THE IMPACT OF BIG DATA ANALYTICS ON SALES PERFORMANCE: THE MEDIATING ROLE OF CUSTOMER PERFORMANCE

by

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Declaration

I hereby declare that this thesis is my work, unassisted work, except as acknowledged in the document.

The thesis is being submitted for the degree of Master of Management at Wits Business School at the University of the Witwatersrand, Johannesburg.

This work has never been submitted before for any degree or examination in this institution or any other university.

Signature ……………………………….

TT Mngomezulu

June 2023

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Abstract

Big Data Analytics (BDA) systems are used for gathering, storing, processing, and generating insights from large data sets. The volume, variety and veracity of the data cannot be collected and processed using traditional database engines, therefore advanced technology is used to capture this data. The outcomes from this data are used to assist stakeholders with making decisions and drive interactions on digital platforms. Organisations are making significant investment in implementing BDA, but the understanding of the impact that these systems have on sales performance (financial outcomes) and customer performance (non-financial outcomes) is limited. It is important to understand the direct and indirect impact BDA has on organisational outcomes because in cases where the impact is indirect, organisations ought to understand what capabilities are needed to mediate the desired outcomes. BDA has the potential to be used to enhance customer performance measures, such as customer satisfaction, customer retention and customer relationship management, through its use. This allows organisations to improve how their customers perceive them, the level of service they offer, customised products and experiences and keep customers making repeat purchases. This capability may translate into happier customers and increased sales performance.

To address this problem, this study investigated the impact of BDA on sales performance. Furthermore, this study investigated if customer performance measures can mediate the improvement of sales performance through the adoption and use of BDA. The data was collected using an online survey. 200 respondents were invited to participate. 126 responded to the survey and 100 responses were valid, leaving a final response rate of 50%. Descriptive statistics was used to show distribution of the data. Exploratory Factor Analysis, as well as Confirmatory Factor Analysis, were carried out to determine uni-dimensitonality. Structural Equation Modelling was then used to measure and analyse the relationships between the model concepts.

This research found that the adoption of BDA does not have a direct impact on sales performance, however the adoption of BDA improves sales performance through mediating factors, i.e., customer satisfaction, customer retention, customer relationship management and market performance. This study gives a balanced view of both financial (sales) and non-financial (customer) outcomes and contributes to the body of knowledge around big data.

The report made several contributions. A theoretical contribution was made by extending the conceptual model of Shahbaz et al. (2020) to include customer performance measures as mediating factors. The customer performance factors include customer satisfaction, customer retention, customer relationship management and market performance. A contextual contribution was also made by conducting the study in the South African business context. Only studies about factors affecting adoption of big data analytics have been done in the South African context and not on the benefits therefore, therefore this is a new contribution in this context. In practical terms, sales and marketing professionals can get a better understanding of the customer performance measures that can be leveraged to increase sales. This can assist practitioners to achieve their key performance indicators in organisations where big data analytics have been adopted.

Keywords

Big Data Analytics, Customer Satisfaction, Customer Retention, Customer Relationship Management, Market Performance, Sales Performance

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CHAPTER 1: INTRODUCTION

1.1 Statement of purpose

The purpose of the study is to investigate the direct impact of Big Data Analytics (BDA) on sales performance and indirectly, through the mediating factors of a balanced view of customer performance (i.e., customer retention, customer satisfaction, customer relationship management (CRM), and market performance). BDA has been extensively studied in the context of sales performance without looking at the influence of customer performance (i.e., customer performance, learning and development) (Hallikainen et al., 2020; Wamba et al., 2017; Li et al., 2015). Considering the current economic conditions where companies are battling to remain profitable due to decrease in sales performance, it is important for organisations to understand whether BDA may have an influence on the sales performance of the organisation. In addition, the role that customer performance has on sales performance needs to be fully understood (Chi & Gursoy, 2009). The study adapted the framework of Shahbaz et al. (2020) which evaluated the impact of BDA on sales performance through customer relationship management as a mediating factor. However, this study did not consider customer retention, customer satisfaction, and market performance as mediating factors. Further, Raguseo (2018) also looked at the impact of BDA on sales performance, however the focus was on customer satisfaction. There is a need to look at the effects of customer performance on sales performance for the organisations to continue to justify the investment made in BDA.

Importantly, customer satisfaction measures how goods and services offered meet or surpass the expectations of customers (Anderson & Sullivan, 1993). This is important in ensuring that customers are happy with products supplied. However, when the performance of the product is below expectations, it may lead to customer dissatisfaction, while performance that exceeds customer's expectations may lead to a satisfied customer (Kotler & Keller, 2003; Mudau, 2021). Customer satisfaction may secure customer loyalty which might result in improvement of sales performance (Storbacka et al., 1994). It is important for an organisation to ensure customer retention in maintaining sales performance (Chumpitaz & Paparoidamis, 2004).

Customer retention refers to the organisation's ability to retain customers over some period (Gerpott et al., 2001). BDA may be used to integrate customer's information and enrich their context to provide a personalised view of the customer's needs and enable better services for each market segment. This may improve customer retention which results in long-term customers who spend more money over time and possibly improve organisation performance (Shutte et al., 2017). BDA may allow organisations to understand customer's needs and choices through customer information available. This assists organisations to allocate the needed resources to the profitable segments, this shifts managerial focus from mere loyalty to customer profitability and profitable loyalty (Kumar, 2016).

The meaning of Customer Relationship Performance (CRM) can be understood in different ways and it is still evolving. CRM can be understood as a business philosophy, a business strategy, a business process or as a technological tool (Rababah et al., 2011). For the purpose of this study, the technological reference is used as it relates to BDA as a technology. CRM is an enabling technology for organisations to foster better relationships with their customers (Hsieh, 2009). CRM may enable improved performance as desired by organisations that adopt it (Soltani et al., 2018; Rodriguez et al., 2018; Rodriguez & Boyer, 2020) while other studies suggest that the impact of CRM on organisation performance may not be conclusive (Navaro, et al., 2020) reflecting a difference in findings. In addition to the difference in findings, none of the mentioned studies considered the focus on sales performance as an outcome nor considered CRM as a mediating factor. In the research where CRM was considered as a mediating factor, the performance of the sales personnel was considered as an outcome and not sales performance of the organisation.

Market performance is about the organisation's ability to penetrate new markets faster than its competitors, introduce new products and services more frequently than its competitors, and have a higher market share compared to its competitors (Mithas et al., 2011; Tippins & Sohi, 2003). Market performance, that is, an organisation's capability to anticipate and advance against its competitors could lead to improved financial performance if the above-mentioned (quick market penetration, introduce new products quickly and high market share) items are executed. Application of BDA could enhance organisational agility and allow firms to recognise market opportunities and adjust product offerings (Corte-Real et al., 2017; Davenport, 2014; Mudau, 2021). There is a need to investigate the impact that the adoption of BDA has on sales performance to justify the investments that organisations are making.

Sales performance in the context of this study is observed based on the perception of the respondents and does not reflect the actual sales performance. Sales performance is about the effective and efficient execution of sales processes by examining winning opportunities and improving closing rates (Rodriguez & Honeycutt, 2011). Sales performance can be measured as sales volume, market share, conversion rates, and number of new customers (Walker et al., 1979). In this study, sales volumes and turnover is used to express sales performance. The conceptual framework of this study is indicated below as Figure 1.

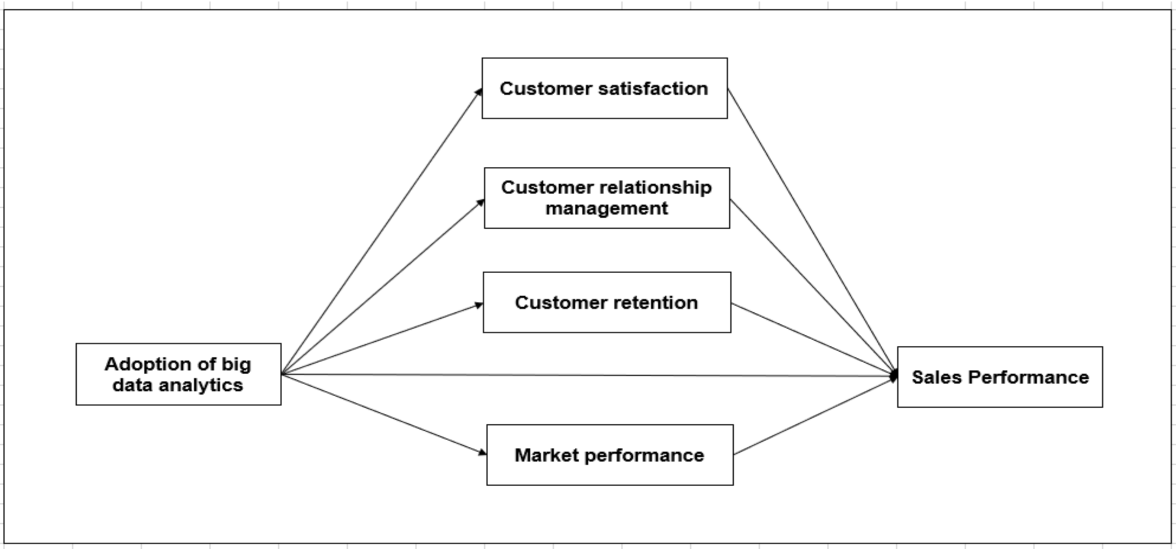


Figure 1: Study conceptual model

Source: Adapted from Shahbaz et al. (2020)

1.2 Background of Big Data

Big Data is defined as data sets whose size and/or type is beyond the ability of "traditional relational databases" to capture, manage and process the data with low latency (Enterprise Management Associates, 2017). A "traditional relational database" refers to a database that stores data in a structured format using rows and columns. BDA on the other hand is the use of advanced analytics techniques against very large and diverse datasets from different sources, and in different sizes from terabytes to zettabytes (Chen et al., 2012). In addition, BDA can also be defined as the processing of a large amount of data using mathematical and statistical techniques that allow organisations to discover patterns, identify anomalies, and generate valuable knowledge (Marchena & De La Vega, 2021). In this study, BDA is defined as the use of advanced statistical computations to discover patterns in large datasets.

The term “Big Data” has been used since the early 1990s. John Mashey has been given credit for making the term popular (Enterprise Big Data Framework, 2019). The evolution of big data can be classified into three phases where each phase has contributed to the contemporary meaning of Big Data as we know it: The first phase is when Big Data was born from the domain of database management, particularly relational databases (Davenport, 2003). Then phase two dates from the early 2000s, when the use of the internet and websites started offering unique opportunities for data collection and analysis (Davenport, 2003). Phase three started around the 2010s when widespread use of smart phones which offered the possibility to extract and analyse behavioural data (i.e., clicks and search queries) and location data (i.e., GPS data) (Bollier, 2010). Big Data technologies were introduced to overcome the costs associated with storing large amounts of data and to make quicker decision by analysing data at speed (Hussain, 2019). Just like any technology, BDA has its own challenges.

Some of the challenges are that Big Data does not integrate automatically into existing Information Technology (IT) resources, therefore additional spending is required to integrate it into a business’ IT environment (Bantleman, 2012). When organisations invest in Big Data tools and software, they must also invest in overhauling their IT environment to integrate big data solutions. Poor data management results in poor data quality which will lead to inaccurate results and potential loss of revenue due to poor decision making (Sarsfield, 2011). Another challenge that has hampered the adoption and deployment of big data is privacy of organisational and customer data because when an individual’s personally identifiable data is augmented with additional data, it can result in divulging very confidential information about such a person (Katal et al., 2013) and if this data is hacked, it can have financial and reputational consequences (Piatetsky., 2014; Fertik, 2012; Zaire, 2021). In order for organisations to continue to justify the investment made on BDA, there is a need to understand the benefits that BDA offers.

Given the vast amount of data being collected from various sources, there is a need for BDA to extract insights from big data and use it to drive actionable outcomes that create financial and non-financial benefits (Chen et al., 2012).The purported benefits of investing in big data analytics includes improvement in product quality, provides a competitive edge against other competitors, improved organisation efficiency, reduced operational costs, improved customer retention, improved customer satisfaction, improved market performance, reduced time taken to resolve customer queries and reduced time to market (Vaidyanathan, 2015; Gregor et al., 2006). Ultimately, the use of BDA should assist an organisation to stay ahead of its competitors (Lin et al., 2009).

BDA has been regarded as disruptive technology, however there are gaps in the implementation of BDA due to a lack of understanding of factors that contribute to success and the decrease in the level of risks and associated costs (Wamba et al., 2017; Shahbaz et al., 2019). In the organisational context, a few studies have adopted an holistic view to validate the adoption of BDA. Under the technology, organisation, and environment (TOE) theoretical framework, which has been widely used to measure BDA adoption (Jong-Hyun et al., 2015; La Valle et al., 2013), previous studies came to varied conclusions (La Valle et al., 2013; Jong-Hyun et al., 2015). In a South African context, studying the adoption of BDA is more relevant as organisations are using 22.7% of analytics. There is a need to fully understand the impact of BDA on sales performance (La Valle et al., 2013).

The growing amount of data being produced by organisations has led on a quest to explore how they can use their data to stay ahead of competitors (Constatiou & Kallinikos, 2015). The adoption of BDA is premised on the proposition that generating insights from large diverse data sets can help organisations transform their business and gain an edge over their competitors (Chen et al., 2012). Although the introduction of BDA has started to have an impact on organisational outcomes (Devenport, 2013), Wamba et al. (2017) argue that the benefits of BDA are not always realised. The benefits of BDA may be dependent on how the organisation improves customer performance (i.e., customer retention, customer satisfaction, CRM, and improvement in market performance). Boone et al. (2021) argued that BDA may lead to improved customer satisfaction, increased customer retention and better positioning in the market.

Research on the impact of BDA on sales performance mediated by customer performance is still surfacing (Chatterjee, 2022; Raguseo & Vitari, 2018). Sales performance is about the effective and efficient execution of sales processes by examining winning opportunities and improving closing rates (Rodriguez & Honeycutt, 2011). Some research (Manyika et al., 2011; Akter et al., 2016; Nam et al., 2019) on adoption of BDA has been done in the context of financial performance without looking at the influence of non-financial performance (i.e., customer retention, customer satisfaction, customer relations management and market performance) (Hallikainen et al., 2020). Mithans et al. (2011) stated that financial performance has various elements, such as profitability, sales performance, and costs. Considering the current economic conditions where companies are battling to be profitable due to stagnant sales performance, it is important for organisations to understand if BDA may have an influence on sales performance of the organisations. Examining the impact of a balanced view customer performance (i.e., customer retention, customer satisfaction, query management and improvement in market performance) will assist an organisation in justifying the decision made to invest in BDA analytics (Chatterjee et al., 2022; Mariani et al., 2018; Bijmolt, 2010). Importantly, the balanced customer performance measurement approach provides organisations an opportunity to better understand the ways in which BDA analytics can influence sales performance (Gorla et al., 2010).

Furthermore, research conducted on BDA in various sectors has rarely focused on customer performance (i.e., customer retention, customer satisfaction, CRM, and market performance) as a mediating factor for increasing sales performance (Akter et al., 2016; Wamba et al., 2016; Mikalef, 2019; Mudau, 2021). It is evident that the current research only considered one element of customer performance without looking at the balanced view of customer performance. Despite the growing number of studies on BDA and sales performance, little attention has been paid on developing countries such as South Africa. Therefore, there is a need to further understand the mediating role that customer performance can have on sales performance within the BDA environment in a South African context. Moreover, the lack of a general understanding on how BDA can optimize operations and strategy in developing countries may generate resistance with regards to investing in BDA application (Joubert et al., 2021).

The research problem and objectives of the study are further outlined in the next section.

1.3 Research problem

The study investigates two main problems:

The *first* problem is examining the direct impact of BDA on sales performance. There is growing interest in the value that organisations can derive from the adoption of BDA due to literature that suggests that BDA enables firms to sense emerging opportunities threats, generate critical insight to assist decision making and adapt their operations to respond to competition (Chen et al., 2012). The development of BDA capabilities and the impact such capabilities may have on firm performance has been considered in prior studies (Hallikainen, 2020; Raguseo, 2018), however firm performance in this case is a broad measure of organisational outcomes and not a direct measure of sales performance. Other studies have only considered the impact of BDA on firm performance through customer relationship management as a mediating factor (Garmaki, Boughzala & Fosso Wamba, 2016; Shahbaz et al., 2020; Jaber & Abbad, 2021; Olabode et al., 2022). This leaves space to understand the direct effect that adoption and use of BDA may have on sales performance.

The *second* problem is examining the impact of BDA on sales growth through customer performance (i.e., customer satisfaction, customer retention, CRM, and market performance) as mediating effects. Customer performance measures organisational growth using customers as primary driver of growth (Kasim & Minai, 2009). While sales performance is an effective and efficient ways of achieving targets in the sales process by examining opportunities and improving closing rates. BDA may aid salespersons in obtaining better closing rates and increasing revenue (Shoemaker, 2001). This allows salespeople to increase their knowledge, targeting and presentation skills by taking advantage of the capabilities of the BDA. Qualtrics (2021) stated that 80% of customers switched to a competitor due to a poor customer experience. Hence, there is a need to understand the impact that BDA has on sales performance through customer performance as mediating effects, as customer service plays a critical role in retain customers.

The adoption of BDA has been studied from the customer relationship management and sales growth context (Hallikainen et al., 2020; Shahbaz et al., 2020; Chatterjee et al., 2022), however customer satisfaction, market performance and customer retention as mediating factors on sales performance were not considered. Examining this relationship will aid management in justifying the decisions that they have made in investing in BDA. Understanding the impact that BDA has on sales performance through customer satisfaction, customer retention, and market performance is important. This may assist in understanding the role that customer performance (customer satisfaction, customer retention, and market performance) has on sales performance. This study aims to examine whether customer retention, customer satisfaction, and market performance are mechanism through which BDA can impact sales performance.

1.4 Research objectives

The objective of the study is to investigate the impact of BDA on sales performance through the mediating effects of a balanced view customer performance (i.e., customer retention, customer satisfaction, market performance and customer relationship management).

Research objective 1 (RO1)

To examine the direct impact of BDA on sales performance.

Research objective 2 (RO2)

To examine the impact of BDA on sales performance through non-financial performance measures (i.e., customer satisfaction, customer retention, CRM, and market performance) as mediating effects.

