BIG DATA ANALYTICS CAPABILITIES AND THE ORGANISATIONAL PERFORMANCE OF SOUTH AFRICAN RETAILERS

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Abstract

Big data analytics capabilities and the organisational performance of South African retailers

Big data analytics is becoming a real source of competitive advantage and growth as it helps organisations to have a better understanding of their insights. Recent studies have identified the resources needed to build a big data analytics capability (BDAC) and examined their relationship with firm performance. Building on this, the study attempts to examine the relationship between BDAC and the organisational performance of South African retailers. The study was guided by three main objectives: To empirically determine the impact of big data analytics tangible capabilities (BDATC) on the organisational performance (OP) of South African retailers, to empirically determine the impact of big data analytics human capabilities (BDAHC) on the organisational performance (OP) of South African retailers and to empirically determine the impact of big data analytics intangible capabilities (BDAIC) on the organisational performance (OP) of South African retailers.

Furthermore, a descriptive research design was used to determine the above relationship and a judgemental sampling technique was adopted to determine the sample size of the study. Additionally, a quantitative method was adopted. Moreover, a questionnaire served as an instrument to collect the required data for the study. The collected data from this questionnaire were analysed using Excel and the Statistical Package for Social Science (SPSS). The population of the study included the Business Intelligence (BI) team members of selected South African retailers. Moreover, the findings of the study confirmed that BDA capabilities (BDATC, BDAHC, and BDAIC) positively and significantly impact the organisational performance of South African retailers. Thus, the three proposed hypotheses were supported. The research concludes that all the BDAC primary dimensions are essential for maximising the organisational performance of retailers. It helps them increase their productivity, sales revenue, profit rate, customer retention, and return on investment.

The assessment of the impact of BDAC on the organisational performance of retailers remains vague. Therefore, this study provides new and additional insights into the topic. In addition, this study provides retailers with a deeper understanding of the various BDA capabilities and the key role they play in maximising organisational performance.

Key words: *Big data, big data analytics, big data analytics capability, organisational performance, retailers, big data analytics tangible capabilities, big data analytics human capabilities, big data analytics intangible capabilities.*

Declaration and approval

I declare that this thesis entitled '**Big data analytics capabilities and the organisational performance of South African retailers'** is my own work, that it has not been submitted before for the award of any degree or examination in any other university, and that all the sources I have used or quoted have been indicated and acknowledged as complete references.

This thesis has been submitted for examination after approval by my academic supervisors.

Signed by:

Diana Welbotha

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List of acronyms

Acronyms	Description
IT	Information Technology
BD	Big Data
BDA	Big Data Analytics
BDAC	Big Data Analytics Capability
BDATC	Big Data Analytics Tangible Capabilities
BDAIC	Big Data Analytics Intangible Capabilities
BDAHC	Big Data Analytics Human Capabilities
OP	Organisational Performance
RBT	Resource-Based Theory
SPSS	Statistical Package for Social Science
ANOVA	Analysis of Variance

CHAPTER 1: INTRODUCTION

1.1 Background to the research problem

The world is inundated with data and this is increasing exponentially day by day (Su, Zeng, Zheng, Jiang, Lin, and Xu, 2021). The volume of data is growing and complexity is increasing due to the ceaseless generation of data from numerous devices and sources such as social media, government records, personal computers, mobile phones, and healthcare records (Jha, Agi, and Ngai, 2020). Hence, investing in big data (BD) has become a crucial resource for organisations to improve their performance and competitive advantage. According to More and Moily (2021:1), BD refers to "a combination of all the processes and tools associated with managing and making use of large data sets". These datasets are often categorised into structured, unstructured, and semi-structured formats according to their behaviour.

BD enables organisations to identify the correct datasets from a large amount of data often characterised by the five Vs (volume, velocity, variety, variability, and value), transform them, and extract meaningful insights for their business strategies (Alwan and Ku-Mahamud, 2020). It generally offers organisations the opportunity to create a more complete and complex picture of their customers hence providing more accurate products and services (Kubina, Varmus, and Kubinova, 2015). Whenever BD is defined appropriately and utilised accordingly, organisations have an improved view of their business hence leading to efficiency in sales and product improvement. In addition, several studies noted the importance of using big data in various sectors such as retailers, healthcare, banking, etc. (Alwan and Ku-Mahamud, 2020; Yaseen and Obaid, 2020; Sabharwal and Miah, 2021). For instance, Sabharwal and Miah, 2021 note that BD helps retailers with the improvement of products and services, the enhancement of customer satisfaction, the detection of online fraud, and risk assessment.

To uncover hidden patterns among large datasets, organisations need to implement strong big data analytics (BDA). According to Zhu and Yang (2021:177), "BDAs help firms use advanced analytical skills to obtain quality information from BD, which enables firms to achieve higher operational efficiency and sustainable performance". BDA usually examines a huge amount of data sets to reveal hidden patterns and uncover correlations, customer preferences, and market trends that can help an organisation in business decision-making (Hong and Ping, 2019). Batko and Slezak (2022:2) define BDA as "techniques and tools used to analyse and extract information from big data." Currently, big data analytics has been considered the predominant method for analysing big data because of its superior ability to capture huge amounts of raw information and apply the best analytical practices (Maroufkhani, Wagner, Ismail, Baroto, and Nourani, 2019). It enables organisations to determine what is currently happening, what will likely happen next, and what should be done to increase performance. Furthermore, prior studies highlighted the benefits of using BDA in various sectors such as retailers (Avinash and Babu, 2018; Shankar, 2019; Prasad and Venkatesham, 2021; Sabharwal and Miah, 2021), banks (Chunarkar-Patil and Bhosale, 2018; Zhu and Yang, 2021; More and Moily, 2021), healthcare (Wang and Alexander, 2019; Batko and Slezak, 2022) and education (Veldkamp, Schildkamp, Keijsers, Visscher, and de Jong, 2021). The ability of an organisation to deploy its BDA resources is often considered "Big Data Analytics Capability" (BDAC). According to Sabharwal and Miah (2021:11), BDAC is "the combined ability to store, process, and analyse large amounts of data so that meaningful information can be provided to users". An organisation that increases its BDA capability should be able to maximise its performance (Maroufkhani et al., 2019). High performance is often derived from a combination of several resources including tangible resources (data, technology, basic resources), human resources (technical and managerial skills), and intangible (data-driven culture, organisational learning) (Munir, Abdul, Aamir, and Ahmed, 2022).

Several studies have highlighted the importance of BDAC to improve firm performance (Marfo and Boateng, 2015; Mikalef et al., 2017; Maroufkhani et al., 2019; Bahmari and Shokouhyar, 2021; Huang, Jianmin, Xie, Li, and He, 2022). Furthermore, prior studies confirmed a positive relationship between BDAC and firm performance (Gupta and George, 2016; Akter, 2016; Fosso Wamba, Gunasekaran, Akter, Ren, Dubey, 2017; Su, Zeng, Zheng, Jiang, Lin, and Xu, 2021). However, few studies focused on understanding the relationship between BDAC and the organisational performance of retailers. Therefore, additional research on this topic is important for retailers to understand the value of BDAC to maximize their performance.

Organisational performance (OP) is considered the essence of an industrial enterprise's existence (Babelova, Starecek, Koltnerova, and Caganova, 2020). It is often defined as the ability of a firm to use its resources effectively and generate results that are consistent with its objectives and goals (Ogbo, Chibueze, Christopher, and Anthony, 2015). Furthermore, Bhasin (2020) notes that OP encompasses three main areas of the organisation's outcome; product market performance (market share, sales, etc.), financial performance (return on investments, profit, etc.), and shareholder return (economic value added).

The retail industry is growing and extending in diverse markets (Ying, Sindakis, Aggarwal, Chen, and Su, 2020). Retailing has drastically transformed business and customers now have access to a wide range of products offered through retail outlets both in the organised and unorganised sectors (Prasad and Venkatesham, 2021). In addition, retailing generally consists of reselling and a retailer is a business or person that purchases products from a wholesaler or manufacturer, and sells them to customers or end-users in small quantities.

Retailers often do not manufacture their products but are experts in sales, merchandise inventory, marketing, and knowing their customers. They sell products such as groceries, durable goods (furniture, cars), clothing, etc. As the African economy continues to improve and expand, retail stores are playing a significant role. Retail groceries and supermarkets are the niches with the largest potential for retail growth among South African retailers (Farfan, 2019). Shoprite, Pick n Pay, Woolworths, and Spar are the largest South African retailers (Patrick, 2022).

Therefore, this study aims to investigate how big data analytics capabilities impact the organisational performance of selected South African retailers. This can be considered an area of interest since this sector often deals with a high volume of data.

1.2 **Statement of the research problem**

The capability to rapidly take good and intelligent decisions is vital for any organisation to improve its performance and outperform competitors. In this time of fierce rivalry, organisations cannot solely rely on their instinct and experience to maximise performance. The effective use of BDA capability allows an organisation to mobilise, deploy and utilise BDA resources to improve its performance and gain a competitive advantage. According to Garmaki, Boughzala, and Wamba (2016:2), BDA capability is "the organisational ability to utilise data assets in combination with physical IT assets and human resources to create competitive advantages". Research has been conducted globally to gain a better understanding of the relationship that exists between BDA capability and firm performance (Garmaki et al., 2016; Akter, 2016; Fosso Wamba et al., 2017; Aydiner et al., 2018; Maroufkhani et al., 2019; Bahmari and Shokouhyar, 2021). However, there is limited literature that focuses on understanding the relationship between BDA capability and the organisational performance of South African retailers. Hence, this research aims to fulfil this gap by attempting to determine the impact of BDAC on the organisational performance of South African retailers.

1.3 **Research questions and objectives**

What is the impact of big data analytics capabilities on the organisational performance of selected South African retailers?

1.3.1 Research sub-questions

To answer the main research question, the following sub-questions are included:

- What is the impact of BDA tangible capabilities on the organisational performance of selected South African retailers?
- What is the impact of BDA human capabilities on the organisational performance of selected South African retailers?
- What is the impact of BDA intangible capabilities on the organisational performance of selected South African retailers?

1.3.2 Research objectives

- To conduct a literature review to understand the impact of big data analytics on firm performance.
- To conduct empirical research to determine the impact of BDA tangible capabilities on the organisational performance of selected South African retailers.
- To conduct empirical research to determine the impact of BDA human capabilities on the organisational performance of selected South African retailers.
- To conduct empirical research to determine the impact of BDA intangible capabilities on the organisational performance of selected South African retailers.

1.4 **Hypotheses**

A hypothesis is often considered as a statement that a researcher intent to investigate. According to Anupama (2018:78), "a hypothesis is a statement of the researcher's expectation or prediction about the relationship among study variables". A good hypothesis should be testable, simple, precise, and consistent with facts (Mourougan and Sethuraman, 2017). The proposed hypotheses included:

H1: There is a positive and significant relationship between BDA tangible capabilities and the organisational performance of selected South African retailers

H2: There is a positive and significant relationship between BDA human capabilities and the organisational performance of selected South African retailers

H3: There is a positive and significant relationship between BDA intangible capabilities and the organisational performance of selected South African retailers.

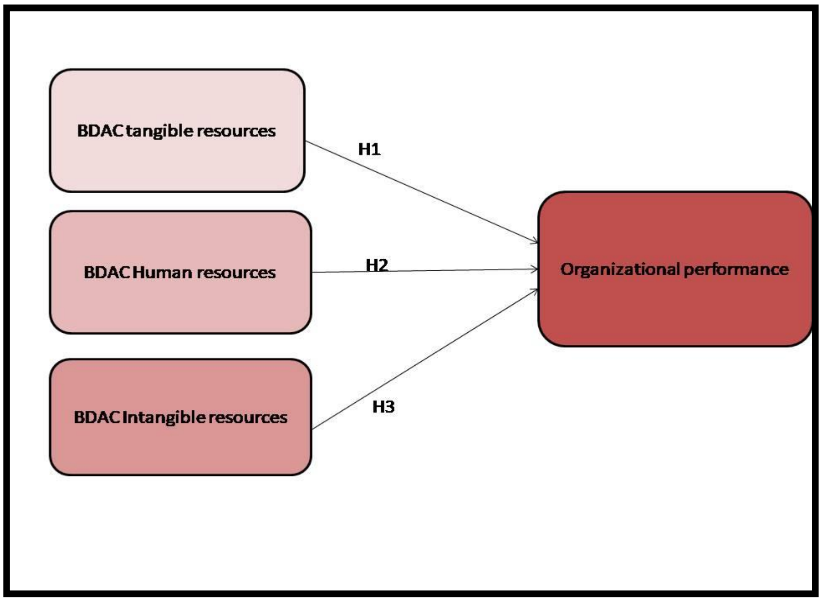

Figure 1.1: Research hypotheses

1.5 Research rationale

The explosion in data accessibility has made it possible for many companies to analyse and obtain important information to improve their performance. Many companies are beginning to employ BDA. However, the deployment of BDA capabilities by South African retailers is not well known. Thus, this study attempts to determine the impact of big data analytics capability on the organisational performance of selected South African retailers. This research will create awareness of the various BDA capabilities (intangible, human, and intangible capabilities) and their significance on the organisational performance of retailers. In addition, the study will likely contribute to the scarce literature that exists on the usage of BDA capability in South African retailers.

1.6 Significance of the study

The review of the literature reveals that few studies have been conducted to evaluate the influence of BDA capability on the organisational performance of South African retailers (Matthew, Johnston, and Brain, 2015; Mneney and Van Belle, 2016). Therefore, this study will serve to expand on this body of knowledge by firstly providing insights into the impact of BDA capability on retail performance. Secondly, providing empirical results of the impact of BDAC (BDATC, BDAHC, and BDAIC) on the organisational performance of selected retailers in South Africa. In addition, the study will provide retailers with a deeper understanding of the value of BDAC to maximize performance. Moreover, the findings of this study can be used by South African retailers as a base to evaluate their organisational performance and make important adjustments to enhance performance within their company and boost operational effectiveness. Additionally, the findings can help South African retailers develop strategies to integrate and deploy BDAC successfully.

1.7 Scope of the study

The study was limited to exploring the impact of BDA capability on the organisational performance of selected South African retailers. The BDA capability variables investigated were BDA tangible, human, and intangible capabilities. The study focused on selected retailers in Cape Town who have implemented big data analytics. Additionally, data was collected via an online questionnaire administered to the BI team members of the selected retailers.

1.8 Overview of research design

Research is a logical search for new insights on a particular topic. It generally follows a research method and design to attain its objectives. According to Mohajan (2017), a research design is often defined as a set of strategies used to address a research problem. There are three main types of research designs: descriptive, explanatory, and exploratory research design (Pawar, 2020) For this study, a descriptive research design was adopted. According to Rahi (2017:2), this type of research design aims at “obtaining information on the current state of phenomena”.

Philosophically, research is based on different paradigms such as positivist, interpretivist, pragmatist, or relativist paradigms. Kivunja and Kuyini (2017:26) define research paradigms as “beliefs and principles that shape how a researcher sees the world and how she/he interprets and acts within that world”. Positivist researchers believe that knowledge is obtained through surveys, experiments, and observations (Nguyen, 2019). Meanwhile, interpretive researchers believe that true knowledge is obtained by the profound understanding and interpretation of a subject (Rahi, 2017). In addition, a positivist paradigm is commonly associated with a quantitative research approach whereas an interpretive paradigm is associated with a qualitative approach (Antwi and Hamza, 2015). The study adopted a positivist paradigm given that it was quantitative, was based on testing hypotheses and collected primary data through a questionnaire that was statistically analysed.

Furthermore, there are two main types of research approaches commonly used in research: quantitative and qualitative research approach. Quantitative research focuses on collecting and analysing numerical data to explain a phenomenon meanwhile qualitative research mostly focuses on understanding and interpreting social interactions (Askarzai and Unhelkar, 2017).

In addition, quantitative research generally makes use of data collection methods such as structured interviews, structured observations, experiments, and surveys (Ragab and Arisha, 2018). Qualitative research generally collects data through field notes, reflections, participant observations, and interviews (Apuka, 2017). A quantitative research method was the most appropriate method for this study since it dealt with a large amount of data, numbers, and statistics.

Moreover, a questionnaire was adopted as a research strategy for this study. According to Amaresan (2022), a questionnaire is a document designed to seek specific information from the respondents. There are two main types of questionnaires commonly used: open-ended and closed-ended questionnaires. This study adopted a seven-Likert scale closed-ended questionnaire which made it easier for the participant to indicate their level of agreement and disagreement with various statements.

A judgment sampling technique was adopted to select the population of the study. The population of the study included the BI team members of selected South African retailers. According to Etikan and Babatope (2019), in this type of sampling technique, the researcher uses his/her own judgment to select the required participants for the study. In addition, the study made use of the formulae developed by Yamane (1967) to calculate the sample size. The sample was estimated to be 109 employees. In addition, the data analysis of this study consisted of two main parts; summarising the collected data (descriptive statistics) and determining the relationship between the dependent and the independent variables (Spearman coefficient correlation). This was done using Excel and Statistical Package for Social Science (SPSS).

1.9 **Ethical considerations**

To carry out this study in an ethical manner, the following ethical issues were considered.

- Informed consent and voluntary participation: The consent of the respondents to participate in the study were asked for. They were made aware of the aims of the study and their right to voluntarily participate and withdraw from the study at any time.
- Confidentiality: the responses and information of the participants were protected and guarded during and after the study. No third parties were given access to the information provided. The Participants were not required to share any information they are not willing to share.
- Respect for the respondents: All the respondents were treated professionally and respectfully both in actions and in words. The researcher ensured that all participants

had a clear understanding of the purpose of the study. Moreover, intellectual property was respected through referencing and the confidentiality of participants was honoured.

1.10 Structure of the thesis

Chapter 1 gives a summary of the study. It presents the background of the study, the problem statement, and the research questions and objectives. In addition, the significance and the rationale of the study were discussed.

Chapter 2 presents an overview of data, big data, big data analytics, BDA capabilities, and the various variables under investigation (BDA tangible capabilities, BDA human capabilities, and BDA intangible capabilities). Based on existing literature, this chapter introduces the conceptual model and hypotheses for the research.

Chapter 3 gives a detailed description of the methodology used in the study. It details the research paradigm and design, sampling technique, tools for data collection, and techniques for analysing the collected data. Additionally, the various ethical considerations are discussed.

Chapter 4 analyses the data collected from the questionnaire using descriptive statistics (frequencies and percentages). A correlation test was run to determine the relationship between the various variables.

Chapter 5 provides a summary of the major findings and conclusions of the study. Additionally, the study limitations and recommendations for further studies are discussed.

1.11 Chapter Summary

In this chapter, the research is introduced and gives an overall understanding of BDA. The background of the study was provided as well as the problem statement. In addition, the research questions and objectives were developed to address the problem of the study. Moreover, the chapter provides a rationale and justification for the study. The following chapter provides a review of key theories and past literature related to the study.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The main aim of this study is to understand the impact of BDA capability on the organisational performance of South African retailers. To achieve this objective, the chapter starts by providing insights into the resource-based theory of a firm. This is followed by an overview of big data and big data analytics (types of analytics, BDA technologies, advantages, and disadvantages of using BDA in retailers). Additionally, the chapter explains in detail the concept of BDA capability and provides a summary of existing literature examining the relationship that exists between big data analytics capabilities and firm performance. Finally, the chapter presents a critical review of the various BDA capability resources (independent variables).

2.2 The resource-based theory of the firm

The resource-based theory (RBT) of a firm was originally founded by Barney (1991) and is often considered the main theoretical foundation used to explain how the resources of an organisation can create a competitive advantage. According to Gupta and George (2016:2), RBT "is a principal paradigm for theoretically and empirically assessing the relationship between organisational resources and organisational performance". Several researchers have argued the importance of RBT in explaining the impact of information technology resources on firm performance (Akter et al., 2016; Gupta and George, 2016; Anwar et al., 2018). According to Utami and Alamanos (2022), this theory relies on two main assumptions (resource heterogeneity and resource immobility).

The assumption of resource heterogeneity indicates "the capability of some firms in accomplishing certain functions with the help of their unique resources" (Akter et al., 2016:6). Besides, the assumption of resource immobility indicates that resources cannot move from one firm to another. Furthermore, Apriliyanti (2022) notes that RBT often evaluates competitive advantage based on the VRIN (valuable, rare, inimitable, and non-substitutable) criteria. They argue that an organisation can obtain a competitive advantage by possessing intangible and tangible resources that have these criteria. In addition, Utami and Alamanos (2022) highlight that the "VRIN" criteria, became the "VRIO" criteria, where the non-substitutable (N) resource was replaced by organisation (O).

Moreover, several studies consider RBT as one of the most important theories in IS that clearly explain the relationship that exists between organisational resources and firm performance. For example, Chae, Koh, and Prybutok (2014) note that the importance of IS resources in organisational performance can further be expanded by utilising RBT. Similarly, Gu and Jung (2013) consider RBT as a strong framework that helps in identifying and classifying IS resources. In addition, it helps in measuring the impact of these resources on an organisation's performance and competitive advantage. Besides, this theory is also well accepted in other business disciplines such as strategic management (Sciarelli, Corte, and Barney, 2012), operation management and supply chain (Sodhi, 2015; Hitt, Xu, and Carnes, 2015), and marketing (Kozlenkoza, Samaha and Palmatier, 2014). Apart from RBT, dynamic capabilities and the knowledge-based view of the firm have equally gained consideration from IT strategy researchers (Gupta and George, 2016).

Furthermore, Apriliyanti (2022) notes that capabilities and resources are the major components of RBT. Resources often refer to intangible and tangible assets meanwhile capabilities are the non-transferable firm resources that aim to improve productivity (Davis and Dewitt, 2021). In addition, Akter et al. (2016:8) note that "capabilities are also identified as tangible or intangible processes that facilitate deployment of other resources to enhance overall productivity".

According to RBT, the capability of an organisation depends on its ability to successfully deal with basic resources to obtain firm performance. Munir et al. (2022) stipulate the various types of resources needed to obtain firm performance. These resources include financial resources (equity, debt, and retained earnings), human resources (all the knowledge, experience, risk, wisdom, and judgment of individuals associated with an organisation), physical resources (all the manufacturing facilities, machines, buildings needed for an organisation's operations) and organisational resources (organisational culture, trust, and relationships). Moreover, Su et al. (2021) classify these resources into intangible resources (organisational learning and culture), human resources (managerial and technical skills), and tangible resources (data, technology, and basic resources). Based on this, the study will follow the same classification to categorise the various resources that will be discussed later on.

Given that the primary goal of this study is to determine the impact of BDA capabilities on the organisational performance of retailers, RBT seems to be the most appropriate theoretical framework for this study. This is consistent with Gupta and George (2016) who note that RBT generally provides a means to evaluate the value of organisational resources and displays a clear relationship between an independent variable and a dependent variable.

