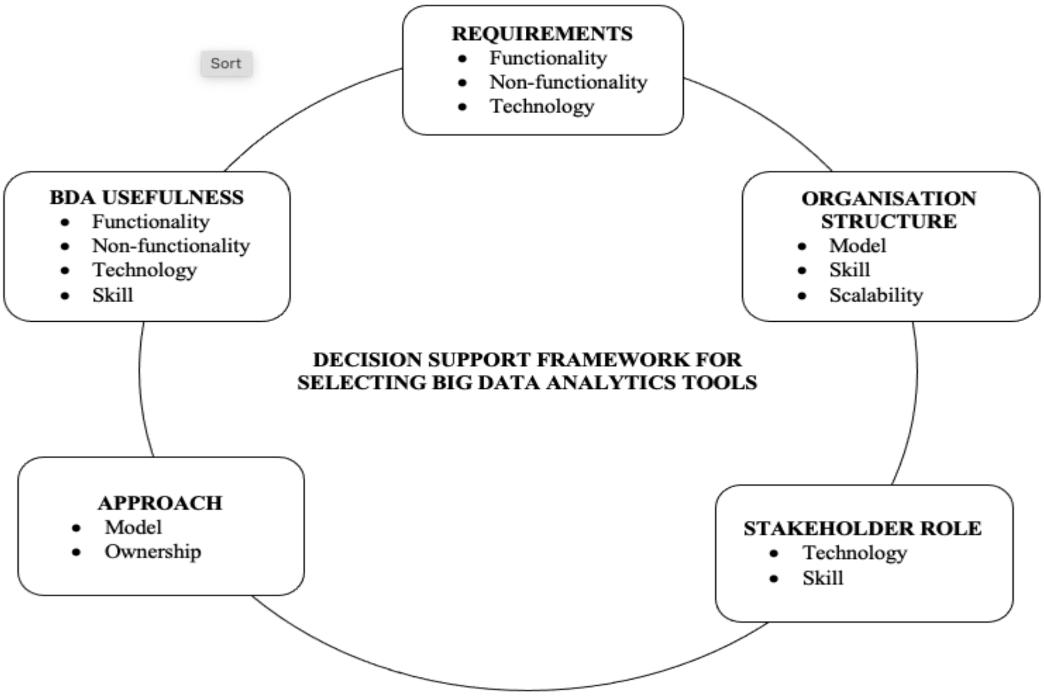

Figure 5.2 Decision Support Framework for Selecting BDA Tools

5.6.1 Requirements

Requirements provide a description of the functionality and features of a software tool (Leffingwell, 2010). Within the decision support framework, organisations need to formulate a list of requirements needed for the selection and use of BDA tools. These requirements are grouped into functional and non-functional requirements. Organisations intending to select big data analytics tools should describe all the requirements within each group. Furthermore, an analysis of the current technology environment needs to be done and documented. This is to establish the strengths and shortcomings of the technology infrastructure in place at the organisations. The technology capacity and limitiations will have an effect on the BDA tools for selection and use (Riggins & Wamba, 2015).

5.6.2 Organisational Structure

A review of the structure of the organisation should be done to understand the limitations and strengths of the human resources within an organisation (Prakash & Gupta, 2008). It is imperative for this review to be done as it will assist in selecting the BDA tools that can be handled by the human capacity within the organisation. Additionally, should there be limitiations, this will guide the organisations in formulating strategies to fill the gaps in resource capacity. A review of the organisational structure begins with a study of the organigram, which is a model of the organisation (Adjei, Aigbavboa & Thwala, 2018). Each role and the person within that role is studied to uncover the skillset each employee has (Groth, Hennig-Thurau & Walsh, 2009). The skills needed for the effective use of big data analytics tools and the skills available within the organisation should be compared in order to establish whether or not the skills in place will complement the BDA tools. Lastly, the organisational structure should be reviewed for its scalability. this is to ascertain if it can be modified or changed in size and structure to suit the technology requirements.

5.6.3 Stakeholder Role

Within any technology project, there are internal and external stakeholders involved (McAulay, Doherty & Keval, 2002). Both types of stakeholders as previously mentioned can provide both monetary sustenance and organisational support (De Vries, Verheul & Willemse, 2003). In selecting BDA tools, organisations need to create a list of internal and external stakeholders. External stakeholders would be the BDA tools suppliers. Organisations need to establish and understand the types of technology supplied by each prospective BDA tools vendor, and the support provided with each tool (Ndubisi, Gupta & Massoud, 2003). Internal stakeholders include the executive management, the business and the IT departments. A review of the organisational structure would have uncovered the skills each of these stakeholders have. The limitations in internal skillset should be able to be addressed through the support provided by a big data analytics tools vendor.