1.5 Rationale

The research aims to contribute in line with the purpose and objectives of the study in four ways, namely theoretical, contextual, methodological and practical.

The theoretical contribution is made by assessing the impact of BDA on sales performance through the mediating role of customer and market performance by drawing on and extending the model as developed by Shahbaz et al. (2020). The role of customer and market performance in facilitating the impact of BDA on sales performance has not been sufficiently explored. The model proposed for this study tests the utility of the underlying theories in explaining the mediating role of customer and market performance between the adoption of BDA and its impact on sales performance. This study provides a balanced view of how adoption of BDA affects both customer performance (non-financial performance) and sales performance (financial performance). The impact of BDA on organisation performance has been mostly studied from a financial perspective while the customer performance perspective is not well understood.

Second, the study makes a contextual contribution by examining impact of BDA at an organisation level in the South African business environment. The study enhances understanding of perceived outcomes as a result of BDA investments made within organisations. There is limited research on the adoption of BDA and sales performance from the South African context (Mudau, 2021).

Third, the study contributed methodologically by operationalising the measures of customer satisfaction, customer retention, CRM, market performance and sales performance. The results of the study enhance understanding of the impact of customer performance measures on sales performance as a result of BDA investment.

Fourth, the outcomes of this study assist organisations to make informed decisions on investing of BDA technology.

1.6 Limitations of the study

- The researcher has limited time to send surveys, collect data, conduct analysis, and compile the final study report.
- There was uncertainty of whether all selected respondents would accept the invitation to participate in the study.
- The data collected is based on the perceptions of the respondents and therefore may be subject to bias and inaccuracies.

1.7 Definition of terms

- Big data analytics – is about the use of advanced analytics techniques against large, diverse data sets that include structured, semi-structured and unstructured data from different sources and in different sizes from terabytes to zettabytes (Enterprise Management Associates, 2017).
- Customer performance measurement – customer performance is a business approach to measuring performance in terms of customer retention, customer satisfaction, service response time, etc. Using this approach, all processes in

the business are customized to meet and satisfy customer requirements (NIBusinessInfo, 2022).

- Sales performance – Sales performance is about the effective and efficient execution of sales processes by examining winning opportunities and improving closing rates (Rodriguez & Honeycutt, 2011).
- Customer relationship management – CRM is the method used by organisations to manage relationships with their customers to maintain long-term prosperous engagements (Navimipour & Soltani, 2016).
- Customer satisfaction – Customer satisfaction is a result of how goods and services' performance meet or surpass the expectations of customers (Anderson & Sullivan, 1993).
- Customer retention – Customer retention is a customer's commitment to an organisation and its offering for an extended period and engaging in repeat purchases (Jeng & Bailey, 2012).
- Market performance – Market performance refers to the ability of an organisation to achieve outcomes in market share, market share growth, sales volume and product development relative to its goals (Sarkar et al., 2001).

1.8 Assumptions

- The organisations where the study was conducted have adopted and are using BDA.
- There are no limits to the answers the respondents can give due to privileged information.
- The respondents answered truthfully and to the best of their knowledge.
- A reasonable response rate that allowed the study to proceed was achieved.

1.9 Chapter outline

The following is an outline of the structure of the report:

Chapter 1: Introduction

This chapter has provided the purpose of the study, the background of the study and the research problem. It also provided a set of research questions, the limitations and the key terms used in the study.

Chapter 2: literature review

This chapter provides a theoretical background of the research. Findings from prior research from international and local studies covering the impact of big data analytics on sales performance are discussed in this section. Topics covered in the literature include factors affecting the adoption of big data, limitations of academic studies into the impact of big data on organisation performance and customer relationship management as a mediator for sales growth.

Chapter 3: Research methodology

The details relating to the research design and the methodology used in this study are presented in chapter 3. This chapter also articulates the motivations for adopting a descriptive research method using a questionnaire sampling leader in analytics environments of South African corporates.

Chapter 4: Presentation of the results

Presents the quantitative data collected from the surveys

Chapter 5: Discussion of results

This section provides a detailed account of the key findings of the research results in terms of the literature on which the research is grounded

Chapter 6: Recommendations and conclusions

This section provides pertinent recommendations for business, possible future research on BDA and customer performance.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

In the previous chapter (chapter 1), the objectives of the study were formulated. This chapter presents a review of the literature on the adoption of BDA in an organisation and its impact on an organisation's sales growth. This chapter also reviews the literature on the mediating role of customer performance between big data analytics and sales growth. This chapter is divided into five main sections.

The first section provides an overview of big data and its characteristics. The second section focuses on an overview of big data analytics, as well as the 5Vs (volume, variety, velocity, veracity and value) that have been known to characterise big data as we know it in the modern world. The second section highlights the advantages as well as the challenges that can be brought about by big data. The next section then discusses how big data is adopted into the organisation; this includes the requirements for adopting and integrating it into existing environment. The following section demonstrates the conceptual framework formation and how it was adopted. Lastly, the section is concluded by outlining the gaps in the literature and the areas that need attention.

2.2 Background of Big Data

"Big Data" has become a ubiquitous term. Given its shared origin in academia, business, and the media there is no unified meaning (Ward & Barker, 2013), therefore, relying on one definition of BDA is an impractical exercise (Lugmayr et al., 2017). BDA may mean different things to different people depending on the context in which it is being used. BDA can be defied as the use of advanced analytic techniques against very large, diverse big data sets that include structured, semi-structured, and unstructured data from different sources (IBM, 2022). Another definition by NewVantage Partners LLC (2017) states that BDA is the utilisation of "Big Data" and related analytics methods to deliver value by reducing expenses and creating new avenues for innovation. "Big Data" refers to the high-volume, high-velocity and high-variety data which requires advanced and innovative processing techniques to enable enhanced insight and decision making (Chen et al., 2012; Warren et al., 2015; Jiang & Chai, 2016).

The term ‘big data’ has been used since the early 1990s. John Mashey has been given credit for making the term popular (Enterprise Big Data Framework, 2019). The evolution of big data can be classified into three phases where each phase has contributed into the contemporary meaning of Big Data as we know it.

2.2.1 History of Big Data

The first phase is when Big Data is born from the domain of database management, particularly relational databases. Database warehousing and management are the basic components of big data in the first phase (Bollier, 2010). Phase two was from the early 2000s, when the websites started offering opportunities for data collection and analysis. Internet companies such as eBay, Yahoo and Amazon expanded their online shop offerings to include personalisation through analysing customer data. The Hypertext Transfer Protocol (HTTP) type of content on web pages increased semi-structured and unstructured data which meant organisations needed to find new storage solutions for this type of data (Doan et al., 2011). Years later, the advent of social media increased the requirement for technologies, tools and analytics techniques that could extract valuable information from this unstructured data. Then phase three arose in the 2010s with large-scale use of smart phones with multiple internet-based applications that provided the possibility to extract and analyse behavioural data (clicks and search queries) and location data (O’Reilly, 2005). The proliferation of Internet-of-Things (IoT), which is sensor-based internet enabled devices, is allowing millions of homes, industrial and personal devices to generate zettabytes of data every day. Analysing the data generated from these devices gives birth to new terms ‘Big Data Analysis’ (Bollier, 2010).

2.2.2 Characteristics of Big Data

The 3Vs (volume, velocity, and variety) are characteristics which can be observed in big data that sets it apart from traditional data sets as they were defined by Doug Laney (2001). Firstly, it is the volume of the data. This refers to the large quantity of data that is generated, extracted, gathered, and processed in sizes of petabytes and above (Younas, 2019). This aspect of volume is the one that comes to mind when most people think of big data. Velocity is the second attribute, this refers to the speed at which the data is generated, processed, and transported across different systems and devices (Ishwarappa & Anuradha, 2015).

The third attribute is variety. This characteristic refers to the different types of data that can be used to achieve the desired results. The types and formats of big data include structured, semi-structured and unstructured data (Younas, 2019). Structured data refers to data that is organised into rows and columns and can be stored in a spreadsheet or in a relational database. This data is usually easy to manipulate and analyse with each column containing a specific data type. Semi-structured data is data that is not formatted in conventional ways of rows and columns, it does not have a fixed schema. It is not completely unstructured as it contains elements such as tags and metadata which makes it possible to analyse. Some examples of semi-structured data are Hypertext Markup Language (HTML) code, graphs, tables, emails, and Extensible Markup Language (XML) documents. Unstructured data refers to unfiltered information that does not follow any fixed organisation principles. Common examples include web logs, images, videos, and audio files. As much as 80% of data is unstructured and contains more noise than value, strong analytical skills and tools are required to extract value from unstructured data (Teradata, 2022).

Veracity is the fourth attribute. This refers to the quality, correctness, trust, security, and reliability. This means data should be used for the reasons which were stated upon collection and should be collected by a trusted system (Younas, 2019). The last attribute is value. There are different types of value that can be drawn from big data, including, but not limited to monetary value, social value, research/educational, etc. (Younas, 2019). It is a costly project to implement and if the organisation does not realise a return on investment, then it becomes a loss-making exercise (Ishwarappa & Anuradha, 2015). The attributes of Big Data have been articulated, the following sections outlines the beginnings of Big Data and how it has evolved over time.

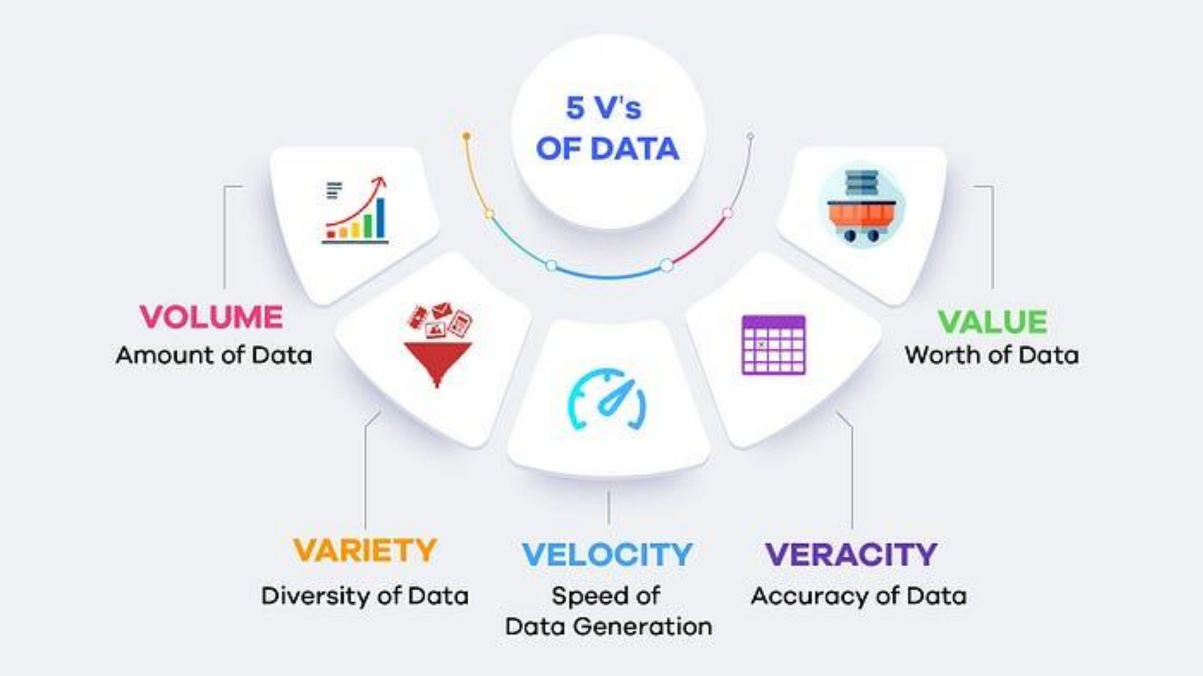


Figure 2: The 5Vs of Big Data

Source: Medium, 2022

2.2.3 Benefits and challenges of Big Data

It is also important to understand the benefits and challenges associated with Big Data. Potential benefits of Big Data can range from information technology (IT) infrastructure benefits, operational benefits, organisational benefits, managerial and strategic benefits (Shang & Shadon, 2002); due to limitations of the length to which they can be covered in this study, only a few are covered in detail. By collecting and observing customer data across multiple interaction points, organisations can observe customer behaviour and present personalised offers to attract or retain customers (Mills, 2019)., but these business environments require risk management processes. BDA has played a role in developing risk management solutions which can enable organisations to thrive in the risk industries (e.g., insurance). Big data can be instrumental in improving the effectiveness of risk management models, developing smarter strategies, and identifying potential risks (Mills, 2019). Big data continues to play a role in helping companies improve existing products while developing new ones (Mills, 2019). Organisations are enhancing their product offerings by building information platforms on top of their products and offering it as platform-as-a-service (Davenport, 2006). BDA is also being used in operations to identify customer pain points and use those insights with the intention to improve customer experience (Mudau, 2021). Some challenges in relation to the use of BDA are also discussed in various literature.

The velocity and volume of data stored and processed may overwhelm organisations (Spiegel, 2016) and this can make it difficult for organisations to separate the valuable data from the noise, therefore, it may be a challenge to identify the right data and it's uses. Customer and user data involving call records, medical data, insurance, security etc. are stored in databanks which are vulnerable to hacking, therefore, this may present a security risk (Phillip-Wren *et al*., 2015). In 2020, for the second time in a row the number of job posts for analysis skills including machine learning, data engineering, data science, and visualisation specialists surpassed traditional skills such as engineering, marketing, administration, and public relations. With organisations ramping up artificial intelligence talent to build their decision-making capabilities, the demand for data professionals will likely outstrip the available supply for some time (Jarvis, 2020) presenting a skills shortage challenge. The technology landscape in the world is evolving very rapidly, this means organisations must create adaptive architecture that can accommodate changes efficiently (Spiegel, 2016). The above discussion is an account of some of the challenges that organisations might face when adopting BDA.

2.2.4 Adoption of Big Data

The Diffusion of Innovation (DOI) Theory is useful in providing an account of how technological innovations, such as BDA, transition from invention to widespread use or not (Micheni, 2015). An innovation is an idea, practice, or object that is perceived as new by an individual or another unit of adoption, and diffusion is the process by which an innovation is communicated through certain channels over time among the members of a social system (Rogers, 1995). He further articulates that the innovation-diffusion process is a process to decrease uncertainty about an innovation. Adoption is a decision that individual makes each time they consider taking up an innovation (Rangaswamy & Gupta, 1999; Rogers, 2003). The diffusion of innovation theory concepts can provide an effective mechanism for leaders of organisations to maximise adoption of BDA innovations (Micheni, 2015). The diffusion of innovation is characterised by four main elements, namely, innovation, communication channels, time, and a social system (Rogers, 2003). This study does not reference DOI as understanding the diffusion of BDA is not the aim of the study, it was only referenced to point out how technologies may move from adoption to widespread use.

2.3 Adoption of BDA, customer performance and sales performance

This sub-section reviews literature on the adoption of BDA, as shown in the above figure 2.

2.3.1 Adoption of BDA

BDA is adopted by firms to be used for the creation of innovation avenues and to foster disruption (NewVantage Partners, 2017), furthermore it enables organisations to strengthen their business operations and customer relationship management (Gunasekaran *et al*., 2017; Nam, Lee & Lee, 2019). Big Data has the potential to create incremental value in a variety of aspects (OECD, 2013), further, it has been hailed as the next big thing in innovation (Gobble, 2013; Wamba *et al*., 2017). Organisations adopt BDA because they wish to leverage the vast amounts of data available from many sources, such as social media, radio frequency identification (RFID) tags, mobile phones and other customer interaction points (Davenport, 2014). BDA is a driver of both financial and non-financial outcomes across various functions and industries (McAfee *et al*., 2012) and organisations are investing heavily to create value and drive their digital business strategies (Bharadwaj *et al*., 2013). There has been substantive work done to understand factors influencing adoption and research can now focus on evaluating the benefits of such initiatives (Walker & Brown, 2019). Prior research has found a direct link between general information technology investments and organisation performance (Huang *et al*., 2016; Melville *et al*., 2004) and recently, links between BDA investments and organisation performance have been found (Akter *et al*., 2016; Nam *et al*., 2019 Wamba *et al*., 2017; Wang & Hajili, 2017). Many organisations do not understand how BDA is related to their business activities and therefore may not realise the benefits of adopting the system (Lycett, 2013). It is therefore important to advance research that will help organisations understand how to best capture value from their BDA investments.

2.3.2 Customer satisfaction

Customer satisfaction is a result of how goods and services' performance meet or surpass the expectations of customers (Anderson & Sullivan, 1993). When the performance of the product is below expectations, it leads to a dissatisfied customer while performance that exceeds expectations leads to a satisfied customer (Kotler & Keller, 2003). Another definition positions that customer satisfaction is the judgement that customers pass towards a product or service after they have used it (Jamal & Aser, 2003). Customer satisfaction is the key to securing customer loyalty and could be an important driver of superior long-term financial performance (Jones, 1996; Storbacka *et al*., 1994; Chi & Gursoy, 2009; Mendonca & Zhou, 2019). Customers are a key stakeholder group and could be the most important economic asset of an organisation, therefore measuring customer satisfaction provides an indication of how successful an organisation is at offering products/services that exceed the expectations of customers (John, 2003).

Improved understanding of customer needs can lead to increased customer satisfaction which can be related to improved financial performance. Customer satisfaction and repeat purchases (loyalty) may be closely related (Mittal & Kamakura, 2018) and since loyal customers are thought to be cheaper to service than new, this reduces operational costs and results in higher profits (Liu, 2014). Organisations that have long-term relationships with customers can charge a premium for their services (Reichheld, 2009), on condition of high levels of customer satisfaction, the customers then place high value on the relationship willing to pay the high premium (Zeithaml *et al*., 1996). Another way that customer satisfaction possibly impacts revenue is when satisfied customers recommend the products and services of the organisation to others (Reichheld & Sasser, 2009), thereby unlocking new sources of revenue for organisations. Literature has explored the possible relationships between customer satisfaction and financial performance and has also articulated the mechanisms through which the relationship can take place, however these relationships have not been explored in the context of BDA and sales performance. Organisations can attempt using BDA to impact customer satisfaction (Wamba, Ngai, *et al.*, 2017).