2.3 An overview of big data (BD)

Data is essential in any organisation and the world itself is built on the foundations of data (Olusola and Ibitayo, 2018). Large amounts of data are produced each day in various forms and from different sources. According to Cuenca, Urbina, Cordova, and Cuenca (2021), data may come from various sources such as organisations, medical and scientific data, climate data, energy consumption data, demographic data, etc. Big data has been defined in many different ways but is essentially derived from business intelligence and analytics. According to Batko and Slezak (2022:2), big data is "a is a massive amount of data sets that cannot be stored, processed, or analysed using traditional tools". In addition, Doko, Miskovski, and Mirchev (2019:11) define big data as the "collection and analyses of large volumes of structured and unstructured data, potentially in real time to create value for companies".

Big data is usually in the form of structured, unstructured, and semi-structured data. According to Alwan and Mahamud (2020), structured data are often stored in an organised relational databases table which generally consists of rows and columns. Unstructured data is raw, disorganised, and accounts for everything else (Taylor, 2022). Examples include text files (.doc, PDFs), various kinds of messages (text, emails), social media posts, video and audio files, and presentations. Lastly, Semi-structured data is often in the form of structured data.

Moreover, according to Riahi and Riahi (2018:526) "big data generally refers to data that exceeds the typical storage, processing, and computing capacity of conventional databases and data analysis techniques". This term is often characterized by what is called the five Vs (Volume, Variety, Velocity, veracity, and Value) (See figure 2.1).

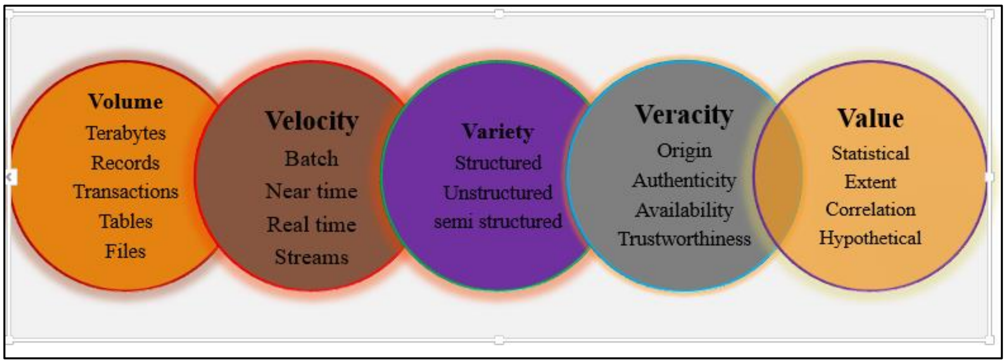

Figure 2.1: Characteristics of Big Data (Raihi and Raihi, 2018).

According to Avinash and Babu (2018:379), the **volume** of the data refers to "the amount of data being created that is vast compared to traditional data sources". This huge amount of data is often generated, gathered, and processed (Prasad and Ventatesham, 2021). For instance, millions of tweets are received and processed on Twitter regularly. The volume of data is often measured in terabytes or petabytes and can be quantified with the number of tables, files, transactions, or records.

Further, Yaseen and Obaid (2020:47) state that **velocity** often “deals with how fast data is being produced and processed to meet the needs and requirements of the consumer”. This implies a massive and continuous flow of data. According to Sowmya and Sravanthi (2017), this real-time data enables organisations and researchers to take valuable decisions that often lead to competitive advantages.

The key factor of big data is the **variety** of information. According to Alwan and Ku-Mahamud (2020:2), the variety of data refers to “the range of data types and sources”. It often originates from various data sources (social networks, transaction records, video, and sensors) with structured, unstructured, and semi-structured data. The variety of unstructured data usually creates a problem for mining, storing, and analysing data.

The fourth V refers to **veracity** which often includes data quality such as trust, reliability, security, correctness, and consistency (Yaseen and Obaid, 2020). According to Prasad and Ventatesham (2021:35), veracity refers to “the process of being able to handle and manage data efficiently”. Improved veracity of big data often leads to controlled business risks related to decision-making (Venkatraman, 2019).

Value is the most important characteristic of big data (Ishwarappa and Anuradha, 2019). According to Hadi, Shnain, Hadishaheed, and Ahmad (2015:21), the value dimension refers to “the important feature of the data which is defined by the added-value that the collected data can bring to the intended process, activity or predictive analysis/hypothesis”. Examples often include social value, education value, and monetary value. In addition, this dimension enables organisations to undertake the correct BD strategy to gain the required data insights to solve their business problems. Therefore, these characteristics contribute to the understanding of big data and mostly emphasize the technical aspects (Gupta and George, 2016).

Several studies noted the importance of big data in organisations. For instance, Cuenca et al. (2021) point out several ways in which big data enable organisations to create business value. These include innovating new business models, increasing transparency, segmenting populations, enabling experimentation, and supporting human decision-making. Several prior studies focused on understanding the impact of big data in different sectors such as banking, sport, medical, retail, etc. For instance, Shankar (2019), discusses various benefits of using big data in retail sectors. Some of these benefits include enhanced pricing, personalised products, forming strategic decisions, predicting trends, estimate customer buying habits. Similarly, More and Moily (2021) cite the advantages of using big data in banking sectors. The banking sector can use BD to increase its effectiveness by identifying the key client, enhancing the client feedback system, detecting when they are going to lose a client, improving the passive and active security system, and efficiently assessing the system (More and Moily, 2021). Wang and Alexander (2019) stipulate that in the healthcare sector, the power of big data enables staff to easily predict disease patterns and find new cures hence improving the quality of life.

2.4 **Big data analytics (BDA)**

Big data analytics is increasingly shaping the way organisations manage their decision-making processes, create new services and products, and gain competitive advantage (Radovilsky, Hedge, Acharya, and Uma, 2018). According to Riahi and Riahi (2019:525), big data analytics is “a set of technologies and techniques that require new forms of integration to disclose large hidden values from large datasets that are different from the usual ones, more complex, and of a large enormous scale”. In addition, Prasad and Venkatesham (2021:35) define BDA as “a form of advanced analytics, which involves complex applications with elements such as predictive models, statistical algorithms and what-if analysis powered by analytics systems". It enhances business effectiveness and efficiency because of its high strategic and operational potential. According to Balachandran and Prasad (2017), the main aim of BDA is to extract useful information from a large data set and convert it into comprehensive structures for further use. Furthermore, Pathak (2021) notes that there are mainly four types of analytics (predictive, prescriptive, diagnostic, and descriptive) which are often used for different types of data.

The concept of big data analytics has left no sector untouched (Sabharwal and Miah, 2021). For instance, retailers can use big data analytics to gain new insights about their customers to inform decision-making around pricing and marketing (Prasad and Venkatesham (2021). Besides, most banking sectors make use of BDA to prevent major fraud and disasters, better understand their customer behaviour, enhance the customer feedback system, and improve their security system (Doko et al., 2019; More and Moily, 2021;). In health sectors, BDA help to improve care, enhance the quality of life as well as reduce operational costs (Cozzoli, Salvatore, Faccilongo, and Milone 2022). In addition, BDA enables academic performance to be assessed in real-time. This helps to monitor the performance of the students after each module and give immediate feedback on their learning patterns (Veldkamp et al., 2021).

Furthermore, several studies have provided empirical evidence that there is a link between big data analytics and firm performance. For instance, Shabbir and Gardezi (2020) assert that big data is positively related to organisational performance. Hussain, Rehman, Khokhar, and Ejoz

(2021) identify a positive relationship between big data analytics competency and firm performance. Furthermore, Nejjari and Aamoum (2021) aim to understand the direct impact of big data analytics on the financial performance of a firm. In addition, Maroufkhani et al. (2019) present a systematic literature review to understand the link between big data analytics and firm performance. They identify various key factors that impact the adoption of big data analytics and enhance firm performance. These factors include individual aspects, organisational aspects, big data analytics capability, data-related aspects, business analytics capability, absorptive capacity, open innovation, and market orientation (Maroufkhani et al., 2019).

2.4.1 Type of analytics

There are mainly four types of analytics (descriptive, diagnostic, predictive, and prescriptive) which are often used for different types of data. Descriptive analytics is the entry-level in analytics taxonomy. According to Ajah and Nweke (2019:7), this analytics is “a simple statistical technique (graph) that describes what is contained in a data set or database”. Descriptive statistics often include frequency and probability distribution, graphs, charts, measures of dispersion (standard deviation), and measures of central tendency (mode, mean, median). Descriptive analytics generally determine what is happening by analysing the root cause of an event (Lepenroti, Bousdekis, Apostolou, and Mentzas, 2020). In addition, it provides future trends and probabilities and gives a scenario of what might happen next. This type of analysis enables retailers to collect raw data from various sources using business intelligence tools to generate insights into performance. According to Satish and Yusof (2017:276), “descriptive analysis can be used to mine the customer experiences to know what is happening in real-time.

Diagnostic analytics generally uses past data analysis to determine the root cause of certain events (Mia, 2020). This method evaluates the data to respond to the question “why did it happen?”. According to Chunarkar-Patil and Bhosale (2018:328), “it is usually used to uncover any hidden patterns which help for the complete root cause as well as identify any factors that are directly or indirectly causing effect”.

Predictive analytics apply forecasting to past information to predict the future. According to Pattnaik and Behera (2016:212), “predictive analytics is a process of developing data mining techniques that use analytical models discovering hidden patterns and apply them to predict future trends and behaviours”. It helps to identify patterns and trends, providing decision-makers with the necessary information for their decisions (Pathak, 2021). This analytical method is one of the most commonly used methods for sales lead scoring, social media, and consumer relationship management data (Chunarkar-Patil & Bhosale, 2018). It uses techniques such as artificial intelligence and data mining to evaluate the current data and predict future scenarios. Moreover, predictive analytics is considered a significant tool for organisations in the competitive race. For instance, it enables retailers to predict customers' satisfaction and future sales based on data patterns. In addition, Hall (2021) highlights various benefits of using predictive analytics in retailers. It enables retailers to determine which items generate the highest level of profits, personalise offerings based on customer data, detects and prevent online frauds, determine optimal pricing of services and products, recommend product offerings to specific customers.

Prescriptive analytics is often used to identify an issue before it happens using modelling and statistics (Lakshmanan, Sorman, and Flores, 2020). It is dedicated to finding the right action to be taken (Riahi and Riahi, 2018). Prescriptive analytics uses a variety of technologies (machine learning, recommendation engines, and models) and techniques (optimisation, data mining, and knowledge data discovery) to reveal optimal actions. According to Lakshmanan et al. (2020:1424), "prescriptive analytics can be used to identify the possibilities of online recommendations by considering the real-time sensor data, particularly in the area of decision-making for condition-based maintenance" This method is often not preferred by organisations but can show impressive results if correctly used.

Therefore, descriptive analytics consists of knowing what is currently happening, diagnostic analytics consists of understanding why it happened, predictive analytics consists of determining what is likely to happen and prescriptive analytics consists of finding solutions (See Figure 2.2).

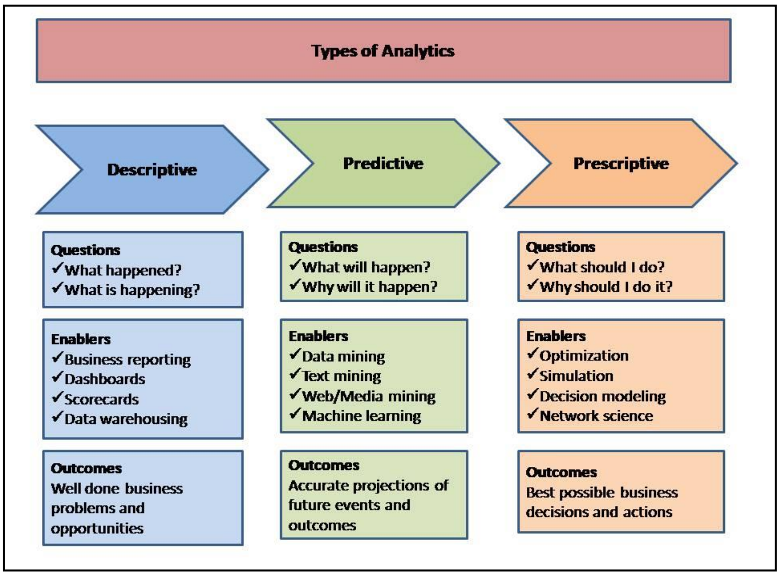

Figure 2.2: A simple taxonomy for analytics (Delen and Ram, 2018).

2.4.2 Big data analytics technologies

2.4.2.1 Extraction, transformation, and loading (ETL)

Extraction, transformation, and loading (ETL) are often defined as the extraction of data from various sources e.g. operational systems to the data warehouse. According to Yulianto, (2019:64), ETL is considered "the set of processes for getting data from OLTP (On-Line Transaction Processing) systems into a data warehouse". Also, they are used to ease the tasks of database administrators who link various branches of databases as well as add/modify existing databases (Taylor, 2022).

Furthermore, Ashtari (2022) notes that the ETL process consists of three database functions that enable the transfer of data from one database to another. These database functions include extract, transform and load. The extract function generally consists of extracting data (structured and unstructured) from various sources (internal and external). According to Thirumagal et al. (2014:65), "the goal of the extraction phase is to convert the data into a single format appropriate for transformation processing". After this phase, the data extracted are sent to the Data Staging Area (DSA) in the warehouse for transformation, homogenization, and cleansing. According to Yulianto, (2019:64), the transform function consists of "detecting and removing errors and inconsistencies from data to improve the quality of data". In addition, data transformation is considered the most costly step in the ETL process and the most difficult in terms of time processing (Preeti and Sharma, 2016). Lastly, the load function consists of loading the data in the data warehouse and all its counterparts (data marts) (Barahama and Wardani, 2021).

Moreover, Subramani (2018) notes that with a clearly defined ETL retailers can limit all unnecessary manual efforts thus saving time and costs. In addition, the quality and availability of data increase thus leading to improved forecasts and data-based planning.

2.4.2.2 Data warehouses

A data warehouse (DW) stores data and is usually built to improve the data quality of organisations. According to Barahama and Wardani (2021), DW is a computer file containing an organisation’s data designed to assist with the production of reports and analyses. This approach enables organisations to easily organize, understand and analyse their data hence leading to better decision-making. Furthermore, a data warehouse is often characterized by four keywords; subject-oriented, integrated, time-variant, and non-volatile (Dhaouadi, Bousselmi, Gammoudi, Monnet, and Hammoudi, 2022).

Data Warehouses are usually considered subject-oriented because they organize around enterprise-specific concepts such as products/services, customers, sales, and suppliers (Barahama and Wardani, 2021). Nowicki, Rot, and Ziora (2007:2) note that time-variant indicates that “in operational systems, data is valid from the moment of access, whereas in data warehouse systems the data is valid from a defined moment in time”. Lastly, non-volatile implies that when the data is incorporated in the data warehouse, it is not modifiable (neither changed nor removed).

Maguire (2020) notes various benefits of deploying a data warehouse. These include enhancing turnaround time for reporting and analysis, reducing costs for accessing historical data, integrating data from various sources, performing new analytic methods, and easy sharing and access to data. Also, DW is essential for the success of retailers. It enables them to use relevant data to meet their needs and obtain valuable customer insights. In addition, it provides retailers with enhanced business intelligence, scaling of operations and demand forecasting, a better understanding of customers, and operation efficiency (Menon, 2019). Most importantly, it can be used to forecast demand for cash management, inventory management, and overall profitability.

2.4.2.3 Hadoop BDA ecosystem

The Hadoop ecosystem is a framework or platform that helps in solving various big data problems. According to Mehta and Mehta (2016:557), “Hadoop ecosystem is a framework of various types of complex and evolving tools and components which have proficient advantage in solving problems". This framework has four main layers: data management, data access, data processing, and data storage (Nagdive and Tugnayatt, 2018).

The data storage layer includes Hadoop Distributed File System (HDFS) and HBase. HDFS is generally considered the backbone of the Hadoop ecosystem. According to Abdulali and Gultepe (2020:56), "HDFS is the basic file system that enables disks in a distributed environment to function as a single virtual disk". Additionally, it enables us to store various types of huge data sets (semi-structured, structured, and unstructured data). Besides, Mehta and Mehta (2016:558) define HBase as "a scalable, distributed database that supports structured data storage for large tables". It facilitates the writing and reading of big data efficiently and randomly in real-time.

The data processing layer includes MapReduce and YARN. According to Janani and Christopher (2021), MapReduce is a programming model used to process large datasets in a distributed environment. On the other hand, YARN which stands for Yet Another Resource Negotiator is often considered the brain of the Hadoop ecosystem. It performs all the processing activities by scheduling tasks and allocating resources.

The data access layer consists of Pig, Hive, Mahout, and Sqoop. Pig is generally considered as a platform used to process and analyse huge data sets. According to Nagdive and Tugnayat (2018:36), Hive is "a data warehouse tool basically used for analyzing, querying and summarizing of analyzed data concepts on top of the Hadoop framework". Besides, Mahout is a data-mining and machine-learning library designed for regression testing, data clustering, classification, collaborative filtering, and statistical modeling (Suguna and Devi, 2016). In addition, sqoop is a connectivity tool used to transfer large amounts of data between relational databases (MySQL, Oracle, PostgreSQL) and Hadoop (Nagdive and Tugnayat, 2018).

The data management layer includes Oozie,Chukwa, Flume, and Zookeper. Oozie is often defined as a workflow scheduler that schedules, excutes, and supports several Hadoop jobs. These jobs include MapReduce, Sqoop, Pig, and Hive. Besides, Chukwa is a data collection system used to monitor large distributed file systems. According to Mehta Mehta (2016:561), this system includes "a flexible and powerful toolkit for displaying, monitoring and analyzing results to make the best use of the collected data". Flume is generally defined as a distributed and reliable service that enables us to efficiently collect, aggregate, and move huge amounts of data sets. In addition, Nagdive and Tugnayat (2018:36) define Zookeeper as "an open source centralized service which is used to provide coordination between distributed applications of Hadoop".

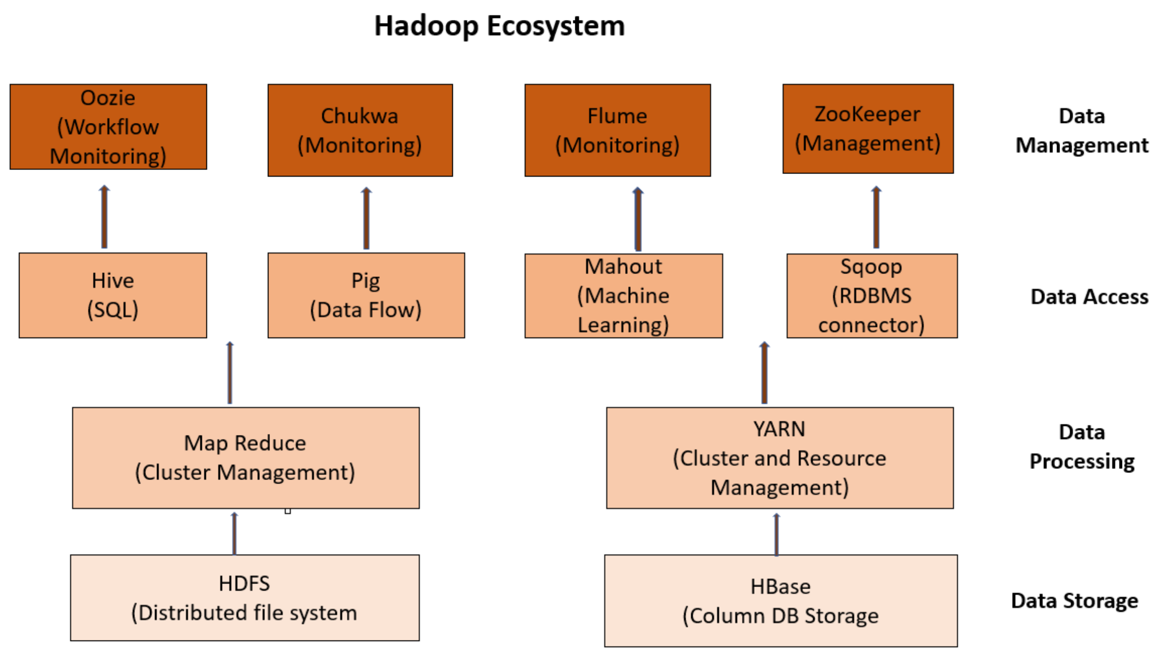

Figure 2.3: Hadoop Ecosystem (Nagdive and Tugnayat, 2018).

Furthermore, Abu-Alsaad (2019) notes various benefits of applying Hadoop in retailers. Hadoop helps retailers to know their customers and optimise their experience, localise and personalise promotions, analyse brand sentiment, optimise websites and redesign store layouts. Moreover, research conducted by Desai (2022) highlighted some key differences between the Hadoop ecosystem and the Google Cloud Platform (GCP) ecosystem which is often defined as a set of cloud services that google offers. These key differences included;

- Hadoop is an open-source software designed for the manipulation of data meanwhile GCP offers services to manage data remotely on a demand basis
- Hadoop helps businesses to analyse business problems such as fraud detection, sentiment analysis, and product recommendations while GCP reduces the cost of maintaining and managing IT systems.
- Hadoop offers an increased system availability and appropriate response times meanwhile GCP provides a secure, reliable, and a consistent Quality-of-Service (QoS)management
- Hadoop focuses on manipulating huge data sets with unstructured and structured data meanwhile GCP focuses on data security, network performance, availability, and system performance

2.5 Benefits of using big data analytics in retailers

2.5.1 Personalise products

Personalisation is the act of designing the output of a system to meet the profile of a user. It often relies on user information such as interests, preferences, opinions or geographical location.

Analytics has made it easy for retailers to understand the exact preferences of their various customers. For instance, Shankar (2019) notes that the use of big data analytics by retailers enables them to optimise their supply chains, predict their customer purchases and personalise offerings and recommendations. Real-time data analytics helps organisations to offer promotions and personalise services to customers (Akter and Wamba, 2016). In addition, Stefano (2022) notes that machine learning enables retailers to identify user patterns which helps them better understand the behaviour of their customers. Big data enables the offering of the right services or products to the right person at the right time through the right channel for the right price (Le and Liaw, 2017). Therefore, in this case, analytics enable retailers to reach their customers at the right time, right place, and through the right channel. Furthermore, BDA enables retailers to offer personalise prices to their customers. In other words, it can engage in price discrimination based on an assessment of the customer's preference and tolerance (Chatterjee, 2019). Hence, sellers can increase income by quoting a greater price to clients willing and ready to pay more.