5.6.4 Approach

As presented in 5.4, there are two approaches that organisations can choose from in the selection of big data analytics tools. These are the top-down approach and the bottom-up approach. Organisations should model their approach based on the organisational structure. In each approach, the ownership of the selection and use of BDA should be established. It is imperative to create a model based on the approach as this will guide the selection and use of BDA tools within an organisation.

5.6.5 BDA Usefulness

Organisations need to establish the usefulness of BDA tools in the market to their business needs. In order to determine the usefulness of BDA tools, a review should be carried out. The review involves the study of the non-functional and functional requirements of each prospective tool (Bouwers, van Deursen & Visser, 2013). Additionally, organisations should look at the technology infrastructure and needs required in the implementation and use of the BDA tools (Al-Mudimigh, Zairi & Al-Mashari, 2001). Lastly, the skills needed to use and implement the tools should be established. Organisations need to conduct this review to look at the features, functionality and technology of BDA tools, as well as the skills required and provided in order to ascertain whether or not it is the best fit for the organisation. This review is done in comparison with sections 5.6.1, 5.6.2 and 5.6.3 to assist in the selection of BDA tools.

5.6. Summary

The findings in both healthcare facilities and financial institutions were explained. Based on these findings, the factors that influence the selection of big data analytics tools were formulated and a diagram was created. Furthermore, together with the findings and the factors formulated, the criteria for the selection of big data analytics tools was presented and a table was created. Lastly, those findings were interpreted and a decision support framework for selecting big data analytics tools in an organisation was created. This framework can be adopted by organisations within healthcare and financial services for selecting BDA tools. This is due to the study having been carried out by looking at healthcare facilities and financial institutions. The following chapter concludes the study and proposes recommendations.

CHAPTER 6
CONCLUSIONS AND RECOMMENDATIONS

6.1. Introduction

This chapter discusses the conclusions and recommendations in relation to the research. The aim of this study was to propose a decision support framework for selecting big data analytics tools in an organisation. The chapter further reviews how the research aim, research objectives and research questions were addressed. This chapter is divided into the following sections: 1) provides a summary of the study; 2) presents how the research questions were addressed through an evaluation of the study; 3) provides the theoretical and practical research contributions; 4) presents the limitations of the study; 5) presents the research recommendations; 6) provides the benefits of the study, and 7) presents recommendations for further research.

6.2. Summary of study

Chapter 1 provided an overview of the study and identified the research problem. Organisations face challenges in selecting and adopting appropriate BDA tools that are able to provide actionable insights for their operations. Such selection decisions can lead to the introduction of complexities in the IT environment and the failure to realise return on investments. This informed the research objectives which are 1) to examine and understand the factors that influence the selection of BDA tools in an organisation, and 2) to formulate a set of criteria that can be used to guide the selection of big data analytics tools in an organisation.

Chapter 2 provides a review of literature in the following areas in relation to the aim of the study:

1) Information Systems and Technologies
2) Big Data Analytics
3) Big Data Analytics Methods
4) Decision Support Framework
5) Actor-Network Theory

Chapter 3 provides an in-depth discussion of the research methodology employed in the study. The sections covered within this chapter include 1) Research Philosophy; 2) Research

Approach; 3) Research Methods; 4) Research Design; 5) Data Collection; 6) Data Analysis; 7) Ethical Considerations.

Chapter 4 presents an overview of the case selected for the study. This includes the environment in which the study was created, the type of data collected, and the source of the data collected.

Chapter 5 presents the data analysis using the moments of translation from the actor-network theory perspective. From the analysis, the factors that influence the selection of BDA tools in organisations were identified, and a set of criteria that assist in the selection of BDA tools in organisations was formulated. Subsequently, a decision support framework that will assist in the selection of BDA tools in organisations was proposed.

6.3. Evaluation of Study

The research questions as presented in chapter one is revisited in this section in order to evaluate the study.

1. How can a decision support framework be proposed to address the challenges that are encountered in selecting BDA tools in an organisation?

iii. What are the factors that influence the selection of BDA tools in an organisation?

iv. What are the criteria that can be used to guide the selection of BDA tools in an organisation?

Dane (2010:12) suggests six components (who? what? where? when? how? and why?) as an approach for the evaluation of a research. As such, the Dane approach was used to evaluate this study. The six components are presented in table 6.1 below.