2.3.3 Customer retention

Customer retention refers to the company’s ability to retain customers over some period (Gerpott et al., 2001). Another definition states that customer retention can be characterised as a continuous flow of customer profitability (Lenskold Group, 2003). Customer retention is the customer’s commitment to an organisation and its offering for an extended period and engaging in repeat purchases (Jeng & Bailey, 2012). To achieve customer retention, an organisation must consistently provide a superior customer experience (Kotler & Keller, 2016).

Literature emphasises the benefits of customer retention over customer acquisition because customer acquisition is six time more expensive than retaining existing customers (Jahromi *et al*., 2014; Rosenburg & Czepiel, 1984). Another benefit of loyal customers is that they are the least price sensitive to increases in price, which may result in higher profits since costs do not increase as price is increased (Mela *et al*., 1997; Srinivasan *et al*., 2002; Umashankar, 2016); this phenomenon materialises on condition that the customers perceive the service received as superior.

BDA may be used to integrate the customer’s information and enrich their context to provide a personalised view of the customer’s needs, enabling better services. This may improve customer retention and possibly improve organisation financial performance. Through this mechanism, customer retention may have an impact on profitability (Molise-Khosa, 2014; Almohaimmed, 2019; Orantes-Jimenez, 2017; Shutte *et al*., 2017). The literature above focuses on the impact that customer retention has on the financial aspects of the organisation, while the literature discussed in the next section considers customer retention and its relationship with non-financial measures. Hence, consideration of non-financial metrics is also important as it provides a balanced view of the organisation (Ryals & Knox, 2005).

Customer retention may have an impact on customer satisfaction (Gengeswari, 2013). While the impact of customer satisfaction on customer retention does not appear to be evident (Almohaimmed, 2019), it seems to appear in other findings (Yee et al., 2010; Barusman *et al*., 2019). Customer retention is one of the central topics related to CRM (Viljoen et al., 2005; Ang & Buttle, 2006; Godson, 2009; Peng *et al*., 2013). CRM is suggested to have a positive relationship with customer retention directly (Barusman *et al*., 2019) and can be viewed as an opportunity to enable improved customer retention (Kasin & Minai, 2009). Even though there are several studies related to customer performance and analytics, there are only a limited number of studies that combine these two themes (Saynatjoki, 2009).

2.3.4 Customer Relationship Management (CRM)

CRM is the method used by organisations to manage relationships with their customers to maintain long-term prosperous engagements (Navimipour & Soltani, 2016). Stojkovic and Dubricic (2012) define the CRM philosophy as an iterative process of four activities, which are, discovery of knowledge, market planning, customer interaction and customer data analysis while Elkordy (2014) also adds that this iterative process involves the integration of sub-processes to enhance the organisation's capability to effectively manage its profitable customers. CRM as a technological tool is an enabler for organisations to foster better relationships with their customers (Hsieh, 2009). CRM technology, as a tool, links front office functions (e.g., marketing, sales, and customer service) and back-office functions (e.g., financial, operations, logistics, and human resources) with the organisation's customer touchpoints to form a single view of the customer (Fickel, 1999). Customer touchpoints may include websites, call centre, stores, email, and apps. If CRM technology is used effectively, it can improve customer lifetime value by retaining customers, satisfying them and keeping them loyal (Xu & Walton, 2005).

There seems to be a positive relationship between CRM and customer satisfaction (Richards & Jones, 2009; Adalikwu, 2012; Stojkovic & Dubricic, 2012; Elkordy, 2014; Khedkar, 2015; Singh & Singh, 2016). The relationship between CRM and profitability has also been studied (Pan & Lee, 2003; Jimenez *et al*., 2017) and the findings suggest that there may be a positive relationship between the two variables. CRM has the capability to identify and retain profitable customers and improve the profitability of unprofitable customers (Wang & Feng, 2012). Further studies have investigated the deployment of CRM with the intention of delivering profits by improving customer satisfaction and customer retention (Lin & Su, 2003; Daghfous & Barkhi, 2009). There is extant literature covering CRM and its ability to influence profitability directly or through some mediating variables but limited research on the CRM impact in the context of BDA has been explored.

2.3.5 Market performance

Market performance has to do with an organisation's positioning against its competitors and its ability to anticipate and advance against other organisations who trade similar goods and services (Mithas, Ramasubbu, & Sambamurthy 2011; Tippins & Sohi, 2003). Marketing performance measurement is a formal tool of setting and measuring metrics related to the firm's market performance goals (Rust *et al*., 2004; Stewart 2009), therefore market performance comprises a set of goals informed by an organisation's marketing efforts. Some of the goals may include expanding into new markets (Homburg, Grozdanovic, & Klarmann, 2007), increasing market share and delivering superior products and services.

2.3.6 Sales performance

Sales performance is "a behaviour that has been evaluated in terms of its contribution to the goals of an organisation"; this definition uses subjective self-or-manager reported behaviour-based measures while other perspectives view sales performance as an objective outcome, such as sales volumes, conversion rate, market share, etc., (Walker et al., 1979). Other schools of thought position that sales performance can be measured as both objective outcome and subjective (Anderson & Oliver, 1987). Criteria used in this study are outcome based i.e., sales volume.

Sales processes have undergone transformation over the years with the introduction of Information Technology infrastructure like CRM and it can be used to enhance sales when combined with a trained salesforce and management support (Bhardwaj, 2000). The outcome of improved sales performance may not be directly attributed to CRM use, as improved behaviours may be the mediating factor (Hartline *et al*., 2000). Improved sales performance may be achieved when the relationship between the organisation and the customer is transformed to satisfy the needs of the customer (Canon & Perreault, 1999). Factors that influence the performance of sales personnel (i.e., skills, orientation towards performance, feedback, hard work, etc.) should be understood by the organisation as they ultimately impact sales outcomes (Sujan *et al*., 1994). Sales can be initiated by the customer when they have a problem that can be addressed by buying the offerings of an organisation. Information Technologies have also transformed sales from being organisation-driven to a self-service format by giving customers the power to complete transactions without the assistance of sales personnel (Gavin *et al*., 2020). Traditionally digital platforms were used by Business-to-Consumers organisations to fulfil sales, but now that is gradually increasing in Business-to-Business organisations as well (Gavin *et al*., 2020), further cementing that sales taking place outside of assisted channels (driven by sales personnel) should be considered as part of overall sales outcome to give a holistic picture.

2.4 Analytical frameworks and hypothesis development

The conceptual framework that organises this study is presented in the proposed research model, figure 2. The conceptual model was adopted from Shahbaz *et al*. (2020). The model in its original form only considered CRM as a mediating factor. For this study, customer satisfaction, customer retention and market performance were added as mediating factors to enhance the understanding of the impact of customer performance measures.

2.4.1 Impact of adoption of BDA on customer performance measures

Adoption of BDA has to do with the use of analytics systems to create incremental value for the organisation (OECD, 2013). Avci (2010) indicates that firm performance is often looked at from the lens of sales performance and often customer performance measures are ignored. Both practitioners and academics agree that firm performance should also be evaluated, based on non-financial (customer performance) outcomes (Reichel & Haber, 2005). Overall, BDA enhances the ability of the organisation to respond to general market and customer changes (Erevelles *et al*., 2016). Using BDA to better understand dynamic customer preferences and the positioning of the organisation in the market can improve customer performance, therefore this study sets out to understand the impact that BDA can have on the customer performance measures of an organisation.

In conclusion, the adoption of BDA could impact non-financial performance of an organisation. The study therefore hypothesises that:

H1a: *The adoption of BDA has a positive and direct impact on customer satisfaction.*

H1b: *The adoption of BDA has a positive and direct impact on customer relationship management.*

H1c: *The adoption of BDA has a positive and direct impact on customer retention.*

H1d: *The adoption of BDA has a positive and direct impact on market performance.*

2.4.2 Impact of customer satisfaction on sales performance

Customer satisfaction is a function of by how much goods and services meet and exceed customer expectations. Customers are satisfied when the perceived performance of the products or service is greater than the expected performance. Customer satisfaction is considered to affect retention and, therefore, financial performance (Anderson & Sullivan, 1993). Customer satisfaction is critical in achieving loyalty and generating sustainable long-term financial performance (Storbacka, Strandvik & Gronroos, 1994). Past research has discussed the positive relationship between customer satisfaction and financial performance (Chi & Gursoy). An improvement in customer satisfaction can be related to better understanding of customer needs, via BDA, so that customer loyalty is increased, and financial performance is improved. Organisations can use BDA to attempt to improve financial performance through improved customer satisfaction (Wamba *et al*., 2017). Emerging literature has found a positive relationship between the adoption of BDA and improved organisational performance though a decrease of customer acquisition costs (Liu, 2014), better customer relationship (Cheng, Zhang & Qin, 2016) and over improved customer experience ((Tan *et al*., 2015; Tweney, 2013).

Customer satisfaction could be an important mediator between the adoption of BDA and sales performance of an organisation. The study therefore hypothesises:

H2: *Customer satisfaction has a positive mediating effect on the relationship between adoption of BDA and sales performance.*

2.4.3 Impact of customer relationship management (CRM) on sales performance

CRM is an iterative process of four activities, which are, discovery of knowledge, market planning, customer interaction and customer data analysis (Stojkovic & Dubricic, 2012); this process also involves the integration of sub-processes to enhance the organisation's ability to better manage its valuable customers and improve profitability of its unprofitable customers (Elkordy, 2014). The debate of benefits from CRM investments has been on-going between academics (Reinmann, Schilke & Thomas, 2010). Some studies have found a positive relationship between CRM and firm performance while other studies have reported no positive relationship (Reimann *et al*., 2010; Chaudhuri & Vrontis, 2022). Using BDA to meet customer needs by using CRM as a technological tool can lead to increased financial performance (Van der Lan *et al*., 2008) as some organisations see CRM as a revenue enhancing tool (Payne & Frow, 2005). There are varying views on the mediating effect of CRM on organisational performance, therefore this study sets out to explore this relationship further.

Customer relationship management could be an important mediator between the adoption of BDA and sales performance of an organisation. The study therefore hypothesises that:

H3: *Customer relationship management has a positive mediating effect on the relationship between the adoption of BDA and sales performance.*

2.4.4 Impact of customer retention on sales performance

Customer retention is the continuous flow of customer profitability (Lenskold Group, 2003). For an organisation to maintain sustainable profitability, it needs to develop strategies for customer retention. Customer retention is significantly linked to financial performance (Dubihlela & Molise-Khosa, 2014). Another advantage for organisations is that it is significantly cheaper to retain customers than to acquire new ones which leads to improved financial performance (Ghavani & Olyaei, 2006). Retained customers do not mind paying slightly higher prices as they perceive this as receiving additional value (Honts & Hanson, 2011).

In conclusion, customer retention could be an important mediator between the adoption of BDA and sales performance of an organisation. The study therefore hypothesises:

H3: *Customer retention has a positive mediating effect on the relationship between the adoption of BDA and sales performance.*

2.4.5 Impact of market performance on sales performance

Market performance has to do with an organisation’s ability to introduce new products frequently, enter new markets faster than its competitors and have a greater market share. These can lead to an organisation gaining increased financial performance. Introducing new products and services can increase sales and thereby improve financial performance (Szymanski & Henard, 2001). Another way that market enhances revenue is penetrating a new market and selling goods and service to a new base of customers (Homburg *et al*., 2007). What still needs to be understood is if the adoption of BDA and market performance can be used in conjunction to enhance sales performance as it has been explored in other contexts (Chumpitaz & Paparoidamis, 2004). Usage of BDA could stimulate organisational ability to recognise market opportunities and threats, deploy market responsive products and services and quickly grab marker opportunities (Corte-Real *et al*., 2017; Davenport, 2014). Another opportunity can be the creation of new revenue streams that sells information and platforms integrally with the traditional good and services that a firm offers (Opresnik & Taisch, 2015).

In conclusion, market performance could be an important mediator between the adoption of BDA and sales performance of an organisation. The study therefore hypothesises:

H5: *Market performance has a positive mediating effect on the relationship between the adoption of BDA and sales performance.*

2.4.6 Impact of BDA on sales performance

Prior research has found a direct relationship between general information technology and organisational performance (Huang *et al*., 2006; Melville, Kraemer & Gurbaxani, 2004), meanwhile, recent studies have found a strong relationship between an organisation's ability to use BDA and improved firm performance (Akter *et al*., 2016). Because BDA enables organisations to gather and analyse real-time data to respond to customer needs, it may influence sales performance (Xu *et al*., 2016; Hallikainen *et al*., 2020).

Adoption of BDA could have a direct impact on sales performance of an organisation. The study therefore hypothesises:

H6: *Adoption of BDA has a direct impact on sales performance.*

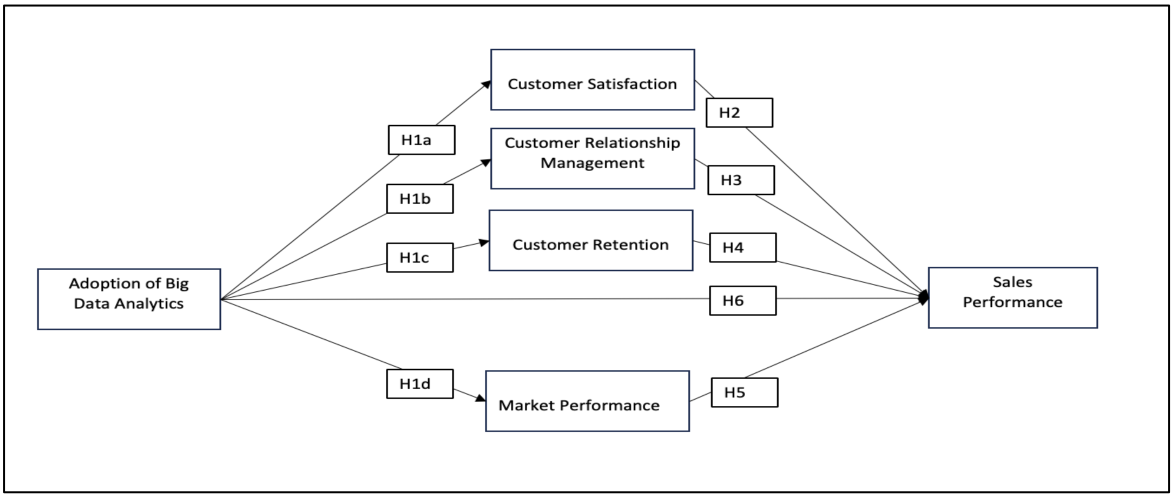


Figure 3: Conceptual model

Source: Adapted from Shahbaz *et al*. (2020)

2.5 Conclusion

The above literature has demonstrated that big data has various definitions, and it does not universally mean the same thing to everyone. The benefits, challenges, history, and attributes of BDA were also discussed. Furthermore, literature around the various model constructs have been explored and there seem to be various relationships, either as mediating factors or relationships between the model constructs themselves. The hypothesised relationships were developed.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

In chapter 2, the study reviewed literature on BDA, as well as the study's models and hypothesis were presented. Chapter 3 presents the methodology used for gathering and analysing data to test the hypotheses and answer the research questions. This chapter highlights the research methodology with reference to the research focus, research approach, research strategy, data collection method, instrument, data analysis, reliability, validity, and limitations.

3.2 Research design and approach

This study is informed by a philosophy consistent with positivism, based on the intention to test hypothesised relationships using data collected and measured with a degree of accuracy (Cohen *et al*., 2007). The positivist notion is reflected by formulating empirically testable theory to establish generalisation (Evans, 2010). Generalisation for the population is derived by using statistical techniques on the data collected (Saunders, Thornhill, & Lewis, 2009). Studies that adopt a positivist approach do so on the basis that the social world can be studied just as the natural world can be studied (Collis & Hussey, 2009).

There are two broad approaches for performing research, namely, deductive, and inductive (Suanders *et al*., 2012). The approach followed for this study is deductive, in line with positivism. The deductive approach results when the conclusion is arrived at logically from a set of premises when all premises are true (Ketokivi & Mantere, 2010). This is done by hypothesising, based on a theory that is obtainable and designing a research strategy to test the hypothesis (Wilson, 2010). In short, 'deductive' means reasoning from the broad to the specific (Zalaghi & Khazaei, 2016).

Another consideration is the application of quantitative or qualitative approaches. Since the objective of the study is to evaluate the relationship between independent, dependent, and mediating variables, it can thus be explained as "explanatory research". Explanatory research has to do with explaining the effect that one variable may have on another variable (Petty *et al*., 2012). The quantitative approach deals with statistical, mathematical, or numerical analysis of data and can be used for testing hypotheses, causality, and objective measurement (Collis & Hussey, 2009). The opinions expressed by the respondents can be aggregated by statistical means to formulate a general opinion relating to the phenomena being studied (Ponterotto, 2005). This study aims to aggregate data and generalise an observed phenomenon, therefore adopts a mono-method quantitative approach.

3.3 Research strategy and time horizons

The research strategy for this deductive, quantitative, and explanatory study is a survey, an online survey to be specific. Surveys can be used in quantitative studies which allows for gathering of data from a large representative sample, thus improving the confidence when generalising for the population (Gong *et al*., 2004). The survey provides a cost-effective way to collect data (Collis & Hussey, 2009).

This survey is a cross-sectional design. “Cross-sectional” design collects responses from a sample of the population at a single point in time (Ponterotto, 2005). This study is not continuous as it records responses via a survey which is sent out once-off and not on a continuous basis.

3.4 Target population and sampling strategy

A survey can be conducted from a population or a sample. A population is the entire group that researchers aim to draw conclusion about while a sample is the specific group from which the data is collected (Bhandari, 2022). When data from the entire population is collected, a census survey is used (Evans, 2010). Sampling is a method of identifying the members of the population that are selected and surveyed. Two methods of sampling exist, namely, “probability” and “non-probability” sampling (McCombes, 2022). Probability sampling involves random selection, allowing the researcher to make strong inferences about the group while “non-probability” sampling is not random and the sample is chosen based on the convenience or other criteria that the researcher selects (McCombes, 2022).

This study used use “non-probability” sampling method. Data collection for this study was limited to managers and practitioners within Sales and Marketing functions of Johannesburg Stock Exchange (JSE) listed companies and subsidiary entities. The number of JSE listed companies as of July 2022 was 311 (CEIC, 2022). The individuals within sales and marketing functions were selected because they would be able to respond to questions related to how BDA is used to improve sales performance. Of the 311 population of JSE listed organisations, the top 200 organisations ranked by market capitalisation (highest to lowest) were used as the sample to test the hypothesis for the population. “The market capitalisation refers to the total Rand value of a company’s outstanding shares. Since a company is represented by X number of shares, multiplying X with the per share price represents the total rand value of the company. Outstanding shares signify the shares of the company presently held by all its shareholders” (JSE, 2022).