2.5.2 Improved customer service

Providing high-quality customer service is an important key to keeping customers happy (Le and Liaw, 2017). The use of BDA enables retailers to improve their customer service, attract new customers and retain existing ones. For instance, when customers complain online, data analysis detects the background of the issue, enabling customer care to address it and improve the service. This often results in a quicker resolution of customers' queries and results in greater customer satisfaction. Furthermore, BDA enhances customer service by analysing the products that customers often purchase and offering suggestions. For instance, through BDA an online site may give suggestions to a customer buying a mobile phone to equally buy a mobile cover (Bethi, 2020). Hence, this enables retailers to improve customer satisfaction and increase their sales.

Moreover, Akter and Wamba (2016) describe the use of BDA in the e-commerce context and noted that BDA provides exceptional customer service more than any other system and highly influences the performance of organisations. In addition, Cuenca et al. (2021) conducted a study to understand the potential impact of BDA on organisations and noted that BDA can enable organisations to collect data from various communication channels (email, phone, instant messages) which can assist their customer service staff to quickly understand and address customer issues. Big data analytics can also be used to analyse transaction activities in real-time, detect fraudulent activities, and promptly notify clients of potential issues (Cuenca et al., 2021).

2.5.3 Price optimisation

Price optimisation is the process of finding the best price point for your service/product based on customer data and the market (Kirsch, 2021). The price of a product often depends on several factors such as competitor's pricing, inventory, market demand, etc. Big data analytics plays an important role in determining the price (Chandramana, 2017). Through algorithms, sellers can provide the right discount rate using the transaction data, and buyers' long-time and short-time preferences over products (Shreyashi, 2020). Thus, this helps retailers to determine when prices should drop (Markdown optimisation) (Chandramana, 2017). In the past, most retailers would simply decrease costs at the end of a purchasing season for a specific product offering when the demand has nearly gone. But now with the help of data analytics, retailers can make use of machine learning to adjust their prices in real-time and send offers or recommendations to a specific set of customers (Aktas and Meng, 2017).

2.5.4 Inventory management

Inventory management is the process of monitoring and controlling inventory levels and ensuring adequate replenishment to meet customer demand (Priniotakis and Argyropoulos, 2018). Vu (2018) notes that BDA greatly contributes to inventory management improvement. For instance, once retailers understand the buying trends of their customers, they focus on the sectors where there will be high demand (Chandramana, 2017). This often involves gathering economic, demographic, and seasonal indicators to understand the purchase behaviour across the targeted market. In addition, BDA significantly improves the visibility in inventory tracking and preciseness in forecasting demand (Vu, 2018).

Moreover, Bethi (2020) notes that BDA can help organisations enhance their inventory management. For instance, combining datasets of seasonal sales and sales histories can help retailers predict changes in demand and enhance stock forecasting (Chandramana, 2017). In addition, retailers can automate the replenishment of their stock by analysing data from bar code systems which can limit stock delays.

2.5.5 Predicting trends

Prediction is forecasting what will happen in the future. Retailers can predict trends accurately and have a better understanding of market demands based on economic indicators and demographic data. Nowadays, sentiment analysis is very common among marketers (Bethi, 2020). They often use this technique to examine the sentiments of the market. Sentiment analysis can be used to process unstructured text written by a user to discover their interests, opinions, preferences, etc. (Kumar, 2020). The gathered data can effectively be utilised to come out with top-selling products in any particular category very accurately (Kaur and Jagdev, 2017). Moreover, Akter and Wamba (2016) described the use of BDA in the e-commerce context and noted that predictive analytics enables organisations to draw up their revenue budgets to better forecast and properly manage inventory. Predictive analytics also bring additional benefits like fraud minimisation and overall supply chain management (Chatterjee, 2019).

2.5.6 Greater Customisation

Customers often have different ways of shopping with the same retailer. They usually shop using mobile apps, websites, etc. When data are collected in real-time for analysis from multiple sources, companies can provide a customised experience for customers (Seetharaman et al., 2016). For instance, data analytics help retailers to make proper customer segmentation which facilitates the provision of relevant offers to the most important customers. According to Kaur and Jagdev (2017), it is important to give priority to such customers because it is more costly to build relationships with new users than to keep the best users.

Customer segmentation is now much more refined and data-driven based on customers' transaction history, basket analysis, loyalty programs, and social media interactions (Chandramana, 2017). Hence, it is easier for retailers to have a 360-degree view of their customers and customise products based on their preference history.

2.6 **Challenges of using big data analytics**

2.6.1 Data security and privacy

One of the most pronounced criticisms of data and analytics is security (Delen and Ram, 2018). People consciously or unconsciously reveal their personal information by performing daily activities such as: exchanging emails, paying taxes, sharing photos, communicating with family, groceries shopping, and so on (Mai, 2016).

Using big data often consists of storing information on various storage sites such as social media, servers, and cloud-based storage, hence making it difficult for retailers to have total control over the security of their customer's data. According to Le and Liaw (2017), a large volume of data is an appealing target for hackers. The security of these large datasets can be improved by using techniques of encryption, authorisation, and authentication. In addition to security, personal privacy is also a concern. As big data technologies mature, the extensive collection of personal data raises serious concerns for individuals, firms, and governments (Lee, 2017). According to Delen and Ram (2018:5), the "use of personal data about the customers (existing or prospective), even if it is within the legal boundaries, should be avoided or highly scrutinized to prevent the organisation from bad publicity and public outcry". Data security and privacy must thus be considered before the adoption of any protocol for sharing information (Al-Shiakhli, 2019).

2.6.2 Lack of analytics skills

Big data brings along with it some huge analytical challenges (Satyanarayana, 2015). The analysis of large amounts of data (structured, unstructured, or semi-structured) often requires analytical skills. As the need to manipulate unstructured data such as text, video, and images increases rapidly, the need for more competent data scientists grows (Lee, 2017). However, these scientists are difficult to find in the market and even when they are available, salaries for such professionals may be too high (Goddard, 2021). Hence, retailers are faced with the challenge of finding people with the required skills to take advantage of their large datasets. According to Seleh, Ismail, Ibrahim, and Hussin (2018), organisations need to organise training programs to train their existing staff with the appropriate skill set.

2.6.3 Heterogeneous data

Unstructured data often represents data being produced from fax transfers, PDF documents, emails, recorded meetings, and social media (Satyanarayana, 2015). Working with this data type can be very difficult and costly. In addition, the bad governance of these high volumes of data may lead to inconsistencies in information (Bindu, 2018). Moreover, analysing heterogeneous data sources has become a privacy and security problem due to the communication with other external systems (Amalina, Hasham, Firdaus, and Imran, 2019). Also, transforming unstructured data into structured data is not feasible.

Along with that structured data is highly organised, managed, and integrates with databases easily but in the case of unstructured, it is completely raw and unorganised (Chunarkar-Patil and Bhosale, 2018).

2.6.4 Quality of data

Data quality refers to the fitness of data for a specific purpose of usage (Lee, 2017). It plays an important role in decision-making. For this reason, an organisation must consider employing necessary actions to manage data acquisition, data extraction, data cleansing, and data integration (Seleh, Ismail, Ibrahim, and Hussin (2018). The data analysed often comes from different sources and formats and may contain wrong information, contradictions, and duplications. Carefully structured data is essential for efficient and accurate data analysis (Seleh et al., 2018). On the other hand, data of inferior quality or incomplete data often leads to wrong data analysis which in turn results in poor decision, judgment, and results (Bulger, Taylor, and Schroeder, 2014). According to Lee (2017), a data quality control process needs to be implemented to assess data quality and repair data errors.

2.7 **Big data analytics capability (BDAC)**

Big data analytics capability is often considered as the ability of an organisation to mobilise, deploy and utilise big data analytics resources effectively to enhance its performance (Munir et al., 2022). It is generally concerned with the ability of firms to leverage BDA to attain strategic objectives. Additionally, it enables organisations to manipulate data to obtain a more accurate organisational performance analysis. Akhtar, Frynas, Mellahi, and Ullah (2018:2), consider BD capability as "an effective combination of relevant human resources, prerequisite big data skills (both functional and team-based), advanced technologies, mathematical and statistical techniques, and machine learning tools that produce and process large datasets to generate analytical reports and actionable insights utilised for improving performance". In addition, Gupta and George (2016:1) define this concept as "a firm's ability to assemble, integrate and deploy its big data-specific resources".

Furthermore, Aker, Wamba, and Gunasekaran (2016) note that BDAC is often categorised into three primary dimensions i.e. BDA management capability, BDA technology capability, and BDA talent capability. BDA management capability consists of "ensuring that solid business decisions are made applying proper management framework" (Akter et al., 2016:18). BDA technology capability refers to the ability of data scientists to quickly develop and deploy IT infrastructures (Akter et al., 2016). BDA talent capability refers to "the ability of an analytics professional (e.g., someone with analytics skills or knowledge) to perform assigned tasks in the big data environment" (Akter et al., 2016:20). Also, Wang, Kung, and Byrd (2018) highlighted four dimensions of BDA capabilities i.e. data interpretation capability, analytical capability, data integration capability, and predictive capability. Similarly, Cosic, Shanks, and Maynard (2012) categorise BA capabilities into four different groups (technology, people, culture, and governance).

Several studies focused on investigating and understanding the concept of BDA capability. For instance, Garmaki et al. (2016) aimed to understand the impact of BDA capability on a firm's financial and market performance. They derive four BDA capability dimensions (infrastructure, management, relational, and personnel capabilities) from IT capability to better understand the current firm's abilities and their influence on performance. These four dimensions are further explained by eleven constructs: investment, BDA planning, coordination, connectivity, control, compatibility, modularity, relational knowledge, technical knowledge, business knowledge, and technology management knowledge. According to Garmaki et al. (2016:3), "the overall integrated BDA capability is the result of the interrelated relationship among these four dimensions and the synergies between them enable firms to change business processes, which in turn, lead to superior firm performance".

Similar to the BDA capability model created by Gupta and George (2016), Mikalef et al (2017), Huang et al. (2022) draw on the resource-based theory of the firm (RBT) to identify the various resources needed to create a firm's BDA capability and to test the relationship between BDA capability and firm performance. Three types of resources are proposed including tangible resources (data, technology, and other basic resources), intangible resources (data-driven culture and organisational learning), and human resources (managerial and technical big data skills). The empirical results of these studies provide evidence that BDAC leads to high firm performance. This study adopts the BDA capability constructs by Gupta and George (2016) to test the research question and hypotheses.

2.7.1 IT capabilities and big data analytics capability

Several researchers argue that it is necessary to have a broader view of information technology (IT) to better understand the business value of information systems (IS) investments (Nabeel-Rehman, 2019; Bakan and Sekkeli, 2017). They further suggest focusing on IT capability which is often defined as "a bond of competencies (skills and knowledge) and IT resources (infrastructure) which are created by a particular organisation and is implemented through activities to achieve business objectives" (Pintarie and Bronzin, 2013:105). Eldin (2018), Oliveira and Macada (2017), and Turulja and Bajgoric (2016) argued that this concept usually comprises three dimensions (IT infrastructure capabilities, IT human capabilities, and IT management capabilities). In addition, BDAC is also considered "an important organisational capability leading to sustainable competitive advantage in the big data environment" Fosso Wamba et al. (2017:357). Furthermore, Hershanty and Jafrizal (2021), note that only organisations with strong IT capabilities can provide quality data for decision-making and survive the uncertainty of technology and achieve high performance. Also, this concept is based on the assumption that resources can easily be imitated meanwhile organisational capabilities cannot which often leads to competitive advantage (Wamba et al., 2017).

Moreover, several typologies of IT capabilities have been proposed. For instance, Bakan and Sekkeli (2017) conceptualise four types of capabilities: IT infrastructure (network resources, hardware, and software), IT business experience (quality of IT business and strategy expertise), IT relationship resources (compounding IT functions with IT resources) and IT human resources (organisational capability and resource) to understand their impact on firm competitiveness. Besides, a study conducted by Eldin (2018) considered IT capability as a function of IT infrastructure capability, IT personnel capability, and IT management capability and found that these capabilities have a positive impact on firm performance. This finding is consistent with other studies that evaluated the relationship between IT capability and firm performance (Mazidi and Latifi, 2014; Oliveira and Macada, 2017; Nabbel-Rehman and Nazri, 2019). Similar to the IT capabilities literature, the study conducted a review of BDAC and presented three main dimensions: BDA tangible capabilities, BDA human capabilities, and BDA intangible capabilities.

2.7.2 Big data analytics capability and firm performance

A significant number of studies have explored and proved a positive relationship between BDA capability and firm performance. For instance, Gupta and George (2016) tested their model based on the resource-based theory of the firm to examine the relationship between BDAC and firm performance and found that BDAC positively impacts both operational and market performance. Based on the same theory, Shabbir and Gadezi (2020) tested their model to examine the relationship that exists between BDA and the organisational performance of small and medium enterprises with the mediating role of knowledge management practices. The findings indicated that BDA has a positive and significant influence on OP and that knowledge management practices partially mediated the relationship between BDA and OP in small and medium enterprises.

Furthermore, FossoWamba et al. (2017) tested the relation between their BDAC model and firm performance. They found that BDAC has a positive influence on firm performance and that dynamic capabilities play a strong mediating role in improving this performance. Similarly, Akter et al. (2016) made use of the same model and found a positive relationship between BDAC and firm performance with a significant influence on analytics capability-business strategy alignment. Moreover, Garmaki et al. (2016) proposed a conceptual model based on IT capability to assess the relationship between BDA capability and firm performance. They found a positive impact of BDA capability on finance and market performance with operational performance being the mediator of this relationship.

In addition, Anwar, Khan, and Shad (2018) examined the influence of big data capabilities on firm performance with the competitive advantage being a mediating role. They found that big data technology capabilities and big data personal capabilities have a significant positive impact on firm performance and competitive advantage. The results indicated that there is a significant positive association between competitive advantage and firm performance. Besides, Wang et al. (2018) examined the impact of BDAC in healthcare industries and found that it leads to business value creation. Moreover, Amankwah-Amoh and Adomako (2019) adopted a different technique to examine the impact of BDA on firm performance. They developed a four-domain framework that clarifies how various approaches toward BDA adoption and implementation can lead to various results.

Therefore, several studies proved that BDA capability and firm performance are positively related to different moderating and mediating variables.

2.8 BDA capability resources

Nowadays, organisations need to possess several resources to fully obtain the benefits that big data offers (Munir et al., 2022). Even though limited research was conducted on BDA capability, some studies focused on understanding the resources needed to develop such a capability (Gupta and George, 2016; Mikalef et al., 2017; Su et al., 2021; Munir et al., 2022; Huang et al., 2022). Mikalef, Boura, Lekakos, and Krogstie (2019), note that an organisation needs a combination of tangible, intangible, and human resources to build a big data analytics capability. These resources are fundamental in the formation of an organisation's overall BDA capability. Therefore, it is important to examine important debates regarding each of these resources.

To date, most studies have discussed the processes and resources needed to deploy BDA but have provided little insight into how organisations can create a strong BDA capability (Gupta and George, 2016). Building on the foundations of the resource-based theory of the firm and several information technologies (IT) work, the main resources necessary to build a strong BDAC were identified. These resources are divided into three main groups: tangible resources (data, technology, and basic resources), intangible resources (data-driven culture and organisational learning), and human resources (technical skills and managerial skills). Also, this study will adopt the BDAC constructs proposed by Gupta and George (2016) to test the research questions and hypotheses. These constructs include seven resources drawn from the resource-based theory of the firm (See figure 2.4). These resources are discussed in more detail below.

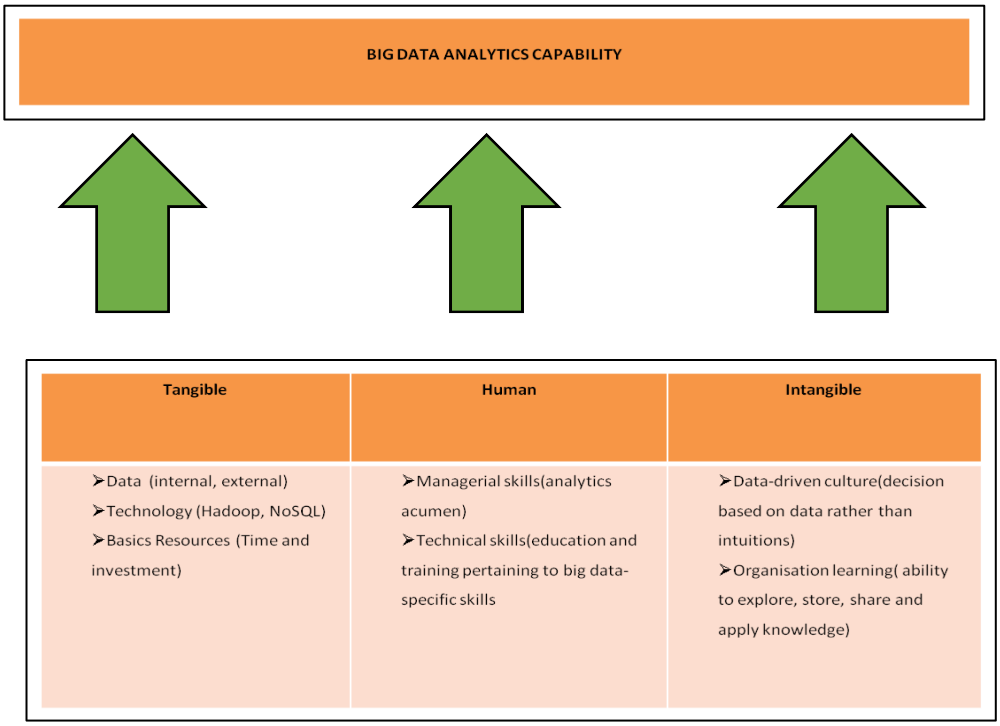

Figure 2.4: BDA capability resources (Gupta and George, 2016).

2.8.1 BDA tangible capabilities

Tangible resources are often considered as the organisational structures, physical assets (e.g., facilities, equipment, etc.), and financial resources (e.g., equity, debt, etc.) needed for the operation of an organisation. According to RBT, tangible resources are the ones that can be sold or bought in a market (Gupta and George, 2016). They often enable the BDA staff to rapidly develop, install/deploy and support the system components necessary for an organisation. When it comes to tangible resources, data, technology, and other basic resources are noted as being fundamental to big data success (Mikalef et al., 2019).

2.8.1.1 Data

In addition to land, labour, and capital, data is an important factor of production for an organisation. While in the past organisations mainly focused on the data that could be stored in relational databases, today they tend to capture every bit of information (structure of data, size of data, and speed of the data) (Munir et al., 2022). An organisation's data can be categorised into internal and external data. According to Gupta and George (2016:4), "internal data refer to enterprise-specific data, which are created as a result of the firm's internal operations such as inventory updates, accounting transactions, sales, and human resource management". On the other hand, external data are also known as "population-level data" which refer to data collected from the organisation's external sources. Examples include sensors, mobile phones, e-commerce communities, and the internet. In addition, organisations usually buy data to enhance their analytics thus gaining more insights into their operations and customers (Mikalef et al., 2017). Organisations interested in building a strong BDA capability must fully integrate both their internal and external data.

Moreover, Gupta and George (2016) identify five data sources: community data (data generated by social communities such as Twitter, Facebook, etc.), self-quantification data (data generated from wearable technologies), and data exhaust (data that has no direct value), private data (datasets owned by a firm) and public data (datasets owned by the government). Fosso Wamba et al. (2015) emphasize the benefits of the availability and integration of data from different sources.

2.8.1.2 Technology

Organisations need to have an infrastructure capable of analysing, sharing, and storing data (Mikalef et al., 2017). Datasets require advanced technologies that can handle the issues often posed by gigantic and fast-moving data. Relational database management systems (RDBMS) have remained a popular choice for organisations to store structured data such as employees' records, customer orders, inventory management data, and financial transactions (Gupta and George, 2016). Furthermore, to gain insights from organisational data, organisations often depend on the extract, transform and load (ETL) method to build data warehouses. According to Barahama and Wardani (2021:1), a data warehouse is "a database that contains large amounts of data that aims to help organisations, fields, and institutions specifically for decision-making".

Moreover, Garmaki et al. (2016), highlight that 80% of an organisation's data is unstructured. Hence, organisations are adopting new data storage and analysis methods such as structured query language (SQL) and Hadoop. In addition, emerging technologies such as; Apache Cassandra, Hadoop, MongoDB, Hazelcat, and Monet facilitate storage distribution via Hadoop Distributed File System (HDFS) (Cetindamar, Shdifat, and Erfani, 2020). These technologies enable the continuous processing of information in real-time (Fosso Wamba et al., 2015).

Meanwhile, some studies examined the BD infrastructures of an organisation (Kamioka and Tapanainen, 2014), while others focused on the characteristics of technology (Garmaki et al., 2016; Akter et al., 2016; Fosso Wamba et al., 2015). In particular, scalability and connectivity are cited as important, since the data accumulated and processes used fluctuate continuously (Mikalef, Pappas, Krogstie, and Giannakos, 2017).

2.8.1.3 Basic resources

Apart from data and technology, organisations should also invest in their BD initiatives. Basic resources often refer to the investments made in BD initiatives and the time given to attain objectives. Firms must be persistent and devote enough time to their BDA initiatives to achieve their analytical objectives (Gupta and George, 2016). In addition, they should make an appropriate investment in their big data initiatives. Prior studies suggested investment and time as dimensions of basic resources (Mikalef et al., 2017; Lozada, Arias-Perez, and Perdomo-Charry, 2019).

2.8.2 BDA human capabilities

The human resources of an organisation often consist of the knowledge, experience, business insights, relationship, problem-solving abilities, and leadership qualities of its employees. Prior research has suggested managerial and technical skills as dimensions of human resources (Mikalef et al., 2017; Munir et al., 2022)**.** Lozada et al. (2019), note that human resources are categorised into two main groups. The first group consists of people with technical skills such as machine learning, statistical analysis, artificial intelligence, programming, and extraction of data. The second group consists of people in charge of planning and implementing big data-related resources. This study proposes managerial and technical skills as the two main aspects of a firm’s human resources.

2.8.2.1 Technical skills

Technical skills refer to “the know-how required to use new forms of technology to extract intelligence from big data” (Gupta and George, 2016:4). These skills often include competencies in data extraction and cleaning, machine learning, programming paradigms, and statistical analysis. Even though several courses on these skills are being offered by universities, there is still a shortage of individuals with BD technical skills (Chen, Chiang, and Storey, 2012). According to Nasir, Farzeeha, Noordin, and Nordin (2011), technical skills can be acquired in formal and non-formal ways. These skills are obtained formally through academic channels (institutions of higher education), attending seminars and courses organised by world bodies. On the other hand, they are obtained informally through progressive tutorials. For some businesses, the biggest challenge in deploying BDA may not be the technology itself, but how to find data scientists to work with these technologies (Cetindamar et al., 2020). Therefore, technical skills play a vital role in organisational performance and building competency (Hussain et al., 2021).