Table 6.1: Evaluation of research

Components	Evaluation
Who	Ideas and views were gathered from a set of selected participants and documents. The organisations to which the participants belonged were chosen on the basis of a set of criteria. The types of the documents were selected based on set criteria. The criteria used to select participants in the study are mentioned below: i) IT and Business employees working in an organisation that makes use of BDA tools

Components	Evaluation
	ii) All employees must have been working with BDA tools for at least 2 years The study has 2 participants from a financial institution. The identities of the participants were hidden through the use of the coding: FIN_INT01 and FIN_INT02. These code names are used to identify the participants. The criteria employed to select the organisation in this study are as follows: i) An organisation that utilises BDA tools ii) The organisation should be in a developing country iii) The organisation should either be in the healthcare or financial services industry The criteria governing the types of documents sourced are as follows: i) Peer-reviewed articles and white papers ii) Documents should cover the selection, use and adoption of BDA tools iii) Documents should either be in the healthcare or financial services industry iv) Documents must have been published between the years 2009 and 2019 v) Documents should cover the developing countries' landscape
What	The selection and use of BDA tools in organisations were investigated. Many organisations are making use of BDA tools to aid their business processes and gain competitive advantage. As such, the selection of the appropriate BDA tools is vital in achieving organisational goals. The investigation of BDA tools was in relation to the selection and use of tools in various organisational contexts; namely, financial institutions and healthcare facilities. This study uncovered the factors that influence the selection of BDA tools in organisations, and formulated a set of criteria that can be used to guide the selection of BDA tools in organisations. The aim of this study was to propose a decision support framework for the selection of BDA tools in an organisation.

Components	Evaluation
Where	The location for carrying out the study is two-fold. Firstly, the interviews were conducted at the offices FIN_INT in Cape Town, South Africa. Within FIN_INT the data was collected from the IT and business employees who make use of BDA tools. Secondly, the documents collected were sourced from academic journals and company websites.
When	The study was conducted over a period of 3 years. Delays were experienced throughout this research. This can be attributed to various factors; delays in attaining approval from prospective organisations to conduct interviews which saw the researcher modify data collection methods, and factors that are personal in nature. The data was collected between 8 October 2019 and 11 February 2020.
How	The appropriate methodology was followed in the study, based on the objectives of the research. The research methodology has been discussed in Chapter 3. The ontological assumption for this study was subjective in nature; that is to say that BDA tools are being used in various environments and that challenges exist in the selection of these tools. The study thus followed an interpretivist epistemological approach. The qualitative research method was used to understand the selection and use of BDA tools based on the subjective ideas from the data collected. The data was collected using the documentation technique and semi-structured interviews. The interviews were conducted and transcribed by another researcher. The data collected from the interviews was used as secondary data to complement the data collected from the documents. The process of coding the documents has been discussed in Chapter 3. Subsequently, the data was analysed using the moments of translation from the perspective of Actor-Network Theory as a lens to guide the analysis. Finally, the analysis was used to propose a decision support framework for the selection of BDA tools in organisations.
Why	The study of big data analytics and specifically the selection and adoption of BDA tools was based on the keen interest of the researcher in the subject matters. From literature, it is evident that BDA tools are being used by many organisations. However, organisations still experience challenges

Components	Evaluation
	in the decision-making process of selecting suitable big data analytics tools which can be attributed to their variety and complexity. As such, the researcher saw a gap in the need of a framework that will assist organisational decision making in the selection of BDA tools. Thus, the researcher sought to uncover the factors that influence the decisions in selecting BDA in organisations and the criteria used to guide their selection in organisations.

Research Sub-Question 1

a. What are the factors that influence the selection of big data analytics tools in an organization?

From the detailed analysis conducted in Chapter 5, the factors that influence the selection of BDA tools in an organisation were presented and discussed. Figure 5.1 in Chapter 5 illustrates these factors, which are Requirements; Approach: Top-down vs Bottom-up; Stakeholder Role; BDA Usefulness, and Organisational Structure.

Research Sub-Question 2

b. What are the criteria that can be used to guide the selection of big data analytics tools in an organisation?

Based on the analysis conducted in Chapter 5, the factors that influence the selection of BDA tools contain a set of components that guide the selection. The components and their associated factors are used to formulate the criteria used to guide the selection of BDA tools in organisations. As revealed from the study, the factors are contained in Table 5.2 in Chapter 5. These factors can be used as the criteria to guide the selection of big data analytics tools in organisations. The criteria are Scalability, Functionality, Non-functionality, Technology, Ownership, Model, and Skill.