A total of 200 participants were invited to take part in the survey. One sales or marketing manager was selected from each of the organisations to represent the organisation which had been selected for the study. The determination of the final sample involved a blend of judgement and referencing prior studies. Sample sizes from previous research was used to give direction as to how many participants are typically involved in studies of this nature. Table 1 shows the examples of the sample sizes from prior studies.

Table 1: Examples of previous studies’ samples

Scope of the study	**Sample used**	**Data analysis**	**Authors**
Impact of BDA on sales performance	800 (416 reponses)	SEM	Shahbaz *et al*., 2021
Fostering B2B sales with customer BDA	551 (417 responses)	SEM	*Hallikainen et al*., 2020
BDA and organisation performance	700 (295 responses)	PLS SEM	Wamba *et al*., 2017
Market orientation impact on organisation performance	600	Regression	Wei and Lau, 2008
CRM impact on organisation performance	260 (150 responses)	Partial Least Squares	Soltani *et al*., 2018
Customer satisfaction impact of business performance	100 (95 responses)	Logistic regression	Zakari and Ibrahim, 2021

3.5 Instrument construction

The instrument construction process was done in four steps as illustrated below (figure 4).

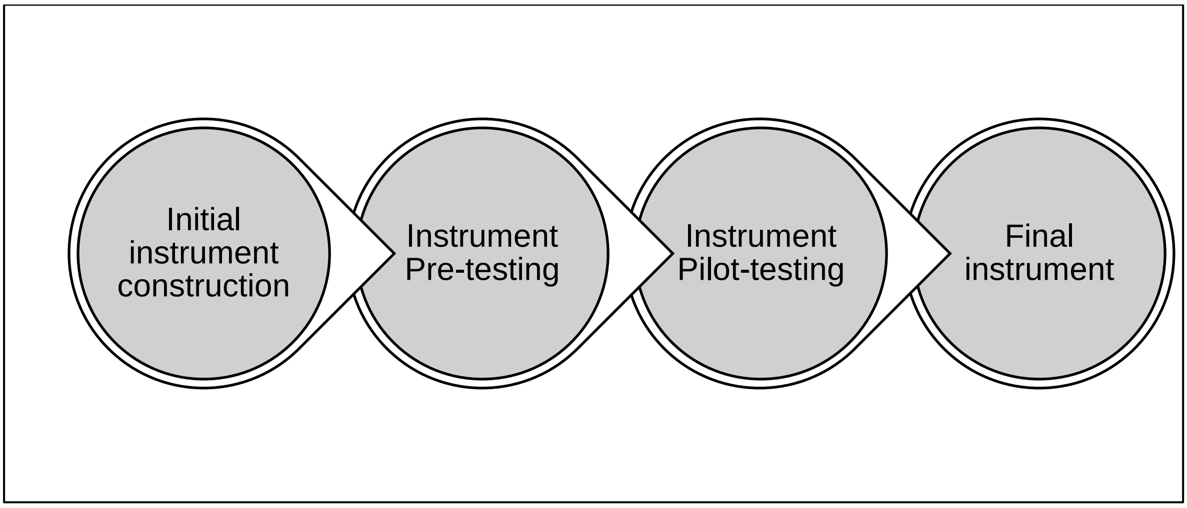


Figure 4: Instrument construction process

3.6 Initial instrument construction

In addressing RO1 and RO2, the research model (Figure 2) comprises six constructs, namely BDA adoption, customer satisfaction, customer retention, CRM, market performance, and sales performance. Table 2 shows example items of the constructs and the respective sources. The data collection was divided into two parts. The first part was about the respondent's demographic details and the second part contained items of the variables. A seven-point Likert scale (1 = strongly disagree to 7 = strongly agree) was adopted to numerically measure the items of the model constructs because it is a widely used method (Preston & Colman, 2000; Krosnick & Presser, 2010). The seven-point Likert scale was used to rate items that were used to operationalise the constructs as they cannot be directly measured.

Table 2: Operationalisation of constructs to examine impact of BDA on sales performance through mediating factors

Variable	Example questionnaire item	Number of items	Literature source
BDA adoption	• We have explored or adopted new forms of databases, such as Not Only SQL(NoSQL)	5	Mikalef *et al*., 2019
Customer satisfaction	• BDA has the assisting ability to increase customer satisfaction	4	Mithas *et al*., 2011; Vohries and Morgan, 2005
Customer retention	• BDA can help to rebuild a good relationship with migrating or inactive customers	4	Shahbaz *et al*., 2020
Market performance	• Our market share has exceeded that of our competitors	4	Tippins and Sohi, 2003;Wang *et al*., 2012
CRM	• BDA will provide better Customer information infrastructure	6	Shahbaz et al., 2021; Rodriguez *et al*., 2018
Sales performance	• The utilization of BDA helps improve overall conversion rates	5	Shahbaz et al., 2020; Sujan *et al*, 1994

3.7 Instrument pre- and pilot testing

One of the requirements for ensuring quality of instruments is the extent to which they measure all aspects of the construct, this is known as content validity (Vonglao, 2017). The pilot study could not be conducted because the study did not invent a new construct. Existing constructs from prior studies were used. The study proceeded administration of the final instrument.

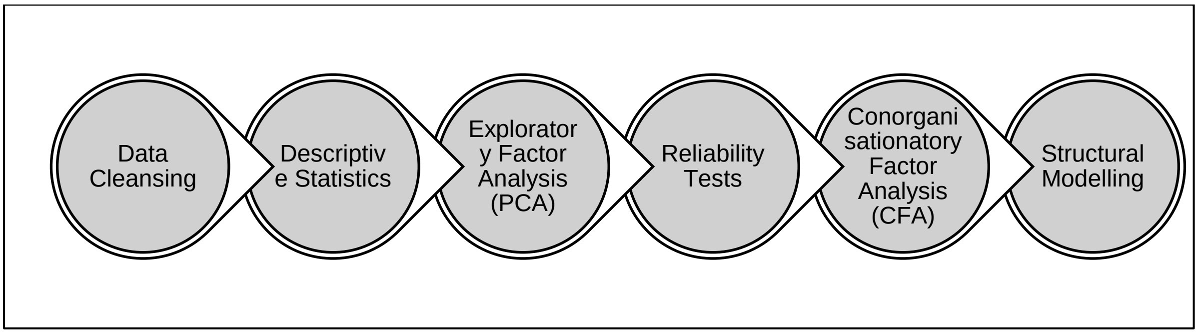
3.8 Final instrument administration

The final questionnaire for the study (refer Appendix A) was administered electronically to the individuals selected in the sample. The questionnaire was distributed via the Wits student email or directly through LinkedIn direct messaging to the respondents. The email contained the participant invitation sheet as well the link to the online survey, if they agree to participate, they clicked on the link embedded on the information sheet and it leads them to the online questionnaire. Two weeks after the initial communication was sent, a reminder communication was sent to improve response rates.

3.9 Data analysis strategies and interpretation

The quantitative analysis of the data collected was done in six sequential steps, as shown in figure 4.

Figure 5: Data analysis steps



3.10 Data cleansing

Data screening is done to check the hygiene of the data to ensure that it can be processed. Data was checked for inconsistent, invalid, missing and outlier data. Data cleansing was performed to resolve data inconsistencies or errors to improve the quality of data. An error in this case may be blank or corrupted values (Bhandari, 2022).

3.11 Descriptive statistics

Descriptive statistics were used to summarise and organise the characteristics of the data that was collected. Descriptive statistics can include distribution, central tendency, and variability statistics (Bhandari, 2022).

The data from the survey was collected by measuring items using Likert scales and the analysis was done using parametric test. Norman (2010) found that parametric tests such as Covariance-Based Structural Equation Modelling (CB-SEM) can be used to analyse data from scales such as Likert scales.

3.12 Exploratory factor analysis

Exploratory Factor Analysis (EFA) was carried out to determine the uni-dimensionality and underlying factors structure of the study's variables (Hair, Black, Babin & Anderson, 2010). Before reliability and validity can be tested, uni-dimensionality must be tested first. Items with factors loadings less than 0.7 were deleted in the EFA stage.

EFA was carried out using Principal Component Analysis (PCA) which allows testing convergent and discriminant validity. Validity is defined as the extent to which a concept is accurately measured in a quantitative study (Heale & Twycross, 2015), for example, a survey that is designed to measure depression, but measures anxiety, is not valid. To ensure validity, items with factor loadings less than 0.7 were deleted as this is an acceptable level. There are limits to external validity that need to be acknowledged in this study. External validity refers to the degree that the results of the study can be used in different applications due to the extent to which the findings can be generalised (Bhandari, 2022). The data in this study was collected using cross-sectional surveys which means responses were captured at a single point in time. Applying the outcomes at a different point in time when the context may have changed might present challenges. Sample bias may be present as the participants were not randomly selected from a population.

3.13 Reliability tests

Reliability refers to the extent which the results can be reproduced when the research is conducted under the same conditions. This confirms that the measurement is consistent and reputable (Collis & Hussey, 2009). Reliable instruments reduce errors and bias when analysing findings (Petty *et al*., 2012), allowing for consistent measurements over time (Maxwell, 2005). This study adopts internal consistency as a measure of reliability which is common when conducting surveys. Cronbach's alpha was adopted and employ the generally accepted cut-off at 0.7 (Hair *et al*., 2010). This study recommends that values 0.7 may contain too many errors.

3.14 Confirmatory factor analysis and structural equation modelling

SEM can distinguish the direct and indirect relationships between latent and measured variables which sets it apart from other simpler relational modelling techniques (Fan & Sivo, 2005; Russolillo, 2012). AMOS was used to perform SEM.

Confirmatory Factor Analysis (CFA) was used to test if the measured variables selected are aligned with the proposed models or theories (Lee & Hings, 2008). The initial test for uni-dimensionality was tested using EFA while the final test for uni-dimensionality was done using CFA. The process of deleting items that do not meet the minimum cut-ff is repeated at this stage to further strengthen validity and reliability.

Studies by various authors (Shahbaz *et al*., 2020; Wamba *et al*, 2016; Akter et al, 2016) that have informed the conceptualisation of the model for this study have all used SEM to analyse the data they collected using Likert scales. SEM was used due to its ability to test the strength of hypothesised path relationships between variables of the research model at once (Hair, Ringle & Sarstedt, 2011). If the model and the observed covariance metrices are equal then the hypothesis will not be rejected as that would mean that the model fits the data (Awang, Afthanorhan & Mamat, 2016).

Maximum Likelihood Estimation (MLE) was used to estimate the parameters of the model. MLE can achieve this by obtaining parameter values that maximise the likelihood of making the observation (Myuang, 2003). MLE also makes it possible to calculate the chi-square as the most common measure of model fit (Fan & Sivo, 2005).

One of the major tests that is performed when using SEM is model fit to establish how well it models the data. Table 3 below shows all the fit statistics that were used to confirm if the hypotheses fit.

Table 3: Model fit criteria and acceptable levels

Model Fit Criteria	Description	Acceptable level	Source
Goodness-of-fit (GFI)	The GFI is the degree of fit between the hypothesised model and the observed covariance matrix.	0 (no fit) to 1 (perfect fit)	Barrett, 2007
Normed fit index (NFI)	The NFI evaluates the difference between the chi-squared value of the hypothesised model and the chi-squared value of the null model.	Value must be over 0.9	Fan and Sivo, 2005; Byrne, 2013
Comparative fit index (CFI)	The CFI assumes that all latent variables are uncorrelated and compares the sample covariance matrix with the null model.	Value must be over 0.9	Fan and Sivo, 2005
Incremental fit index (IFI)	The IFI's purpose is to correct the issue of parsimony and sample size related to NFI.	Value must be over 0.9	Byrne, 2013; Hoe, 2008
Root mean square error of approximation (RMSEA)	Informs how well the model, with indefinite but optimally selected parameter estimates, would fit the population's covariance matrix.	Value must be <0.05	Cheung and Rensvold, 2002
Chi-square ($\chi 2$ /DF)	To assess the magnitude of discrepancy between the sample and fitted covariance matrices. The estimation	Value must be below 3	Cheung and Rensvold, 2002

Model Fit Criteria	Description	Acceptable level	Source
	process is dependent on the sample data		
Tucker-Lewis Index (TLI)	The TLC uses easier models and is known to address the issue of sample size associated with NFI.	Value must be over 0.9	Hoe, 2008.
Relative Fit Index (RFI)	The RFI compares the chi-square for the hypothesised model to one from a "null", or "baseline" model.	Value must be over 0.9	Byrne, 2013

3.15 Ethical considerations

The researcher ensured compliance with all ethical requirements of the University. The researcher ensured that participation was on a voluntary basis and the anonymity of the respondents was guaranteed by not revealing their personally identifiable information.

The responses will not be shared with anyone and will be destroyed after the study has been concluded. The respondent's answers were reported at an individual level but were reported at an aggregated level. The researcher also ensured that reporting does not reflect the names of organisations where the respondents are employed when reporting on the outcomes of the survey. Prior to collecting data, ethics clearance from the "Human Research Ethics Committee (Non-Medical) office at the University of the Witwatersrand" was granted to the researcher. Protocol number WBS/DB1488952/669 (Appendix B). The researcher agreed to adhere to the guidelines stipulated by the "Ethics Committee" with respect to conducting research involving human respondents.

CHAPTER 4: PRESENTATION OF THE RESULTS

4.1 Empirical results

In chapter 3, the research method was developed to address data collection and analyses. This chapter analyses data collected from the empirical study. The RO1 and RQ1 "*To examine the direct impact of BDA on sales performance*" is investigated and empirically tested. In addition, the RO2 and RQ2 "*To examine the impact of BDA on sales performance through non-financial performance measures (i.e., customer satisfaction, customer retention, customer relationship management and market performance) as mediating effects*" is investigated and empirically tested. A survey was conducted by means of distributing online questionnaires to sales and marketing professionals who represent their respective organisations. The data collected from the respondents was used to test the hypothesised model of the direct and indirect impact of BDA on sales performance. The initial sections in this chapter discuss the sample size, demographics, data screening and outliers of the respondents. In addition, the subsequent sections unpack the descriptive statistics, assessment of normality, and sample adequacy of the data analysed. Additionally, the principal component analysis, reliability and validity, and correlation matrix are performed before the confirmatory factor analysis is evaluated. The results of the structural model are then discussed, and the conclusions are presented.

4.2 Sample size

Invitations were sent out to 200 participants to participate in the survey of the study. A total of 126 (a response rate = 63%) representatives participated in the study. The relatively high response rate of the study minimises the threat of non-response bias. 26 responses were eliminated due to incomplete responses therefore leaving a total of 100 responses that are usable (50% response rate).

4.3 Demographics

Descriptive statistics are presented to give an overview of the sample. The demographic make-up of the respondents is shown in Table 4.

The results show that 8% (92% have adopted BDA) of organisations have not adopted BDA, while those that have been using BDA have been doing so for varying periods from less than five years to over 10 years. 50% of the respondents recorded their seniority level as managers which should give them enough oversight of the activities in their functional departments to make a meaningful contribution to the study. 68% of the respondents have been employed at the organisations for under five years but this does not reflect their overall working experience in years as professionals. Most organisations have been in operation for over 10 years, with 20% having been in operation for over 50 years. The biggest vertical representatives are in the finance sector with 24% and telecommunications with 20% respectively. The organisations in question are considerably large in revenue terms with 64% earning over R500 million annually. Overall, the demographic data indicates coverage of a wide range of organisations across various sectors, except for mining, utilities, and retail, which make up less than 10% combined. The data suggests a significant majority of the organisations have adopted and are using BDA in the execution of marketing and sales activities; with this insight, data analysis could proceed to the next step.

Table 4: Demographic Information

Demographics	Category	Frequency	Percent
Years company using analytics	0 Years	8	8
	Less than 5 years	30	30
	5 to 10 years	30	30
	Over 10 years	32	32
Organisational revenue	Under R20 million	6	6
	Between R21 million to R100 million	10	10
	Between R101 million and R500 million	20	20
	Between R501 million to R1 billion	18	18
	Between R1 billion to R10 billion	20	20
	Over R10 billion	26	26
Organisation's industry	Mining	4	4
	Retail	2	2
	Manufacturing	12	12
	Telecom	20	20
	Service	14	14
	Finance sector	24	24
	Utilities and energy	2	2
	Pharmaceutical	2	2
	Other	20	20
Job title	Chief Sales/Marketing Officer	2	2
	Executive Director	8	8

Demographics	Category	Frequency	Percent
	Managing Director	4	4
	Sales/Marketing Director	4	4
	Sales/Marketing Manager	50	50
	Other	32	32
Years of experience	Under 5 years	68	68
	Between 6 and 10 years	16	16
	Between 11 to 15 years	8	8
	Over 16 years	8	8
Years in operation	Under 5 years	4	4
	Between 6 and 10 years	8	8
	Between 11 and 20 years	24	24
	Between 21 and 30 years	26	26
	Between 31 and 50 years	18	18
	Over 50 years	20	20

4.4 Data screening

The data collected was analysed and screened using the "Statistical Package for the Social Sciences (SPSS) Version 25". The software license for SPSS version 25 was provided to use without any cost implication on the researcher, that is one of the reasons for choosing the software. The software is user friendly and doesn't require programming skills and allows for analysis without challenges. The software also contains pre-built analytical functions i.e., mean, mode, PCA, correlation analysis etc. All the responses had 100% completion rates, so no data issues were observed. There were eight respondents who indicated that that their organisations were not using BDA, which represents 8% of the sample. The completion rate for all the usable responses is 100%.

4.5 Sample outliers

Outliers can be defined as data points that vary significantly from other observations (Hair *et al*., 2010). Unusually high or unusually low values were screened to check if there are any outliers in the set of responses. Extreme values are typically a response that is three standard deviations above or below the sample mean (Hair et al., 2010). The standardized scores of each respondent were examined on all the questionnaire items and none met the criteria to be classified as an outlier. This was an expected outcome given that the questionnaire items were answered using a defined scale.