2.8.2.2 Managerial skills

Meanwhile, organisations develop technical skills by training their employees, managerial skill is developed over time within the organisation. Mikalef et al. (2017) define managerial skills as the ability of employees to interpret information extracted from BDA and utilise them. Some of these skills include decision-making, conceptual, communication, technical, interpersonal, teamwork, and problem-solving skills. These skills are often created as a result of a solid bond between organisational individuals working in the same/different departments.

Within the context of a firm's BD function, the intelligence gathered from the data may be of no use if the managers fail to understand which gathered insights could be useful (Cetindamar et al., 2020). Thus, a manager must have a sharp understanding of how and where to apply the insights extracted by their technical teams (Gupta and George, 2016). In addition, BD managers should be able to understand and predict the future needs of customers and other business units and partners. Furthermore, Gupta and George (2016), note that a good working connection and mutual trust between BD managers and functional managers often lead to the improvement of human BD skills. The success of BDAC in an organisation often depends on soft skills such as the ability to trust and interpersonal skills (Cetindamar et al., 2020).

2.8.3 BDA intangible capabilities

Intangible resources generally have no physical existence. They often include brand recognition, goodwill, and intellectual property (copyrights, trademarks, and patents). In addition, Munir et al. (2022) suggest data-driven culture and organisational learning as the intangible resources that are needed by firms to fully obtain the benefits that big data offers.

2.8.3.1 Organisational learning

Organisational learning is the process of improving actions through better knowledge and understanding (Odor, 2018). Teece et al. (2015), note that organisations that can adjust their resources according to environmental changes will have a sustained competitive advantage. This ability of an organisation is often affected by the intensity of organisational learning (Gupta and George, 2016). Organisational learning is often defined as the ability of an organisation to develop and use insights and knowledge to continuously enhance its performance. According to Gupta and George (2016:5), "firms with high intensity of organisational learning will likely have an advantage of applying their stocks of knowledge to further validate the initial insights gleaned from big data". Moreover, with the emergence of new technologies, knowledge might be outdated with time. Hence, organisations need to continuously respond to the changing market demand. Based on several studies, organisational learning helps build a strong BDAC to address performance-related issues (Cetindamar et al., 2020; Mikalef et al., 2017).

2.8.3.2 Data-driven culture

Big data analytics implementation is not an easy task, especially when you don't have a data-driven culture. A data-driven culture is a pre-requisite for the successful implementation of big data (Lozada et al., 2019). Mikael, Daniel, and Thomas (2018:1) note that it is often "characterised by a decision process that emphasises testing and experimentation, where data outweighs opinions and where failure is accepted as long as something is learnt from it". It plays an important role in the adoption and development of BDA capability (Cao, Duan, and Li, 2015).

According to Cetindamar et al. (2020:212), it "is an intangible resource, which is very difficult to understand and describe". In addition, data culture is a fundamental factor in the analysis of BDA competency (Hussain et al., 2021). Provost and Fawcett (2013), note that even though several organisations implement BD projects, the majority rely on intuition or managerial experience rather than the information extracted from data analysis. According to Gupta and George (2016), employees at all levels of an organisation need to be involved in data-driven decision-making. All organisational members (top-level executives, Middle-level managers, and low-level employees) should take decisions based on the extracted information.

Moreover, the various aspects that contribute to a data-driven culture include a fact-based culture, top management support in BDA decisions, and prioritising BDA investments (Lamba and Dubey, 2015; Kamioka and Tapanainen, 2014; Olszak, 2014). According to Mikalef et al.

(2017:15), "organisations that are successful with BDA are those that have managed to instil the importance of data-driven insights to a breadth of departments".

2.9 Research model and conceptualisation

Drawing on the RBT of the firm and BDA capabilities literature, this study proposes a research model as depicted in Figure 2.5. This model shows a pictorial description of the relationship between the independent variables (BDA tangible, human, and intangible resources) and the dependent variable (organisational performance). In addition, it suggests that an organisation needs a mix of both intangible, tangible, and human resources to build a BDA capability.

The RBT of the firm suggests that resources are necessary for organisations to gain sustainable performance (Hao, Zhang, and Song, 2019). While intangible resources cannot create a strong BDAC by themselves, the same applies to tangible and human resources (Mikalef et al., 2019). Hence, BDAC often comprises intangible, tangible, and human resources each consisting of more than one dimension as demonstrated below. These three resources have been used in several IT capability literature (Gupta and George, 2016; Mikalef et al., 2017; Hao et al., 2019; Hussain et al., 2021).

Gupta and George (2016) developed a research model suggesting that BDAC leads to firm performance. Following this logic, the study suggests that BDAC will positively and significantly impact the organisational performance of South African retailers.

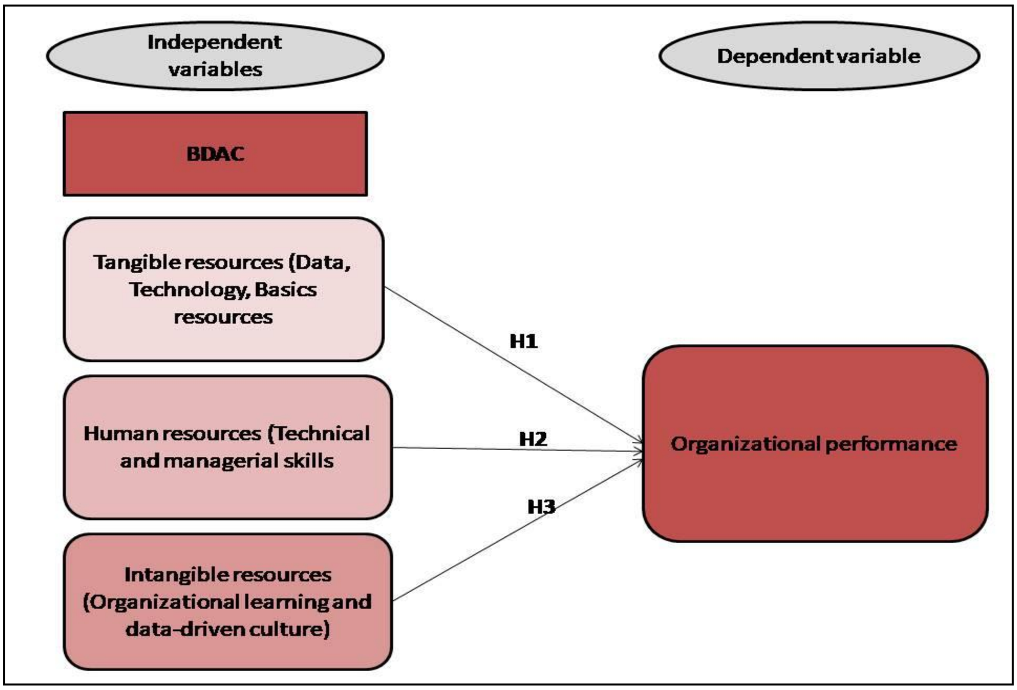

Figure 2.5: Research model

2.10 **Hypothesis development**

2.10.1 Research hypothesis 1: BDA tangible capabilities and organisational performance

Organisations need a variety of intangible and tangible resources to build strong organisational competencies which often leads to organisational performance (Munir et al., 2022). Data, technology, and basic resources are the core components of BDA's tangible capability (Hussain et al., 2021). According to Schreiber and Lowstedt (2015), tangible resources usually create competitive advantages which are unlikely sustained since they are often sold and bought in the market at price equal to their economic value. Several researchers suggest that these resources are sources of competitive advantage and high performance (Kamasak, 2017; Gaya, 2017; Su et al., 2021). Gaya (2017), notes that several organisations have attained high performance and competitive advantage by using tangible resources. In addition, Hussain et al. (2021) note that organisations can obtain high performance and a durable competitive advantage through the usage of advanced technologies and BD analytics. Furthermore, technological strategies provide organisations with new opportunities and help them provide an immediate response to market change (Neirotti and Raguseo, 2017). They have become a necessity and crucial approach for organisations and often contribute to positive performance (Soto-Acosta et al., 2016).

Moreover, the RBT of the firm claims that organisations compete based on resources that are rare, valuable, non-sustainable, and difficult to imitate by competitors (Gupta and George, 2016). These special resources enable organisations to achieve long-term performance and competitive advantage (Masood et al., 2017). Furthermore, Su et al. (2021) note that more than 90 % of data is often presented in unstructured forms. Hence, sophisticated BD tools are needed to enable organisations to obtain meaningful information. Additionally, these tools enable organisations to conduct real-time analysis of data and identify their customer needs accurately. Several studies concluded that BDAC tangible resources have a positive and significant effect on firm performance (Akter, 2016; Anwar, Khan, and Shah, 2018; Hussain et al., 2021; Su et al. 2021). Hence, the study proposes the following hypothesis:

H1: There is a positive and significant relationship between BDA tangible capabilities and the organisational performance of selected South African retailers

2.10.2 Research hypothesis 2: BDA human capabilities and organisational performance

Human resource capability is often irreplaceable, rare, and difficult to imitate hence it is essential for maximising organisational performance. According to Su et al. (2021), technical and managerial skills are the main elements of BDA's human capability. According to Hussain et al. (2021:1157) technical skills “entail the level of expertise employees own related to knowledge and usage of sophisticated technologies to treat big data”. On the other hand, managerial skills can be defined as certain abilities that an executive should have to perform certain tasks in a company. BD software systems help top management to take long-term decisions, withstand risks and survive in the market (Silahtaroglu and Alayoglu, 2016). According to Anwar et al. (2018:7), “leaders from every sector are required to grapple with BD implications”. Moreover, Anwar et al. (2018:7) note that “top management support, firm data environment, external pressure, industry type, and perceived cost are the major factors that cause hurdles in the adaptation of BD”. Despite the vital role of BD in various performance dimensions, Verma and Bhattacharyya (2017) note that traditional management is still reluctant to adopt BD because of its environmental and technological difficulties.

Furthermore, BD analytics increasingly offers value to organisations by using technology, processes, and people to change data into a usable form to solve business issues (Akter and Wamba, 2016). Patel (2015), notes that 90% of organisations often fail because they do not meet the demand and expectations of the customer thus, they should consider having skilful BD scientists to keep customer and market records to date. Value creation is often seen in the manager’s capabilities to contextualize, democratize, investigate and implement data in a suitable style (Zeng and Glaister, 2017). Organisation leaders often recognise BD as a strong asset used to improve their return on investment (Russell and Bennett, 2015).

Organisations, especially those in retailing, telecom and financial services are presently investing in BD scientists because they strongly believe that they can create new opportunities thus leading to a competitive advantage (Verhoef and Lemon, 2016). BD analytics usually offers new dimensions in strategic management which enable managers to provide value-based products and services to customers. Several studies conducted confirmed that there is a positive relationship between BDA human resources and organisational performance (Chuang, Liu, and Chen, 2015; Hamid, Maheen, Cheem, and Yaseen, 2017; Anwar and Abdullah, 2021). Hence, the study proposes the following hypothesis:

H2: There is a positive and significant relationship between BDA human capabilities and the organisational performance of selected South African retailers

2.10.3 Research hypothesis 3: BDA Intangible capabilities and organisational performance

The most important intangible resources considered for an organisation's success and development include data-driven culture and organisational learning (Hussain et al., 2021).

These resources continuously encourage companies to better adapt to internal and external changes, analyse market trends and improve their overall effectiveness. Data-driven is often considered an important element of BD analytics competency. According to Su et al. (2021:1146), “companies with better data-driven culture will use data more widely and develop some related processes from which employees can easily obtain necessary information”. Furthermore, with the rapid development of technology, organisations should inject the concept of continuous learning (organisational learning) within the company. Su et al. (2021:1146) define organisational learning as “a notion that organisational members focus on utilizing existing knowledge and continuously explore new knowledge to keep up with unpredictable market conditions”.

Several studies stressed the relationship between intangible resources and firm performance. For instance, a study conducted by Kamasak (2017) revealed that intangible resources contribute positively to firm performance. Similarly, Okoye, Offor, and Juliana (2019) found that intangible resources significantly impact performance. In addition, Rua and Franca (2017) concluded that a positive relationship exists between intangible resources and performance with innovation as the mediating effect. Izedonme, Odeyile, and Kuegbe (2013) provided evidence that intangible resources and human capital has a significant effect on organisational performance. Hence, the study proposes the following hypothesis:

H3: There is a positive and significant relationship between BDA intangible capabilities and the organisational performance of selected South African retailers.

2.11 Chapter summary

This chapter reviewed the literature on big data, BD analytics, BDA capabilities, and organisational performance. Different sources of literature were reviewed including company reports, journal articles, blogs, and dissertations. In addition, a research model was developed to show the relationship between the independent variables and the dependent variable. The next chapter covered the research methodology used in the study.

CHAPTER 3: RESEARCH DESIGN AND METHODOLOGY

3.1 Introduction

Ugwu, Ekere, and Onoh (2021) define research as the study of sources and materials to gain knowledge, address societal issues, and solve problems. Research generally consists of preparing hypotheses, and accumulating, and analysing information or data. It often follows a research methodology to attain its objectives. Patel and Patel (2019) describe research methodology as the various steps used to solve a research problem. This chapter thoroughly describes the research design and methodology employed in the study to answer the following research questions:

- What is the impact of BDA tangible capabilities on the organisational performance of selected South African retailers?
- What is the impact of BDA human capabilities on the organisational performance of selected South African retailers?
- What is the impact of BDA intangible capabilities on the organisational performance of selected South African retailers?

Research methodology generally consists of various methodological processes such as choosing the appropriate research paradigm, data collection method, research approach and design, study population, and analysing data. These methodological processes are discussed below.

3.2 Research paradigm

Khatri (2020:1436) defines a research paradigm as "a basic and comprehensive belief system to view the research phenomena". It is generally viewed as a set of concepts, rules, and procedures that deal with ultimate principles (Aliyu, Singhry, Amadu, and Abubakar, 2015; Ugwu et al., 2021). Additionally, the research paradigm is essential for the researcher, as it directs him/her through the process of investigation. It is often based on components such as ontology, epistemology, and axiology (Ugwu et al., 2021). These components are discussed in detail below.

3.2.1 Ontology

Ontology is the study of reality and existence. It is generally concerned with the presumptions we make to believe that something is real or makes sense. Additionally, it enables researchers to examine philosophical assumptions about the nature of reality and existence (Ugwu et al., 2021). According to Kivunja and Kuyini (2017), these assumptions are crucial to understanding how meaning can be made out of collected data. Moreover, it orientates the researcher's thinking about the research problem, its importance, and how it should be approached. Aliyu et al. (2015) state that considering ontology is of great importance to researchers in information technology studies, as the benefits and services are offered through the utilisation of technology to resolve real-world problems.

Moreover, there are mainly two ontological perspectives: subjective and objective. Subjectivists believe in several realities meanwhile objectivists believe in only one reality (Maharani, 2020). In addition, Aliyu et al., (2015) state that the choice of a research paradigm also depends on the extent to which the researcher is objective (independent) or subjective (influences the research outcome) in the execution of the empirical work (fieldwork).

3.2.2 Epistemology

Epistemology is generally concerned with how we know the reality or truth. According to Nguyen (2019), it focuses on the type of knowledge that researchers can obtain to be able to deepen comprehension in their research field. It provides researchers with guidelines to define their research scope. Moreover, Khatri (2020) notes that epistemology is concerned with the nature and forms of knowledge, and how it is acquired and communicated to others. There are mainly two epistemological positions: interpretivism and positivism (Rehman and Alharthi, 2016).

The positivist paradigm is a philosophy that relies on formulating and testing hypotheses, offering mathematical equations, and deriving conclusions (Kivunja and Kuyini, 2017). It is a form of empiricism commonly associated with quantitative, experimental (cause and effect relationship), and non-experimental research (Ryan, 2018). Positivists believe that knowledge is obtained through surveys, experiments, and observations (Nguyen, 2019). The job of positivist researchers consists of measuring data, processing information, and proposing the best solution to the identified problems.

On the other hand, an interpretivists paradigm focuses on understanding the viewpoint of the researcher (Ngwu, Ekere and Onoh, 2020). Interpretivism (constructivists) believe that true knowledge is obtained through the profound understanding and interpretation of a subject (Rahi, 2017). Interpretive researchers mostly use a qualitative method. They generally make use of data collection methods such as observations, case studies, personal notes, field notes, documents, and open-ended interviews (Antwi and Hamza, 2015). Views concerning positivist and interpretivists paradigms are summarised in Table 3.1 below.

Table 3.1: Research Paradigms (Ragab and Arisha, 2018).

Paradigms	**Scientific**	**Humanistic**
Ontology	Objectivism	Subjectivism
Epistemology	Positivism	Interpretivism
Views	• The researcher is external to and independent of the phenomena being research • Research attempt to reduce phenomena to context-free generalisations • Singular reality • The world is tangible and predates individuals	• The researcher is part of and interacts with the phenomena being researched • The research attempts to provide a contextually bounded understanding of the phenomena • Multiple realities • The world is socially constructed, created by the minds of individual

The positivist paradigm was best suited for this study given that it adopted a quantitative research approach, was based on testing hypotheses and collected primary data through a questionnaire that was statistically analysed.

3.2.3 Axiology

Axiology is a research paradigm that deals with ethical issues that should be considered during the research (Khatri 2020). It involves stating, evaluating, and understanding wrong and right behaviours related to research. According to Okesina (2020), axiology considers what value should be given to the various aspects of research (the data, the respondents, and the examiners). It often addresses the following questions: What is ethical behaviour? What values will guide the research? What should be done to respect all the respondents? What moral issues should be considered? How are the moral issues addressed? How should the research be conducted peacefully and respectfully? How should social, legal, physical, economical, and other harms be minimized? (Khatri 2020).

According to Kivunja and Kuyini (2017), the responses to the above questions are usually guided by four ethical conducts (Fairness, teleology, deontology, and morality). Teleology ensures that research findings satisfy as many people as possible. Deontology is understanding that every action taken during research has a consequence. Morality refers to the intrinsic moral values maintained during research. The criteria of fairness remind the researcher to be fair to all research respondents and ensure that their rights are respected (Kivunja and Kuyini (2017).

3.3 Research design

Research design is often defined as a set of strategies used to address a research problem. It usually outlines the collection, analysis, and measurement of the research data. Additionally, it guides the researcher through the various research processes thus making the study efficient and producing reliable results. Furthermore, a good research design should be grounded, situational, feasible, redundant, and efficient. According to (Akhtar, 2016), it generally responds to questions such as what is the purpose of the study? What is the nature of the study? What type of data is required? What type of sampling should be used? What is the most appropriate data collection method? How will the data be analysed?

3.3.1 Nature of the study

Pawar (2020) identified three main types of research designs. These include descriptive, explanatory, and exploratory research designs. Exploratory research is often conducted for situations and problems that are not clearly defined. Askarzai and Unhelkar (2017) note that this type of research aims to receptively explore data and reveal its pattern. Explanatory research is usually conducted to find a new angle to a situation or problem (Bouchrika, 2022). It helps get a deeper insight into a problem to elaborate and test a theory. This type of research is mostly concerned with the causes of certain phenomena (Akhtar, 2016).

Descriptive research aims at describing a current situation, phenomenon, or case. It generally answers questions such as how, what, who, when, and where (Bouchrika, 2022). In addition, Akhtar (2016) notes that descriptive research is often concerned with the views or attitudes of a person toward any situation. Furthermore, Ragab and Arisha (2018) noted some characteristics of descriptive and exploratory research (see Table 3.2).

Table 3.2: Characteristics of research designs (Ragab and Arisha 2018).

Descriptive research	Exploratory research
The simplest form of research	Involves exploring a general aspect
More specific in nature and working than exploratory research	Includes studying a problem, about which nothing or very little is known
It involves a mutual effort	Follows a very formal approach to research

Helps in identifying various features of a problem	Helps in exploring new ideas.
Existing theories can be easily put to the test by empirical observations	Helps in gathering information to study a specific problem very minutely
Underlines factors that may lead to experimental research	Helps in knowing the feasibility of attempting a study

This study adopted a descriptive research design to determine the impact of big data analytics capability on the organisational performance of selected South African retailers. In addition, the study showed the relationship between an independent variable and dependent variables. According to Vijayamohan (2022), a descriptive study aims to establish or discover the relationship that exists between several aspects of situations.

3.3.2 Research approach

Mohajan (2017) describes a research approach as a plan that directs the researcher on how to effectively and methodically conduct research. Most researchers have agreed that quantitative and qualitative approaches are the most dominating research approach (Askarzai and Unhelkar, 2017; Rahi, 2017; Hameed, 2020). Quantitative research is the process of collecting and analysing numerical data to explain a phenomenon (Askarzai and Unhelkar, 2017). It is often based on the measurement of amount or quantity. This type of research answer questions such as how, when, where, what, who, and how many. Additionally, quantitative studies generally make use of research methods such as structured interviews, structured observations, experiments, and surveys (Ragab and Arisha, 2018).

In contrast, qualitative research mostly focuses on understanding and interpreting social interactions. It is the process of collecting and analysing non-numerical data (audio, text, or video) to understand experiences, opinions, and concepts (Bhandari, 2022). In this approach, data is often collected through field notes, reflections, participant observations, and interviews (Apuka, 2017). Moreover, Neuman (2014) highlighted the main differences between qualitative and quantitative methods (see Table 3.3)

Table 3.3: Quantitative vs. Qualitative method (Neuman, 2014).

Quantitative	**Qualitative**
Concepts are in the form of distinct variables.	Concepts are in the form of themes, ideas, generalisations, and taxonomies.

Creates measures systematically before data are collected and standardised.	Creates measures in a required manner and specific to the individual setting or researcher.
Data are represented in the form of numbers.	Data are represented in the form of words and images.
Theory is largely causal and deductive.	Theory can be causal or non-causal and is inductive.
Research processes are standard, and repetition is common.	Research processes are particular, and repetition is not common.
The researcher use statistics, tables, or charts to analyse data, plus the findings and discussion reflect how what they show relates to the hypotheses.	The researcher extracts themes or generalisations from evidence to analyse data and organise data to present a clear, consistent picture

A quantitative research method was the most appropriate method for this study since it made use of a questionnaire for data collection and dealt with a large amount of data, numbers, and statistics. In addition, the main aim of a quantitative research study is to determine the relationship between an independent variable and a dependent variable (Ragab and Arisha, 2018). Hence, this study employed a quantitative approach to achieve its objectives. The independent variables included the various components of big data analytics capability (BDA tangible, human, and intangible capabilities) and organisational performance was considered as the dependent variable.