Main Research Question

c. How can a decision support framework be proposed to address the challenges that are encountered in selecting big data analytics tools in an organisation?

From the analysis conducted in Chapter 5, a Decision Support Framework for Selecting BDA Tools was proposed and presented in Figure 5.2 in Chapter 5. Organisations can make use of this framework to aid their decision-making process of selecting BDA tools for use. The framework highlights areas of importance that organisations need to be aware of in the selection of BDA tools. These areas of importance are notably the factors and criteria which are discussed in detail in Chapter 5.

6.4. Contributions of research

This section presents the theoretical and practical contributions of the research.

6.4.1 Theoretical Contribution

The use of the moments of translation from the perspective of the actor-network theory as a guide to analyse the data allowed the study to identify the actors and networks that exist, the roles of the various networks, how the networks come into being, and to examine the interactions between actors and their roles to influence the selection of BDA tools in an organisation, as wells as examine the associations of the actors and networks in formulating the criteria that guide the selection of BDA tools in an organisation.

Furthermore, the study highlights the factors which influence the selection of BDA in organisations. These factors include Requirements; Approach: Top-down vs Bottom-up; Stakeholder Role; BDA Usefulness, and Organisational Structure.

6.4.2 Practical Contribution

The practical contribution of the study is the decision support framework which was proposed. The decision support framework is intended to guide the selection of BDA tools in organisations.

6.5. Limitations of the study

This study was limited to proposing a decision support framework which organisations can use to guide the selection of BDA tools.

6.6. Recommendations

In order for organisations to make use of the decision support framework proposed in this study, both the business and IT departments need to be involved in the decision-making processes. There are aspects of the decision support framework that will provide IT departments with a better insight, such as technology, technical requirements, and the usefulness of BDA tools. Whereas aspects such as organisational structure, business requirements, stakeholders etc., will provide the business departments with better insights. As such, it is important that there is an organisational synergy between business and IT to efficiently make use of the decision support framework.

6.7. Benefits of the study

The benefits of this study can be noted as contributing to the body of knowledge and to guide organisations that plan to make use of BDA tools and those already making use of the tools. These benefits are presented below:

This study will create awareness for organisations already making use of BDA tools on aspects that are vital for consideration in selecting the tools. Organisations that are planning on making use of BDA tools are provided with a framework to enable them to make informed decisions in the selection for their business processes. Ultimately, the study brings forward factors and criteria that organisations can consider when selecting BDA tools.

This study presents empirical evidence on the factors that influence the selection of BDA tools in organisations and the criteria used to guide their selection, in organisations. Additionally, it explains the use of the actor-network theory (ANT) in analysing data on the selection, use, and adoption of BDA tools in organisations. The use of ANT helped to establish the need for actors and networks and how networks are formed to influence the selection of BDA tools. Subsequently, a decision support framework for the selection of BDA tools in organisations was proposed and the aim of the study was achieved.

6.8. Further Research

This study was extensively and thoroughly carried out as outlined in Chapter 1. Further research relating to the selection and use of big data analytics tools can be conducted. A few suggestions include 1) the use of a different theoretical framework to analyse the data, such as the Activity Theory (AT) or the Technology Acceptance Model (TAM); 2) as the study was only limited to the selection of BDA tools, the creation of a framework that includes both the selection and adoption decisions could be an area for further study, and 3) a study of the implementation of the decision support framework in an organisation could be explored.

6.9. Summary

This chapter discusses the summary of the study through the evaluation of the research and presents how the research questions were answered and research aims and objectives achieved. The theoretical and practical research contributions for this study were also given. Additionally, the recommendations for organisations making use of this study were provided. The academic and organisational benefits of the study were presented. Finally, the chapter provides recommendations for further research.

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APPENDIX A: ETHICAL CLEARANCE

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Office of the Research Ethics Committee	**Faculty of Informatics and Design**

25 February 2019

The Faculty Research Ethics Committee hereby grants ethical clearance to Ms Tonata Nakashololo, student number 211145904, for research activities related to the MTech in Information Technology at the Faculty of Informatics and Design.

Title of thesis:	A decision support framework for selecting big data analytics tools in an organisation

<u>Data collection permission</u>:

The Ethics Committee confirms that data collection permission is <u>not</u> required as all research data is currently in the public domain and no human participants will be utilised for this study.

Signed: Faculty Research Ethics Committee	25/2/2019 **Date**

RESEARCH ETHICS COMMITTEE
INFORMATICS AND DESIGN
ETHICS APPROVAL GRANTED
25 FEB 2019
Cape Peninsula
University of Technology