4.6 Descriptive statistics of construct items

The constructs investigated in this study were measured using two different scales. The construct “adoption of BDA” was measured on a seven-point Likert scale where the value of 1 corresponds with “Strongly Disagree” and the value of 7 corresponds with “Strongly Agree”. The constructs “customer service”, “market performance”, “customer relationship management”, “sales performance” and “customer retention” were also measured using a seven-point Likert scale with the value 1 corresponding to “Much Worse Than Expected” and the value 7 corresponding to “Much Better Than Expected” with the midpoint of the scale being the value “3.5”. Thus, responses with values below 3.5 indicate that the perceived outcomes were worse than expected, while values of between 3.5 and 4.5 indicate a more neutral response where outcomes were neither worse nor better than expected. Values greater than 4.5 indicate that the perceived outcomes were better than expected. The descriptive statistics table (mean, standard deviation, skewness, and kurtosis) is presented in table 5 below.

Table 5: Summary of Descriptive Statistics per Construct

	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Adoption of BDA (AD)	3.29	6.57	5.66	0.84	-1.25	0.49
Customer Service (CS)	3.57	6.43	5.17	0.82	-0.09	-1.12
Market Performance (MP)	3.00	6.50	4.83	0.89	-0.18	-0.38
Customer Relationship Management (CRM)	2.00	6.43	4.74	1.18	-0.51	-0.58
Sales Performance (SP)	1.89	6.33	4.37	1.03	-0.46	0.22
Customer Retention (CR)	3.57	6.71	5.39	0.78	-0.59	-0.27

* composite scores for each construct calculated as the arithmetic average of its original scale items weighted equally.

4.6.1 Adoption of Big Data Analytics (AD)

The “adoption of BDA” scale was developed to extract information on organisational beliefs that the use of BDA supports various sales and marketing functions (i.e., developing customer profiles, segmenting markets, customising offers, identifying best customers, assessing customer lifetime value, identifying best performing channels and customer retention behaviour). The overall mean is 5.7 and the standard deviation is 0.8 as presented in table 5 above. Seven items were adopted from prior work related to the “adoption of BDA” and what it is used for in the organisations (Mikalef *et al*., 2019), and were “measured using 7-point Likert scale”. Table 6 shows that the mean of the items ranges from 5.46 to 5.96. This suggests that “most respondents tend to mostly agree that the adoption of BDA” is supporting the sales and marketing functions to improve sales performance.

Table 6: Statistical Results of AD Items

	Observations	Minimum	Maximum	Mean	Std. Deviation
AD1	100	3	7	5.70	1.17
AD2	100	2	7	5.82	1.11
AD3	100	3	7	5.34	1.03
AD4	100	3	7	5.74	0.96
AD5	100	2	7	5.46	1.32
AD6	100	3	7	5.62	1.08
AD7	100	3	7	5.96	1.27

4.6.2 Customer Satisfaction (CS)

The customer satisfaction construct was developed to obtain information on organisational beliefs on the improvement of customer satisfaction in the organisation. The overall mean is 5.2 and the standard deviation is 0.82, as presented in table 6 above. Seven items for “customer satisfaction” were adopted from prior work relating to customer performance (Mithas et al., 2011; Vohries & Morgan, 2005); this was “measured using a 7-point Likert scale”. The mean for customer satisfaction items ranges from 4.98 to 5.32, as shown in table 7 below. This suggests that respondents’ perceptions of improvement of customer satisfaction have, on average, been somewhat better than expected.

Table 7: Statistical Results of CS Items

	Observations	Minimum	Maximum	Mean	Std. Deviation
CS1	100	3	7	5.22	1.17
CS2	100	3	7	5.16	1.14
CS3	100	3	7	5.32	1.09
CS4	100	3	7	4.98	1.12
CS5	100	3	7	5.20	1.18
CS6	100	2	7	5.02	1.23
CS7	100	3	7	5.32	0.99

4.6.3 Customer Retention (CR)

The customer retention construct was developed to obtain information on organisational perceptions on the improvement of customer retention in the organisation. The overall mean is 5.39 and the standard deviation is 0.78, as presented in table 8 below. Seven items for customer retention were adopted from prior work relating to customer retention and performance (Mithas et al., 2011; Vohries & Morgan, 2005); this was “measured using a 7-point Likert scale”. The mean for customer retention items ranges from 5.07 to 5.75, as shown in table 8 below. This suggests that respondents’ perceptions on improvement of customer retention have, on average, been somewhat better than expected.

Table 8: Statistical Results of CR Items

	Observations	Minimum	Maximum	Mean	Std. Deviation
CR1	100	3	7	5.58	0.90
CR2	100	3	7	5.07	1.06
CR3	100	3	7	5.21	1.05
CR4	100	3	7	5.61	1.12
CR5	100	3	7	5.21	1.17
CR6	100	3	7	5.35	1.11
CR7	100	3	7	5.75	1.02

4.6.4 Customer Relationship Management (CRM)

The customer relationship management construct was developed to obtain information on organisational perceptions on the improvement of customer relationship management in the organisation. The overall mean is 4.74 and the standard deviation is 1.18, as presented in table 9 below. Seven items for customer relationship management were adopted from prior work relating to customer relationship management (Shahbaz et al., 2021; Rodriguez et al., 2018); this was “measured using a 7-point Likert scale”. The mean for customer relationship management items ranges from 4.54 to 4.91, as shown in table 9 below. This suggests that respondents’ perceptions of improvement of customer relationship management have on average, been somewhat better than expected.

Table 9: Statistical Results of CRM Items

	Observations	Minimum	Maximum	Mean	Std. Deviation
CRM1	100	1	7	4.73	1.47
CRM2	100	1	7	4.61	1.66
CRM3	100	1	7	4.54	1.52
CRM4	100	2	7	4.85	1.28
CRM5	100	2	7	4.75	1.44
CRM6	100	1	7	4.91	1.44
CRM7	100	2	7	4.82	1.20

4.6.5 Market Performance (MP)

The market performance scale was constructed in this study to extract information on organisational beliefs on the improvement of market performance of the organization. The overall mean is 4.83 and the standard deviation is 0.89 as presented below in table 10. Four items for market performance were adopted from prior work relating to organizational performance (Tippins & Sohi, 2003; Wang et al., 2012); this was “measured using a 7-point Likert scale”. The mean for market performance items ranges from 4.54 to 4.91 as shown in table 9 below. This suggests that respondents’ perceptions of improvement of market performance have on average, been somewhat better than expected.

Table 10: Statistical Results of MP Items

	Observations	Minimum	Maximum	Mean	Std. Deviation
MP1	100	2	7	4.76	1.24
MP2	100	3	7	4.70	1.19
MP3	100	3	7	4.86	1.08
MP4	100	2	7	5.02	1.11

4.6.6 Sales Performance (SP)

The sales performance scale was constructed in this study to extract information on organisational beliefs in the improvement of sales performance of the organisation. The overall mean is 4.37 and the standard deviation is 1.03 as presented below in table 11. Nine items for market performance were adopted from prior work relating to organizational performance (Shahbaz et al., 2020; Sujan et al., 1994); this was "measured using a 7-point Likert scale". The mean for sales performance items ranges from 4.04 to 4.54 as shown in table 11 below. This suggests that respondents' perceptions of improvement of market performance have on average, been somewhat better than expected.

Table 11: Statistical Results of SP Items

	Observations	Minimum	Maximum	Mean	Std. Deviation
SP1	100	1	7	4.54	1.32
SP2	100	2	6	4.04	1.08
SP3	100	2	7	4.32	1.34
SP4	100	1	7	4.68	1.51
SP5	100	1	7	4.26	1.52
SP6	100	2	7	4.20	1.08
SP7	100	2	7	4.64	1.13
SP8	100	2	7	4.16	1.22
SP9	100	2	7	4.54	1.48

4.7 Assessment of normality

Table 5 above shows "Skewness and Kurtosis coefficients" of the constructs that form part of the study. Values for skewness and kurtosis that are between -2 and +2 indicate an acceptable range of normality (George & Mallery, 2010). The skewness and kurtosis values for the data collected in this study range between -1.25 and 0.49. This falls within the acceptable range. Therefore, principal component analysis could proceed to establish if the items are loading with the latent constructs.

4.7.1 Sampling adequacy

"Kaiser-Meyer-Olkin (KMO)" is a test that measures sampling characteristics of the "ratio of the squared correlations between variables to the squared partial correlation between variables". KMO was used to measure the adequacy of the sample. The test was designed by Kaiser and Rice (1974). The values of the correlations range between 0 and 1. The closer the values get to 1, the more they will produce reliable factors (Field, 2009). Values that are below 0.49 are unacceptable, values that are between 0.5 and 0.69 are bad, between 0.7 and 0.79 are good, between 0.8 and 0.89 are meritorious and above 0.9 are excellent (Abdi, 2010). The outcome of the KMO test for this study is shown in table 13 below. The value for KMO for this study is 0.84 which falls in the meritorious description. Therefore, this implies that that the sample can produce reliable factors.

Table 12: KMO and Bartlett's

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	.837
Approx. Chi-Square	9,659
df	325
Sig.	.000

To determine if the research can proceed with principal component analysis, a test to measure the Chi-square was conducted to determine whether the correlations between survey items were large enough for appropriate factor analysis. The test was developed by Bartlett (1954). The Chi-square score for this research is 9.659 and its significance is less than 0.001 as shown in table 12 above. This shows that the sample size is appropriate to proceed with the principal component analysis.

4.7.2 Principal component analysis (PCA)

The orthogonal rotation (Varimax) method was used to conduct factor analysis in this study. Factor analysis assumes that observable and measurable variance can be reduced to a few latent variables that share a common variance (Vonglao, 2017). This is known as dimensionality reduction. The latent variables are not measured directly but are important in the hypothetical model. An exploratory factor analysis (EFA) was selected for this study as there is not sufficient research evidence on the impact of BDA on sales performance and the mediating role of customer performance in the South African context to proceed directly to confirmatory factor analysis.

For a construct to be labelled a factor, it must contain at least three variables (Hair et al., 2010) and all the factors in this study contain at least three variables so factors analysis can proceed. Rotation matrix is used to maximise high item loadings while minimising low item cross-loadings; this enables the production of a more interpretable and simplified solution. There are various methods for rotation on SPSS such as varimax, quarimax, equamax, direct oblimin and promax (Sangthong, 2020); this study used varimax rotation. Loadings of less than 0.5 were suppressed from the output while values of less than 0.6 were completely removed. The total explained variance is 71%. The lowest item loading was 0.63.

Table 13: Principal Component Analysis

"Rotated Component Matrix"						
	Component					
	1	**2**	**3**	**4**	**5**	**6**
AD2				0,726		
AD3				0,794		
AD4				0,731		
AD5				0,772		
CS1					0,697	
CS5					0,736	
CS6					0,816	
CS7					0,627	
CR4			0,850			
CR5			0,648			
CR6			0,756			
CR7			0,793			
MP1						0,828
MP2						0,760
MP3						0,776
CRM1		0,722				
CRM2		0,843				
CRM3		0,804				
CRM4		0,724				
SP1	0,763					
SP2	0,744					
SP3	0,804					
SP5	0,738					
SP7	0,773					
SP8	0,791					
SP9	0,712					

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
Variance = 71,8%

Adoption of BDA (AD) was measured through seven items. As shown in table 13, three items were dropped due to lower factor loading.

Customer Service (CS) was measured through seven items. As shown in table 13, three items were dropped due to lower factor loading.

Customer Retention (CR) was measured through seven items. As shown in table 13, three items were dropped due to lower factor loading.

Market Performance (MP) was measured through four items. As shown in table 13, one item was dropped due to lower factor loading.

Customer Relationship Management (CRM) was measured through seven items. As shown in table 13, three items were dropped due to lower factor loading.

Sales Performance (SP) was measured through nine items. As shown in table 13, two items were dropped due to lower factor loading.

The factor structure extracted by the PCA provided intermediary confirmation of the hypothesised measurement model which had six multi-item constructs. The analysis then proceeded to test the reliability of the scales based on the remaining measurement items.

4.8 Scale reliability and validity

For the scale to be usable and yield practical validity, it must be reliable (Byrne, 2013). Reliability is defined as the ability to achieve the same results if the scale is to be used under the same conditions with the same objectives (Hair et al., 2010). The scale used six factors for this study to measure the proposed conceptual framework, namely, adoption of BDA, customer retention, customer satisfaction, customer relationship management, market performance and sales performance. Table 14 presents the results of the “Cronbach’s alpha”, “Average Variance Extended (AVE) and Composite Reliability (CR)”. To measure reliability, the “Cronbach’s alpha was used”. The scale is regarded as reliable if the “Cronbach alpha is 0.7 and above” (Hair et al., 2010). As per the results show below in table 14, all the values for Cronbach alpha are above the recommended value of 0.7 thereby indicating that all the scales are reliable.

Table 14: Results for reliability and validity

	Number of initial items	Number of surviving items	Cronbach's Alpha	Average Variance Explained (AVE)	Composite reliability (CR)
AD	7	4	0,863	0,756	0,842
CS	7	4	0,851	0,719	0,812
MP	4	3	0,777	0,788	0,788
CRM	7	4	0,921	0,773	0,857
SP	9	7	0,924	0,888	0,942
CR	7	4	0,855	0,762	0,848

4.9 Correlation matrix of composite scores

Through the examination of loadings and AVE values, the results shown above provide evidence of scale reliability and convergent validity. The results for the inter-correlation have been calculated and presented in table 15 below. The results for the “discriminant validity” confirmed that the constructs of the study share more variance with their own items than with other constructs in the model, this is the required outcome to proceed with further testing. All results confirm the “reliabilities”, “convergent” and “discriminant validities” of the constructs.

Table 15: Results of matrix of composite scores

	Mean	STD	AD	CS	MP	CRM	SP	CR
AD	5.66	0.84	0,756					
CS	5.17	0.82	.261**	0,719				
MP	4.83	0.89	.174*	.206*	0,788			
CRM	4.74	1.18	.151	.173	.409**	0,773		
SP	4.37	1.03	.161	.234*	.404**	.709**	0,888	
CR	5.39	0.78	.344**	.643**	.330**	.220*	.275**	0,762

**. “Correlation is significant at the 0.01 level (2-tailed)”.
*. “Correlation is significant at the 0.05 level (2-tailed)”.

4.10 Results of model testing

In this section, the “structural model” and measurement of the study is tested. It is advisable to perform a Confirmatory Factor Analysis (CFA) to test the “measurement model” in order to establish if all the items are loading as expected on the hypothesised model, whereafter the hypothesised “structure model can be tested”. The CFA used the 26 items measuring the main variables that had survived from the “exploratory factor analysis”. The CFA was used to confirm that the proposed factor structure is a good fit for the data.

After conducting CFA, the next step is to use “Structural Equation Modelling (SEM)” to test the hypothesised relationships proposed in the structural model. AMOS version 25 is used to conduct the SEM model.

4.10.1 CFA model results

The CFA was used to assess the relationships between various constructs within the developed theoretical model. It is critical to assess the “measurement model fit” and measure the “validity of the model” when doing the model assessment. Figure 6 below shows the variables being linked together. The measured variables (construct items) are shown in rectangular shapes. In figure 6 below, covariance is shown by two headed arrows and the causal relationship is indicated by one-headed arrows. The results of the model focus only on the adoption of BDA, customer retention, customer satisfaction, customer relationship management, market performance and sales performance. Only the 26 items that survived in the PCA were used in the computation of the CFA.

4.10.2 Goodness of fit indices

The “maximum-likelihood method” was used to estimate the model’s parameters. There are various model fit indices that need to be considered when calculating the various measures of model goodness-of-fit. The first measure is the Chi-square of the model. The ratio of the square was found to be four which is above the recommended value of three, which indicates that the data does not fit the model. The results of the CFA model fit indices are show in table 16 below. While some of the CFA indices indicate that the indices scores were not entirely satisfactory, the aim of the CFA model was to assess if all the items of the scale were loading on the hypothesised constructs and to confirm construct validity and factor loadings (Serrano Archimi, Reynaud, Yasin & Bhatti, 2018). The factor loadings of this model contain values between 0.629 and 0.891 which is reasonably above the prescribed threshold of 0.50. The items with factor loadings less than 0.6 were deleted. The items deleted are as follows; AD2, CS7 after failing to meet the requirements for the CFA.

Table 16: Results of the Fit Indices CFA and structural model

Fit Index	**Recommended Value**	**CFA Results**	**Final Structural Model**
Goodness-of-fit (GFI)	Less than 0.80 (No fit) Between [0.80-0.90] (acceptable) Above 0.90 (Perfect fit)	0,702	0.970
Normed fit index (NFI)	Less than .80 (poor) Between [0.80-0.90] (acceptable) Above 0.90 (good)	0,665	0.944
Comparative fit index (CFI)	Less than 0.90 (poor) Above 0.90 (good)	0,757	0.970
Incremental fit index (IFI)	Less than 0.90 (poor) Above 0.90 (good)	0,763	0.972
Root mean square error of approximation (RMSEA)	Less than 0.05 (good) Between [0.06-1] (acceptable) Above 1 (poor)	0,98	0.020
Chi-square (χ2 /DF)	Less than 3 (good) Between [3-5] (acceptable) Above 5 (poor)	4	2
Tucker-Lewis Index (TLI)	Less than 0.80 (poor) Between [0.80-0.90] (acceptable) Above 0.90 (good)	0,718	0.911
Relative Fit Index (RFI)	Less than 0.80 (poor) Between [.80-.90] (acceptable) Above .90 (good)	0,611	0.831

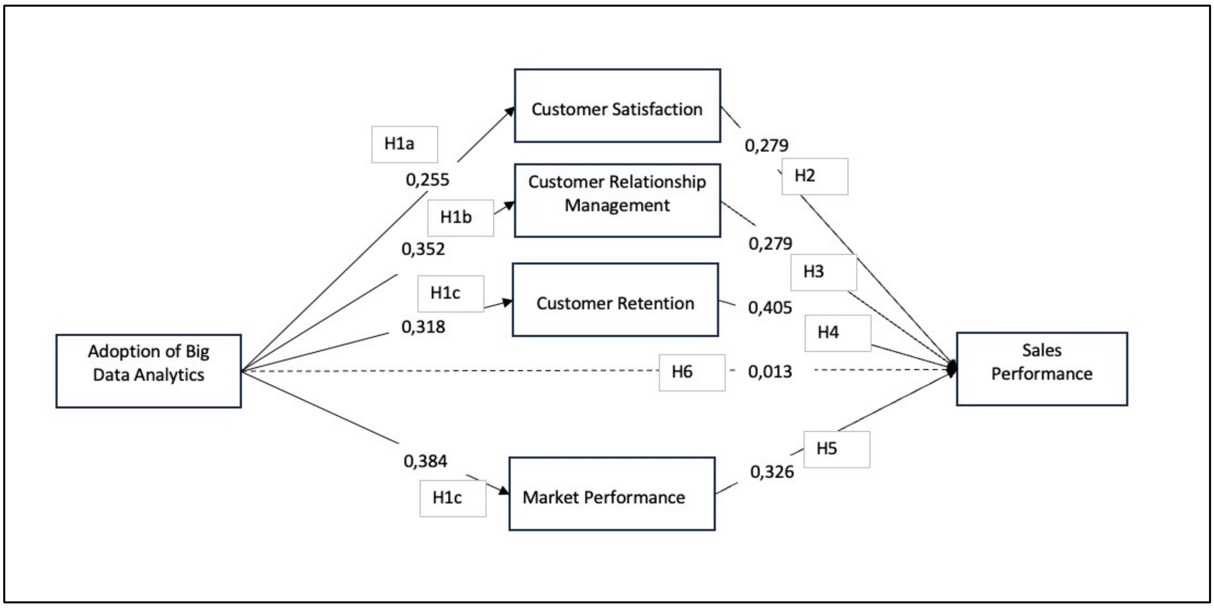


Figure 6: Measurement Model Test Results

Source: Adopted from Shahbaz et al. (2020)

4.10.3 Final Model Testing

The results of the final SEM AMOS model are presented in table 17 below. The final model fit has p=0,005 which is good and a Chi-square of two which is acceptable and less than the recommended value of three. The fit indices of the final model generally improved when compared to the fit indices results achieved in the CFA. The final model fit indices, as presented in table 17, indicate a good model fit in all the indices. The hypothesised relationships are presented in figure 5. The final goodness of fit indices' values allow for the research to proceed with examination of the hypothesised relationships. Table 18 presents the R-squared coefficients for the dependent variables. The model explained 16.8% of customer service variance, 30% of market performance variance, while customer relationship management, customer retention and sales performance explained 38%, 21.9% and 51.5% of the variance observed respectively.