3.3.3 Research strategy

Research strategy involves the collection and interpretation of data (Rahi, 2017). In this study, a questionnaire was adopted as the research strategy. A questionnaire is a document designed to seek specific information from the participants (Pahwa, 2021). It is a series of questions used to obtain statistical information on certain topics. Additionally, a questionnaire is considered a quick, efficient, and cheap way of acquiring a large amount of quantitative data from a large sample (Etikan and Bala, 2017).

Furthermore, this study adopted a closed-ended questionnaire to facilitate the statistical analysis of the collected data. Closed-ended questions are often considered as being cheap, easy to answer, and fast to complete (Young, 2016). Hence, the study adopted this type of questionnaire to facilitate broader participation. In addition, it enables the coding and analyses of the collected data and eases the comparison of the various responses.

3.4 **Population and sampling**

3.4.1 Population

The population generally refers to all individuals or units of interest (Momoh, 2022). Etikan and Babatope (2019) define this term as a group of people, items, and objects with the same attributes or characteristics. For this study, the population included employees of selected South African retailers. The target population was limited to the BI team members of the selected retailers. To reduce the size of the population, only retailers in Cape Town were targeted. Moreover, the sample for this study comprised BI team members of the selected retailers. The sample size was estimated to be 109 employees.

3.4.2 Sampling design

Sampling is the process of selecting a sample from a large group of the population for investigation (Rahi, 2017). This tool helps researchers to select the population of interest for their studies. According to Ragab and Arisha (2018), sampling allows research projects to be implemented within budget limits and time. It generally consists of determining the sample frame, sample technique, and sample size.

3.4.2.1 Sampling frame

A sampling frame is often representative of the population. According to Taherdoost (2016:20), it is “a list of the actual cases from which a sample will be drawn”. For this study, the sample frame included all the BI team members of the selected retailers. The scope was limited to selected retailers in Cape Town.

3.4.2.2 Sampling Technique

The sampling technique is generally divided into two main groups: probability sampling and non-probability sampling (Taherdoost, 2016). Probability sampling is an approach that offers each unit an equal chance of being selected (Rahi, 2017). This sampling often includes simple, stratified, cluster, systematic, and multi-stage sampling. On the other hand, according to Rahi (2017:3), “non-probability sampling is the sampling approach in which the chance or probability of each unit to be selected is not known or confirmed”. This sampling is often associated with qualitative research and case study research design (Majid, 2018). In addition, it includes quota, snowball, judgment, and convenience sampling.

For this study, a judgment (purposive) sampling technique was used. In this type of sampling, the researcher uses his/her judgment to select the required participants for the study (Etikan and Babatope, 2019). The selected sample for this study was determined by the researcher and included all the BI team members of the selected retailers. See Table 3.4 for an explanation.

Table 3.4: Sampling techniques (Ragab and Arisha, 2018).

Sampling techniques	Description
Simple	Selecting the sample randomly from the sampling frame using random numbers obtained from tables or generated by a computer.
Stratified	Dividing the population into a number of groups based on certain attributes, then applying random sampling (simple or systematic) to each group.
Cluster	Dividing the population into a number of groups (clusters) based on naturally occurring attributes, then applying random sampling to select clusters.
Systematic	Selecting the sample at regular intervals from the sampling frame.
Quota	Using stratified sampling and selecting individuals from each group using predefined quotas for each group.
Snowball	Contacting a few individuals and asking them to nominate other individuals until the desired sample size is reached.
Judgment (Purposive)	Using judgment to select particularly informative individuals will enable the researcher to meet research objectives.
Convenience	Selecting individuals that are easiest to access at random until the desired sample size is reached.

3.4.2.3 Sampling Size

A sample size often determines the number of individuals chosen to represent the target population (Kaur, 2017). According to Etikan and Babatope (2019), selecting appropriate sample sizes help to reduce sampling biases and errors in research. In addition, Kaur (2017) notes that the sample size of a study should be big enough to provide the appropriate data confidence. There are various statistical methods for calculating sample size. However, the formula developed by Yamane (1967) was used.

n = N/(1+Ne2) where;

n = Sample size

N = target population

e = acceptable sampling error

In calculating the estimated sample size, a 95% confidence interval and a 5% sampling error were used by the researcher. Therefore, using the above formula the sample size was obtained as n = 150/1+ 150(0.05)2 = 109

3.5 Data collection

Data collection is often defined as the process of collecting information on variables of interest to answer research questions and test hypotheses. The data of a study can either be collected from primary or secondary data. Primary data refers to the data gathered by the researcher. Sources of primary data often include interviews, questionnaires, observations, and surveys. On the other hand, Martins, Cunha and Serra (2018) define secondary data as data obtained from previous research work. Sources of secondary data generally include government publications, company records, and industry analysis. In addition, Ajayi (2017) noted the main differences between primary and secondary data (see Table 3.5).

Table 3.5: Primary data vs. Secondary data (Ajayi, 2017).

Basics comparison	Primary data	Secondary data
Meaning	Primary data refers to the data gathered by the researcher himself	Secondary data refers to data already collected by someone else
Data	Real-time data	Past data
Process	Very involved	Quick and easy
Source	Personal interviews, questionnaires, experiments, observations, and surveys	Government publications, websites, journal articles, books, internal records, etc
Cost-effectiveness	Expensive	Economical
Collection time	Long	Short
Available	Crude form	Refined form
Accuracy and reliability	More	Relatively less

For this study, primary data was collected through questionnaires from BI team members of the selected retailers. According to Pahwa (2021), a questionnaire is a data collection tool used to collect quantitative data from one or more respondents". It often helps the researcher in getting a quicker, more efficient, and more affordable means of acquiring a huge amount of data from a large number of people. This was the most suitable tool for data collection since the study was descriptive.

Furthermore, there are two main types of questionnaires commonly used: open-ended and closed-ended questionnaires. According to Etikan and Bala (2017), closed-ended questionnaires produce very crucial, numerical, and summarised data that are easier to code and statistically analyse. (Aithal, Architha, and Sreeramana, 2020) listed the three main types of closed-ended questions commonly used in research. These include Yes/No questions, scaled questions, and multiple choice. On the other hand, open questionnaires allow the respondent to express themselves in detail using their own words. There are various types of open-ended questions such as completely unstructured questions, word association, sentence completion, story completion, and picture completion. In addition, this type of questionnaire generally takes a longer period to be completed and can be time-consuming for data analysis (Etikan and Bala, 2017). This study adopted a closed-ended questionnaire.

Moreover, the questionnaire consisted of a Likert scale which made it easier for the participant to indicate their level of agreement and disagreement with various statements. A Likert scale is often used in a research survey to measure the attitudes, feelings, and opinions of the respondents toward a particular subject (Elliott, 2021). There are two types of Likert scales commonly used in research (5-point Likert scale and 7-point Likert scale). The questionnaire for this study made use of a 7-point Likert scale. According to Joshi, Kale, and Chandel (2015), this type of Likert scale provides several options which better reflect the respondent's true opinion. In addition, Khandelwal (2021) describes the 7-point Likert scale as the most accurate Likert scale which provides reliable results. This Likert scale generally requires respondents to respond to the various questions based on seven degrees (See Table 3.6)

Table 3.6: 7-point Likert scale

1	2	3	4	5	6	7
Strongly disagree	Disagree	Slightly disagree	Neutral	Slightly agree	Agree	Strongly agree

3.5.1 Questionnaire design

The questionnaire for this study was drawn up based on various constructs adopted by Gupta and George (2016). It was formulated to capture the impact of BDA tangible, human, and intangible capabilities on the organisational performance of selected South African retailers. To answer the main research question, the questionnaire was divided into five sections (See Table 3.7)

Table 3.7: Structure of the questionnaire (See Appendix A)

Section	Name	Question
A	General information	1-4
B	BDA tangible capabilities	1-15
C	BDA human capabilities	1-15
D	BDA intangible capabilities	1-15
E	Organisational Performance	1-9

Section A: general information

This section aimed at collecting the necessary details about the respondents and the organisation. In this section, the questionnaire captures the age, gender, level of education of the respondents, and their duration in the organisation.

Section B: BDA tangible capabilities

In this section, the first research objective was addressed. The researcher made use of questions to determine the impact of BDA tangible capabilities on the organisational performance of selected South African retailers. The questions were based on the following constructs: data, technology, and basic resources.

Section D: BDA human capabilities

In this section, the second research objective was addressed. The researcher made use of questions to determine the impact of BDA human capabilities on the organisational performance of selected South African retailers. The questions were based on the following constructs: data-driven culture and organisational learning.

Section C: BDA intangible capabilities

In section, the third research objective will be addressed. The researcher made use of questions to determine the impact of BDA intangible capabilities on the organisational performance of selected South African retailers. The questions were based on the following constructs: technical skills and managerial skills.

Section E: Performance

This section attempted to understand the level of organisational performance of the various retailers.

3.6 Research Procedures

The research process started with the preparation of the research proposal and the selection of the sample and target population for the study. Thereafter, the questionnaires for the study were prepared and sent for approval to the University of Western Cape's Humanities and Social Science Research Ethics Committee (HSSREC) (see Appendix B). Once approved, the researcher conducted a pilot test with some targeted respondents to ensure the reliability and validity of the questionnaire.

The researcher contacted respondents via email to distribute the questionnaires to the targeted respondents (109 employees). A cover letter giving a summary of the study and a consent form was attached to the questionnaire. The respondents took a couple of weeks to fill out the questionnaire. During this period, a constant reminder was sent to the participants via emails and phone calls to complete the survey. In addition, the returned responses were coded in Excel, and thereafter analysed in SPSS. Lastly, the analysed data were used to draw conclusions for the study and make recommendations for future research.

3.7 Data analysis

Data analysis consists of editing, coding, and data entry to ensure the accuracy of data and convert it into appropriate forms for analysis. It generally consists of developing answers to questions through the interpretation of data. According to Arora (2022), it is the process of applying statistical techniques to describe, condense, and evaluate data. The data analysis of this study consisted of two main parts: summarising the collected data (Descriptive statistics) and determining the relationship between the dependent and the independent variable (Spearman Correlation) This was done using Excel and Statistical Package for Social Science (SPSS). William (2022) defines SPSS as a software program used for complex statistical analyses and data management.

Furthermore, the responses from the questionnaire were coded and entered into SPSS. Then the data were analysed using descriptive statistics (frequency distribution). Descriptive statistics are generally used to make research data summaries. Additionally, a correlation test was run to determine the relationship between the variables. According to Hayes (2022), correlation is a statistical tool that measures the association between two or more variables. A correlation can either be positive (variables moving in the same direction), negative (variables moving in opposite directions), or Zero (variables moving in unrelated directions). Rebekic, Petrovic, and Loncaric (2015) note that there are three types of correlation coefficients. These include Pearson, Spearman, and Kendall correlation. For this study, a Spearman coefficient correlation was used to test the relationship between the independent variables (BDA intangible, human, and tangible capabilities) and the dependent variable (organisational performance). It was used to determine whether BDA capability is positively and significantly related to the organisational performance of South African retailers. According to Al-Hameed (2022:3250), Spearman coefficient correlation is “a coefficient that expresses the strength and direction of the relationship between two phenomena only”. This type of correlation is generally used when the variables are measured on an ordinal scale, not normally distributed, and when the sample size is small. Therefore, Spearman coefficient correlation was the appropriate correlation analysis for the study because it had a small sample size and discrete ordinal data (Likert scale data).

3.8 **Ethics**

Research ethics is often defined as a set of guidelines that govern how research is performed and disseminated. According to Akaranga and Makau (2016:2), “research ethics is important in our daily life research endeavours and requires that researchers should protect the dignity of their subjects”. Every researcher has the responsibility to follow an ethical code that generally requires integrity, honesty, objectivity, respectfulness, and confidentiality.

Considering the importance of ethical guidelines, a research proposal was submitted to the University of Western Cape’s Humanities and Social Science Research Ethics Committee (HSSREC), and ethical clearance was received with reference number HS20/9/58 (see Appendix B). The researcher was obliged to adhere to the University of Western Cape’s ethical guidelines. The retailers voluntarily participated in the study and were informed about their confidentiality, the aim, and the significance of the study. Moreover, to carry out this study in an ethical manner, the following ethical issues were considered.

- Informed consent and voluntary participation: The consent of the respondents to participate in the study were acquired. They were made aware of the aims of the study and their right to voluntarily participate and withdraw from the study at any time.
- Confidentiality: the responses and information of the participants were protected and guarded during and after the study. No third parties were given access to the information provided. The Participants were not required to share any information they are not willing to share.
- Respect for the respondents: All the respondents were treated professionally and respectfully both in actions and in words. The researcher ensured that all participants had a clear understanding of the purpose of the study. Moreover, intellectual property was respected through referencing and the confidentiality of participants was honoured.

3.9 Chapter Summary

This chapter discussed the research design and methodology that was used in the study. The research opted for a descriptive research design and questionnaire as a research strategy. It made use of a questionnaire to collect relevant data to attain its objectives. Further, it outlined how data was collected and analysed using inferential and descriptive statistics to determine the impact of BDAC on the organisational performance of selected South African retailers. In addition, the steps of the research procedure were equally outlined. The following chapter presents the results and findings of the analysis.

CHAPTER 4: RESULTS AND FINDINGS

4.1 Introduction

In this chapter, the analysed data and overall findings of the study are presented based on the data collected. The main objective of the study was to determine the Impact of BDAC on the organisational performance of South African retailers. The independent variables were BDA tangible capabilities (BDATC), BDA human capabilities (BDAHC), and BDA intangible capabilities (BDAIC) while organisational performance (OP) was considered as the dependent variable. This chapter is divided into two main parts. Part one presents the findings on the response rate and the demographic characteristics of all the respondents (gender age level of education and duration with current employer). Part two presents the frequency distribution of the various variables and the Spearman correlation results of the independent and dependent variables.

4.2 Response rate

The study targeted 109 participants and received responses from 68 participants resulting in a 62.4% response rate which was satisfactory for the analysis according to Mugenda and Mugenda (2016) who state that a 70% response rate is very good, 60% good and 50% adequate. The response rate of the study is presented in Table 4.1.

Table 4.1: Response rate

Category	Frequency	Percentage
Responded	68	62.4%
Not responded	41	37.6%
Total	109	100.0%

4.3 Demographic characteristics

This section presented the demographic characteristics of all the respondents: age, gender, level of education, and duration with the employer.

4.3.1 Gender of participants

The figure below illustrates the distribution of the participants based on their gender. The results revealed that (47%, n=32) of the participants were female and (53%, n=36) were male (see Figure 4.1). It was promising to achieve a good distribution between male and female participants.

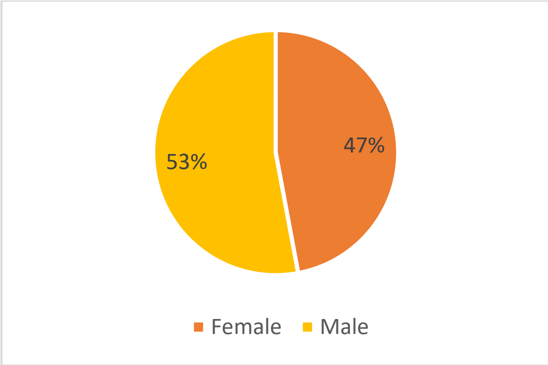

Figure 4.1: Gender of participants

4.3.2 Age of participants

Figure 4.2 shows the distribution of the participants based on their ages. The majority of the participants (32%) were in the younger age brackets (22-29 years). They were followed by those aged between 38-45 years (27%, n=18) and 46+ (22%, n=15). Lastly, those aged between 30-37 years represented a minority of 19.1%.

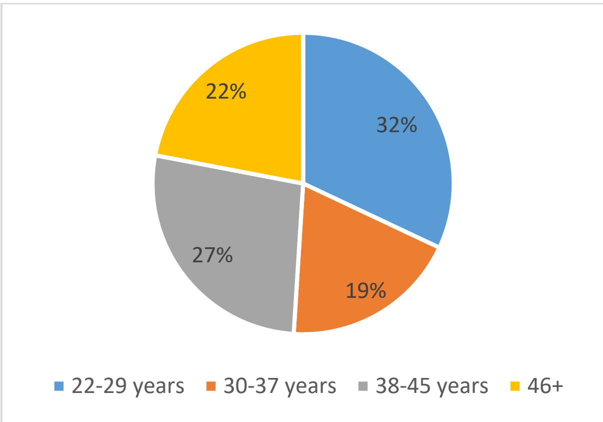

Figure 4.2: Age of participants

4.3.3 Level of education of participants

The results revealed that the majority of the participants of this study were honours degree holders (33.8%, n=23) and bachelor's degree holders (33.8%, n=23). Holders of master's degrees were represented by 22%. Lastly, secondary school holders represented a minority of 10%. Therefore, the above results show that most of the participants were well-educated.

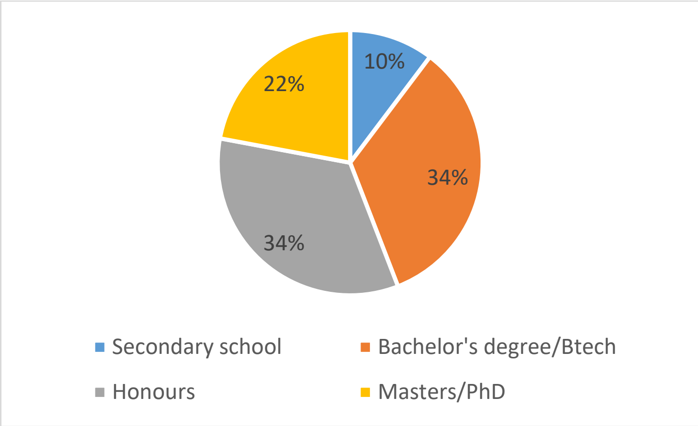

Figure 4.3: Level of education of participants

4.3.4 Duration with current employer

Figure 4.4 shows that most of the participants (35.3%, n=24) had worked for 2-4 years with their current employer. This was followed by the group that worked for 5-7 years (23%, n=16) and 0-1 year (21%, n=14). Those that stayed with their employer for more than 10 years were represented by (12%, n=8). Lastly, those that worked for 8-10 years represented a minority of 9% (n=6).

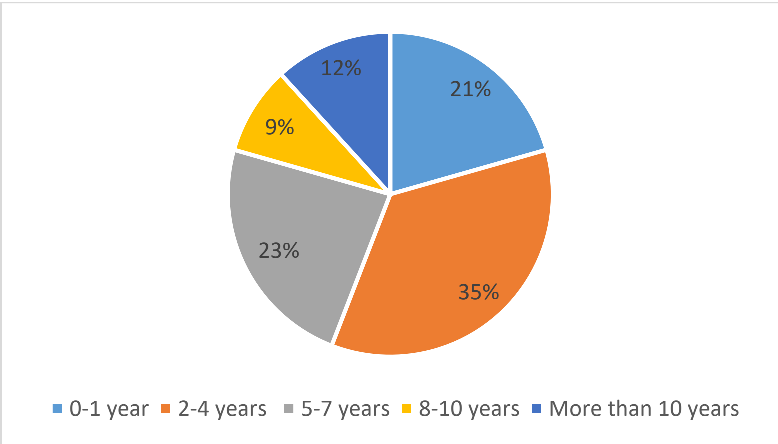

Figure 4.4: Duration with current employer

4.4 Descriptive statistics

This study aimed to determine the impact of BDA capabilities (tangible, human, and intangible capabilities) on the organisational performance of South African retailers. This was measured using a seven Likert scale (strongly disagree, disagree, slightly disagree, neutral, slightly agree, agree, strongly agree).

4.4.1 *Reliability statistics*

Reliability often refers to the consistency of study constructs. According to Surucu and Maslakci (2020:2707), it refers to "the stability of the measuring instrument used and its consistency over time". In this study, construct reliability was assessed using Cronbach's Alpha. According to Nwat, Tabi, Samat, and Mustapha (2020:22), "Cronbach alpha is used to measure the consistency or reliability between several items, measurements or ratings". It is frequently used to test the stability of the assessment instrument of the study.

Furthermore, Frost (2022) noted some limitations of Cronbach alpha. According to the author, Cronbach alpha only measures reliability (whether responses are consistent), not validity (whether the variables measure the right concept). In addition, meanwhile, high Cronbach values reveal consistency, they do not automatically prove that the variables are unidimensional (measuring a single characteristic). Variables can measure different related concepts thus producing high alpha values (Frost, 2023).

Moreover, according to Surucu and Maslakci (2020:2713), Cronbach alpha is considered as "the most popular method used in research to test internal consistency". A construct is generally considered reliable when the alpha value is greater than 0.70 (Taherdoost, 2016).

Table 4.2: Reliability statistics for BDA tangible capabilities (BDATC)

BDATC constructs	Number of items	Cronbach alpha reliability test	Comments
Data (D)	3	.719	High reliability
Technology (T)	10	.838	High reliability
Basic resources (BR)	2	.924	High reliability

Table 4.2 indicates that all BDA tangible capability constructs have a reliability score of 0.7 and above (high reliability). The findings revealed that data had a reliability score of .719 with three items and technology a reliability score of .838 with ten items. Similarly, basic resources were also found reliable with a Cronbach alpha of .924 and two items. Reliability findings are summarised in Table 4.2.

Table 4.3: Reliability statistics for BDA human capabilities (BDAHC)

BDAHC constructs	Number of items	Cronbach alpha reliability test	Comments

Technical skills (TS)	10	.875	High reliability
Managerial skills (MS)	5	.950	High reliability

Table 4.3 indicates that all BDA human capability constructs have a reliability score of 0.7 and above (high reliability). The findings revealed that technical skills had a Cronbach alpha of .875 with ten items. Similarly, managerial skills have a Cronbach alpha of .950 with ten items. Reliability findings are summarised in Table 4.3.

Table 4.4: Reliability statistics for BDA intangible capabilities (BDAIC)

BDAIC constructs	Number of items	Cronbach alpha reliability test	Comments
Data-driven culture (DD)	10	.839	High reliability
Organisational learning (OL)	5	.909	High reliability

Moreover, results revealed that data-driven culture had ten items with a Cronbach alpha of .839 and organisational learning had five items with a Cronbach alpha of .909. This implies that all BDA intangible capability constructs were reliable. The results are summarised in Table 4.4.

4.4.2 Validity statistics

Validity is often concerned with the meaningfulness and accuracy of study constructs. According to Heale and Twycross (2015:66), it refers to "the extent to which a concept is accurately measured in a quantitative study". When research is highly valid, it implies that its results are consistent with reality (Bahariniya, Ezatiasar, and Madadizadeh, 2021). There are mainly four types of validity namely, content validity, face validity construct validity, and criterion validity (Taherdoost, 2016). This study adopted construct validity which is often defined as "the extent to which a research instrument (or tool) measures the intended construct" (Heale and Twycross (2015:66). According to Bahariniya, Ezatiasar, and Madadizadeh (2021), this type of validity is often evaluated by factor analysis.

Factor analysis is usually considered as a data reduction technique. According to Tavakol and Wetzel (2020:245), this technique "allows us to simplify a set of complex variables or items using statistical procedures to explore the underlying dimensions that explain the relationships between the multiple variables/items". There are two main types of factor analysis namely; exploratory and confirmatory factor analysis (Shrestha, 2021). Exploratory factor analysis is a statistical technique used to evaluate the relationships and dimensionality of measured variables meanwhile confirmatory factor analysis is a statistical method used to evaluate the significance and the relationship between two or more factor loading (Tavakol and Wetzel, 2020). This study adopted a confirmatory factor analysis to determine the validity of the various constructs used in the study. According to Sujati, Sajidan, Akhyar, and Gunarhadi (2020), confirmatory factor analysis is one of the statistical tools suitable for determining construct validity.

Moreover, factor analysis is often associated with factor loading which is defined as the correlation between the variable and the factor (Tavakol and Wetzel, 2020). According to Shrestha (2021:9), "the variables with large loadings values > 0.40 indicate that they are representative of the factor". A construct is generally considered valid when the factor loading is greater than 0.4 (Wanjiru, Muathe and Kinyua, 2019).

Table 4.5: Factor analysis of BDA tangible capabilities (BDATC)

DATC constructs	Factor loadings
Data (D)	.801
Technology (T)	.807
Basic resources (BR)	.706

Summarised results in Table 4.5 indicate that the factor loads used in measuring BDA tangible capabilities ranged from 0.706 to 0.807. The results revealed that technology had the highest factor loading (.801) and basic resources had the lowest factor loading (.706). Therefore, the analysis revealed that all the variables used to measure BDATC had a coefficient greater than 0.4. This implies that all the BDATC variables were feasible and significant to be used in data collection.

Table 4.6: Factor analysis of BDA human capabilities (BDAHC)

BDAHC constructs	Factor loadings
Technical skills (TS)	.888
Managerial skills (MS)	.888

Similarly, the results in Table 4.6 reveal that both technical skills and managerial skills had a factor loading of .888. The factor analysis indicated that the two variables used to measure BDAHC exceeded 0.4. Hence, this implies that BDAHC variables contributed meaningfully to data collection.

Table 4.7: Factor analysis of BDA intangible capabilities (BDAIC)

BDATC constructs	Factor loadings
Data-driven culture (DD)	.901
Organisational learning (OL)	.901

The findings in Table 4.7 reveal that both data-driven culture and organisational learning had a factor loading of .901. The factor analysis indicated that the two variables used to measure BDAHC had a coefficient greater than 0.4. Hence, this implies that BDAHC variables were feasible and significant to be used in data collection.

4.4.3 Frequency distributions

4.4.3.1 BDA tangible capabilities distribution

BDA tangible capabilities generally refer to the organisational structures, physical assets, and financial resources needed for the operation of an organisation. This included three main constructs (data, technology, and basic resources). This study sought to know the level of agreement and disagreement of the respondents regarding each item under the BDATC constructs.

The frequency distribution for “Data” (D) is presented in Table 4.8. D1 sought to determine the extent to which the selected retailers have access to very large, unstructured, or fast-moving data for analysis. The majority (33.8%) of the respondents rated this statement as “strongly agreed”. In addition, 30.9% agreed, 22.1% slightly agreed, and 5.9% disagreed with D1. Moreover, 4.4% of the respondents rated D1 as “neutral”. Lastly, a minority of 3% rated D1 as “strongly disagree” and “slightly disagree”.

D2 sought to determine the extent to which the selected retailers integrate data from multiple internal sources into a data warehouse for easy access. In regard to this, the majority (47.1%) of the respondents slightly agreed with this statement. 29.4% of the respondents agreed, 11.8% slightly agreed, and 2.9% disagreed with D2. In addition, 5.9% of the respondents rated D2 as “neutral”. Lastly, a minority of 1.5% strongly disagreed with D2.

D3 sought to determine the extent to which the selected retailers integrate external data with internal to facilitate high-value analysis of their business development. The majority (26.5%) of the respondents rated D3 as “agree”. 19.1% strongly agreed, 11.8% slightly agreed, and 8.8% slightly disagreed with this statement. Additionally, 26.5% of the respondents rated D3 as “neutral”. Lastly, a minority of 7.4% disagreed with D3. Therefore, the results reveal that

D1, D2, and D3 were mostly rated as "strongly agree" and "agree". This shows a positive utilisation of BDA data capabilities by South African retailers.

Table 4.8: Data

D1 [We have access to very large, unstructured, or fast-moving data for analysis]	**Frequency**	**Percentage**
Strongly disagree	1	1.5%
Disagree	4	5.9%
Slightly disagree	1	1.5%
Neutral	3	4.4%
Slightly agree	15	22.1%
Agree	21	30.9%
Strongly Agree	23	33.8%
Total	68	100.0%
D2 [We integrate data from multiple internal sources into a data warehouse or mart for easy access]	**Frequency**	**Percentage**
Strongly disagree	1	1.5%
Disagree	2	2.9%
Slightly agree	0	0.0%
Neutral	4	5.9%
Slightly agree	8	11.8%
Agree	20	29.4%
Strongly Agree	32	47.1%
Total	67	98.5%
D3 [We integrate external data with internal to facilitate high-value analysis of our business development]	**Frequency**	**Percentage**
Strongly agree	0	0.0%
Disagree	5	7.4%
Slightly disagree	6	8.8%
Neutral	18	26.5%
Slightly agree	8	11.8%
Agree	18	26.5%
Strongly Agree	13	19.1%

Total	68	100.0%

The frequency distribution for "Technology" (T) is presented in table 4.9. T1 sought to determine the extent to which the selected retailers have integrated external data and explored parallel computing approaches such as Hadoop. In regard to this, the majority (26.5%) of the respondents rated T1 as "agree". 19.1% of the respondents strongly agreed, 14.7% slightly agree, and 10.3% disagreed with T1. In addition, 19.1% of the respondents rated T1 as "neutral". Lastly, a minority of 2.9% strongly disagreed.

T2 sought to determine the extent to which the selected retailers have explored different data visualisation tools. The majority of the respondents (41.2%) agreed and the minority (2.9%) disagreed with this statement. Additionally, 27.9% slightly agreed, 19.1% strongly agreed, and 5.9% slightly disagreed with T2. Lastly, 2.9% of the respondents rated T2 as "neutral".

T3 sought to determine the extent to which the selected retailers have explored cloud-based services for processing data and performing analytics. 36.8 % of the respondents mostly agreed with this statement. In addition, 29.4 % strongly agreed and 27.9% slightly agreed with T3. Lastly, a minority of 5.8% rated T3 as "slightly agree" and "Neutral".

T4 sought to determine the extent to which the retailers have explored open-source software for big data analytics. The majority of the respondents (26.5%) agreed and the minority (1.5%) strongly disagreed with this statement. Additionally, 22.1% slightly agreed and 13.2% disagreed with T4. Lastly, 20.6% of the respondents rated T4 as "slightly disagree" and "strongly agree".

T5 sought to determine the extent to which the retailers have explored new forms of databases such as SQL for storing data. In regard to this, the majority (29.4%) of the respondents rated T5 as "neutral". 26.5% agreed and 20.6% slightly agreed with this statement. In addition, 8.8% of the respondents slightly disagreed, 5.9% disagreed, and 5.9% strongly agreed with T5. Lastly, a minority of 1.5% strongly disagreed.

T6 sought to determine the extent to which the user interfaces of the selected retailers provide transparent access to all platforms and applications. The majority of the respondents (38.2%) agreed and the minority (4.4%) strongly disagreed with this statement. Additionally, 17.6% slightly agreed, 16.2% slightly disagreed, and 8.8% disagreed with T6. Lastly, 14.8% of the respondents rated T6 as "neutral" and "strongly agree".

T7 sought to determine the extent to which the selected retailers provide multiple analytics interfaces or entry points for external end-users. A greater number of the respondents (38.2%)

agreed with this statement. 25% slightly agreed, 17.6% slightly disagreed, and 4.4% strongly agreed with T7. In addition, 5.9% of the respondents rated T7 as “neutral”. Lastly, a minority of 2.9% strongly disagreed with T7.

T8 sought to determine the extent to which the selected retailers share analytics-driven information seamlessly across their organisations, regardless of the location. The majority of the respondents (32.4%) agreed and the minority (1.5%) strongly disagreed with this statement. Additionally, 17.6% slightly agreed, 14.7% slightly disagreed, and 10.3% strongly agreed with T8. Lastly, 23.6% of the respondents rated T8 as “disagree” and “neutral”.

T9 sought to determine the extent to which the retailers widely use reusable software modules in new analytics model development. A greater number of the respondents (35.3%) agreed with this statement. 26.5% slightly agreed and 7.4% strongly agreed with T9. Moreover, 19.1 % of the respondents rated T7 as “neutral”. Additionally, 8.8% rated T7 as “disagree” and “slightly disagree”. Lastly, a minority of 1.5 % strongly disagreed.

T10 sought to determine the extent to which the selected retailers utilise object-oriented technologies to minimise the development time for new analytics applications. In regard to this, the majority (32.4%) of the respondents rated T10 as “neutral”. In addition, 25% of the respondents agreed, 22.1% slightly agreed, and 10.3 slightly disagreed with T10. Lastly, a minority of 8.8% rated T10 as “strongly agreed”.

Therefore, results reveal that T1, T2, T3, T4, T6, T7, T8, T9 were mostly rated as “agree” meanwhile T5 and T10 were mostly rated as “neutral”. This indicates a positive utilisation of BDA technological capabilitiesby South African retailers.

Table 4.9: Technology

T1 [We integrate external data with internal and have explored or adopted parallel computing approaches (e.g., Hadoop) to big data processing]	**Frequency**	**Percentage**
Strongly disagree	2	2.9%
Disagree	7	10.3%
Slightly disagree	5	7.4%
Neutral	13	19.1%
Slightly agree	10	14.7%
Agree	18	26.5%
Strongly Agree	13	19.1%

Total	68	100.0%
T2 [We have explored or adopted different data visualisation tools]	**Frequency**	**Percentage**
Strongly disagree	0	0.0%
Disagree	2	2.9%
Slightly disagree	4	5.9%
Neutral	2	2.9%
Slightly agree	19	27.9%
Agree	28	41.2%
Strongly Agree	13	19.1%
Total	68	100.0%
T3 [We have explored or adopted cloud-based services for processing data and performing analytics]	**Frequency**	**Percentage**
Strongly disagree	0	0.0%
Disagree	0	0.0%
Slightly disagree	2	2.9%
Neutral	2	2.9%
Slightly agree	19	27.9%
Agree	25	36.8%
Strongly Agree	20	29.4%
Total	68	100.0%
T4 [We have explored or adopted open-source software for big data analytics]	**Frequency**	**Percentage**
Strongly disagree	1	1.5%
Disagree	9	13.2%
Slightly disagree	7	10.3%
Neutral	8	11.8%
Slightly agree	15	22.1%
Agree	18	26.5%
Strongly Agree	7	10.3%
Total	65	95.6%

T5 [We have explored or adopted new forms of databases such as Not Only SQL (NoSQL) for storing data]	**Frequency**	**Percentage**
Strongly disagree	1	1.5%
Disagree	4	5.9%
Slightly disagree	6	8.8%
Neutral	20	29.4%
Slightly agree	14	20.6%
Agree	18	26.5%
Strongly Agree	4	5.9%
Total	67	98.5%
T6 [Our user interfaces provide transparent access to all platforms and applications]	**Frequency**	**Percentage**
Strongly disagree	3	4.4%
Disagree	6	8.8%
Slightly disagree	11	16.2%
Neutral	5	7.4%
Slightly agree	12	17.6%
Agree	26	38.2%
Strongly Agree	5	7.4%
Total	68	100.0%
T7 [Our organisation provides multiple analytics interfaces or entry points for external end-users]	**Frequency**	**Percentage**
Strongly disagree	2	2.9%
Disagree	4	5.9%
Slightly disagree	12	17.6%
Neutral	4	5.9%
Slightly agree	17	25.0%
Agree	26	38.2%
Strongly Agree	3	4.4%
Total	68	100.0%

T8 [Analytics-driven information is shared seamlessly across our organisation, regardless of the location]	Frequency	Percentage
Strongly disagree	1	1.5%
Disagree	8	11.8%
Slightly disagree	10	14.7%
Neutral	8	11.8%
Slightly agree	12	17.6%
Agree	22	32.4%
Strongly Agree	7	10.3%
Total	68	100.0%
T9 [Reusable software modules are widely used in new analytics model development]	**Frequency**	**Percentage**
Strongly disagree	1	1.5%
Disagree	3	4.4%
Slightly disagree	3	4.4%
Neutral	13	19.1%
Slightly agree	18	26.5%
Agree	24	35.3%
Strongly Agree	5	7.4%
Total	67	98.5%
T10 [Object-oriented technologies are utilised to minimise the development time for new analytics applications]	**Frequency**	**Percentage**
Strongly disagree	0	0.0%
Disagree	0	0.0%
Slightly disagree	7	10.3%
Neutral	22	32.4%
Slightly agree	15	22.1%
Agree	17	25.0%
Strongly Agree	6	8.8%
Total	67	98.5%

The frequency distribution for “Basic Resources” (BR) is presented in Table 4.10. BR1 sought to determine the extent to which the big data analytics projects of the selected retailers are adequately funded. The majority of the respondents (33.8%) agreed and the minority (7.4%) slightly disagreed with this statement. Additionally, 17.6% slightly agreed, 16.2% strongly agreed and 8.8 % disagreed with BR1. Lastly, 16.2% of the respondents rated BR1 as “neutral”. BR2 sought to determine the extent to which the big data analytics projects of the selected retailers are given enough time to achieve their objectives. The majority of the respondents (35.3%) agreed and the minority (7.4%) disagreed with this statement. In addition, 29.4% slightly agreed, 10.3% strongly agreed and 4.4% disagreed with BR1. Lastly, 13.2% of the respondents rated BR2 as “neutral”.
Hence, results reveal that BR1 and BR2 were mostly rated as “agree”. This indicates a positive utilisation of BDA basic resources by South African retailers.

Table 4.10: Basic resources

BR1 [Our big data analytics projects are adequately funded]	**Frequency**	**Percentage**
Strongly disagree	0	0.0%
Disagree	6	8.8%
Slightly disagree	5	7.4%
Neutral	11	16.2%
Slightly agree	12	17.6%
Agree	23	33.8%
Strongly Agree	11	16.2%
Total	68	100.0%
BR2 [Our big data analytics projects are given enough time to achieve their objectives]	**Frequency**	**Percent**
Strongly disagree	0	0.0%
Disagree	5	7.4%
Slightly disagree	3	4.4%
Neutral	9	13.2%
Slightly agree	20	29.4%
Agree	24	35.3%
Strongly Agree	7	10.3%

Total	68	100.0%

4.4.3.2 BDA human capabilities distribution

BDA human capabilities often consist of the knowledge, experience, business insights, relationship, problem-solving abilities, and leadership qualities of the employees of an organisation. This included two main constructs (technical skills and managerial skills). The study sought to know the level of agreement and disagreement of the respondents regarding each item under the BDAHC constructs.

The frequency distribution for "Technical Skills" (TS) is presented in Table 4.11. TS1 sought to determine the extent to which the selected retailers provide big data analytics training to their employees. In regard to this, the majority (22.1%) of the respondents rated this statement as "slightly agree". In addition, 14.7% of the respondents rated TS1 as "slightly disagree". Moreover, 16.2% of the respondents agreed, 14.7% disagreed, and 13.2% strongly agreed with TS1. Lastly, a minority of 7.4% strongly disagreed with TS1.

TS2 sought to determine the extent to which the selected retailers hire new employees that already have big data analytics skills. The majority of the respondents (35.3%) agreed and the minority (1.5%) disagreed with this statement. Additionally, 27.9% slightly agreed, 11.8% strongly agreed, and 5.9% slightly disagreed with TS2. Lastly, 17.6% of the respondents rated TS2 as "neutral" and "disagree".

TS3 sought to determine the extent to which the big data analytics staff of the selected retailers have the right skills to accomplish their jobs successfully. The majority **(**32.4%) of the respondents agreed with this statement. 26.5% slightly agreed, 17.6% strongly agreed, and 2.9% slightly disagreed with TS3. Additionally, 16.2% of the respondents rated TS3 as "Neutral". Lastly, a minority of 4.4% disagreed with TS3.

TS4 sought to determine the extent to which the big data analytics staff of the selected retailers hold suitable work experience to accomplish their jobs successfully. The majority (42.6%) of the respondents agreed and the minority (5.9%) strongly disagreed with this statement. In addition, 19.1% slightly agreed and 10.3% strongly agreed with TS4. Lastly, 22.1% of the respondents rated TS4 as "neutral".

TS5 sought to determine the extent to which the analytics personnel of the selected retailers show a superior understanding of technological trends. In regard to this, the majority (42.6%) of the respondents rated this statement as "agree". In addition, 14.7% of the respondents rated

TS5 as “neutral”. Lastly, 30.9% of the respondents slightly agreed, 7.4% strongly agreed and a minority of 4.4% slightly disagreed with TS5.

TS6 sought to determine the extent to which the analytics personnel of the selected retailers shows a superior ability to learn new technologies. The majority of the respondents (48.5%) agreed and the minority (4.4%) slightly disagreed with this statement. Additionally, 26.5% of the respondents slightly agreed and 16.2% strongly agreed with TS6. Lastly, 4.4% rated TS6 as “neutral”.

TS7 sought to determine the extent to which the analytics personnel of the selected retailers are capable of interpreting business problems and developing appropriate technical solutions. A greater number of the respondents (47.1%) agreed with this statement. Additionally, 29.4% slightly agreed, 16.2% strongly agreed, and 2.9% slightly disagreed with TS7. Moreover, 2.9% of the respondents rated TS7 as “neutral”. Lastly, a minority of 1.5% disagreed with TS7.

TS8 sought to determine the extent to which the analytics personnel of the selected retailers work closely with customers and maintain productive client relationships. Half of the respondents (50%) agreed with this statement. In addition, 17.6% slightly agreed, 10.3% strongly agreed, and 5.9% slightly disagreed with TS8. Moreover, 14.7% of the respondents rated TS8 as “neutral”. Lastly, a minority of 1.5% disagreed with TS8.

TS9 sought to determine the extent to which the analytics personnel of the selected retailers are knowledgeable about the critical factors for the success of their organisation. the majority (44.1%) of the respondents agreed and the minority (1.5%) disagreed with this statement. In addition, 26.5% slightly agreed and 14.7% strongly agreed, and 2.9% slightly disagreed with TS9. Lastly, 2.4% of the respondents rated TS9 as “neutral”.

TS10 sought to determine the extent to which the analytics personnel of the selected retailers are knowledgeable about the role of big data analytics as a means, not an end. A greater number of the respondents (48.5%) agreed with TS10. Additionally, 19.1% slightly agreed, 13.2% strongly agreed, and 2.9% slightly disagreed with TS10. Moreover, 11.8% of the respondents rated TS10 as “neutral”. Lastly, a minority of 2.9% disagreed.

Therefore, results reveal that all the items under technology were mostly rated as “agree”. This shows a positive utilisation of BDA technical skills by South African retailers.

Table 4.11: Technical Skills

TS1 [We provide big data analytics training to our employees]	**Frequency**	**Percentage**

Strongly disagree	5	7.4%
Disagree	10	14.7%
Slightly disagree	10	14.7%
Neutral	8	11.8%
Slightly agree	15	22.1%
Agree	11	16.2%
Strongly Agree	9	13.2%
Total	68	100.0%
TS2[We hire new employees that already have the big data analytics skills]	**Frequency**	**Percent**
Strongly disagree	1	1.5%
Disagree	6	8.8%
Slightly disagree	4	5.9%
Neutral	6	8.8%
Slightly agree	19	27.9%
Agree	24	35.3%
Strongly Agree	8	11.8%
Total	68	100.0%
TS3 [Our big data analytics staff have the right skills/education to accomplish their jobs successfully]	**Frequency**	**Percent**
Strongly disagree	0	0.0%
Disagree	3	4.4%
Slightly disagree	2	2.9%
Neutral	11	16.2%
Slightly agree	18	26.5%
Agree	22	32.4%
Strongly Agree	12	17.6%
Total	68	100.0%
TS4 [Our big data analytics staff hold suitable work experience to accomplish their jobs successfully]	**Frequency**	**Percent**
Strongly disagree	0	0.0%
Disagree	0	0.0%

Slightly disagree	4	5.9%
Neutral	15	22.1%
Slightly agree	13	19.1%
Agree	29	42.6%
Strongly Agree	7	10.3%
Total	68	100.0%
TS5 [Our analytics personnel show superior understanding of technological trends]	**Frequency**	**Percent**
Strongly disagree	0	0.0%
Disagree	0	0.0%
Slightly disagree	3	4.4%
Neutral	10	14.7%
Slightly agree	21	30.9%
Agree	29	42.6%
Strongly Agree	5	7.4%
Total	68	100.0%
TS6 [Our analytics personnel show superior ability to learn new technologies]	**Frequency**	**Percent**
Strongly disagree	0	0.0%
Disagree	0	0.0%
Slightly disagree	3	4.4%
Neutral	3	4.4%
Slightly agree	18	26.5%
Agree	33	48.5%
Strongly Agree	11	16.2%
Total	68	100.0%
TS7 [Our analytics personnel are very capable in interpreting business problems and developing appropriate technical solutions]	**Frequency**	**Percent**
Strongly disagree	0	0.0%
Disagree	1	1.5%
Slightly disagree	2	2.9%

Neutral	2	2.9%
Slightly agree	20	29.4%
Agree	32	47.1%
Strongly Agree	11	16.2%
Total	68	100.0%
TS8 [Our analytics personnel work closely with customers and maintain productive user/client relationships]	**Frequency**	**Percent**
Strongly disagree	0	0.0%
Disagree	1	1.5%
Slightly disagree	4	5.9%
Neutral	10	14.7%
Slightly agree	12	17.6%
Agree	34	50.0%
Strongly Agree	7	10.3%
Total	68	100.0%
TS9 [Our analytics personnel are very knowledgeable about the critical factors for the success of our organisation]	**Frequency**	**Percent**
Strongly disagree	0	0.0%
Disagree	1	1.5%
Slightly disagree	2	2.9%
Neutral	5	7.4%
Slightly agree	18	26.5%
Agree	30	44.1%
Strongly Agree	10	14.7%
Total	66	97.1%
TS10 [Our analytics personnel are very knowledgeable about the role of big data analytics as a means, not an end]	**Frequency**	**Percent**
Strongly disagree	0	0.0%
Disagree	2	2.9%
Slightly disagree	2	2.9%
Neutral	8	11.8%
Slightly agree	13	19.1%

Agree	33	48.5%
Strongly Agree	9	13.2%
Total	67	98.5%

The frequency distribution for “Managerial Skills” (MS) is presented in Table 4.12. MS1 sought to determine the extent to which big data analytics managers of the selected retailers understand and appreciate the business needs of other functional managers, suppliers, and customers. The majority (38.2%) of the respondents agreed and the minority (2.9%) disagreed with this statement. In addition, 26.5% slightly agreed, 20.6% strongly agreed, and 7.4% slightly disagreed with MS1. Lastly, 4.4% of the respondents rated TS4 as “neutral”.