The study model was developed to measure the impact of the adoption of BDA on sales performance through the mediating effects of customer performance. Adoption of BDA is the dependent variable in the model, and it is measuring the extent to which BDA has been diffused in the organisation and is used to influence decisions when dealing with customers.

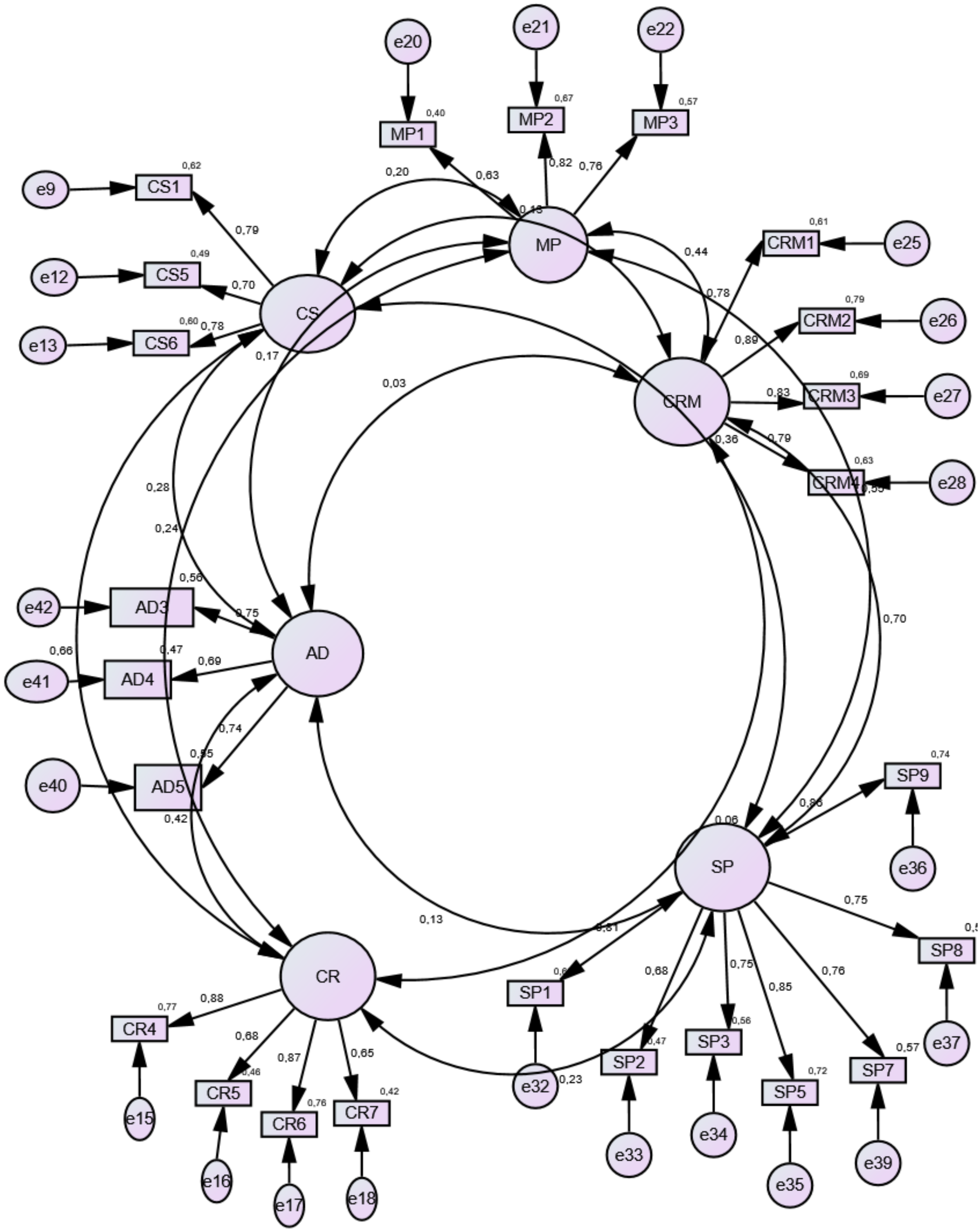


Figure 7: CFA measurement model

Table 17: The results of hypothesised model

Hypothesis	Path	Estimate	S.E.	C.R.	P	Supported
H1a	AD ---> CS	0,255	0,095	2,694	0,007	Yes
H1b	AD ---> CRM	0,352	0,139	2,532	0,015	Yes
H1c	AD ---> CR	0,318	0,087	3,651	***	Yes
H1d	AD ---> MP	0,384	0,105	3,657	***	Yes
H2	CS ---> SP	0,279	0,113	2,469	0,03	Yes
H3	CRM --->SP	0,559	0,143	3,909	***	Yes
H4	CR --->SP	0,405	0,124	3,266	***	Yes
H5	MP ---> SP	0,326	0,091	3,582	***	Yes
H6	AD ---> SP	0,013	0,9	0,014	0,888	No

Table 18: R-squared results

Variables	Estimate
CS	0,168
MP	0,300
CRM	0,380
CR	0,219
SP	0,515

As presented in table 17, seven out of eight of the hypotheses were supported by the model tested. The adoption of BDA was found to have a significant positive influence on customer satisfaction ($p<0.01$), customer relationship management ($p<0.01$), customer retention ($p<0.001$), market performance ($p<0.001$). Therefore, H1a, H1b, H1c and H1d are supported. This confirms that the adoption of BDA improves customer performance of the organisations.

In addition, customer satisfaction has been found to have a significant positive impact on sales performance ($p<0.05$). This confirms that customer satisfaction does play a mediating role in improving sales performance through the adoption of BDA. Therefore, H2 is supported. Customer relationship management has been found to have a significant positive impact on sales performance ($p<0.001$). This confirms that customer relationship management does play a mediating role in improving sales performance through the adoption of BDA. Therefore, H3 is supported. Furthermore, customer retention has been found to have a significant positive impact on sales performance ($p<0.001$). This confirms that customer retention plays a mediating role in improving sales performance through the adoption of BDA. This supports H4. Additionally, market performance has been found to have a significant positive impact on sales performance ($p<0.001$). This confirms that market performance plays a mediating role in improving sales performance through the adoption of BDA. This supports H5. However, the adoption of BDA was found to have no direct significant influence on sales performance ($p>0.05$). This confirms that adoption of BDA does not have a direct impact on improving sales performance of an organisation, therefore H6 is rejected.

The model hypothesised that the adoption of BDA has a direct influence on sales performance which was then rejected, however it was found that adoption and use of BDA can indirectly improve sales performance through mediating effects, namely, customer satisfaction, customer retention, customer relationship management and market performance.

The improvement in sales performance through mediating factors may occur because organisations that have long-term relationships with satisfied customers can charge a premium for their services resulting in higher sales (Zeithaml et al., 1996). CRM can improve revenue when it is used to identify and manage profitable customers (Wang & Feng, 2012). Through retaining customers and sustaining repeat purchases, customer retention can result in improved profitability (Molise-Khosa, 2014; Almohaimmed, 2019).

4.11 Conclusion

This chapter has presented the analysis of the results collected from the surveys. The detailed analysis has surfaced insights as well as addressed the two research objectives of the study. Some of the insightful outcomes is that 92% of organisations that participated in the study have adopted BDA. The detailed analysis addresses both research objectives of the study. The first research objective was to determine if the adoption of BDA has a direct impact on sales performance. Through the results, it has been shown that the adoption of BDA does not have a direct impact on sales performance. The second objective was to determine if customer performance plays a mediating role between adoption of BDA and sales performance. Through the results that have been presented, there is evidence that customer performance plays a mediating role on sales performance. In the next chapter, the results are discussed in detail. The elements influencing the results are explored.

CHAPTER 5: DISCUSSION OF THE RESULTS

5.1 Introduction

The previous chapter (chapter 4) presented the empirical results of the study. This study has two main objectives, the first one being to examine the impact of the adoption of Big Data Analytics (BDA) on the sales performance of an organisation. The second objective is to examine the impact of BDA on sales performance through customer performance as a mediating factor. Adoption of BDA has to do with the purchasing and use of BDA systems to improve business operations (Gunasekaran et al., 2017). Most of the organisations (92%) that participated in the survey indicated that they have adopted BDA. Two main outcomes were found from this study. The first finding is that adoption of BDA does not have a direct impact on sales performance of an organisation. The second finding is that adoption of BDA has an impact on sales performance through customer performance measures as mediating factors. The findings of the study are discussed in detail below.

5.2 Adoption of BDA and Customer Performance

The aim of adopting BDA is to generate incremental value for the organisation by using analytical systems (OECD, 2013). Organisations also adopt BDA for the creation of innovation and to foster disruption (NewVantage Partners, 2017). Organisations adopt BDA because they wish to leverage the vast amounts of data available from many sources, such as social media, RFID tags, mobile phones and other customer interactions points (Davenport, 2014). Of the organisations surveyed for this study, 92% of them indicated that they had adopted BDA and that it is being used in sales and marketing functions.

Adoption of BDA was found to have significant influence on customer satisfaction. This supports H1a. Customer satisfaction is a result of how goods and services' performance meet or surpass the expectations of customers (Anderson & Sullivan, 1993). The customer's expectation can be exceeded by resolving queries timeously, interacting with customers on their preferred channels, delivering products and services on time, etc. BDA can be used to improve customer satisfaction by identifying demand patterns and predicting what customers need (Ernst & Young, 2014). Anticipating what customers need and suggesting those products can reduce time taken shopping online. Suggesting products can also help customers discover items that they may like. BDA systems can collect customer data and use it to build intelligence on each individual customer to deliver personalised experiences, e.g., suggesting yoghurt for customers who have muesli in their grocery cart. This enhances customer experience and makes customers feel that they are given special treatment that is unique. Paradigma (2015) found that big data has a positive impact on customer satisfaction, however their study focused on data from social media only. The Paradigma (2015) study provides outcomes based on a single source of data which is limited, considering the different types of data sources to which BDA can be applied. Therefore, this study provides more insight into the implications of BDA on customer satisfaction.

Importantly, adoption of BDA was found to have a positive significant influence on Customer Relationship Management (CRM). CRM, as a function, is an enabler for organisations to build customer relationships and improve customer service (Hsieh, 2009). CRM capabilities provide customer details to front office workers to have enriched interactions with customers. BDA feeds relevant customer insights into CRM tools and therefore allows front office (marketing, sales, and customer service) workers to have better interactions. CRM is about better interaction with customers. BDA can be used to identify open queries from customers and resolve them timeously. BDA can also be used to segment customers and supply the segments to CRM functions for targeted marketing. Managing the business pipeline, identifying high win opportunities, and the current share of wallet can be achieved by using BDA. This can increase chances of making impactful proposals for clients. This study's findings that BDA enhances CRM performance are new and supports H1b. Findings by Shahbaz et al. (2021) measured the impact that individual's perceptions of BDA may have on CRM capabilities while this study measured the impact of the adoption of BDA.

In addition, the adoption of BDA was found to have a positive significant influence on customer retention. This is in line with the study's hypothesis that organisations which have adopted BDA, experience an improvement in customer retention and therefore supports H1c. Customer retention refers to the organisation's ability to keep customers coming back to buy more products and services (Gerpott et al., 2001). Customer retention is also about sustaining continuous profitability of customers (Lenskold

Group, 2003). Customer retention can be achieved by responding to queries timeously, rewarding loyal customers with incentives, upgrading expiring products, etc. BDA can be used to enhance customer retention capabilities. BDA can be used to predict customers who are inactive or likely to churn and offer them sweet deals, so they are retained. BDA can also be used to analyse customer feedback from phone calls, emails, social media, etc. to gauge their sentiment. Having such insights allows organisations to appreciate the customers' feelings and interact with them accordingly. Using BDA, organisations can identify when the products customers have do not suit their needs, for example, if a customer depletes their data bundle allocation 15 days into the month. Such customers can be offered higher packages to fulfill their needs and keep them engaged. Cross-sell opportunities can also be identified using BDA. Cross-selling is about selling a different product or service to an existing customer (Shopify, 2022). The more a customer holds different products from the same supplier, the harder it is for the customer to leave, especially for integrated products such as Apple products, thereby ensuring retention. This is a demonstration of how BDA adoption impacts customer retention. This is a new contribution as Giebe et al. (2019) measured the impact of BDA on customer loyalty and not specifically the customer retention aspect.

BDA was found to have a positive significant influence on market performance. Market performance is about the ability to penetrate new markets faster than competitors, introduce new products and services more frequently than competitors and control a majority stake of the market (Mithas, Ramasubbu & Sambamurthy, 2011; Tippins & Sohi, 2003). In summary, market performance is about doing better than competitors. As the amount of data available to organisations increases and the insights drawn from such data are applied to meet customer needs, this can lead to a market advantage. For example, BDA can be used to mine competitor pricing from their website to compile a competitor pricing analysis. Another way to gain market advantage is extracting data from Annual Financial Statements to understand how much their competitors are spending on products. If the gap between what they spend and what the organisation earns is large, that can be an opportunity to increase share of wallet. As such, when the data analysed is used to make strategic decisions that lead to positive market outcomes, then it can be said that investments in BDA improves market performance. This study contributed new evidence that shows BDA improves market performance and supports H1d. Previous studies by Olabode et al. (2022) found that BDA improves market performance through mediating factors, while this study did not consider mediating factors.

5.3 Customer Performance and Sales Performance

Sales performance as an objective outcome can be viewed as sales volumes, conversion rate, market share, etc. but for the purpose of this study, sales volumes was considered (Walker et al., 1979). For this study, perceived sales performance from the view of the respondent is used. Actual sales volumes from Annual Financial Statements are not used to evaluate the results for this study.

This study found that customer satisfaction has a positive significant impact on sales performance therefore confirming H2. Customer satisfaction occurs when organisations deliver better products and services than the customer expected. Customers are satisfied when the perceived performance of the products or service is greater than the expected performance. Customer satisfaction is considered to affect retention, leading to long term repeat purchases (sales) (Anderson & Sullivan, 1993). Customer satisfaction can also be achieved by resolving customer queries faster through the channels that the customer prefers. BDA can be leveraged to mine data on customer's most used and preferred channels and therefore to contact customers on those channels. When customers perceive the service they receive as superior, they perceive this as receiving better value for more, thereby they are less incentivised to move to competitors.

This study also found that CRM has a positive significant impact on sales performance thereby supporting H3. The main benefit of CRM is better customer service. Better customer service leads to retained and satisfied customers, which can convince customers not to spend their money with competitors. CRM also uses advanced analytics to nurture leads by sending out alerts to salespersons to reach out to customers when they hit certain milestones. This allows sales to position products when customers need them, thereby increasing chances of conversion. CRM is also used during a sales process, and it shows customer information, such as demographics, product holding, current spend, etc. When the salesperson has this information at their disposal, it can be easier to recommend products that suit the customers' needs, increasing chances of conversion. This is how CRM improves sales performance. CRM capabilities are supported by BDA systems through the supply of customer data and insights. The quality of CRM capabilities in the organisation improves with that of the analysed information. The results of the study are not surprising as they are in line with prior studies by Chatterjee, Chaudhuri and Vrontis (2022), which also found a positive relationship between CRM capabilities and improved sales performance. This study advances the understanding of CRM as a mediating factor between the adoption of BDA and sales performance.

Customer retention was found to have a positive mediating relationship between the adoption of BDA and sales performance. This finding supports H4. Customer retention is when a customer makes repeat purchases of products or services. When a customer stays longer in a relationship with an organisation, the more profits occur, since acquisition costs are generated at the beginning of the relationship (Edvardsson et al., 2000). Using upselling, cross-selling as a retention strategy can be used to increase sales performance (Edvardsson et al., 2000). Upsell and cross-sell happen when organisations leverage existing relationships to increase sales. One way to increase sales is to migrate existing customers to higher packages in the product portfolio or by cross-selling different product classes. Increasing product penetration across the customer base also improves overall sales. Customers can also be offered discounts, so they make more purchases, thereby improving sales. The study by Shahbaz et al., (2020) investigated the impact of customer relationship upgrading capability (CRUC) and customer win-back capability (CWBC) on sales performance. The two factors are different to customer retention as they refer to winning back customers who stopped engaging the organisation, while customer retention is about preventing existing customers from leaving. The study of Shahbaz et al. (2020) found a positive relationship between CRUC and CWBC and sales performance. This study contributed new knowledge by considering customer retention. Since customer retention is used in the context of the adoption of BDA, it can be said that the adoption of BDA improves sales performance through the mediating effect of customer retention.