MS2 sought to determine the extent to which big data analytics managers of the selected retailers can work with functional managers, suppliers, and customers to determine opportunities that big data might bring to their business. In regard to this, the majority (41.2%) of the respondents agreed with this statement. In addition, 30.9% of the respondents slightly agreed, 13.2% strongly agreed, and a minority of 1.5% slightly disagreed with MS2. Moreover, 5.8% of the respondents rated MS2 as “disagree” and “strongly disagree”. Lastly, 7.4% rated MS2 as “neutral”.

MS3 sought to determine the extent to which big data analytics managers of the selected retailers can coordinate big data-related activities in ways that support other functional managers, suppliers, and customers. The majority (35.3%) of the respondents rated this statement as “agree”. In addition, 33.8% slightly agreed, 14.7% strongly agreed, and a minority 7.4% disagreed with MS3. Lastly, 8.8% of the respondents rated MS3 as “neutral”.

MS4 sought to determine the extent to which big data analytics managers of the selected retailers can anticipate the future business needs of functional managers, suppliers, and customers. A greater number of the respondents (36.8%) agreed with this statement. In addition, 29.4% slightly agreed, 11.8% strongly agreed, and 4.4% disagreed with MS4. Moreover, 16.2% of the respondents rated MS4 as “neutral”. Lastly, a minority of 1.5% slightly disagreed.

MS5 sought to determine the extent to which big data analytics managers of the selected retailers have a good sense of where to apply big data. The majority (30.9%) of the respondents agreed and the minority (1.5%) slightly disagreed with this statement. In addition, 27.9% slightly agreed, 16.2% strongly agreed, and 7.4% disagreed with MS5. Lastly, 16.2% of the respondents rated MS5 as “neutral”.

Therefore, results reveal that all the items under managerial skills were mostly rated as "agree". Consequently, this indicates a positive utilisation of BDA managerial skills by South African retailers.

Table 4.12: Managerial skills

MS1 [Our big data analytics managers understand and appreciate the business needs of other functional managers, suppliers, and customers]	**Frequency**	**Percent**
Strongly disagree	0	0.0%
Disagree	2	2.9%
Slightly disagree	5	7.4%
Neutral	3	4.4%
Slightly agree	18	26.5%
Agree	26	38.2%
Strongly Agree	14	20.6%
Total	68	100.0%
MS2 [Our big data analytics managers are able to work with functional managers, suppliers, and customers to determine opportunities that big data might bring to our business]	**Frequency**	**Percent**
Strongly disagree	2	2.9%
Disagree	2	2.9%
Slightly disagree	1	1.5%
Neutral	5	7.4%
Slightly agree	21	30.9%
Agree	28	41.2%
Strongly Agree	9	13.2%
Total	68	100.0%
MS3 [Our big data analytics managers are able to coordinate big data-related activities in ways that support other functional managers, suppliers, and customers]	**Frequency**	**Percent**
Strongly disagree	0	0.0%
Disagree	0	0.0%
Disagree	5	7.4%

Neutral	6	8.8%
Slightly agree	23	33.8%
Agree	24	35.3%
Strongly Agree	10	14.7%
Total	68	100.0%
MS4 [Our big data analytics managers are able to anticipate the future business needs of functional managers, suppliers, and customers]	**Frequency**	**Percent**
Strongly disagree	0	0.0%
Disagree	3	4.4%
Slightly disagree	1	1.5%
Neutral	11	16.2%
Slightly agree	20	29.4%
Agree	25	36.8%
Strongly Agree	8	11.8%
Total	68	100.0%
MS5 [Our big data analytics managers have a good sense of where to apply big data]	**Frequency**	**Percent**
Strongly disagree	0	0.0%
Disagree	5	7.4%
Slightly disagree	1	1.5%
Neutral	11	16.2%
Slightly agree	19	27.9%
Agree	21	30.9%
Strongly Agree	11	16.2%
Total	68	100.0%

4.4.3.3 BDA intangible capabilities distribution

BDA intangible capabilities generally refer to resources that have no physical existence. This included two main constructs (data-driven culture and organisational learning). The study sought to know the level of agreement and disagreement of the respondents regarding each item under the BDAIC constructs.

The frequency distribution for “Data-Driven Culture” (DD) is presented in Table 4.13. DD1 sought to determine the extent to which the selected retailers consider data as tangible data. In regard to this, the majority (44.1%) of the respondents rated T1 as “agree”. Additionally, 23.5% of the respondents strongly agreed, 11.8% slightly agreed, and 4.4% slightly disagreed with DD1. Moreover, 13.2% of the respondents rated DD1 as “neutral”. Lastly, a minority of 3% rated DD1 as “strongly disagree” and “disagree”.

DD2 sought to determine the extent to which the selected retailers base their decisions on data rather than on instinct. The majority of the respondents (41.2%) agreed and the minority of (1.5%) disagreed with this statement. 19.1% slightly agreed, 16.2% strongly agreed, and 8.8% disagreed with DD2. Additionally, 10.3% respondents rated DD2 as “neutral”. Lastly, 2.9% of the respondents slightly disagreed with DD2.

DD3 sought to determine the extent to which the selected retailers are willing to override their own intuition when data contradict their viewpoints. The majority of the respondents (29.4%) rated this statement as “neutral”. In addition, 23.5% agreed, 14.7% slightly agreed, and 13.2% disagreed with DD3. Moreover, 10.3% of the respondents rated DD3 as “strongly agree”. Lastly, a minority of 8.8% rated DD3 as “strongly disagree” and “slightly disagree”.

DD4 sought to determine the extent to which the selected retailers continuously assess and improve their business rules in response to insights extracted from data. The majority of the respondents (48.5%) agreed and the minority (7.4%) slightly disagreed with this statement. Additionally, 16.2% slightly agreed and 8.8% disagreed with DD4. Lastly, 16.2% of the respondents rated DD4 as “neutral”.

DD5 sought to determine the extent to which the selected retailers continuously coach their employees to make decisions based on data. In regard to this, the majority (42.6%) of the respondents agreed with this statement. In addition, 19.1% slightly agreed and 14.7% strongly agreed with DD5. 8.8% of the respondents rated DD5 as “disagree” and “slightly disagree”. Lastly, a minority of 1.5% strongly disagreed with DD5.

DD6 sought to determine the extent to which the selected retailers continuously examine their innovative opportunities for the strategic use of big data analytics. The majority of the respondents (39.7%) agreed with this statement. In addition, 29.4% slightly agreed and 19.1% strongly agreed with DD6. 4.4% of the respondents rated DD6 as “neutral” Lastly, 5.9% disagreed with DD6.

DD7 sought to determine the extent to which the selected retailers enforce adequate plans for the introduction and utilisation of big data analytics. A greater number of the respondents (41.2%) rated DD7 as “slightly agreed”. Additionally, 19.1% of the respondents rated DD7 as "neutral". Moreover, 30.9% agreed and 5.9% strongly agreed with DD7. Lastly a minority of 2.9% disagreed.

DD8 sought to determine the extent to which the selected retailers frequently adjust big data analytics plans to better adapt to changing conditions. The majority of the respondents (38.2%) slightly agreed and the minority (1.5%) disagreed with this statement. Additionally, 26.5% agreed, 8.8% strongly agreed, and 4.4% slightly disagreed with DD8. Lastly, 20.6% of the respondents rated DD8 as "neutral".

DD9 sought to determine the extent to which the selected retailers share information between their business analysts and line people in order to have access to all available know-how. A greater number of the respondents (27.9%) slightly agreed with this statement. In addition, 26.5% agreed and 10.3% strongly agreed with DD9. Moreover, 23.5% of the respondents rated DD9 as "neutral". Lastly, 5.9% slightly disagreed and 5.9% disagreed with DD9.

DD10 sought to determine the extent to which the selected retailers constantly monitor the performance of their big data analytics function. In regard to this, the majority (30.9%) of the respondents agreed with this statement. In addition, 27.9% slightly agreed, 7.4% strongly agreed, and 4.4% strongly disagreed with DD10. 26.5% of the respondents rated DD10 as "neutral". Lastly, a minority of 2.9% slightly disagreed.

Hence, results reveal that DD1, DD2, DD3, DD4, DD5 were mostly rated as "agree" meanwhile DD6, DD7, DD8, DD9, DD10 were mostly rated as "slightly agree. This indicates that BDA data-driven culture capabilities are not fully deployed by South African retailers.

Table 4.13: Data-driven culture

DD1 [We consider data as a tangible asset]	**Frequency**	**Percent**
Strongly disagree	1	1.5%
Disagree	1	1.5%
Slightly disagree	3	4.4%
Neutral	9	13.2%
Slightly agree	8	11.8%
Agree	30	44.1%
Strongly Agree	16	23.5%
Total	68	100.0%
DD2 [We base our decisions on data rather than on instinct]	**Frequency**	**Percent**

Strongly disagree	1	1.5%
Disagree	6	8.8%
Slightly disagree	2	2.9%
Neutral	7	10.3%
Slightly agree	13	19.1%
Agree	28	41.2%
Strongly Agree	11	16.2%
Total	68	100.0%
DD3 [We are willing to override our own intuition when data contradict our viewpoints]	**Frequency**	**Percent**
Strongly disagree	3	4.4%
Disagree	9	13.2%
Slightly disagree	3	4.4%
Neutral	20	29.4%
Slightly agree	10	14.7%
Agree	16	23.5%
Strongly Agree	7	10.3%
Total	68	100.0%
DD4 [We continuously assess and improve the business rules in response to insights extracted from data]	**Frequency**	**Percent**
Strongly disagree	0	0.0%
Disagree	0	0.0%
Slightly disagree	5	7.4%
Neutral	11	16.2%
Slightly agree	13	19.1%
Agree	33	48.5%
Strongly Agree	6	8.8%
Total	68	100.0%
DD5 [We continuously coach our employees to make decisions based on data]	**Frequency**	**Percent**
Strongly disagree	1	1.5%
Disagree	3	4.4%

Slightly disagree	3	4.4%
Neutral	8	11.8%
Slightly agree	13	19.1%
Agree	29	42.6%
Strongly Agree	10	14.7%
Total	67	98.5%
DD6 [We continuously examine the innovative opportunities for the strategic use of big data analytics]	**Frequency**	**Percent**
Strongly disagree	0	0.0%
Disagree	4	5.9%
Slightly disagree	0	0.0%
Neutral	3	4.4%
Slightly agree	20	29.4%
Agree	27	39.7%
Strongly Agree	13	19.1%
Total	67	98.5%
DD7 [We enforce adequate plans for the introduction and utilization of big data analytics]	**Frequency**	**Percent**
Strongly disagree	0	0.0%
Disagree	0	0.0%
Disagree	2	2.9%
Neutral	13	19.1%
Slightly agree	28	41.2%
Agree	21	30.9%
Strongly Agree	4	5.9%
Total	68	100.0%
DD8 [We frequently adjust big data analytics plans to better adapt to changing conditions]	**Frequency**	**Percent**
Strongly disagree	0	0.0%
Disagree	1	1.5%
Slightly disagree	3	4.4%
Neutral	14	20.6%

Slightly agree	26	38.2%
Agree	18	26.5%
Strongly Agree	6	8.8%
Total	68	100.0%
DD9 [In our organisation, information is widely shared between business analysts and line people so that those who make decisions or perform jobs have access to all available know-how]	**Frequency**	**Percent**
Strongly disagree	0	0.0%
Disagree	4	5.9%
Slightly disagree	4	5.9%
Neutral	16	23.5%
Slightly agree	19	27.9%
Agree	18	26.5%
Strongly Agree	7	10.3%
Total	68	100.0%
DD10 [We constantly monitor the performance of the big data analytics function]	**Frequency**	**Percent**
Strongly disagree	0	0.0%
Disagree	3	4.4%
Slightly disagree	2	2.9%
Neutral	18	26.5%
Slightly agree	19	27.9%
Agree	21	30.9%
Strongly Agree	5	7.4%
Total	68	100.0%

The frequency distribution for “Organisation Learning” (OL) is presented in Table 4.14. OL1 sought to determine the extent to which the selected retailers can search for new and relevant knowledge. The majority (41.2%) of the respondents agreed and the minority (2.9%) disagreed with this statement. In addition, 29.4% of the respondents slightly agreed and 20.6% strongly agreed with OL1. Lastly, 5.9% of the respondents rated OL1 as “neutral”.

OL2 sought to determine the extent to which the selected retailers can acquire new and relevant knowledge. In regard to this, the majority (36.8%) of the respondents agreed with this statement. 26.5% of the respondents slightly agreed and 22.1% strongly agreed with OL2. Additionally, 13.2% of the respondents rated OL2 as "neutral". Lastly, a minority of 1.5% disagreed with OL2.

OL3 sought to determine the extent to which the selected retailers can assimilate relevant knowledge. The majority (42.6%) of the respondents agreed with this statement. Additionally, 26.5% slightly agreed, 13.2% strongly agreed, and 2.9% disagreed with this statement. Moreover, 13.2% of the respondents rated OL3 as "neutral". Lastly, a minority of 1.5% slightly disagreed with OL3.

OL4 sought to determine the extent to which the selected retailers can apply relevant knowledge. More than half of the respondents (52.9%) agreed with OL4. In addition, 20.6% slightly agreed and 16.2% strongly agreed with OL4. Lastly, 10.3% of the respondents rated OL4 as "neutral".

OL5 sought to determine the extent to which the selected retailers have made concerted efforts for the exploitation of existing competencies and exploration of new knowledge. 39.7% of the respondents slightly agreed with this statement. In addition, 29.4% slightly agreed and 16.2% strongly agreed with OL5. Lastly, 14.7% of the respondents rated OL5 as "neutral".

Therefore, results reveal that the majority of the respondents agreed with all the items under OL. This indicates a positive utilisation of BDA organisational learning capabilities by South African retailers.

Table 4.14: Organisational Learning

OL1 [We are able to search for new and relevant knowledge]	**Frequency**	**Percent**
Strongly disagree	0	0.0%
Disagree	2	2.9%
Slightly disagree	0	0.0%
Neutral	4	5.9%
Slightly agree	20	29.4%
Agree	28	41.2%
Strongly Agree	14	20.6%
Total	68	100.0%

OL2 [We are able to acquire new and relevant knowledge]	Frequency	Percent
Strongly disagree	0	0.0%
Disagree	1	1.5%
Slightly disagree	0	0.0%
Neutral	9	13.2%
Slightly agree	18	26.5%
Agree	25	36.8%
Strongly Agree	15	22.1%
Total	68	100.0%
OL3 [We are able to assimilate relevant knowledge]	**Frequency**	**Percent**
Strongly disagree	0	0.0%
Disagree	2	2.9%
Slightly disagree	1	1.5%
Neutral	9	13.2%
Slightly agree	18	26.5%
Agree	29	42.6%
Strongly Agree	9	13.2%
Total	68	100.0%
OL4 [We are able to apply relevant knowledge]	**Frequency**	**Percent**
Strongly disagree	0	0.0%
Disagree	0	0.0%
Slightly disagree	0	0.0%
Neutral	7	10.3%
Slightly agree	14	20.6%
Agree	36	52.9%
Strongly Agree	11	16.2%
Total	68	100.0%
OL5 [We have made concerted efforts for the exploitation of existing competencies and exploration of new knowledge]	**Frequency**	**Percent**
Strongly disagree	0	0.0%

Disagree	0	0.0%
Slightly disagree	0	0.0%
Neutral	10	14.7%
Slightly agree	27	39.7%
Agree	20	29.4%
Strongly Agree	11	16.2%
Total	68	100.0%

4.5 Spearman coefficient correlation between BDA capabilities and organisational performance

Spearman correlation was used to determine the relationship that exists between big data analytics tangible capabilities (BDATC), data analytics human capabilities (BDAHC), data analytics intangible capabilities (BDAIC), and organisational performance (OP) of South African retailers. The study proposed the following hypotheses:

H1 There is a positive and significant relationship between BDA tangible capabilities and the organisational performance of selected South African retailers

H2: There is a positive and significant relationship between BDA human capabilities and the organisational performance of selected South African retailers

H3: There is a positive and significant relationship between BDA intangible capabilities and the organisational performance of selected South African retailers

A spearman correlation coefficient was run to determine the relationship between each independent variable and the dependent variable. H1 assesses whether BDATC is positively and significantly related to the organisational performance of South African retailers. The relationship between BDATC and OP is displayed in Table 4.15. The results reveal a spearman correlation of .306 and a probability sig. (2-tailed) of .011. This implies that there is a moderate positive correlation between BDATC and the organisational performance of South African retailers, which is statistically significant. Additionally, it indicates that as retailers increase their BDA tangible capabilities, their organisational performance increases as well. Therefore, H1 was supported.

Table 4.15: Correlation between BDATC and organisational performance

			BDATC	OP
Spearman's rho	BDATC	Correlation Coefficient	1.000	.306*

		Sig. (2-tailed)	.	.011
		N	68	68
	OP	Correlation Coefficient	.306*	1.000
		Sig. (2-tailed)	.011	.
		N	68	68

*. Correlation is significant at the 0.05 level (2-tailed).

H2 evaluates whether BDAHC is positively and significantly related to the organisational performance of South African retailers. The relationship between BDAHC and OP is displayed in Table 4.16. The results reveal a spearman correlation of .225 and a probability sig. (2-tailed) of .035. This implies that there is a significant positive correlation between BDATC and the organisational performance of South African retailers. In addition, results indicate that as retailers increase their BDA human capabilities, their organisational performance increases as well. Hence, H2 was supported.

Table 4.16: Correlation between BDAHC and organisational performance

			BDAHC	OP
Spearman's rho	BDAHC	Correlation Coefficient	1.000	.225
		Sig. (2-tailed)	.	.035
		N	68	68
	OP	Correlation Coefficient	.225	1.000
		Sig. (2-tailed)	.065	.
		N	68	68

*. Correlation is significant at the 0.05 level (2-tailed).

H3 assesses whether BDAIC is positively and significantly related to the organisational performance of South African retailers. The relationship between BDAIC and OP is displayed in Table 4.17. The results reveal that BDAIC is positively and significantly related to the organisational performance of South African retailers (r = .627, p = .001). This implies that there is a strong relationship between both, suggesting that an increase in the BDAIC of retailers will lead to an increase in their Organisational performance. Consequently, H3 was supported.

Table 4.17: Correlation between BDA Intangible capabilities and organisational performance

			BDAIC	OP
Spearman's rho	BDAIC	Correlation Coefficient	1.000	.627**
		Sig. (2-tailed)	.	.001
		N	68	68

OP	Correlation Coefficient	.627**	1.000
	Sig. (2-tailed)	.001	.
	N	68	68

**. Correlation is significant at the 0.01 level (2-tailed).

The overall findings of the study reveal that BDA capabilities positively and significantly impact the organisational performance of South African retailers. Hence, all the proposed hypotheses were supported. The summary of the findings is presented in Table 4.18

Table 4.18: Summary of the findings

Hypotheses	Findings
H1 There is a positive and significant relationship between BDA tangible capabilities and the organisational performance of selected South African retailers	Supported
H2 There is a positive and significant relationship between BDA human capabilities and the organisational performance of selected South African retailers	Supported
H3 There is a positive and significant relationship between BDA intangible capabilities and the organisational performance of selected South African retailers	Supported

4.6 Chapter Summary

This chapter presented the overall results and findings of the analysed data. From the results, it is evident that BDAC (BDA tangible, human, and intangible capabilities) is positively and significantly related to the organisational performance of South African retailers. The following chapter presents discussions, conclusions, and recommendations on the research findings.

CHAPTER 5: DISCUSSION, CONCLUSIONS, AND RECOMMENDATIONS

5.1 Introduction

In this last chapter, a discussion of the findings, conclusion, and recommendations for further research will be presented. In the discussion section, comparisons of various similar studies will be made to approve the presented findings. The conclusion will focus on the research objectives meanwhile recommendations will be drawn from the discussion and conclusion of the findings.

5.1.1 Research question and sub-questions

5.1.1.1 Research question

What is the impact of big data analytics capabilities on the organisational performance of selected South African retailers?

5.1.1.2 Research sub-questions

- ➢ What is the impact of BDA tangible capabilities on the organisational performance of selected South African retailers?
- ➢ What is the impact of BDA human capabilities on the organisational performance of selected South African retailers?
- ➢ What is the impact of BDA intangible capabilities on the organisational performance of selected South African retailers?

5.1.2 Research objectives

- ➢ To conduct empirical research to determine the impact of BDA tangible capabilities on the organisational performance of selected South African retailers.
- ➢ To conduct empirical research to determine the impact of BDA human capabilities on the organisational performance of selected South African retailers.
- ➢ To conduct empirical research to determine the impact of BDA intangible capabilities on the organisational performance of selected South African retailers.

5.2 Summary of Findings

The main aim of this study was to determine the impact of BDA capabilities on the organisational performance of South African retailers. The study specifically aimed at determining how BDA tangible, human and intangible capabilities impacted the organisational performance of South African retailers.

This research adopted a descriptive research design to determine the impact of BDA capabilities on the organisational performance of South African retailers. The population of this study included BI team members of selected South African retailers and a judgemental sampling technique was adopted. A sample size of 109 was obtained using the Yamane formulae (1967). A total of 68 respondents participated in the study. Furthermore, the data analysis of this study consisted of two main parts: summarising the collected data (Descriptive statistics) and running a spearman correlation test to determine the relationship between the dependent variable (organisational performance) and the independent variables (BDA tangible, BDA human and BDA intangible capabilities). This was done using Excel and Statistical Package for Social Science (SPSS).

Objective one aimed at determining the impact of BDA tangible capabilities on the organisational performance of South African retailers. BDATC included three main dimensions (data, technology, and basic resources). Findings from descriptive statistics revealed that the majority of the respondents agreed with most of the items under these dimensions. Hence, this implies a positive utilisation of data, technology, and basic resources by South African retailers. Furthermore, the findings from the correlation test revealed that BDTC is positively and significantly correlated to the organisational performance of South African retailers ($r = .306$, $P = .011$).

Objective two aimed at determining the impact of BDA human capabilities on the organisational performance of South African retailers. BDAHC included two main dimensions (technical skills and managerial skills). Findings from descriptive statistics revealed that most of the participants agreed with most of the items under these dimensions. Hence, this indicates a positive utilisation of BDA human capabilities by South African retailers. Moreover, the findings from the correlation test revealed that BDHC is positively and significantly related to the organisational performance of South African retailers ($r = .225$, $p = .035$).

Lastly, objective three aimed at determining the impact of BDA intangible capabilities on the organisational performance of South African retailers. BDAIC included two main dimensions (data-driven culture and organisational learning). Findings from descriptive statistics revealed that most of the participants agreed with most of the items under these dimensions. Hence, this indicates a positive utilisation of BDA intangible capabilities by South African retailers. Additionally, findings from the regression analysis revealed that BDAIC is positively and significantly related to the organisational performance of retailers ($r = .627$, $p = .001$).

Overall, the results of the study revealed that the organisational performance of South African retailers is positively and significantly impacted by BDA capabilities. Participants agreed that the following aspects of organisational performance were impacted by BDAC: productivity, sales revenue, profit rate, customer retention, and return on investment.

5.3 Discussion

Several researchers have been working toward understanding BDA capability and examining its relationship with firm performance (Garmaki et al., 2016; Akter, 2016; Fosso Wamba et al., 2017; Maroufkhani et al., 2019). Prior studies on this topic confirmed a positive relationship between BDAC and firm performance (Gupta and George, 2016; Akter, 2016; Su et al., 2021; Anwar and Abdullah, 2021). However, few studies have focused on understanding this relationship in retail sectors. Thus, this study aims at filling this gap by examining the impact of BDA capabilities on the organisational performance of retailers.

Empirical research was conducted and insights were provided on the relationship between BDAC and the organisational performance of South African retailers. Based on the findings from prior studies, three hypotheses were proposed.

Hypothesis 1: There is a positive and significant relationship between BDA tangible capabilities and the organisational performance of selected South African retailers

Firstly, it was assumed that BDA tangible capabilities positively and significantly impact the organisational performance of South African retailers. The findings from the analyses revealed that there is a positive and significant relation between BDATC and the organisational performance of South African retailers ($r = .306$, $P = .011$). Hence, H1 was supported. This significant relationship shows that South African retailers should deploy BDA tangible resources to maximise their organisational performance. The above findings correspond to a study conducted by Su et al. (2021) whose results revealed that BDA tangible resources have a positive impact on organisational performance. Similarly, other studies confirmed a positive relationship BDATC and organisational performance (Ong and Chen, 2013; Tambe, 2014; Akter, 2016; Anwar, Khan, and Shah, 2018).

Moreover, the findings of the study revealed a positive impact of BDA tangible capabilities (data, technology, and basic resources) on selected South African retailers. Hence, all South African retailers should consider employing BDA tangible capabilities to enhance their organisational performance, and competitive advantage and save their money and time. In addition, retailers should reinforce the performance of their BD analytics platforms in terms of compatibility, connectivity, and modularity to maximise their organisational performance.

Hypothesis 2: There is a positive and significant relationship between BDA human capabilities and the organisational performance of selected South African retailers

Secondly, it was hypothesised that BDA human capabilities have a positive and significant impact on the organisational performance of South African retailers. The results reveal that the relationship between BDA human capabilities and organisational performance was positive and significant (r = .225, p = .035). Consequently, H2 was supported. The above result is consistent with previous studies that found that BDA human capabilities enhance organisational performance (Chuang et al., 2015; Hamid et al.,2017; Anwar and Abdullah, 2021). For instance, Anwar, Khan, and Shah (2018) reported that BDA human capabilities significantly and positively impact the performance of an organisation. Similarly, Su et al. (2021) concluded that BDA human resources positively impact organisational performance.

Furthermore, the findings of the study revealed a positive impact of BDA human capabilities (technical Skills and managerial skills) on selected South African retailers. Consequently, all South African retailers should consider deploying BDA human capabilities as this has a direct impact on organisational performance. Moreover, to maximise organisational performance through this capability, retailers should consider investing in the training of their staff to have a well-trained BDA team that is eager to be efficient, attentive, and creative. Additionally, retailers should consider recruiting more technically trained senior managers with real BDA experience. Managers that correctly understand how BDA works and hire people with the right knowledge and skills.

Hypothesis 3: There is a positive and significant relationship between BDA intangible capabilities and the organisational performance of selected South African retailers

Thirdly, it was hypothesised that BDA intangible capabilities positively and significantly impact the organisational performance of South African retailers. The findings from the analyses reveal that BDAIC is positively and significantly correlated to the organisational performance of South African retailers (r = .627, p = .001). Thus, H3 was supported. The finding of this study corresponds to prior studies that examined the relationship between BDA intangible capabilities and organisational performance (Izedonme, Odeyile, and Kuegbe, 2013; Kamasak, 2017; Rua and Franca, 2017, Su et al. 2021). Additionally, Gupta and George, 2016 provided evidence that BDA intangible resources significantly impact organisational performance.

Moreover, the findings of the study revealed a positive impact of BDA tangible capabilities (technical Skills and managerial skills) on selected South African retailers. Hence, South African retailers should consider employing BDA human capabilities to enhance their organisational performance. Furthermore, to maximise organisational performance through this capability, retailers should consider building a data-driven culture, enhancing data management skills, developing decision-making capabilities, and expanding the various data-driven decision-making that combines intuition and analytical insights. In addition, retailers should encourage organisational learning to understand the dynamic and complex environment.

Therefore, the study concludes that all the BDAC primary dimensions (BDA tangible, BDA human, BDA intangible capabilities) has a positive and significant impact on the organisational performance of South African retailers. This implies that the high market and operational performance of South African retailers is a result of well-deployed BDA tangible, intangible, and human resources. In addition, this study provides retailers with evidence that the deployment of BDAC is essential for the improvement of organisational performance.

5.4 Theoretical contribution

This study contributes to the existing BDA capability literature in various ways. Firstly, the study is among the first to investigate the impact of BDA capabilities on the organisational performance of South African retailers. The findings of the research confirmed a positive and significant impact BDAC on the organisational performance of South African retailers. Hence, this provides new insights into the main building blocks of BDAC and their roles in the improvement of the organisational performance of retailers.

Secondly, Gupta and George (2016) stated that the empirical evidence for the relationship between BDAC and firm performance is still limited. Hence, this study conducted empirical research to determine the impact of BDAC on the organisational performance of retailers. In accordance with previous studies, this study confirms that BDAC leads to greater organisational performance. It supports the fact that big data analytics radically transform the way organisations run their business and create value (Gupta and George, 2016; Fosso Wamba et al., 2017).

Thirdly, previous literature reveals that most of the studies on BDAC and organisational performance were conducted in Europe, USA, Asia with a few exceptions in Africa. Hence, this study was of significance to build on the existing knowledge base. In addition, the above studies mostly focused on sectors such as banks, telecommunications, health care, automobile, etc. This study is among the few studies that consider the retail sector of South Africa. This can serve as a framework for South African retailers utilising BDA to maximise their organisational performance.

5.5 Managerial contributions

This research has significant implications for managers who are engaged in BDA. Firstly, the study suggests that BDA capability is a key enabler for improved organisational performance. The findings reveal that the enhancement of overall BDA Capability can be linked with sub-dimensional levels. For instance, BDA tangible capability (BDATC) could be enhanced by improving the performance of BD analytics platforms in terms of compatibility, connectivity, and modularity. Similarly, BDA human capability (BDAHC) could be improved by training to obtain better knowledge and skills of the workforce. Finally, BDA intangible capability (BDAIC) could be improved by enhancing the quality of investment, planning, and coordination. Hence, the multidimensional BDA capability model enables managers to have a clearer understanding of the BDAC model antecedents and its relationship with each of the capability dimensions.

Furthermore, the study emphasises that tangible, intangible, and human resources are essential for creating a strong BDA capability. Thus, this enables managers to be cautious that maximising organisational performance through BDA is not just about huge investments or access to the latest technology. It is important to also have the right organisational culture and organisational learning and possessing the right BD technical and managerial skills.

Moreover, the majority of BD investments fail because organisations do not take decisions based on relevant data. Hence, the finding of this study could be relevant for managers involved in making IT decisions. Additionally, the findings of this study reveal that organisations that adopt and fully deploy BDAC are likely to outperform their competitors in terms of operational and market value. Thus, managers would profit from investing in such a capability.

5.6 Limitations and further research

As with any other research, the study had a series of limitations. Firstly, this research was limited only to South African retailers. It is difficult to apply the results of this study to other industries such as manufacturing, banking, automobile, etc. Thus, future researchers can focus on different countries and different sectors using the same study model.

Secondly, the study targeted 109 respondents to take part in the research survey, only 68 responses were collected and deemed satisfactory for analysis. Hence, future researchers can target larger sample sizes and obtain a higher response rate which may lead to more pertinent results. Additionally, the study adopted a quantitative approach to analyse the collected data. Future researchers can adopt a mixed-method (quantitative-qualitative approach) to validate the proposed findings.

Thirdly, this study focused on investigating the impact of BDAC on the overall organisational performance and not a specific area. Hence, future researchers can investigate the impact of BDA capability within a specific department such as supply chain management, etc. Moreover, since most organisations are in the adoption and development process of BDAC, future researchers should consider improving this research by including other dimensions not mentioned in the study.

5.7 Recommendations

The findings of this study revealed that all the BDAC dimensions (tangible, human, and intangible capabilities) have a positive impact on the organisational performance of selected South African retailers. It shows that the essential resources for improving organisational performance include data, technology, basic resources, technical skills, managerial skills, data-driven culture, and organisational learning. To maximise organisational performance through these capabilities, the following recommendations should be taken into consideration:

- Retailers should be willing to consider BDA as part of their operations and improve their overall BDA capabilities as it has a direct impact on their organisational performance. Additionally, these capabilities can improve their competitive advantage and help them save time and money.
- The findings of the study reveal that tangible and intangible capabilities were more highly related to the organisational performance of South African retailers than human capabilities. This shows that South African retailers need to enhance their human resources. Employees are the most important asset for any organisation hence, retailers should consider constantly assessing their BDA human skills and hiring people with the right skills.
- To maximise the benefit of BDA tangible capabilities, retailers should reinforce the performance of their BD analytics platforms in terms of compatibility, connectivity, and modularity.
- To maximise the benefit of BDA human capabilities, retailers should constantly invest in the training of their BDA team to gain better knowledge and skills.
- To maximise the benefit of BDA intangible capabilities, retailers should enhance the quality of investment, planning, and coordination. This will help them improve the quality of their services and innovativeness their products.

- Retailers should consider real-time monitoring of their competitors and customers to identify the various bottlenecks and deficiencies in their operations. Additionally, this will enable them to predict changes in the business and economic environment.

5.8 Conclusions

The goal of this study was to determine the impact of BDA capabilities on the organisational performance of South African retailers. The study was guided by two main objectives. Firstly, a literature review was conducted to understand the impact of BDA capabilities on organisational performance. Secondly, empirical research was conducted to determine the impact of BDA tangible, intangible and human capabilities on the organisational performance of South African retailers.

Data were collected from South African retailers through an online questionnaire to measure the level to which BDA capabilities impact the improvement of their organisational performance. The collected data was then analysed through SPSS and a correlation test was conducted to determine whether the proposed hypotheses of the study were accepted or rejected. The study proposed three hypotheses.

Firstly, it was hypothesised that BDA tangible capabilities and the organisational performance of South African retailers are positively and significantly related. The findings of the study validate this hypothesis thus the research concludes that BDATC impacts the organisational performance of South African retailers. Additionally, this implies that the more retailers deploy BDA tangible resources, the higher their organisational performance.

Furthermore, the study proposed that a positive and significant association exists between BDA human capabilities and the organisational performance of South African retailers. The findings of the study provide evidence that this hypothesis is true thus the research concludes that BDAHC impacts the organisational performance of South African retailers. This implies that BDAHC is a key factor that should be considered by all retailers as they adopt big data analytics. It is evident that the use of BDA human resources is essential for increasing productivity, sales revenue, profit rate, and return on investment.

Moreover, the study predicted that BDA intangible capabilities and the organisational performance of South African retailers are positively and significantly related The results of the study provide validation of this relationship, thus the research concludes that BDAIC impacts the organisational performance of South African retailers. This implies that the more retailers deploy BDA intangible resources, the higher their organisational performance. In addition, this shows that BDAIC is of importance to South African retailers.

Overall, the study attempted to examine the impact of BDA capabilities on the organisational performance of retail industries in South Africa and the findings stated that these capabilities have a positive and significant impact on organisational performance. This study provides retailers with a deeper understanding of the various BDA capabilities and the key role they play in maximising organisational performance.

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7. Appendices

7.1 Appendix A: Online questionnaire (adopted from Gupta and George, 2016)

Section A: Background Information

Instruction(s): Please answer the following questions. Where applicable mark the appropriate response with a cross (X)

1. What is your gender?

Male	
Female	
Not willing to disclose	

2. What is your age bracket?

22-29 years	
30-37 years	
38-45 years	
46+	

3. What is your highest level of education?

Secondary school	
Bachelor’s degree/ BTech	
Honours	
Masters/PhD	

4. How long have you been with your current employer?

0-1 Years	
2-4 years	

5-7 years	
8-10 years	
More than 10 years	

Section B: Tangible resources

Rate the following based on your view. Use the following scale to indicate your level of agreement and disagreement with each statement

1= Strongly disagree, 2= Disagree, 3= Slightly disagree 4= Neutral, 5= Slightly agree, 6= Agree, 7= Strongly agree

DATA							
1. We have access to very large, unstructured, or fast moving data for analysis	**1**	**2**	**3**	**4**	**5**	**6**	**7**
2. We integrate data from multiple internal sources into a data warehouse or mart for easy access	**1**	**2**	**3**	**4**	**5**	**6**	**7**
3. We integrate external data with internal to facilitate high-value analysis of our business development	**1**	**2**	**3**	**4**	**5**	**6**	**7**
TECHNOLOGY							
4. We integrate external data with internal and have explored or adopted parallel computing approaches (e.g., Hadoop) to big data processing	**1**	**2**	**3**	**4**	**5**	**6**	**7**
5. We have explored or adopted different data visualization tools	**1**	**2**	**3**	**4**	**5**	**6**	**7**
6. We have explored or adopted cloud-based services for processing data and performing analytics	**1**	**2**	**3**	**4**	**5**	**6**	**7**
7. We have explored or adopted open-source software for big data analytics	**1**	**2**	**3**	**4**	**5**	**6**	**7**
8. We have explored or adopted new forms of databases such as Not Only SQL (NoSQL) for storing data	**1**	**2**	**3**	**4**	**5**	**6**	**7**
9. Our user interfaces provide transparent access to all platforms and applications	**1**	**2**	**3**	**4**	**5**	**6**	**7**

10. Our organisation provides multiple analytics interfaces or entry points for external end-users	**1**	**2**	**3**	**4**	**5**	**6**	**7**
11. Analytics-driven information is shared seamlessly across our organisation, regardless of the location	**1**	**2**	**3**	**4**	**5**	**6**	**7**
12. Reusable software modules are widely used in new analytics model development	**1**	**2**	**3**	**4**	**5**	**6**	**7**
13. Object-oriented technologies are utilised to minimize the development time for new analytics applications	**1**	**2**	**3**	**4**	**5**	**6**	**7**
BASICS RESOURCES							
14. Our big data analytics projects are adequately funded	**1**	**2**	**3**	**4**	**5**	**6**	**7**
15. Our big data analytics projects are given enough time to achieve their objectives	**1**	**2**	**3**	**4**	**5**	**6**	**7**

Section C: Human resources

Rate the following based on your view. Use the following scale to indicate your level of agreement and disagreement with each statement

1= Strongly disagree, 2= Disagree, 3= Slightly disagree 4= Neutral, 5= Slightly agree, 6= Agree, 7= Strongly agree

TECHNICAL SKILLS							
1. We provide big data analytics training to our employees	**1**	**2**	**3**	**4**	**5**	**6**	**7**
2. We hire new employees that already have the big data analytics skills	**1**	**2**	**3**	**4**	**5**	**6**	**7**
3. Our big data analytics staff have the right skills to accomplish their jobs successfully	**1**	**2**	**3**	**4**	**5**	**6**	**7**
4. Our big data analytics staff hold suitable work experience to accomplish their jobs successfully	**1**	**2**	**3**	**4**	**5**	**6**	**7**
5. Our analytics personnel show superior understanding of technological trends	**1**	**2**	**3**	**4**	**5**	**6**	**7**
6. Our analytics personnel show superior ability to learn new technologies	**1**	**2**	**3**	**4**	**5**	**6**	**7**

7. Our analytics personnel are very capable in interpreting business problems and developing appropriate technical solutions	**1**	**2**	**3**	**4**	**5**	**6**	**7**
8. Our analytics personnel work closely with customers and maintain productive user/client relationships	**1**	**2**	**3**	**4**	**5**	**6**	**7**
9. Our analytics personnel are very knowledgeable about the critical factors for the success of our organisation	**1**	**2**	**3**	**4**	**5**	**6**	**7**
10. Our analytics personnel are very knowledgeable about the role of big data analytics as a means, not an end	**1**	**2**	**3**	**4**	**5**	**6**	**7**
MANAGERIAL SKILLS							
11. Our big data analytics managers understand and appreciate the business needs of other functional managers, suppliers, and customers	**1**	**2**	**3**	**4**	**5**	**6**	**7**
12. Our big data analytics managers are able to work with functional managers, suppliers, and customers to determine opportunities that big data might bring to our business	**1**	**2**	**3**	**4**	**5**	**6**	**7**
13. Our big data analytics managers are able to coordinate big data-related activities in ways that support other functional managers, suppliers, and customers	**1**	**2**	**3**	**4**	**5**	**6**	**7**
14. Our big data analytics managers are able to anticipate the future business needs of functional managers, suppliers, and customers	**1**	**2**	**3**	**4**	**5**	**6**	**7**
15. Our big data analytics managers have a good sense of where to apply big data	**1**	**2**	**3**	**4**	**5**	**6**	**7**

Section D: Intangible resources

Rate the following based on your view. Use the following scale to indicate your level of agreement and disagreement with each statement

1= Strongly disagree, 2= Disagree, 3= Slightly disagree 4= Neutral, 5= Slightly agree, 6= Agree, 7= Strongly agree

DATA-DRIVEN CULTURE

1. We consider data a tangible asset	**1**	**2**	**3**	**4**	**5**	**6**	**7**
2. base our decisions on data rather than on instinct	**1**	**2**	**3**	**4**	**5**	**6**	**7**
3. We are willing to override our own intuition when data contradict our viewpoints	**1**	**2**	**3**	**4**	**5**	**6**	**7**
4. We continuously assess and improve the business rules in response to insights extracted from data	**1**	**2**	**3**	**4**	**5**	**6**	**7**
5. We continuously coach our employees to make decisions based on data	**1**	**2**	**3**	**4**	**5**	**6**	**7**
6. We continuously examine the innovative opportunities for the strategic use of big data analytics	**1**	**2**	**3**	**4**	**5**	**6**	**7**
7. We enforce adequate plans for the introduction and utilization of big data analytics	**1**	**2**	**3**	**4**	**5**	**6**	**7**
8. We frequently adjust big data analytics plans to better adapt to changing conditions	**1**	**2**	**3**	**4**	**5**	**6**	**7**
9. In our organisation, information is widely shared between business analysts and line people so that those who make decisions or perform jobs have access to all available know-how	**1**	**2**	**3**	**4**	**5**	**6**	**7**
10. We constantly monitor the performance of the big data analytics function	**1**	**2**	**3**	**4**	**5**	**6**	**7**
ORGANISATIONAL LEARNING							
11. We are able to search for new and relevant knowledge	**1**	**2**	**3**	**4**	**5**	**6**	**7**
12. We are able to acquire new and relevant knowledge	**1**	**2**	**3**	**4**	**5**	**6**	**7**
13. We are able to assimilate relevant knowledge	**1**	**2**	**3**	**4**	**5**	**6**	**7**
14. We are able to apply relevant knowledge	**1**	**2**	**3**	**4**	**5**	**6**	**7**
15. We have made concerted efforts for the exploitation of existing competencies and exploration of new knowledge	**1**	**2**	**3**	**4**	**5**	**6**	**7**

Section E: Performance

Rate the following based on your view. Use the following scale to indicate your level of agreement and disagreement with each statement

1= strongly disagree, 2= disagree, 3= neutral, 4= agree, 5= strongly disagree

MARKET PERFORMANCE							
1. We have entered new markets more quickly than our competitors	**1**	**2**	**3**	**4**	**5**	**6**	**7**
2. We have introduced new products or services into the market faster than our competitors	**1**	**2**	**3**	**4**	**5**	**6**	**7**
3. Our success rate of new products or services has been higher than our competitor	**1**	**2**	**3**	**4**	**5**	**6**	**7**
4. Our market share has exceeded that of our competitors	**1**	**2**	**3**	**4**	**5**	**6**	**7**
5. Our productivity has exceeded that of our competitors	**1**	**2**	**3**	**4**	**5**	**6**	**7**
6. Our profit rate has exceeded that of our competitors	**1**	**2**	**3**	**4**	**5**	**6**	**7**
7. Our return on investment (ROI) has exceeded that of our competitors	**1**	**2**	**3**	**4**	**5**	**6**	**7**
8. Our sales revenue has exceeded that of our competitors	**1**	**2**	**3**	**4**	**5**	**6**	**7**
9. We have a greater customer retention	**1**	**2**	**3**	**4**	**5**	**6**	**7**

7.2 Appendix B: Ethical Clearance

UNIVERSITY *of the* WESTERN CAPE

60 YEARS *of hope, action & knowledge*

26 January 2021

Ms D Welbotha Hollong
Information System
Faculty of Economic and Management Sciences

Ethics Reference Number:	HS20/9/58
Project Title:	The impact of big data analytics capabilities on the performance of selected retailers in the Western Cape.
Approval Period:	21 January 2021 – 21 January 2024

I hereby certify that the Humanities and Social Science Research Ethics Committee of the mentioned research project.

Any amendments, extension or other modifications to the protocol must be submitted to the Ethics Committee for approval.

Please remember to submit a progress report by 30 November each year for the duration of the project.

The permission to conduct the study must be submitted to HSSREC for record keeping purposes.

The Committee must be informed of any serious adverse events and/or termination of the study.

Ms Patricia Josias
Research Ethics Committee Officer
University of the Western Cape