Additionally, this study found that market performance has a significant and positive impact on sales performance, and this therefore supports H5. Market performance can increase sales performance in various ways, namely, stimulating sales by selling in new markets, introducing new products and in turn, generating positive recommendations among customers. BDA informs strategic marketing, new products development and segmenting customers, thus creating a market positioning capability that is used to stimulate sales (Tan et al., 2015; Wamba et al., 2015; Wamba, Ngai, Riggins & Akter, 2017). Given the importance of market performance on sales performance, it was critical for this study to evaluate the mediating role between BDA adoption and sales performance. Raguseo and Vitari (2017) found that market performance does not play a mediating role between the adoption of BDA and sales performance. This study has found differently to Raguseo and Vitari (2017), thereby making a new contribution to this field of research.

Adoption of BDA was found to have a non-significant influence on sales performance. This outcome supports H6. The p-value for the path of adoption of BDA to sales performance is 0.888 which points to the study's hypothesis not being supported. These results came as a surprise as numerous studies previously came to conclusions that the adoption of BDA has a direct impact on financial performance (Raguseo & Vitari, 2018; Hallikainene, Savimaki & Laukkanen, 2019; Wamba et al., 2019). The outcomes of this study provide new evidence that sales performance cannot be improved directly by adopting BDA. The evidence however, shows that the adoption of BDA can improve sales performance through customer performance as a mediating factor. This is a critical development in the study of BDA and firm performance.

5.4 Conclusion

This chapter exhibited the interpretation of the key findings for the structural model in detail. The model for this study tested the relationships between the observed and latent variables. The model focused on testing the direct and indirect impact that the adoption of BDA may have on sales performance. The study contributed to literature by introducing customer performance (non-financial performance) to the measurement of BDA adoption outcomes. Furthermore, the study examined the different customer performance measures independently instead of aggregating them. The study extends on the work of Shahbaz et al. (2020) by adding additional customer performance measures, namely, customer retention, customer satisfaction and market performance whereas the study by Shahbaz et al. (2020) only considered CRM as the non-financial performance measure. The study by Shahbaz et al. (2020) broke down the CRM capability into three components namely, customer interaction capability, customer relationship upgrading capability and customer win-back capability, these components however are different to the ones proposed in the current study and therefore the study contributes new knowledge. The study found that the adoption of BDA has a positive impact on customer performance measures. The study also found that the adoption of BDA has an indirect impact on sales performance through customer performance as mediating factors. The direct impact of BDA on sales performance outcomes is insignificant.

CHAPTER 6: CONCLUSION AND RECOMMENDATIONS

6.1 Introduction

The previous chapter (chapter 5) showed the impact that BDA adoption has on sales and customer performance outcomes of the organisation. This chapter provides the conclusions of the research findings. The chapter starts by providing the overall summary of this research and thereafter, highlights the contributions of the study which range from theoretical, contextual, methodological, and practical contributions. In addition, the section discusses the research limitations and how future studies can extend the work of this study. The last section provides an overall conclusion to the report.

6.2 Summary of the study

In chapter 1, the study introduced the research problems along with the motivation of conducting the study. The study investigated two research problems. The first problem that the study investigated is the direct impact that adoption of BDA has on sales performance of an organisation. It was found that previous studies have not focused on sales performance as an outcome, but rather focused on firm performance which is a generic measure of organisational outcomes. The second problem that the study investigated is the impact that adoption of BDA has on sales performance through non-financial performance measures as mediating factors. Prior studies have not combined the investigation of sales performance (financial) and customer performance (non-financial) outcomes because of adopting BDA, thereby not giving a balanced view of organisational outcomes. This has resulted in understanding financial or non-financial outcomes in isolation, thereby not providing a balanced view. In addressing the two research problems, two research objectives were developed namely RO1 and RO2.

In chapter 2, the literature review was presented. The study introduced BDA and its components by giving a background and history of how it evolved from earlier technologies to where it is today. The characteristics observed in Big Data are also discussed and it is further articulated what Big Data is and what it is not. The chapter also discussed the benefits associated with deploying Big Data technologies as well as challenges that are faced by organisations that have deployed these systems and the risks that may be faced by organisations which are considering adoption. Prior research had provided a view of the impact of BDA on firm performance and not a view of sales performance as an outcome, therefore the literature indicated that there was a need to understand sales performance outcomes. Further, the use of non-financial performance measures as mediating factors between the adoption of BDA and sales performance needed to be understood. The results of the investigation would contribute much needed evidence for organisations that need to understand how to derive value from their BDA investments.

In chapter 3, the research methodology that was used to test the research models was presented and discussed. The study was informed by a positivist perspective and a quantitative deductive approach to hypothesis testing was implemented. The study used online surveys to collect data from sales and marketing professionals who represented the top 200 (by market capitalisation) organisations listed on the JSE. Multi-item scales were used to collect the data and reliability and validity tests were implemented to ensure conformity to relevant testing standards. The model was tested using SEM techniques. The data was analysed using statistical software, SPSS AMOS version 25.

Chapter 4 presented the detailed findings and interpretations of the structural model hypothesising the effects of the adoption of BDA on sales performance, both directly and indirectly. The results of the study confirm that the adoption of BDA positively improves customer performance ("customer retention", "customer relationship management", "customer satisfaction" and "market performance"). In addition, the study found that the adoption of BDA does not directly improve sales performance. Overall, eight of nine of the hypothesis for this study were supported.

Chapter 5 discussed the findings of the study. It articulates in detail how the causal relationships between adoption of BDA, customer performance measures and sales performance. This chapter presented the detailed interpretations of the impacts of the model concepts on sales performance and how those impacts are achieved.

6.3 Contribution of the study

This report examined the use of BDA systems and their impact on the sales performance. This has allowed the report to make theoretical, contextual, methodological, and practical contributions.

6.3.1 Theoretical contribution

First, a theoretical contribution is made by adopting and extending the conceptual model by Shahbaz et al. (2020). The study by Shahbaz et al. (2020) investigated the impact of BDA on sales performance directly and through CRM as a mediating factor. This study extended their model by adding customer retention, customer satisfaction and market performance as mediating factors. The addition of more mediating factors provides a broader understanding of other factors (beyond CRM) that mediate the relationship between BDA and sales performance.

6.3.2 Contextual contribution

Secondly, the study makes a contextual contribution by examining the impact of BDA at organisational level in the South African business context. The study enhances understanding of perceived outcomes because of BDA investment. The study further highlights the context in which the adoption of BDA results in improved sales. Understanding that adoption of BDA alone is not sufficient to improve sales performance is important for business context. The use of BDA should be in the context of mediating factors such as customer satisfaction, customer retention, CRM, and market performance. This will help organisations create the environment necessary to derive value from BDA investments.

6.3.3 Methodological contribution

The study contributes methodologically by operationalising the measures of customer satisfaction, customer retention, CRM, market performance and sales performance, as informed by the literature studied. The results of the study enhances understanding of benefits from customer performance measures and the sales performance perspective. The study uses structural equation modelling (SEM) to understand the success of the adoption of BDA. SEM is a multivariate statistical procedure that encompasses both multiple regression analysis and factor analysis in testing the hypothesised model, to establish causality within latent (or construct) and observed variables that are part of the model (Barrett, 2007; Sangthong, 2020). This study demonstrates how SEM can be used in BDA and performance research as a technique for analysis.

6.3.4 Practical contribution

The practical contribution that this study has made is that it can assist organisations to improve decision making when adopting BDA systems. The study also showed the types of mediating factors that can be used to achieve positive outcomes.

There are practical consequences for understanding how to derive value from BDA investments. This study found that adopting BDA does not automatically lead to a positive impact on sales performance. Future research should use qualitative techniques to understand why this does not occur. The study also found that adoption of BDA leads to improved sales performance when mediating factors are employed. The mediating factors that enhance sales performance are customer satisfaction, customer retention, customer relationship management and market performance. Organisations should consider building these performance measures to improve sales when adopting BDA. Sales and marketing practitioners can now understand which customer performance factors can be enhanced by using BDA. BDA can play a role in improving their KPIs if BDA is used in their functions to support customer performance.

6.4 Limitations

There are several limitations to which this study is subjected which need to be acknowledged. The data was collected using a cross-sectional survey, which represents perceptions at a single point in time. Common method bias may exist as a result of the above limitation. The second limitation is that data on all variables was collected from a single respondent which may also cause common method bias. The third limitation arises with respect to response bias such as self-reflection bias and social desirability bias (Byrne, 2013). Fourthly, time constrains may have prevented some respondents from filling in the survey. Fifth, the surveys measure the perception of the respondents with respect to performance, not the actual performance.

6.5 Recommendations for future research

Future research should continue to find balanced ways of reporting on the impact of BDA adoption not just to focus on sales performance outcomes. Other customer performance mediating factors beyond customer and market performance should be researched to advance the understanding of which factors may mediate the improvement of sales performance. There are a variety of factors that could be considered as mediating factors such as internal business processes, automation, and decision support. These were not included in the study due to the focus of the scope, but they may be important measures that could impact financial performance through the adoption of BDA.

One of the study's hypotheses, H6, was not supported. The study found that adoption of BDA does not have a direct impact on sales performance. To further probe this finding, future research may use qualitative case study analysis to explore why this may be the case.

6.6 Conclusion

This study has demonstrated that adoption of BDA by South Africa organisations does not lead to the direct improvement of financial performance, however, it does lead to the improvement of customer performance (non-financial performance) and leads to indirect improvement of sales performance (financial performance) through mediating factors. The results confirm that the usage of BDA improves customer performance, as well as improves sales performance indirectly through mediating factors. The results also confirm that the use of BDA does not directly improve sales performance. This study has shown that organisations can justify investments into BDA, given that customer performance capabilities are developed to foster improved sales growth. BDA investments can also be justified when improving customer and sales performance is the aim.

REFERENCES

Ahearne, M., Hughes, D. & Schillewaert, N., 2007. Why sales reps should welcome information technology: Measuring the impact of CRM-based IT on sales effectiveness. *International Journal of Research in Marketing,* 24(4), pp. 336 - 349.

Ahrens, J. P. et al., 2011. Data-intensive science in the US DOE: case studies and future challenges. *Comput. Sci. Eng,* 13(6), pp. 14-24.

Akter, S. et al., 2016. How to improve firm performance using big data analytics capability and business strategy alignment. *International Journal of Production Economics,* 182(1), pp. 113-131.

Almohaimmeed, B., 2019. Pillars of customer retention: An emperical study on the influence of customer satisfaction, customer loyalty, customer profitability on customer retention. *Serbian Journal of Management,* 14(2), pp. 421-435.

Ang, L. & Buttle, F., 2006. Customer retention management processes: A quantitative study. *European Journal of Marketing,* 40(1), pp. 83-99.

Bantleman, J., 2012. *Forbes.* [Online]
Available at: https://www.forbes.com/sites/ciocentral/2012/04/16/the-big-cost-of-big-data/?sh=638d29cc5a3b
[Accessed 22 April 2023].

Barusman, A., Rulian, E. & Susanto, S., 2019. The antecedent of customer satisfaction and its impact on customer retention in tourism as tospitality industry.. *International Journal of Advanced Science and Technology,* 28(8), pp. 322-330.

Bhandari, P., 2022. *Scribbr.* [Online]
Available at: https://www.scribbr.com/methodology/external-validity/
[Accessed 30 January 2023].

Bollier, D., 2010. *The promise and peril of Big Data,* Washington: Aspen Institute Communications and Society Program.

Buldoo, D., 2018. *Leveraging Big Data Analytics for Competitive Advantage in South African Banking,* Pretoria: Gordon Institute of Business Science.

Byrne, B. M., 2013. *Structural Equation Modeling with AMOS: Basic Concepts, Applications, and Programming.* London: Routledge.

CEIC, 2022. *CEIC.* [Online]
Available at: https://www.ceicdata.com/en/south-africa/johannesburg-stock-exchange-number-of-companies/no-of-listed-companies-jse
[Accessed 11 February 2023].

Chen, H., Chiang, R. & Storey, V., 2012. Business intelligence and analytics: From big data to big impact. *MIS Quartely,* 36(4), pp. 1165-1188.

Chi, C. & Gursoy, D., 2009. Employee satisfaction, customer satisfaction, and financial performance: An empirical examination. *International Journal of Hospitality Management,* 28(2), pp. 245 - 253.

Cohen, L., Manion, L. & & Morrison, K., 2007. *Research Methods in Education.* 6 ed. London and New York: Routledge Falmer.

Coltman, T., Devinney, T. & Midgley, D., 2011. Customer relationship management and firm performance. *Journal of Information Technology,* 26(3), pp. 205 - 219.

Darius, Z., 2007. *Customer performance measurement: Analysis of the benefit of a fuzzy classification approach in customer relationship management,* Friborg: University of Friborg Switzerland.

Davenport, H., 2006. *Competing on analytics,* Massachusetts: Harvard Business Review.

Davenport, T., 2013. *Analytics 3.0,* Massachusetts: Harvard Business Review.

De Mendonca, T. & Zhou, Y., 2019. Environmental performance, customer satisfaction, and profitability: A study among large U.S. Companies. *Sustainability,* 11(19).

Enterprise Big Data Framework, 2019. *Big Data Framework.* [Online]
Available at: https://www.bigdataframework.org/short-history-of-big-data/
[Accessed 18 February 2023].

Enterprise Management Associates, 2017. *Making Sense of Big Data: A Day in the Life of an Enterprise Architect,* Boulder: IBM.

Erevelles, S., Fukawa, N. & Swayne, L., 2015. Big Data consumer analytics and the transformation of marketing. *Journal of Business Research,* 69(2), pp. 897-904.

Fan, W. & Bifet, A., 2012. Mining Big Data: current status, and forecast to the future. *ACM SIGKDD Explorations Newsletter,* 14(2), pp. 1-5.

Fertik, M., 2012. Big Data, privacy, and the huge opportunity in the monetization of trust. *World Economy on Market Research,* 55(4), pp. 2-13.

Fosso Wamba, S. et al., 2017. Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research,* 70(1), pp. 356-365.

Frank, K. A., Zhao, Y. & & Borman, K., 2004. Social capital and the diffusion of innovations within organizations: The case of computer technology in schools. *Sociology of Education,* 77(2), pp. 148 - 171.

Frizzo-Barker, J., Chow-White, P., Mozafari, M. & Ha, A., 2016. An empirical study of the rise of big data in business scholarship. *International Journal of Information Management,* 36(3), pp. 404-413.

Gavin, R. et al., 2020. *The B2B digital inflection point: How sales have changed during COVID-19,* New York: McKinsey & Company.

George, D. &. M. P., 2010. *SPSS for Windows Step by Step: A Simple Guide and Reference 17.0 Update.* Boston: Pearson.

Giebe, C., Hammerstrom, L. & Zwerenz, D., 2019. Big Data & Analytics as a sustainable customer loyalty instrument in banking and finance. *Financial Markets, Institutions and Risks,* 3(4), pp. 74-88.

Godson, M., 2009. *Relationship marketing.* Oxford: Oxford University Press.

Gregor, S. et al., 2006. The transformational dimension in the realization of business value from information technology. *The Journal of Strategic Information Systems,* 15(3), p. 249–270.

Hair, J., Ringle, C. & Sarstedt, M., 2010. Partial least squares: The better approach to structural equation modeling?. *Long Range Planning,* 45(5-6), pp. 312 - 319.

Hallikainen, H., Savimäki, E. & Laukkanen, T., 2020. Fostering B2B sales with customer big data analytics. *Industrial Marketing Management,* 86(1), pp. 90 -98.

Hausmann, R. et al., 2022. *Macroeconomic risks after a decade of microeconomic turbulence,* Tokyo: United Nations University.

Heale, R. & Twycross, A., 2015. Validity and reliability in quantitative studies. *Evidence based nursing,* 18(1), pp. 66-67.

Homburg, C., Koschate, N. & Hoyer, W., 2005. Do satisfied customers really pay more: A study of the relationship between customer satisfaction and willingness to pay. *Journal of Marketing,* 69(2), pp. 84 - 96.

Homburg, C., Vomberg, A., Enke, M. & & Grimm, P., 2015. The loss of the marketing department's influence: Is it really happening? And why worry?. *Journal of the academy of marketing science,* 43(1), pp. 1-13.

Hsieh, M., 2009. A case of managing customer relationship management systems: Empirical insights and lessons learned. *International Journal of Information Management,* 29(5), pp. 416 - 419.

Hussain, S., 2019. *Towards Data Science.* [Online]
Available at: https://medium.com/@syedjunaid.h47/what-is-big-data-why-is-big-data-important-in-todays-era-8dbc9314fb0a
[Accessed 8 September 2022].

IBM, 2022. *IBM.* [Online]
Available at: https://www.ibm.com/za-en/analytics/big-data-analytics#:~:text=Overview-,Overview,sizes%20from%20terabytes%20to%20zettabytes.
[Accessed 20 September 2022].

Ishwarappa & Anuradha, J., 2015. *A brief introduction on Big Data 5Vscharacteristics and hadoop technolgy.* Bhubaneswar, Elsevier, pp. 319 - 324.

Jarvis, D, 2020. *The AI takent shortage isn't over,* New York: Deloitte Insights.

Jeng, D. & Bailey, T., 2012. Assessing customer retention strategies in mobile telecommunications: Hybrid MCDM approach. *Management Decision,* 50(9), pp. 1570 - 1595.

Jiang, W. & Chai, H., 2016. *Research on big data in business model innovation based on GABP model.* Chicago, IEEE, pp. 174 - 117.

Ji-fan Ren, S. et al., 2016. Modelling quality dynamics, business value and firm performance in a big data analytics environment. *International Journal of Production Research,* 55(17), pp. 1 -16.

Jong-Hyun, P., Moon-Koo, K. & Jong-Hyun, P., 2015. *The factors of technology, organization and environment influencing the adoption and usage of Big Data in Korean firms.* Madrid, International Telecommunications Society.

Kaplan, R. & Norton, D., 1996. *Using the balanced scorecard as a strategic management system,* Massachusetts: Harvard Business Review.

Kasim, A. & Minai, B., 2009. Linking CRM strategy, customer performance measures in the hotel industry. *International Journal of Economics and Management,* 3(2), pp. 297 - 316.

Katal, A., Wazid, M. & Gouder, R., 2013. *Big Data: issues, challenges, tools, and good practices..* Nodia, IEEE, pp. 8-10.

Khan, N. et al., 2014. Big Data: Survey, technologies, opportunities and challenges. *The Scientific World Journal Article,* p. 18 pages.

Kotler, P. & Keller, K., 2003. *Marketing management.* London: Pearson Education.

Kotler, P. & Keller, K., 2016. *Marketing Management.* London: Pearson Education.

Krosnick, J. & Presser, S., 2010. *Question and questionnaire design.* Stanford: Stanford University.

Lugmayr, A., Stockleben, B. S. C. & Mailaparampil, M., 2017. Cognitive big data: Survey and reveiw on big data research and its implications. What is really "new" big data?. *Journal of knowledge management,* 21(1), pp. 197-212.

Lycett, M., 2013. Datafication: making sense of (big) data in a complex world. *European Journal of Information Systems,* 22(4), pp. 381 - 386.

Manyika, J. et al., 2011. *Big Data: The next frontier for innovation, competiton, and productivity,* Atlanta: McKinsey Global Institute.

Marchena Sekli, G. & De La Vega, I., 2021. Adoption of Big Data Analytics and Its impact on organizational performance in higher education mediated by knowledge management. *Journal for Open Innovation Technology Marketing Complex,* 7(4), p. 221.

Maxwell, J., 2005. *Qualitative Research Design : An Interactive Approach.* Fairfax: SAGE Publications Inc.

Mayer-Schonberger, V. & Cukier, K., 2013. *Big Data: A revolution that will transform how we live, work, and think.* New York: Houghton Mifflin Harcourt.

McCombes, S., 2022. *Scribbr.* [Online]
Available at: https://www.scribbr.com/methodology/sampling-methods/
[Accessed 2 March 2023].

McKinsey & Company, 2019. *The future of work in South Africa: Digitisation, productivity and job creation.,* Johannesburg: McKinsey & Company.

Melville, N., Kraemer, K. & Gurbaxani, V., 2004. Information technology and organizational performance: An integrative model of IT business value. *MIS Quarterly,* 28(2), pp. 283 - 322.

Micheni, E., 2015. Diffusion of big data and analytics in developing countries. *The International Journal Of Engineering And Science,* pp. 44 - 50.

Mills, T., 2019. *Five Benefits Of Big Data Analytics And How Companies Can Get Started,* New York: Forbes.

Mithas, S., Ramasubbu, N. & Samburthy, V., 2011. How Information Management Capability Influences Firm Performance. *MIS Quarterly,* 35(1), pp. 237-256.

Mneney, J. & Van Belle, W., 2016. *Big Data capabilities and readiness of South African retail organisations.* Cape Town, University of Cape Town, pp. 279 - 286.

Mooney, J. G. V. K. K. L., 2001. *A Process Oriented Framework for Assessing the Business Value of Information Technology.* Irvine, University of California.

Mudau, T., 2021. *The use and impact of business intelligence systems in management accounting: An imperical study in the South African context,* Johannesburg: Wits University.

Naveira, C. F. et al., 2018. *Smarter analytics for banks,* New York: Mckinsey.

NewVantage Partners LLC, 2017. *Big Data Business Impact: Achieving Business Results through Innovation and Disruption,* Boston: NewVantage Partners LLC.

NIBusinessInfo, 2022. *NIBusinessInfo.* [Online]
Available at: https://www.nibusinessinfo.co.uk/print/node/12164
[Accessed 23 September 2022].

Orantes-Jimenez, S. V.-A. G. & Tejeida-Padilla, R., 2017. Impact of customer relationship management on customer loyalty, customer retention and customer profitability for hotelier sector. *Systematics, Cybernetics AND Informatics,* 15(4), pp. 36 - 43.

Oyewo, B., Ajibola, O. & Ajape, A., 2021. Characteristics of consulting firms associated with the diffusion of big data analytics. *Journal of Asian Business and Economic Studies,* 28(4), pp. 281 -302.

Paradigma, 2015. *Big Data applied to Customer Satisfaction intelligence,* s.l.: Paradigma.

Petty, N., Thomson, O. & Stew, G., 2012. Ready for a paradigm shift? Part 2: Introducing qualitative research methodologies and methods. *Manual Therapy,* 17(5), pp. 378 - 384.

Piatetsky, G., 2014. *Research, Creativity, Big Data, and Privacy Part 2.* [Interview] (August 2014).

Preston, C. & Colman, M., 2000. Optimal number of response categories in rating scales: Reliability, validity, discriminating power, and respondent preferences. *Acta Psychologica,* 104(1), pp. 1 - 15.

Pries, K. & Dunnigan., R., 2015. *Big Data Analytics: A practical guide for managers.* New York: CRC Press.

Raguseo, E. & Vitari, C., 2018. Investments in big data analytics and firm performance:an empirical investigation of direct and mediating effects. *International Journal of Production Research,* 56(15), pp. 5206 - 5221.

Rangaswamy, A. & Gupta, S., 1999. *Innovation adoption and diffusion in the digital environment: Some research opportunities.,* philadelphia: The Pennsylvania State University.

Redman, T., 2013. *Data's credibility problem,* Cambridge: Harvard Business Review.

Reichheld, F. & Sasser, W., 2009. *Zero defections: Quality comes to services,* Massachusetts: Harvard Business Review.

Reimann, M., Schilke, O. & Thomas, J., 2010. Customer relationship management and firm performance: The mediating role of business strategy. *Journal of the academy of marketing science,* 38(3), pp. 326 - 346.

Reinman, M. & Schilke, O. T. J., 2009. Customer relationship management and firm performance: The mediating role of business strategy. *Journal of the Academy of Marketing Science,* 38(1), pp. 326-346.

Rodriguez M, H. E., 2011. Customer relationship management (crm)'s impact on b to b sales professionals' collaboration and sales performance.. *Journal of Business-to-Business Mark. ,* p. 335 – 356.

Rogers, E., 2003. *Diffusion of innovations (5th ed.),* New York: Free Press.

Rogers, E. M., 1995. *Diffusion of innovations,* Free Press: New York .

Sangthong, M., 2020. The Effect of the Likert Point Scale and Sample Size on the Efficiency of Parametric and Nonparametric Tests. *Thailand Statistician, 18(1),* pp. 55-64.

Sarsfield, S., 2011. *The Butterfly Effect of Data Quality.* Cambridge, MIT.

Shahbaz, C. et al., 2019. Investigating the adoption of Big Data Analytics in healthcare: the moderating role of resistance to change. *Journal of Big Data,* 6(1), pp. 1 - 20.

Shahbaz, M., Gao, C., Zhai, L. & F., S., 2021. Impact of big data analytics on sales performance in pharmaceutical organizations: The role of customer relationship management capabilities. *PLoS ONE ,* 16(4), pp. 54-67.

Shoemaker, M., 2001. A framework for examining IT-enabled market relationships. *Journal for Personal Sales Management,* 21(2), p. 177 – 185.

Spiegel, E., 2016. *Six challenges of big data.* [Online]
Available at: https://www.wsj.com/articles/BL-258B-2676
[Accessed 25 January 2023].

Statista, 2019. *Big Data Initiatives and Success Rate Among Corporations in the United.* [Online]
Available at: https://www.statista.com/statistics/742935/worldwide-survey-corporate-big-data-initiatives-and-success-rate/
[Accessed 28 August 2022].

Statistics South Africa, 2021. *Quarterly labour force survey, quarter 3, 2021. ,* Pretoria: Statistics South Africa.

Teradata, 2022. *Teradata.* [Online]
Available at: https://www.teradata.com/Glossary/What-is-Unstructured-Data
[Accessed 12 January 2023].

The Insight Partners, 2022. *Big Data Analytics Market,* Pune: The Insight Partners.

Tippins, M. & Sohi, S., 2003. IT competency and firm performance: is organizational learning a missing link?. *Strategic Management Journal,* 24(8), pp. 745-761.

Vaidyanathan, S., 2015. *What are the industry applications of big data analytics?,* Morai: Vel Tech – Technical University.

Van Zyl, G., 2014. *News24.* [Online]
Available at: https://www.news24.com/Fin24/SAs-finance-sector-banking-more-on-big-data-20141207
[Accessed 17 April 2023].

Vonglao, P., 2017. Application of fuzzy logic to improve the Likert scale to measure latent variable. *Kasetsart J Soc Sci, 38(3),* pp. 337-344.

Walker, R. &. B. I., 2019. Big data analytics adoption: A case study in a large South African telecommunications organisation. *South African Journal of Information Management.*

Wang, Y. & Hajli, N., 2017. Exploring the path to big data analytics success in healthcare. *Journal of Business Research,* Volume 70, pp. 287 - 299.

Ward, J. & Barker, A., 2013. *Undefined by data: A survey of big data definitions,* Ithaca: Cornell University Library.

Warren, J., Donald, J., Moffitt, K. & Byrnes, P., 2015. How big data will change accounting. *Accounting Horizons,* 29(2), pp. 397 - 407.

Wernerfelt, B., 171-180. A resource-based view of the firm. *Strategic Management Journal,* 5(2), p. 1984.

Xu, M. & Walton, J., 2005. Gaining customer knowledge through analytical CRM. *Industrial Management and Data Systems,* 105(7), pp. 955 - 971.

Yee, R., Yeung, A. & Cheng, T., 2010. An empirical study of employee loyalty, service quality and firm performance in the service industry. *International Journal of Production Economics,* 124(2), pp. 109-120.

Younas, M., 2019. Research challenges of big data. *Service oriented computing and applications,* 13(1), pp. 105 -107.

Zaire, C., 2021. *Is Data Science Still a Rising Career in 2021?.* [Online]
Available at: https://towardsdatascience.com/is-data-science-still-a-rising-career-in-2021-722281f7074c
[Accessed 4 March 2023].

APPENDIX A: PARTICIPATION INVITATION LETTER AND STUDY INSTRUMENTS

Dear Sir / Madam or Good day

My name is Thando Mngomezulu I am a Master of Management in the field of Digital Business student member 1488952 at the University of the Witwatersrand, Johannesburg. As a degree requirement at Wits, I am conducting a research study on the Mediating Role of Customer Performance on the relationship between Big Data Analytics (BDA) and sales growth. The purpose of the study is to assess whether the adopting Big Data Analytics improves sales directly or whether customer performance measure assist BDA to achieve improved sales performance.

As a user of your organisation's Big Data Analytics, you are invited to take part in a questionnaire If you decide to take part, your participation in this research study will last about 15 minutes. The questionnaire will take place online using a Qualtrics survey. The questionnaire deals with your perceptions about your use of the BDA system and its impact on sales performance. Your response is important and there are no right or wrong answers. This survey is both confidential and anonymous. Anonymity and confidentiality are guaranteed by not needing to enter your name on the questionnaire

With your permission, I would like to record the responses you will give. This data will be stored in Google drive and deleted after one year. Only the researcher will have access to the data.

During the questionnaire, I will need to ask for some personal information about you, including title, organisation name, organisation size and organisation industry.

If you decide to take part in the research study, it should be because you want to volunteer. You do not have to take part. You can stop being in the study at any time. You do not have to answer any questions if you do not want to. You will not get any direct benefits if you choose to join the research study. You will not lose any services, benefits, or rights you would normally have if you decided not to join. Taking part in the research study will not cost you anything. You will not be paid for being in this research study.

This research study will be written up as a research report. The report will be available on the university library website. If you would like to receive a summary of this report, I will be happy to send it to you.

If you have any questions during or afterwards about this research study, feel free to contact me or my supervisor on the details listed below. If you have any concerns or complaints about the ethical procedures of this research study, you are welcome to contact the University Human Research Ethics Committee (Non-Medical), telephone +27(0) 11 717 1408, email hrecnon-medical@wits.ac.za.

Yours sincerely,
Thandolwethu Mngomezulu

Researcher:
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Supervisor:
Dr Norman Mudau, mudauno@yahoo.com

Faculty: Commerce, Law and Management (Chair of Digital Business)
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The Survey is divided into three sections

Part A: Demographic information
Part B: Adoption of BI system
Part C: Impact of BDA on sales performance

This section asks questions about your demographic: Part A information including your experience.

1. Please select the number of years your company has been using Big Data Analytics.

0 years	
<5 years	
5 – 10years	
>10 years	

2. Please indicate the revenue that your organisation generates per annum.

<R20 million	
R21-R100 million	
R101-R500 million	
>R500 million	

3. Please select the industry sector in which your organisation operates.

Manufacturing	
Utilities and energy	
Logistics	
Retail	
Telecom	
Airline	
Pharmaceutical	
Public sector	
Service	
Finance sector	
Mining	
Other (please specify)	

4. Please select your job title.

Chief Sales/Marketing Officer	
Sales/Marketing Manager	
Sales/Marketing Director	
Managing Director	
Executive Director	
Other (please specify)	

5. Please select your years of experience in the organisation.

<5 years	
6-10 years	
11-15 years	
> 16 years	

6. Please indicate the number of years that your company has been in operation.

<5 years	
6-10 years	
11-15 years	
16-20 years	
21-25 years	
26-30 years	
31-35 years	
> 36 years	

Part B: Adoption of BDA system

The purpose of this section is to obtain your opinion on the extent to which Big Data Analytics has been adopted in your organisation.

7. Please indicate the extent in which you agree with each of the following statements related to the Big Data Analytics (BDA) systems that are currently in use in your organisation.

No	Statements	Strongly disagree	Mostly disagree	Disagree	Neutral	Agree	Mostly agree	Strongly agree
AD1	Our organisation uses BDA to develop customer profiles.	1	2	3	4	5	6	7
AD2	Our Organisation uses BDA to segment markets.	1	2	3	4	5	6	7
AD3	Our Organisation uses big data to customize offers.	1	2	3	4	5	6	7
AD4	Our Organisation uses big data to identify our best customers.	1	2	3	4	5	6	7
AD5	Our Organisation uses big data to assess the lifetime value of our customers.	1	2	3	4	5	6	7
AD6	Our Organisation uses big data to identify appropriate channels to reach customers.	1	2	3	4	5	6	7
AD7	Our Organisation uses big data to assess customer retention behaviour.	1	2	3	4	5	6	7

Part C: Impact of BDA on sales performance

The purpose of this section is to obtain your opinion on your organisation's sales performance.

8. Please indicate the extent to which you agree with each of the following statements related to how the organisation has performed relative to the expectation it has set for itself.

No	Statements	Much worse than expected	Worse than expected	Somewhat worse than expected	Neutral	Somewhat better than expected	Better than expected	Much better than expected
CS1	Customer satisfaction performance has been______.	1	2	3	4	5	6	7
CS2	Value delivered to customers has been________	1	2	3	4	5	6	7
CS3	Products and services delivered to customers has been________	1	2	3	4	5	6	7
CS4	Customer interactions through preferred channels has been________	1	2	3	4	5	6	7
CS5	Response time to customers has been_______	1	2	3	4	5	6	7
CS6	Overall customer service rating has been_______	1	2	3	4	5	6	7
CS7	Number of products or services meeting customer's needs has been________							
CR1	Customer product/service choice has been_____	1	2	3	4	5	6	7
CR2	New customer through referral has been______	1	2	3	4	5	6	7
CR3	Time taken to interact with unhappy customer has been_______	1	2	3	4	5	6	7
CR4	Relationship with customers has been_______	1	2	3	4	5	6	7
CR5	Customer retention has been___	1	2	3	4	5	6	7
CR6	Customer feedback has been_______	1	2	3	4	5	6	7
CR7	Organisational image has been______							
MP1	Time to enter new markets has been______	1	2	3	4	5	6	7
MP2	Time to introduce new products/services has been____________	1	2	3	4	5	6	7
MP3	Number of new products/services launched has been_____	1	2	3	4	5	6	7

MP4	Market share performance__________	1	2	3	4	5	6	7
CRM1	Conversion of customer data to customer knowledge has been________	1	2	3	4	5	6	7
CRM2	Customer information infrastructure has been________	1	2	3	4	5	6	7
CRM3	The alignment of incentives, customer strategy, and structure has been________	1	2	3	4	5	6	7
CRM4	Sales team productivity has been_____	1	2	3	4	5	6	7
CRM5	Time taken to resolve customer queries has been__________	1	2	3	4	5	6	7
CRM6	Interactions with customers has been_______	1	2	3	4	5	6	7
CRM7	Sales process performance has been_____							
SP1	The improvement in sales growth rate has been__________	1	2	3	4	5	6	7
SP2	The reduction in sales cost has been________	1	2	3	4	5	6	7
SP3	The sales conversion rate has been________	1	2	3	4	5	6	7
SP4	The increase in turnover has been_________	1	2	3	4	5	6	7
SP5	Sales performance of new products has been_______	1	2	3	4	5	6	7
SP6	The debt collection rate has been_______	1	2	3	4	5	6	7
SP7	Order performance has been_________	1	2	3	4	5	6	7
SP8	Cost per product/service unit has been___________	1	2	3	4	5	6	7
SP9	Number of new sales opportunities has been___________	1	2	3	4	5	6	7

APPENDIX B: ETHICAL CLEARANCE

Graduate School of Business Administration
University of the Witwatersrand, Johannesburg

Wits Business School

Wits Business School Ethics Committee
Constituted under the University Human Research Ethics Committee (Non-Medical)

Ethics Clearance Certificate

Ethics protocol number:	WBS/DB1488952/669

This certificate is only valid with a legitimate ethics protocol number and signed by the Researcher (below).

Project title	The mediating role of customer performance on the relationship between big data analytics and sales
Investigator / Researcher	Mr Thandolwethu Mngomezulu
Nature of Project	MM (Digital Business)
Decision of the Committee	Approved, provided stakeholders and participants are guaranteed confidentialty.
Issue Date of Certificate	2023-02-16
Expiry date	Date of submission of the project / research report
Chairperson	Dr Pius Oba ☎ +27 11 717 3976 +27 82 733 6587 pius.oba@wits.ac.za

Declaration by Researcher

One copy must be signed by the Researcher and returned to the Chairperson of the Wits Business School Ethics Committee.

I fully understand the conditions under which I am authorized to carry out the abovementioned research and I guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I undertake to resubmit the protocol to the Committee.

	18/02/2023
Signature	Date: