Exploring the role of data analytics in enhancing business financial performance within JSE-listed companies in South Africa

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DECLARATION

I **Kholofelo Vincent Monyela** declare herewith that the mini-dissertation titled – exploring the role of data analytics in enhancing business financial performance within JSE-listed companies in South Africa, which I herewith submit to the North-West University in partial compliance with the requirements set for the degree: Master of Business Administration is my own work, has been text edited in accordance with the requirements and has not been submitted to any other university.

Kholofelo Vincent Monyela

26 November 2024

DEDICATION

My mini dissertation is dedicated to my lovely family who taught me love and respect, and treated me with care. I will forever be grateful for your support. I want you to know that I wouldn’t have achieved all the things that I have achieved today if it wasn’t for your love and support. Thank you, a million times!

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ABSTRACT

The purpose of the study is to explore the role of data analytics in enhancing business financial performance within JSE-listed companies in South Africa. The study further investigates how data analytics impact Human Resources (HR) strategy, customer strategy, and production or service design strategy as drivers of business financial performance. Previous researchers have conflicting views on the importance of data analytics in business decision making. Some researchers stated that it is important for business leaders to use an evidence-based approach which includes analysing data before making important business decisions, while others argue that decisions can easily be made if business professionals have relevant experience related to the subject that is linked to that decision. This study aims to investigate whether data analytics is important for decision making, and further explores how businesses can use data analytics effectively to create business value and enhance to business financial performance within the South African business context. The study followed a quantitative research approach, the researcher collected data using an online questionnaire, and the population of the study was data analysts who work in HR, customer, and production or service design departments within JSE-listed companies in South Africa. The results of the study were analysed in line with the purpose, and the results indicated that there is a positive relationship between data analytics and business financial performance. Based on the results of the study, it is recommended that businesses invest in technology, data analytics tools, and upskilling data analysts as elements of data analytics to enhance business financial performance.

Keywords: Data analytics, business financial performance, Human Resource strategy, customer strategy, production strategy, service design strategy, South Africa JSE-listed companies.

LIST OF ABBREVIATIONS

4IR	Fourth Industrial Revolution
AI	Artificial Intelligence
ANOVA	Analysis of Variance
B-DAD	Big – Data Analytics and Decision
CAGR	Compound Annual Growth Rate
CIUBSM	Constraints-based Interesting Unser Behaviour Sequence Mining
EBITDA	Earnings Before Interest, Taxes, Depreciation, and Amortization
EDA	Exploratory Data Analysis
EDW	Enterprise Data Warehouse
EM	Electronic Markets
ERP	Enterprise Graded System and Enterprise Resource Planning
ESS	Employee Self-Service
ETL	Extract Transform Load
HR	Human Resource
HRIS	Human Resource Information System
IoT	The Internet of Things
IT	Information Technology
J2EE	Java 2 Enterprise Edition
JSE	Johannesburg Stock Exchange
MAD	Magnetic Agile Deep
MES	Manufacturing Execution System
ML	Machine Learning
MPP	Massive Parallel Processing
MSS	Manager Self-Service
NPL	Natural Processing Language
NWU	North-West University
OEE	Overall Equipment Efficiencies
PB	Petabytes
RBV	Resource-Based View
VRIN	Valuable, Rare, Inimitable and Non-substitutable
ROI	Return on Investment

RSS	Rich Site Summary
SCM	Supply Chain Management
SDLC	Software Development Life Cycle
SPSS	Statistical Package for Social Science
TB	Terabytes
XML	eXtensible Markup Language

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CHAPTER 1: OVERVIEW OF THE STUDY

1.1. Introduction

The purpose of the study is to explore the role of data analytics in shaping business financial performance within JSE-listed companies in South Africa. The study further investigates how data analytics relates to the drivers of business strategy, and how companies can leverage data analytics to impact these drivers to achieve exceptional business financial performance positively. The drivers are Human Resource (HR) strategy, customer strategy and production and service design strategy.

This study aims to clear researchers' conflicting views on the importance of data analytics in business decision making. According to Schwarz and Murphy (2008:165), business leaders need to follow an evidence-based approach and not intuition when making important business decisions in order to avoid mistakes. Intuitive decisions are often made because of previous experiences or popular beliefs (Schwarz and Murphy, 2008:165). Davenport (2006:100) argues that there is no need to use data when making decisions, one can simply follow his or her instinct to make decisions involving people, customers or processes, based on experiences, which helps to make business decisions faster. Previous research focused on the evolvement of data analytics practice in the global context, which leaves a gap in how data analytics create value for businesses. Many researchers studied this subject in a global context, in broad context and not in narrow context (Rawat & Sood, 2020:184). This research closes the gap in the literature by exploring the impact of data analytics on business financial performance and narrowing the gap by investigating the subject within JSE-listed companies.

Imagine what the world would be like if there was no data storage at all, a place where there was no transaction record performed, a person's details stored or where everything documented is lost immediately after being used. Companies will be left with the dilemma of not being able to extract data and transform it into usable information and knowledge to perform analysis and take advantage of new business opportunities (Khan *et al.*, 2014:3). Data ranging from available products, customers' details, employees' information or number of sales made was not available, and this information is critical for companies in order to make informed decisions. Ross and Maynard (2021:159) stated that data is an important factor and it’s a building block that leverages companies to thrive within the current period and in the future.

According to Ekka and Jayapandian (2020:590), modern advancements in technology and the internet allows companies to make informed decisions related to designing products and services, managing labour, tracking sales and customers, etc. The huge amount of data available, advanced methods of data collection and transformation and increased capability of storing data enable businesses to improve their performance and allow them to be competitive in the market. The amount of data that is accumulated within companies needs to be safely stored and analysed to add value to the business. New techniques of storing data have become cheap and simple, which allows companies to get as much value as they can by using their data (Pansara, 2023:7). Companies that use data properly have the advantage of improving their business’ financial performance by being able to manage their labour, boosting sales and customers and improving productivity, which ultimately contributes positively to the business revenue and profit (Ross & Maynard, 2021:160).

According to Ross and Maynard (2021:160), the size of data, rapid change and its variety need the latest technology, unique data storage platforms, data pipelines and data analytics methods, all of which are big investments for companies. Big data has been a hot topic recently, and as it has been growing over the years, most business leaders show interest in it. They need to understand its importance and value to make the right decisions to invest.

1.2. Background of the study

According to Chowdhury (2024:2169), the essence of business is to create financial benefits for its investors and shareholders. For shareholders and investors, financial performance indicates how well the business is performing and how it will be able to generate a return on investment. For lenders, financial performance indicates how well the business will be able to repay its debts (Chowdhury, 2024:2170). Current studies followed a broad approach and investigated this issue globally. The global findings and recommendations of empirical research related to the role of data analytics in enhancing financial business performance are less relevant in the South African business context (Musanga & Chibaya, 2023:25). Furthermore, the research agenda on data analytics, HR strategy, customer strategy and production and service design strategy are too broad, and it is challenging to specifically apply it to a specific country or region (Musanga & Chibaya, 2023:29). According to Odendaal (2023), South African JSE-listed companies have invested more in technology and innovation compared to the non-listed companies and they have contributed the most to the GDP (35%) in 2023. It is therefore imperative to understand why JSE-listed companies, as big drivers of the economy, invest in data analytics and technology (Odendaal, 2023). According to Chilunjika *et al.* (2022:5), previous research on data analytics, HR strategy, customer strategy and production and service design strategy focused on the evolvement of the practices, their current application and their relevance in the future, and does not cover how leveraging data analytics through these business drivers helps to enhance business financial performance.

Previous studies indicate the importance of data analytics to businesses globally and locally within the South African business context and stated that business leaders have a vested interest in how they can benefit from the investment of data analytics and technology. JSE-listed companies in South Africa make a huge contribution to the economy and they invest more in data analytics and technology in order to stay relevant. It is therefore important to focus on JSE-listed companies when investigating the subject of data analytics and business financial performance. Empirical research focused on the evolution of data analytics and how it influences the HR strategy, customer strategy, production, and service design strategy as the drivers of business strategy, but it does not state how data analytics impact these factors and business financial performance.

The study of Moloi (2020:5) highlighted that JSE-listed companies such as financial services and telecommunication businesses have been improving the quality of their data and leveraging big data analytics for effective decision making and reporting. The companies invest in big data analytics for better decision making which allows them to gain great insights into customer preferences and customer behaviour. Analysing big data enabled the JSE-listed companies to identify and penetrate new markets which yielded in increased customer base, and improved revenue and profitability. JSE-listed companies invest their effort and capital in data analytics which enables them to prepare and include business results in periodic integrated business report to provides both financial and non-financial information to stakeholders including shareholders, employees, customers, suppliers and regulators on how the company meets sustainable practices and how it creates value over time. Companies with positive integrated business report are able to attract investors and retain valued stakeholders. Doorasamy (2016:30), stated that South African JSE-Listed companies in the food manufacturing sector improved their profit margins by making effective business operational decisions through the use of data analytics. The investment in data analytics significantly improved operational performance in the food manufacturing sector in the past years. According to Mittal *et al.* (2018: 199), food manufacturing companies enhance supply chain efficiency by effectively using data analytics to forecast production demands, and to reduce wastage. Leveraging data analytics in manufacturing leads to reduction in production costs and helps companies to avoid supply chain disruptions by tracking production materials and finished goods in real time. Companies that use data analytics enhance quality control by detecting defects and improving quality issues through production automation and artificial intelligence.

1.3. Problem statement

Business leaders need to understand the role of data analytics in shaping business financial performance by focusing on employees, production efficiencies and customers as business performance drivers (Fosso Wamba, 2020). Although data analytics seems to be an area of focus, researchers have conflicting views regarding its importance in decision making (Oesterreich *et al*., 2022:1037). Schwarz and Murphy (2008:165) stated that business leaders need to follow an evidence-based approach, not intuition, when making important decisions, in order to avoid mistakes. Intuitive decisions are often made because of previous experiences or popular beliefs. Davenport (2006:100) argues that there is no need to use data whenever making decisions, one can simply follow his or her instinct to make decisions involving people, customers or processes, based on experiences. Davenport (2006:106) further stated that it is easier to make a quick judgment on a person's character, expected behaviour or anticipated processes; therefore it should not be complicated to make decisions if a person has experience and knowledge of how the business works.

According to Chatterjee *et al*. (2024:890), the contemporary business landscape is increasingly dependent on data analytics to enhance operational efficiency and to improve strategic decision making; however, many organisations still have a challenge to fully leverage data analytics to enhance their business performance. Despite the proliferation of big data and advanced data analytics tools, businesses often face challenges such as a lack of skilled workforce, data silos and inadequate data structures, to leverage data analytics effectively (Kristoffersen *et al*., 2021:10). There is a need to identify how businesses can overcome these challenges and implement a robust data analytics strategy that aligns with business objectives in order to achieve stellar business financial performance. Organisations that can overcome data related challenges have the advantage of being competitive in the market (Kristoffersen *et al*., 2021:12).

The role of data analytics in businesses goes beyond business performance to encompass areas such as customer insights, talent attraction and retention and production efficiency (Ochuba, 2024:571). Previous studies stipulate the importance of leveraging data analytics. The gap in the literature is how businesses can translate data into actionable insights to drive strategy and efficiency and to achieve good business financial performance (Behl, 2022:369). Behl (2022:370) stated that it is important to emphasise the significance of fostering a data driven culture within businesses, where leaders at all business levels have an opportunity to drive strategic planning and innovation. Data driven culture is the core component of business efficiency and enables businesses to unlock new opportunities for financial growth and competitiveness (Aljumah *et al*., 2021:1089).

According to Fitz-enz and Mattox (2014:20), data analytics practices have been successful in business areas such as customer and production departments; however, it has been a challenge in the Human Resources (HR) space. Although other business areas had success in implementing data analytics, it has been a challenge to prove how data analytics and business factors, such as customer retention and production, use data analytics to achieve financial business outcomes. In HR, Production and Customer functions professionals do not have the right skills to analyse data using relevant metrics. This shows that many companies have a gap in effectively implementing and using data analytics to drive business performance. The gap lies in clearly understanding the relationship between data analytics and business factors or drivers in question to achieve good financial business performance (Fitz-enz & Mattox, 2014:22). Furthermore, establishing the right data metrics to use is essential to measuring the relationship between data analytics and HR strategy, customer strategy and production and service design strategy as drivers of financial business performance (Fitz-enz & Mattox, 2014:24). Unlike in production, the complexity of data analytics in HR and customer tracking is that most of the outcomes are not tangible and some of the data points measured are personal variables or behaviours that are not easy to quantify. It is therefore imperative to understand and combat these challenges (Hamilton & Sodeman, 2020:91). There is an opportunity for researchers to close the gap between data analytics and business factors such as HR strategy, customer strategy and production and service design strategy through empirical research (Angrave *et al.*, 2016:4). The emergence of the fourth industrial revolution mainly focused on how manufacturing and supply chain functions can improve productivity through technology, how customer services can improve sales through data analytics and insights, and how HR can make data decisions to manage talent within companies. There is a need to understand how these factors contribute to the company's financial business performance as businesses make big investments in this practice (Chilunjika *et al*., 2022:7).

The key drivers of business financial performance are employees, production efficiencies and customers. The HR strategy helps to manage employees to be engaged and influence them to produce high quality work to meet business financial goals (Olawale *et al*., 2024:667). Customers are at the centre of business strategy, and they are important for meeting business' financial goals. According to Nuseir *et al*. (2023:30), companies implement customer strategy to drive the financial growth of the business and build long term customer loyalty. Many companies aim to produce products or render services at a lower cost through production efficiency and effective service design strategies. Production efficiency optimises processes and maximises capacity, which enables companies to produce products cost effectively (Salamah, 2023:11).

To close the gap in the literature, it is important to investigate how data analytics impact business financial performance, and to achieve this there is a need to understand whether data analytics is important for business decision making. There is also a need to unpack how the drivers of business strategy which are HR strategy, customer strategy, and production and service design strategy relate to data analytics. Investigating data analytics comprehensively and understanding its frameworks within the business context and narrowing it down to the South African business landscape will help researchers and business leaders to understand the importance of data analytics in driving business financial performance. The underlying problem that this study aims to explore is whether data analytics enhances financial business performance through business drivers such as HR strategy, customer strategy and production and service design strategy.

1.4. Research objectives

Primary objective

The primary objective of this study is to explore the role of data analytics in enhancing financial business performance within JSE-listed companies in South Africa.

Secondary objectives

Secondary Objective 1: To understand the relationship between data analytics and Human Resource (HR) strategy.
Secondary Objective 2: To understand the relationship between data analytics and customer strategy.
Secondary Objective 3: To understand the relationship between data analytics and production or service design strategy.

1.5. Research questions

Primary research question:

What is the role of data analytics in enhancing financial business performance?

Secondary research questions:

Secondary Research Question 1: What is the relationship between data analytics and Human Resource (HR) strategy?
Secondary Research Question 2: What is the relationship between data analytics and customer strategy?
Secondary Research Question 3: What is the relationship between data analytics and production or service design strategy?

1.6. Scope of the study/delimitations

1.6.1. Field of study

This study will extend limited research by providing an understanding of the role of data analytics in enhancing financial business performance within JSE-listed companies in South Africa. The study will help the management of the companies to make better decisions related to data analytics, Human Resources (HR) strategy, customer strategy and production and service design strategy. The study will further analyse challenges that data analytics professionals experience and propose the best approaches that the professionals can use to implement data analytics within the companies that they work for.

1.6.2. Sector/industry/business under investigation

The sector that is being investigated is JSE-listed companies within South Africa which have data analysts or data professionals who are working with systems and analytics tools within the Human Resource (HR), Customer and Production or Service Design department.

1.6.3. Layout of the study

The study consists of five chapters.

- Chapter 1: Provides an overview of the study and the scope.
- Chapter 2: It includes the theoretical overview that covers a peer literature review on data analytics, HR strategy, customer strategy, production and service design strategy and business financial performance.
- Chapters 3 and 4: Covers the research methodology and quantitative analysis.
- Chapter 5: It provides conclusion, recommendations and areas for future research.

1.7. Chapter 1 Summary

Chapter 1 gives a brief introduction of the study, which is data analytics within JSE-listed companies in South Africa, and it clearly outlines the objectives and problem statement of the study as well as the scope of the study. The next chapter presents a literature review.

CHAPTER 2: LITERATURE REVIEW

2.1. Introduction

This chapter covers the conceptual review, which includes the definition and components of data analytics. The chapter aims to give readers a comprehensive overview and understanding of the data analytics framework within the business context. This chapter further defines the business drivers, which are HR strategy, customer strategy and production, and service design strategy. It highlights the importance of data analytics in shaping these business drivers, best practices for embedding data analytics practices in alignment with the business drivers and technological solutions for each driver to improve efficiency within organisations. The chapter closes by outlining how businesses strive to improve business efficiency and financial performance by leveraging data analytics within the South African and global business context.

Empirical research highlights that the intention for companies to strive for better business performance is not a new practice, this reflects in Resource – Based View (RBV) theory and dynamic capabilities theory (Lockett *et al.,* 2009:13). Lockett *et al.,* (2009:12) stated that the use of data analytics in improving business performance reflects the concept RBV theory which stated that a company's sustainable performance and competitive advantage is based on its unique capabilities and resources. The RBV theory emphasise that a company's long-term growth and success is dependent on its ability to acquire and use its capabilities and resources in an efficient and unique manner that its competitors cannot imitate. A company that effectively collects, process and analyse data have an advantage of improving its business strategic decision making to better business performance and to generate good financial results. This sets the company apart from its competitors (Newbert, 2014: 271). The Value, Rare, Imitable, and Non-substitutable (VRIN) framework is part of the RBV theory, and the framework emphasises that it is important for companies to structure and manage their tangible and intangible resources effectively for better business outcomes. In the context of VRIN framework, data analytics is an intangible resource and an important asset that companies need to structure and use effectively to improve business efficiency to outperform competitors and to contribute to the long-term profitability. The VRIN framework suggests that companies need to

continuously strive to find new ways of using their resources optimally. In the context of big data analytics, a company that continuously upgrade analytics capabilities, upskill employees and build data driven culture have a good chance of maintaining a competitive advantage and achieving better business financial performance (Aryee, 2014: 1899).
The dynamic capabilities theory is an extend of the traditional Resource Based-View (RBV) theory. The dynamic capabilities theory highlights how important it is for companies to constantly adapt to change, optimise resources and continuously build capability to remain relevant in rapidly changing economic environments. The theory emphasises that a company that build capability and optimise resources have the ability to meet evolving customer demands, address technological disruptions and respond to market changes. In the context of data analytics and business financial performance it can be stated that the dynamic capability theory emphasises the importance for companies to continuously build data analytics capabilities such as artificial intelligence (AI), machine learning (ML) and predictive analytics to remain relevant in the market and to achieve sustainable business financial performance (Teece, 2018:361).

The Fourth Industrial Revolution (4IR) introduced advanced technologies which enabled many organisations to implement technological solutions such as Enterprise Graded Systems (ERPs), data analytics, Artificial Intelligence (AI) and Machine Learning (ML) for daily business operations across multiple functions. Constant changes in technology led to the initiation of new ways of working, which required the adoption of the use of technology and digital transformation within companies (Melville, 2023:741). The adoption of technology and digital transformation enabled most companies to get rid of administrative burdens by streamlining processes, securing business data and making good business decisions using data analytics and reporting (Chilunjika *et al*., 2022:8).

2.2. Conceptual review

2.2.1. Definition and components of data analytics

The term big data has been used to refer to datasets that grow rapidly large and are challenging to range using traditional database management systems. The dataset’s size is huge in a manner that requires applications and sufficient storage systems to be recorded and stored. Big data ranges from thousands of terabytes (TB) to many petabytes

(PB) in one data set (Liu *et al*., 2023:899). The business invests in enterprise solutions that can store a huge amount of data and use advanced applications to extract and analyse it. Data analytics performed on large and small datasets leverage business performance. Real time capabilities are often required for companies to benefit from analysis of complex and large datasets (Elgendy & Elragal, 2014:216).

Data analytics refers to the process of extracting, transforming and presenting big data to provide insights for better decision making. Big data can be defined as large datasets, either in gigabytes or terabytes, that cannot be stored, processed or analysed using a standard database tool Gudivada (2024:29). The data analytics process involves extracting raw data, often referred to as unprocessed data, from information systems, documents, images and cloud platforms and processing it into usable insights presented in a graphical, tabular or summarised view (Abbasi *et al*., 2016:20). According to Gudivada (2024:42), data analytics is conducted using descriptive, prescriptive and predictive statistical analysis. Descriptive statistical analysis involves analysing current- and historical data to determine what, why and how something happened. Prescriptive statistics helps to provide possible solutions, using data to resolve problems. Predictive statistics forecast what is likely to happen in the future when overlaying historical and current data with Artificial Intelligence (AI) algorithms. Predictive statistics tests the relationship between two or more data points in order to establish the cause and effect (Gudivada, 2024:64).

According to Saberi and Mardani (2023:10), using data analytics helps organisations to identify issues and opportunities which enable organisational leaders to come up with solutions that drive better organisational outcomes. Data analytics helps organisational leaders to measure organisational progress in line with organisational strategic objectives. Larger organisations with an employee headcount of more than 250 rely on data for effective decision making and better business outcomes (Saberi & Mardani, 2023:14). Variables measured in data analytics are business costs, sales volumes, customer behaviour, customer demographics, etc., and, in line with these variables, businesses use data analytics globally to generate insights and better understanding of market conditions and customer behaviour (Walker & Brown, 2019:6). Al-Sai *et al.* (2022:2633) stated that data analytics is not only useful to analyse business results, but it can also be correlated with social issues to understand how businesses contribute to social developments. South African organisations are using data analytics to explore frontier opportunities across multiple sectors, including the private sector (Bag *et al.,* 2023:113).

According to Elgendy and Elragal (2014:216), the primary attribute of big data analytics is the size of the dataset, the number of tables, transactions and files. The datasets are often extracted from a variety of data sources such as business enterprise systems, cloud databases, logs, clickstreams and social media. Structured data is often overlayed with unstructured data such as human language, text and semi-structured data such as Rich Site Summary (RSS) feeds or eXtensible Markup Language (XML). The other type of data that is difficult to categorise and is barely analysed for business decision making comes from video, audio or other devices (Elgendy & Elragal (2014:220). Companies often invest in data warehouses to store and extract multi-dimensional data in a more structured manner, in order to add historical context to the data. With the evolution of big data, the traditional methods of data analysis have become less effective, which requires new data analytics methods and infrastructures. Many big companies use the proposed Big – Data, Analytics and Decision (B-DAD) framework to manage and analyse big data. This framework involves advanced big data analytics tools and methods that enable enhanced decision-making processes (Elgendy & Elragal, 2014:225). According to (Khan *et al*., 2024:9), the common methods of managing big data in structured data storage and retrieval include data marts, relational databases and data warehouses. As per Khan *et al*. (2024:3) structured data is uploaded into data storage using Extract, Transform, and Load (ETL) tools which extract data from external data sources, transform it to fit business needs, and load it into a data warehouse or database. This process cleanses the data and prepares it for business analysis and decision making.

Elgendy & Elragal (2014:216) stated that the advancement in big data requires Magnetic, Agile and Deep (MAD) analysis skills which are different from the common Enterprise Data Warehouse (EDW). EDW approaches are not efficient in incorporating new datasets unless they are cleaned and integrated. Datasets and data sources are growing rapidly in huge numbers, and they become more complex to analyse, so data storage platforms should be simplified and allow data analysts to easily access and analyse the data.

According to Brochu *et al*. (2023:4), solutions such as non-relational databases like NoSQL and Massive Parallel Processing (MPP) were developed to manage non-relational databases in a manner that is compatible with relational database solutions such as Python, SQL, JavaScript, C++ and others. Enhanced techniques such as Natural Processing Language (NPL) have also been developed to combine computational language, deep learning models and ML to efficiently analyse text or speech data, which is important in the modern world technology of AI.

As per the empirical research highlighted in the study, big data is a burning topic in businesses globally and locally, and businesses are required to keep up with the big data trend to stay relevant in the market and to improve business performance. Organisations need to have updated technology and data infrastructure to be efficient and remain innovative. Research shows that the evolvement of big data necessitated the new framework of complex business analytics tools and methods such as ETL, AL, ML and IoT. This evolution requires businesses to invest in the upskilling of their employees to ensure that they are ready for the change. Researchers highlighted that data analytics enable businesses to make effective decisions, which helps with the achievement of organisational objectives (Elgendy & Elragal, 2014:225).

2.2.2. Human Resource (HR) analytics and strategy

According to Marler and Boudreau (2017:14), Human Resource (HR) Analytics, often referred to as People Analytics, is a new term used to measure the planning and impact of HR efforts on business performance. HR Analytics uses key measures known, as HR metrics, to break down key deliverables in the Human Resource strategy and have formulas to effectively measure progress towards key deliverables. HR metrics are measures of key Human Resource outcomes classified as effectiveness, efficiency and impact (Marler & Boudreau, 2017:15). Suri and Lakhanpal (2024:134) stated that HR Analytics does not only consist of measures, but it represents experimental approaches and statistical techniques that can be used to analyse the impact of Human Resource Initiatives. In general HR Analytics is part of the decision making or analysis process that management uses to make decisions about employees or factors that affect people and Human Resource strategy (Chalutz Ben-Gal, 2019:1431).

According to Varsha and Shree (2023:196), HR Analytics consists of complex solutions, such as what-if analysis or predictive models, and it is also a systematic reporting based on an array of metrics. HR Analytics is regarded as an evidence-based decision-making approach on the people's side of the business. HR Analytics consists of an array of technologies and tools ranging from simple analysis and reporting of HR metrics to complex methodologies such as predictive and regression analysis (Varsha & Shree, 2023:202). Varsha and Shree (2023:196) defined HR Analytics as a systematic method of demonstrating the direct impact of people on important organisational outcomes.

HR Analytics involves sophisticated analysis of HR data, and it does not exclusively focus on Human Resource functional data, it also involves integrating data from various internal functions (Nyathani, 2023:17). HR Analytics involves collecting, manipulating, analysing and reporting on data using information technology solutions, and it is about linking Human Resource related decisions to organisational performance and business outcomes (Nyathani, 2023:22). According to Durai *et al.* (2019:2), the role of HR Analytics in Human Resource is not only limited to HR Metrics, but to connect Human Resource decisions and processes with business performance. Human Resource management needs to have a more strategic role and join other business functions in supporting business strategy. When Human Resources is driven by data analytics, statistical analysis and technology, it enables HR professionals to make important decisions that drive business impact and organisational performance goals (Durai *et al*., 2019:4).

HR Analytics uses HR metrics and data points to track and measure financial elements of Human Resource activities and initiatives, and these metrics help businesses to determine the impact of Human Resource strategic initiatives, cost effectiveness and efficiency. Human Resource professionals can make informed decisions, identify areas for improvement, and align Human Strategy with financial business goals (Madhani, 2022:36). According to Qin *et al.* (2024:8), the overarching HR metric that each business needs to measure successfully is talent mobility. Talent mobility helps businesses to better understand whether they are attracting and retaining the right talent to remain competitive in the market (Qin *et al.,* 2024:15). HR Metrics, such as cost of Human Resource per employee, cost per hire and ratio of Human Resource headcount per employee assist businesses to assess the cost efficiency of their Human Resource operations (Madhani, 2022:40). HR Metrics helps Human Resource professionals to align their strategy with business financial goals by measuring metrics such as quality of hire and employee attrition rate. Quality of hire and employee attrition rate can have a negative cost impact on the business if not managed effectively (Fernandez & Gallardo-Gallardo, 2021:173). As per the Remchannel's survey, almost 40 000 employees resigned from 82 companies in South Africa, including JSE-listed companies, and the total cost of filling the vacant positions and training new employees was almost R24 billion (Ronnie & Boyd, 2024:44). According to Dahlbom *et al*. (2020:121), another essential HR metric used by businesses is Return on Investment on HR initiatives such as leadership development, training and employee engagement initiatives. The ROI metric has been popular in Human Resources and many business leaders like this metric as it is directly showing the impact of Human Resource initiatives on business financial performance (Dahlbom *et al*., 2020:122).

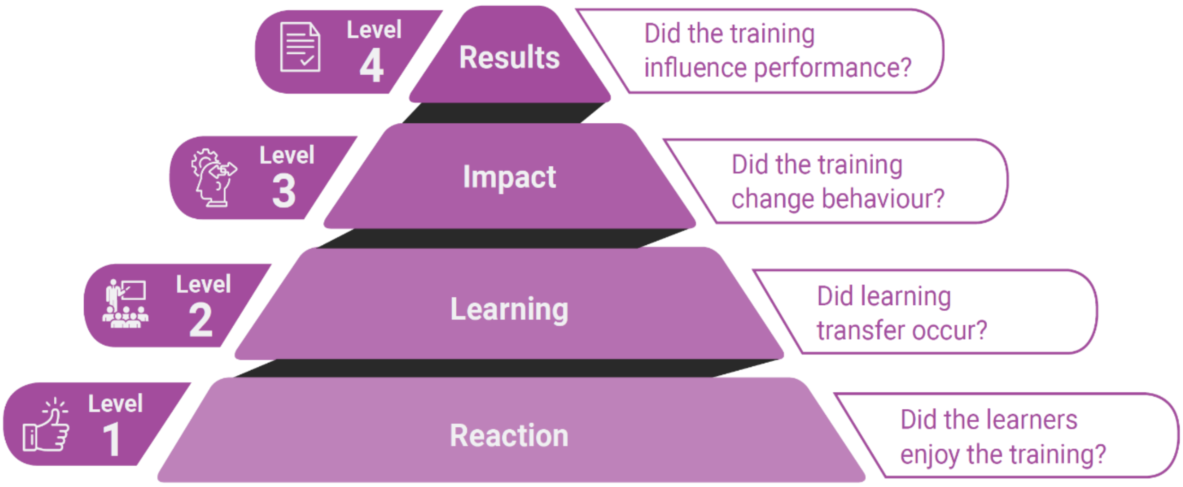

Figure 1: Kirkpatrick Model (Bretz, 2018)

According to Bretz (2018), many Human Resource professionals measure ROI on training related activities, to understand if training yielded expected results. The model followed to measure training ROI is Kirkpatrick's four level training and evaluation model, and the levels are reacting, learning, impact and results (Bretz, 2018). The reaction level focuses on how well the targeted audience received the training, and if they perceive it to be useful. The learning level indicates how confident the trainees feel, and whether they think that the training equipped them with the necessary skills to do their job. The behaviour or impact level helps companies to comprehend how their employees make use of the training and how much of the skills and knowledge gained is applied on the job. The last level, which are the results, helps the company to evaluate the overall success of the training program from performance improvement and ROI perspective. The results level is related to the ROI that businesses get from training interventions, and it has been difficult to measure because business financial performance is not only driven by training, but can also be driven by other things such as new technological implementation or process optimisation (Bretz, 2018).

HR Metrics that have an impact on the efficiency of Human Resources, and enable Human Resources to enhance business financial performance directly or indirectly, are diversity and inclusion, compliance and operational effectiveness (Madhani, 2022:42). Other HR metrics that are essential in HR is diversity and inclusion. These give businesses the advantage of having a diverse workforce which implements creative and innovative solutions to contribute to business financial performance (Madhani, 2022:45). Compliance and operational effectiveness metrics within Human Resources helps businesses to measure whether they are compliant with legislative requirements and if they are managing Human Resource costs effectively. The compliance metrics also help businesses avoid legal fines and loss of company reputation as a result of non-compliance (Fernandez & Gallardo-Gallardo, 2021:175).

HR metrics are part of and puzzle of the Human Resource strategy. People strategy, often referred to as Human Resources (HR) strategy, refers to the strategy of managing employees within an organisation (Tran, 2020:239). The constructs of measuring HR strategy are workforce management, talent management, rewards and recognition, amongst others. Workforce management refers to the set of integrated processes that organisations use to optimise the planning and utilisation of employees. Workforce management includes effective budgeting and planning for employees, in line with business operations, and allocating resources needed for those employees (Manimala & Kurian, 2024:6). Talent management refers to the process of strategically attracting the correctly talented employees into the organisation, developing and retaining them for the benefit of the organisation while taking into consideration the employees' personal and professional needs (Manimala & Kurian, 2024:8). Rewards and recognition are tools used by organisations to motivate and encourage employees to meet and exceed organisational goals. These tools are also designed to make employees feel appreciated and recognised, as the achieve milestones related to personal and organisational goals (Jotaba *et al*., 2022:4).

According to Douthit and Mandore (2014:16), HR Strategy is an essential component of HR management that enables HR professionals to effectively contribute to the organisational strategy by measuring employee management success factors that are directly linked to desired organisational outcomes (Douthit & Mandore, 2014:16). For HR professionals to successfully drive the people agenda and meet people goals within organisations, they need to be equipped with tools such as systems and reporting and analytics platforms to enable them to execute tasks with excellence and make good decisions (Douthit & Mandore, 2014:17). According to Fernandez & Gallardo-Gallardo (2021:173), well developed global companies use HR strategy to drive employees' agenda to achieve broader organisational goals, and that is the greatest investment in each organisation; therefore driving the right culture and taking care of employees yield better business outcomes**.** Tran (2020:248) stated that organisational leaders who provide HR teams with resources to drive the HR strategy often meet organisational goals. Although the use of technology and data analytics is still developing in the South African private sector, there are many initiatives in South Africa initiated through forums such as Chief Human Resources Officer (CHRO) South Africa to support Human Resources excellence, and these initiatives are sponsored by some of the big corporations, including big technology companies (CHRO South Africa, 2019).

Data Analytics in Human Resources, in conjunction with a well-designed Human Resource strategy and HR metrics, helps businesses to be more cost effective (Manimala & Kurian, 2024:9). Although Human Resources does not directly have an impact on profit compared to other departments such as Sales or Marketing, it does help businesses to be cost effective when managing the employees' side of the business. According to Abdullah *et al*. (2020:58), HR professionals can use data and systems effectively to attract and retain the right talent for the business. This will enable the business to have a talented workforce and be competitive in the market. Human Resource professionals can further use data to determine whether they are investing in the right training for their employees and whether the training is contributing towards expected business outcomes. They must stay abreast with the latest technological- and data trends and upskill themselves to contribute to the financial success of the business (Abdullah *et al*.,2020:57).

According to Abdullah *et al*. (2020:57), to run effective HR Analytics within businesses, there is a need for a well configured, integrated HR Information System (HRIS) and advanced technology. Technology has changed ways of working in many business functions including Human Resources and has affected large, medium and small sized organisations' methods of working. Many companies are using HRIS to automate and manage their daily tasks, but the majority of organisations are still using remote access systems, and they lack the use of cloud technology, which is regarded to be more efficient regarding accessibility and data security (Wahyoedi *et al*., 2023:308). Abdullah *et al*. (2020:57) stated that the use of HRIS to effectively manage processes and tasks related to employee documents management, workforce management, recruitment, performance management, talent management and training and development, and companies are benefiting by using HRIS for systematic business procedures such as collecting-, validating, receiving, analysing and managing employee data. This helps the HR team to perform their work effectively. Modern HRIS uses cloud computing, which provides administrative processing capabilities as a service in cloud solutions. Cloud computing is rapidly advancing, it helps with data capacity and security, and it is available for access, which makes it easier for HR specialists to work with the data that is stored on the system at any time and place (Abdullah *et al*.,2020:57).

According to Abdullah *et al*. (2020:58), HRIS is one of the easiest system implementations and it is easy to maintain. One of the popular HRIS implementations was implemented and designed by Ying and Xiao-hui (2009). The framework was designed using Java 2 Enterprise Edition (J2EE). The solution was an expandable enterprise HRMS framework that is flexible and has a high effect on managing employee data. The system consisted of multiple modules including system function management, personal management, pay management, performance evaluation, training management, post management and institution management. The system was not complex to implement, and it was easy to maintain, it had high security features, and it was user friendly (Abdullah *et al*., 2020:58).

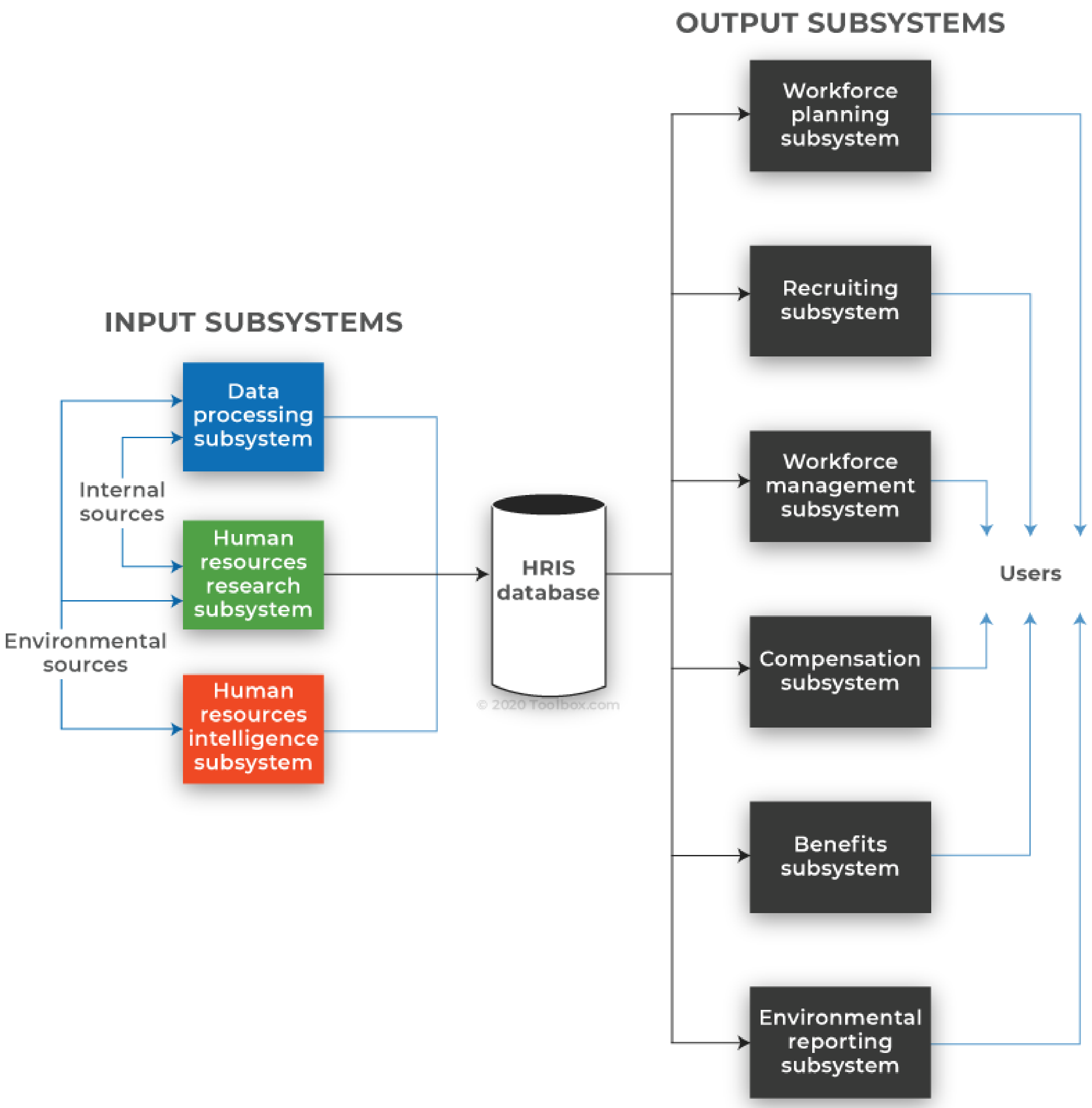

Figure 2: HRIS system model

(Ghosh, 2021)

One of the most critical components of HRIS is database management, and this component stores and manages data for all employees (Ghosh, 2021). Human Resource professionals record and transact employee data within the employee database. The data output or report extracted from the database is called employee master data, which includes employees' personal and biographical information. The employee database is the heart of the HRIS, and it needs to be maintained properly to ensure there is quality data in the system (Ghosh, 2021). According to Ghosh (2021), HRIS further houses additional HR modules essentially for transacting, storing and analysing data within the business. These modules are time and attendance, payroll, remuneration, and benefits, Employee Self-Service (ESS), Manager Self-Service (MSS), recruitment, talent management and reporting. The time and attendance module helps to monitor employees' work schedules by recording the time at which employees clock in and out of the business. The time and attendance module is usually integrated with the payroll module to pay employees according to the shifts that they have worked. Payroll is one of the critical functions within Human Resources (Ghosh, 2021). A well-integrated HRIS enables businesses to easily transact employees' pay data and remunerate them timeously. The remuneration and benefits module helps businesses manage employees' remuneration, benefits and investments while effectively communicating and giving employees feedback related to their benefits. Many companies invest in HRIS, and they consider the system as one of their greatest investments because it helps them to be efficient in managing, attracting, engaging and retaining the best talent through process automation and HR analytics (Touriano *et al*., 2023:541). According to Ghosh (2021), ESS and MSS help to create a culture where employees and managers have the freedom to access and manage their data in a way that enables them to make quick decisions related to business operations, and the reporting module enables Human Resource professionals and line managers to get access to employees' data in a form of visuals and metrics for effective decision making.

According to McMackin and Hefferman (2021:5), the methodology and proposed system architecture development that have been followed by many companies to implement HRIS is agile. The advantage of agile methodology includes the focus on business value, the high quality of the product and the flexibility of work within the project team. Agile is important in Software Development Life Cycle (SDLC). It enables a group of people work together and divide the project into different phases, divide- and execute the work efficiently and make decisions about project flexibly. Many companies in South Africa prefer to purchase off the shelf systems, as they are less costly and require less configuration. Some of the biggest HRIS's used in South Africa include SAP, Oracle, Workday and Sage. Off shelf systems limit the system users to pre-developed and designed processes and functionalities (Ngwenya *et al*., 2019:2). According to Abdullah *et al*. (2020:57), a few companies that have a well-structured Information Technology (IT) capacity opt to develop their HRIS from scratch. To implement a successful HRIS solution from scratch, the company needs tools such as Apache server for cloud solutions, PHP and MySQL as programming languages.

HRIS does not need heavy hardware with big space to function, but it does have minimum requirements which are detailed in the below table.

Table 1: HRIS hardware requirements

Processor Speed	1.8 GHz
Hard Disk	200GB
RAM	3GB

(Abdullah *et al*., 2020:57).

Abdullah *et al*. (2020:62) stated that HRIS is regarded as an enterprise system because it has an extensive structure, it is complex, and it is made up of multiple software solutions. The front end of HRIS is the component that HR professionals interact with, and it is designed to be user friendly, as it is used for quicker and less mentally challenging tasks. The back end of an HRIS is complex and is used by people who have certain skills and capabilities such as IT specialists or Data Engineers. The back end of a big HRIS can store up to 131 data tables of employees' data. According to Abdullah *et al*. (2020:62), the prototype of HRIS implementation includes module implementation, inbound- and outbound data integration, security and systems features. For HR professionals to drive HR strategy and make effective decisions that add business value, they need an excellent HRIS system with advanced analytics features.

HR strategy is an important driver of business performance, as it helps businesses to better manage employees related matters more strategically. The research in this study stipulates that HR strategy, in line with HR metrics, enables businesses to effectively measure efforts related to talent attraction and retention, employee development, diversity and inclusion and workforce management. Research highlights that for businesses to effectively conduct HR metrics, they need efficient and integrated HR systems which enable HR professionals to transact and analyse data. Studies show that, when businesses successfully embed HR strategy and HR analytics in their business strategy, they have the advantage of achieving better business outcomes such as efficiency and business financial performance. Research referenced in this study highlights the importance of following best practices when conducting HR analytics and the importance of upskilling HR professionals so that they can be able to carry out HR analytics work confidently.

2.2.3. Customer analytics and strategy

Many companies invest their efforts in best practices and approaches for attracting customers through techniques such as sales strategies, social media campaigns and marketing, and it is equally important for companies to invest in customer retention as much as they invest in sales and marketing initiatives (Suganda & Priadi, 2023:20). According to Gomes and Meisen (2023:532), customer strategy refers principles used to influence customers to become repeat buyers and prevent them from going to purchase products or services from competitors. Olson (2023) stated that for companies to improve their customer retention, they need to analyse their entire customer experience using customer data. According to Olson (2023), companies need to understand how customers think about their products and how they feel when they see their brand. and invest in creating a seamless experience for their customers to keep them satisfied. Once companies invest in processes, tools and strategies. they are able to entice their customers and achieve return businesses.

Customer strategy outlines guidelines that help businesses to track whether a product or service satisfies existing customers, and if the offering is likely to attract potential new customers. Companies implement customer strategy to achieve a 100% retention rate, no company wishes to lose its customers (Gomes & Meisen, 2023:535). According to Gomes and Meisen (2023:540), customer retention rates benchmarked for different industries are as follows; Insurance (83%), Information Technology (81%), Construction (80%), Finance (78%), Telecommunication (78%), Health (77%) and Banking (75%).

Gomes and Meisen (2023:257) stated that customer strategy is important to guide companies to turn their past and existing customers into repeat buyers. According to Olson (2023), when companies build a good brand and when they can keep customers engaged, they can achieve excellent business results through increased sales and market share.

Data analytics is a factor that is continuously getting attention in the business sphere, and it holds big potential for businesses. Leveraging data analytics in customer and marketing enables businesses to identify customer growth opportunities (Ijomah *et al*., 2024:14). According to Joel and Oguanobi (2024:40), businesses discover growth opportunities through the analysis of customer data. Analysing customer data involves observing trends and identifying customers' behavioural patterns to pinpoint potential business growth. Customer analysis ranges from simple website traffic tracking to understanding customers' behaviour to detailed customer profiling using multiple customer data sources (Joel & Oguanobi, 2024:43). The application of data analytics in the customer function helps with strategic planning, resource allocation and maximising ROI on customers. It also helps to forecast market trends and helps businesses to prepare for potential growth opportunities (Ijomah *et al*., 2024:15). According to (Kitchens *et al*., 2018:550), customer insights derived from data analytics are important in designing campaigns that resonate with the target market. Well-designed customer strategies that are supported by data and insights increase customer engagement rates and awareness and enable business growth.

According to Prabadevi *et al*. (2023:147), many businesses are capitalising on the spur of data analytics to grow their customer base, and big corporations have Customer and Marketing departments that partner with digital marketing agencies to uncover customer growth opportunities using data analytics. Customer analysts use data to analyse the behaviour, preferences and trends related to customers. This helps analysts to derive valuable insights for tailor-made and result orientated customer and marketing approaches (Prabadevi *et al*., 2023:149). Data analytics in the customer space offers big data ranging from customer demographics, seasonal trends and customer behaviour (Raji *et al*., 2024:70). Hossain *et al.* (2022:3), stated that customer analysts can equip themselves with relevant analytical tools that can help them to predict potential market shifts, enabling proactive customer attraction solutions. Although data analytics involves complex processes such as data mining, data transformation, statistical analysis and visualisations, in the customer function the overarching objective of data analytics is getting valuable customer insights to understand market dynamics and to have an advantage over competitors.

According to Khade (2016:988), customer analysts leverage data analytics to segment their customer base, leading to the creation of targeted and effective customer campaigns. They collect data from web interactions to assess customer behaviour. With the use of advanced analytics tools, customer analysts can monitor business competitors' activities and market trends to get customer insights, engage in best practice customer activities and close any gaps that businesses have about customer needs. Chalutz Ben-Gal (2019:1436) stated that the use of data analytics in the customer space helps businesses to make evidence based strategic decisions, improving customers' Return on Investment (ROI) and enhancing the business's competitive advantage. For small businesses, customer data analytics helps to unlock growth opportunities and deploy effective marketing strategies, providing business foundation and allowing further optimisation to achieve better financial results.

According to Mach-Krol and Hadasik (2021:187), data analytics helps to measure the profit that businesses generate from customers over a period. Customer net profit is calculated using customer segments based on costs of products and sales. Measuring net profit within customer departments helps businesses to determine which customers they should invest in. The profitability generated from customers is calculated using different formulas, depending on the metrics that the business wants to measure and the available data (Mach-Krol & Hadasik, 2021:189). According to Egorenkov (2024:2324), customer analysts use data to identify customer patterns, products that they buy the most and shops that they prefer buying. This helps businesses to make the best decisions about their customers. When businesses perform customer profitability analysis effectively, they can reallocate resources toward building brands or designing services for customers who have the potential to drive business growth and increase profit (Egorenkov, 2024:2325). According to Potla and Pottla (2024:1390), many big businesses use customer profitability analysis to identify high margin areas that need more investment or low margin areas that can be targeted for cost cutting. Three important metrics to consider when building customer profitability analysis are revenue, sales volume and cost of goods sold. Revenue is at the heart of every business, products and services need to be marketed and sold through the right channel to generate good revenue. It is important to analyse data related to customer revenue and profit margins to identify product or service lines that the business would financially benefit from. The data also helps to plan marketing budgets accordingly and enables businesses to make tailored promotions to attract the right customers (Potla & Pottla, 2024:1410). Kanade *et al*. (2024:460) stated that many successful businesses leverage predictive analytics and customer profitability to increase sales volumes. Understanding product lines that generate the highest sales volumes is important, as it helps businesses determine where funds should be allocated when creating promotions around products or when launching a new campaign. As per Olson (2023), the cost of goods sold is one of the important metrics and it is directly related to the cost that the business incurs when producing products or designing a sale service. The cost of goods sold helps a business measure its operational effectiveness by planning operations and forecasting future costs associated with production or service design.

According to Nwabekee *et al*. (2024:59), using data analytics, businesses can identify patterns and trends related to customer behaviour, which can help to improve customer experience. Businesses can use data points such as web traffic to measure if their customer base is increasing or decreasing. If the customer base is increasing, the business needs to maintain its standard of serving customers, but if the customer base is decreasing, it is important for businesses to take appropriate measures to close the gap and retain remaining customers (Nwabekee *et al.,* 2024:61). Nwabekee *et al*. (2024:65) stated that areas where data analytics is used to identify customer trends and patterns are customer feedback, customer engagement, customer purchase behaviour and customer interactions. Businesses collect feedback from customers through social media, surveys or reviews, and when analysing the collected feedback businesses can identify common issues that customers experience. This information helps businesses to identify areas of improvement in their products or services (Urefe *et al.,* 2024:298). According to According to Scott *et al*. (2024:202), businesses track customer engagement on their websites or social media, and by analysing customer engagement businesses can identify effective channels for customer engagement and improve channels that have lower engagement. This information helps businesses to focus their efforts and resources on the most effective channels to improve their customer experience. Customer analysts within businesses analyse customer purchase behaviour to identify which products are mostly bought or which service is mostly used by customers. This helps businesses to invest in improving unpopular products or services. Customer behaviour data helps businesses to improve their product or service offerings and design their marketing strategy to meet the needs of specific customer segments (Scott *et al.,* 2024:201). According to Urefe *et al.* (2024:300), businesses can analyse their customer interactions through their customer service representatives by identifying and channelling common customer issues and focusing on improving the issues. Improving customer experience through data analytics involves using customer insights to make factual decisions. Businesses use data analytics to personalise the customer experience and deliver targeted customer service based on customers' preferences. According to Kedi *et al.* (2024:1641), the benefits of improving customer experience are customer satisfaction, loyalty and increasing profit, which contributes to the business's sustainable growth.

According to He and Liu (2024:10), e-commerce has been one of the effective, popular and successful methods for reaching customers globally, and for collecting customers' data for better decision making about how businesses are effectively recruiting and retaining customers. E-commerce refers to the relationship between merchants, service providers and customers, and the relationship is facilitated via an online platform that has product or service purchase capabilities, communication and feedback (Nalla & Reddy, 2024:720). He and Liu (2024:11) stated that businesses use the platforms for reaching out to customers and transact sales, but it has been particularly challenging to effectively integrate e-commerce with the company's business merchant. According to Choi *et al*. (2012:311), with the rapid development of technology and big data, many companies continued to develop their e-commerce platforms, which changed their game, more specifically in the corporate marketing model. Companies have gained recognition in the market by simply utilising their customer data generated from e-commerce platforms and business merchant integration. This enabled the companies to gain a good market share and improve their revenue. This then led to more business investment in the corporate marketing model which encouraged advanced e-commerce platforms with significant innovation and development (He and Liu, 2024:12). Choi *et al*. (2012:314) stated that the corporate marketing model focuses on using customer data for communication, providing feedback and making better decisions to attract and retain customers.

According to Jain *et al.* (2021:668), businesses do not necessarily invest in complex customer or marketing systems or analytics platforms. They use social media and e-commerce as effective tools for measuring customer loyalty instead. Yunita and Gunawan (2018:2) studied a correlation between social media and customer loyalty when they surveyed 257 Facebook users, using multiple linear regression methods. In their study they found that social media plays a big role in collecting and analysing customers' data to influence loyalty behaviour and repeat purchases. Yunita and Gunawan (2018:4) stated that the seller's reputation is important in the e-commerce environment for a potential customer to make an informed decision, and customers need comfort about the security of e-commerce. Companies invest massively in building the security of their e-commerce to protect the vulnerability of their customers from scammers and fraudsters. According to Kedah (2023:53), mobile e-commerce plays an important role in this era, as it helps businesses use modern trends and technologies to provide products and services efficiently while improving business practices. Companies can use mobile e-commerce to mine customer data and analyse their user behaviour to understand what products they buy, when they buy them and where they buy it. Mobile e-commerce data can be segmented into profiles such as age, location and income streams of customers to better design products and services tailor-made for the specific markets. Ahmad *et al.* (2021:33) stated that an effective e-commerce mobile framework used by many businesses is CIUBSM (Constraints-based Interesting Unser Behaviour Sequence Mining) which generates behaviour for mobile e-commerce users that helps customer analysts and businesses to extract interesting insights related to their customers' behaviour.

Customers use e-commerce platforms to make purchases. The process starts with the customer placing an order, and then the platform assembles and produces the products or services according to the customers' different needs in time. This process runs in real time. The importance of real time assembling, and production enables the product or service to be delivered to the customer at a critical moment. Many businesses use the real time model to make relevant adjustments in the market by eliminating unnecessary large-scale production lines with small-batch production based on customers' needs (Rahardja, 2022:180). According to Chaudhuri *et al*. (2021:142), e-commerce simplifies digital customer marketing by building multiple databases and enterprises that collect and record customer data, address customers' latest demand trends and communicate with them in real time. The enterprise can collect customer demand in real time and quickly process it for better decision making. This allows businesses to quickly respond to the market demand. Through enterprise- and e-commerce databases, companies can use technology and organisational engineering to achieve a good combination of services and products. Hendrawan and Zorigoo (2019:393) stated that companies can make good profits from e-commerce because it significantly simplifies product design, and provides products and services quickly in a variety which improves quality, performance, and customer satisfaction.

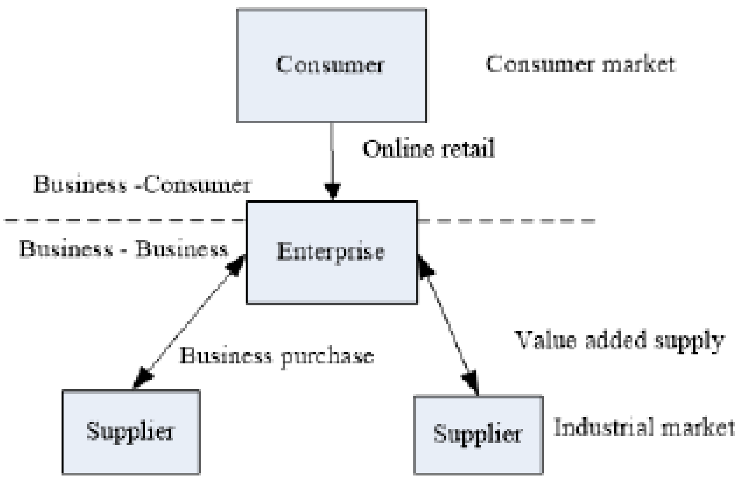

Figure 3: Environmental Model of E-commerce

(He, 2021:6)

The conceptual mode of e-commerce is the description or general abstract of e-commerce activities in the real world. The model includes electronic markets (EM), trading themes, information flows, material flows, capital flows and other important elements. The transaction of the model enables the data flow and compliance with third party processes such as banks, government agencies, banks and enterprises. The electronic markets (EM) are the exchange of business products and services with all participants in the e-commerce environment, connected by communication devices and various business activities through the network, into a collective economic practice (He, 2021:6). According to He (2021:7), transactions occur in the form of quotations, payments, shipments and inquiries. When this model is used effectively, businesses can transfer data (communication and information) with customers and related entities from when a product or service is ordered to when it is delivered.

Empirical research highlights that data analytics is essential for transforming customer insights into business customer strategy. It enables businesses to achieve customer attraction and retention, which translates into increased market share and good business financial performance. As highlighted in the study, e-commerce, social media and partnering with marketing agencies are effective ways of leveraging data analytics to achieve organisational customer strategic goals. Researchers highlight the importance of incorporating data analytics with effective customer practices such as collecting customer feedback to improve customer experience, rewarding loyal customers through loyalty programs and keeping customers engaged through marketing initiatives.

2.2.4. Production and service design analytics and strategy

Ogundipe *et al*. (2024:951) define production as the optimal process of manufacturing goods and services from raw materials to finished goods. Production process inputs and turns them into outputs which are fit for consumption. Ogundipe *et al*. (2024:951) stated that production is one of the essential drivers of business performance. The essential factors of production are land, labour, capital and entrepreneurship. Land can vary in form, such as commercial properties, real estate, agricultural land, factories etc. Labour refers to the effort expended by one person or a group of people to bring a product or service to people (Ogundipe *et al.,* 2024:952). According to Das (2022), capital and entrepreneurship are important elements of production. Capital refers to money used to produce goods or services. Capital facilitates the acquisition of capital goods; these are goods that can be used to produce products and services. Entrepreneurship is the process of combining land, labour and capital effectively to achieve production.

According to Olawale *et al.* (2024:670), data analytics is rapidly becoming an important tool in production, as it helps producers to make informed decisions about production and improving their operation. As data becomes increasingly available, the evolution of production data and production analytics tools increase. This helps companies to leverage data to reduce production costs and improve product quality. Data analytics increases operational efficiency in production by allowing producers to use a large amount of data, analyse it and eliminate inefficiencies within the production process. This helps to improve quality control by identifying trends and patterns that can help detect defects early to prevent product recalls (Wilkinson *et al.,* 2014:12). Sarker (2022:158) stated that data analytics enable producers to effectively manage their supply chain by providing live data on production schedules, shipping and inventory levels. When producers leverage data analytics, they can quickly identify issues that are likely to negatively impact the supply chain process and take proactive measures to resolve them. Producers use data analytics to predict maintenance needed to prevent machine breakdown which can lead to maintenance cost or downtime.

According to Zafari *et al.* (2019:2569), businesses use data analytics to measure the quality of products and improve the quality, based on required quality standards. When businesses generate insights and analytics using past production data and customer reviews, businesses can identify and improve production defects and negative reviews. This gives a clear view of problem areas and enables production analysts to identify the scope for quality improvement. Using predictive analytics and Machine Learning (ML), businesses can build models for early detection of defects and put proactive measures in place to stop any possible defects (Pengcheng, 2020:243). Li and Rashidzadeh (2019:258) stated that production analysts use statistical process control to monitor the process of identifying defects and put corrective actions in place to avoid any production errors. Statistical process control is used to monitor and control the production process to ensure that it meets quality standards. By implementing statistical process control, businesses can reduce defects, reduce waste and improve the production process and the quality of products (Li & Rashidzadeh, 2019:261). According to Rácz-Szabó *et al*. (2020:16), integration of Enterprise Resource Planning (ERP), Supply Chain Management (SCM), and Manufacturing Execution Systems (MES), is the best solution for all manufacturing processes. ERP, SCM, and MES allow seamless integration of data at various production stages, which enables production analysts to make informed decisions to improve the quality of products and proactively manage possible production errors. This also helps production analysts to have real time production data to improve product quality whilst still in production. The study of Guisti *et al*. (2018:3) outlines that in the current business world, customer preferences are changing rapidly because customers continuously use trending products or services and are less interested in using old products. With the use of data analytics, businesses can predict and adapt to future trends and plan manufacturing accordingly to deliver good quality products or services. Continuous improvement, together with feedback from customers, helps businesses to refine products or services to meet the required quality standard.

Organisations track production or service downtime as part of the manufacturing process. The process provides insights into equipment or systems performance, helps to identify production issues and enables proactive maintenance planning (Nobil *et al*., 2023:1740). According to Asadkhani *et al.* (2021:2640), tracking production or service downtime enables businesses to increase productivity and save costs. Meister *et al.* (2019:3) investigated productivity by conducting research at Aberdeen Group, and the findings of the research indicated that businesses with the best overall equipment effectiveness (OEE) measures experience 20% fewer production or service downtime. Salmasnia *et al*. (2022:947) stated that when organisations reduce production downtime, businesses can improve operational efficiency, manage costs and maintain a competitive advantage. Downtime can be measured through equipment or system downtime, and it can also be measured through production or service downtime which is not only limited to equipment or systems. According to Salmasnia *et al.* (2022:949), equipment or systems downtime is a period when a piece of equipment or system is not in operation due to maintenance, failures or upgrades. The overall production- or service downtime includes broader issues such as equipment or system downtime, process inefficiencies, material shortage or labour issues. It is important to automate downtime tracking and monitoring to have quality and real time data.

According to Meister *et al.* (2019:4), many businesses have not yet utilised their most important asset, which is their data. Insights generated from production data could lead to an increase of about 10% in Earnings Before Interest, Taxes, Depreciation and Amortization (EBITDA). A minority of businesses leverage their production data using Internet of Things tools (IoT) and cloud-based production analytics. This helps management and analysts to have a complete view of shop floor production activities, and it allows businesses to automate repetitive tasks. According to Schuetter *et al.*

(2015:658), production analytics are digital solutions created for manufacturing companies to automatically gather, transform and interpret production data for decision making. When organisations make use of production analytics, analysts, managers and executives have access to the data which they need to make informed decisions based on facts. Schuetter *et al.* (2015:659) stated that the primary objective of production analytics is to improve the visibility and productivity of businesses. With advancements in Machine Learning (ML) and Artificial Intelligence (AI), businesses can intelligently automate production tasks to improve productivity, which positively contributes to business profitability. Predictive analytics can save costs and time by proactively scheduling maintenance before machine failure occurs, and AI can help to automate shop floor scheduling for objectives such as on time in full delivery, change over minimisation and just in time scheduling. According to Salmasnia *et al.* (2022:951), by generating detailed insights from production analytics and resource utilisation, businesses can save on operational costs. This includes forecasting machine downtime, minimising waste, improving energy efficiency and optimising inventory levels. When businesses have visibility into their operations, it allows manufacturers to adopt greener practices and meet government regulatory requirements, which can help to avoid fines.

The study of Li and Rashidzadeh (2019:263) highlighted that in the production field, the fourth industrial revolution enabled companies to use various sets of technology to streamline their production processes, comply with safety standards, measure productivity and avoid machine downtime by using smart logic networks, advanced sensors and intelligent machines that are connected to the Internet of Things. The intelligence practice enables companies to store supply chain data in the cloud and allows people in the business to have access to the data through multiple devices connected to the internet (IoT). According to Ali *et al.* (2023:397), it is an outdated practice for big companies to only focus on one form of technology in the production space. The combination of technological components allows businesses to be more advanced in their practices and put them on a competitive edge. Businesses that do not invest in improving their efficiency are essentially compromising their survival.

Figure 4: Internet of Things (IoT) for Modern Production Companies

(Rácz-Szabó *et al*., 2020:16)

According to Rácz-Szabó *et al*. (2020:16), in the modern world, production companies use automation technology that consists of various levels of networks. The first level has automated pyramids with sensors and actuators, and this level is usually connected to the machinery or tools that are used on the production floor. The second level consists of computer engineering capabilities that help transform data or transfer communication from sensors to the next level (third level), the supervisory level, which filters data through to the Manufacturing Execution System (MES) which takes decisions based on sets business processes and rules to improve the business efficiency and effectiveness. Rácz-Szabó *et al*. (2020:16) further stated that the MES integrates with the business Enterprise Resource Planning (ERP) where data for all other business functions is stored collectively for record keeping and analysis.

Researchers highlighted that data analytics and advanced technology are quite critical in production because they help to reduce inefficiencies, provide scheduling in real-time, which helps to improve efficiency and optimise production maintenance by proactively anticipating machine downtime. Empirical research states that it is important for businesses to invest in integrated technological tools such as process automation, AL, ML and IoT to improve operational efficiencies within production and service design to achieve business goals. Businesses that adopt production analytics can respond better to the markets and maintain a competitive advantage in the dynamic markets.

2.2.5. Data analytics in the South African business context (JSE-Listed companies)

According to Sewpersadh (2020:1064), a JSE-listed company is a registered company or entity that is publicly trading on the South African primary stock exchange called Johannesburg Stock Exchange (JSE), and the company shares are publicly available for purchase by investors. Salamah (2023:10) defines financial business outcomes as the company's financial results and cost operational efficiencies about business goals. According to Salamah (2023:11), the constructs for measuring financial business outcomes are operating margins, cost per leads, sales volumes, failure rates and conversion rates, and companies measure financial business outcomes globally to set goals and measure the progress of desired business results in line with the set goals. Jotaba *et al.* (2022:6) stated that, within South African JSE-listed companies, factors such as customer strategy, production and service design strategy, talent retention and HR cost effectiveness are important drivers of financial business performance. Using data analytics professionals can measure the impact of these factors on financial business outcomes and business leaders can make good decisions pertaining their company's future.

According to Van den Heuvel and Bondarouk (2017:160), data analytics has been a focal point for many organisations as technology and big data evolved, and organisations adapted their operating model and adopted new ways of working to align with this evolution. The evolvement of data analytics raised research interest in establishing how functions such as HR, customer and production can use data to make intelligent decisions and drive good business financial performance (Van den Heuvel & Bondarouk, 2017:163). Angrave *et al*. (2016:9) stated that data professionals often use data analytics to resolve HR, customer or production problems, or they use data analytics as a new approach to execute customer, HR or production and service design strategies. According to Kiran *et al*. (2024:3115), to get meaningful insights from the data, data professionals need to fully understand the context in which the data was collected and the purpose of analysing data. This understanding will assist in determining the depth and resources required for the analysis.

ERPs and data analytics became prominent in HR while other business areas such as customer services, finance, risk and supply chain were already at an advanced stage (Shi & Wang, 2018:145). Data professionals within HR use ERPs and data analytics for optimising processes and for capturing employees' data, onboarding, offboarding and workforce reporting (Godard, 2014:7). The study of Douthit & Mandore (2014:18) highlights that data professionals in customer service and marketing use data analytics to collect customer data, to better understand customer behaviour and invest in products and services that customers need. According to Grover *et al.* (2018:390), in the production space, data analytics professionals use data modelling and AI to optimise the production process through automation and overcome production risks through the Internet of Things. As technology rapidly changed the introduction of AI and Machine Learning (ML) made it easier for professionals to get a glimpse of live data, do a deep dive into the details, and automate standard reports, this has been a common practice globally. Furthermore, professionals can use data across multiple disciplines to make good and fact-based decisions.

According to King (2016:486), organisational leaders and data professionals need to develop a clear understanding of how data analytics drives customer strategy, HR strategy and production and service design strategy to contribute to the success of the organisation. This will help to determine the purpose of the analytics effort, the investment in analytics tools and the establishment of relevant data that needs to be used. Organisations that invest in data analytics resources and systems are more likely to make quicker and more valuable data driven decisions because of the reliability and quicker processing of data (King, 2016:488). King (2016:489) stated that advanced data analytics models such as correlation, regression or structural equation are often used to further analyse and predict relationships between two data points, for example, measuring the relationship between employee engagement and organisational performance. Machine Learning (ML) techniques, such as forecasting, help to predict the future using historical data patterns. Predictive analytics helps organisations to build a future fit organisational strategy (Fitz-Enz & Mattox, 2014:16). According to Angrave *et al.* (2016:3), data analytics needs to facilitate experimentation to measure Return on Investment (ROI) and improvements for applied organisational efforts. This involves agile solution driven projects that have clearly defined problem solutions, followed by research and data analysis, ending with findings and organisational implications. If the solution is effective, business leaders can pilot and apply it in other areas within the business.

Kuo (2024:365) stated that many companies use a variety of data sources to help them make product or service pricing decisions which gives them an advantage in understand the pricing and sales landscape of competitors, analysis on their product pricing model and market demand. According to (Ridge *et al*., 2015:689), South African companies, more specifically retail, use data analytics to assess customer micro-segmentation, inventory management and product pricing optimisation. JSE-listed companies such as retail, manufacturing or telecommunications have high volumes for segmentation, which helps to analyse and integrate customer data and allows micro-segments. The micro-segments are used to analyse customer behaviour to better understand their personalised product and service needs, in order to improve customer satisfaction and drive business financial performance.

According to Molefe (2013:78), South African organisations are not advanced in the application of data analytics in HR, customer and production management. This is because the data profession still produces reports that are traditional and reactive, as opposed to being proactive by predicting the future and helping organisational leaders make better HR decisions. Molefe (2013:78) stated that the barrier for South African organisations to applying data analytics in HR, customer and production is limited by resources, such as well integrated data systems and developed data pipelines, as well as by having skilled data analytics employees. Employees who work in HR, Customer and Production departments need to understand data analytics and its importance in day-to-day operations.

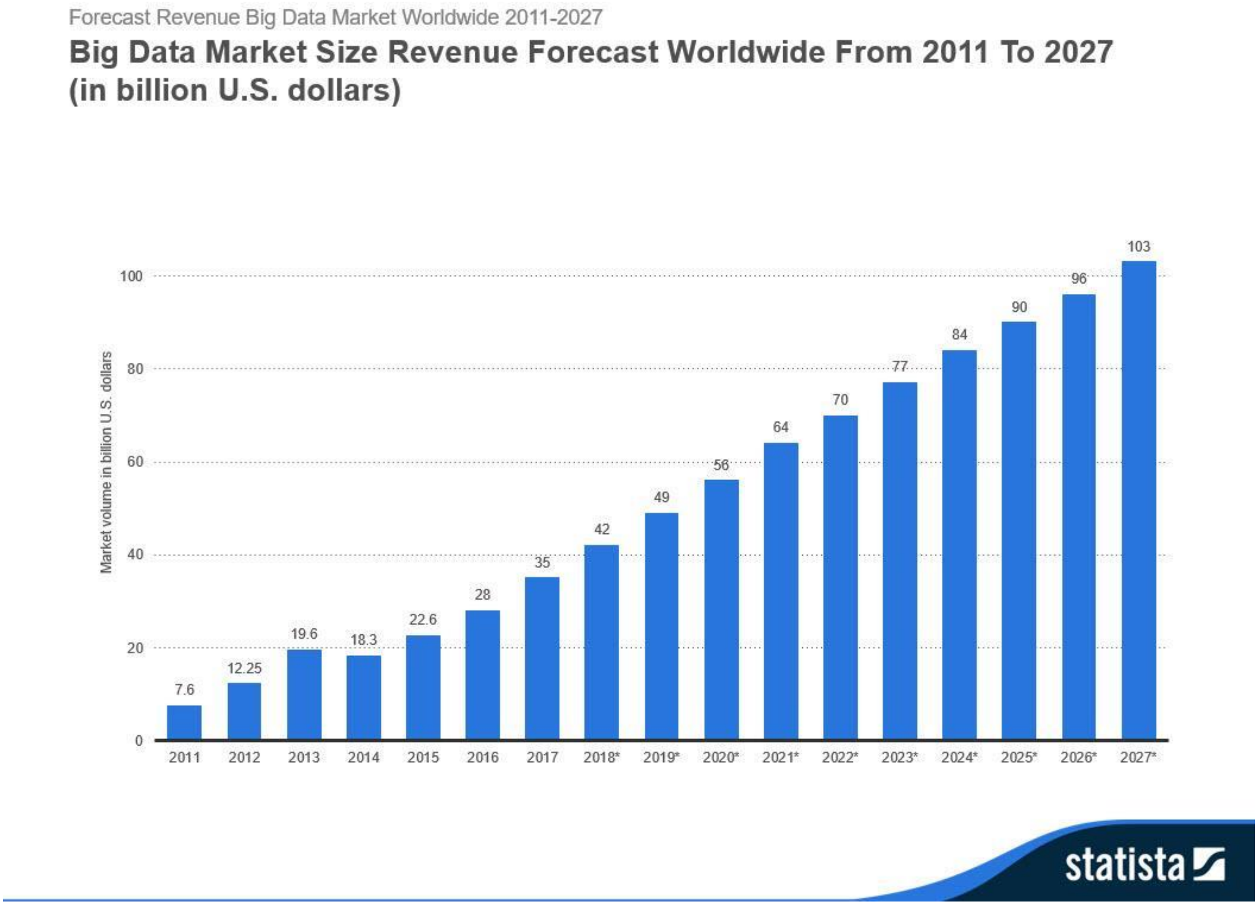

Figure 5: Data Analytics Market Revenues

The graph above illustrates the worldwide big data market revenues and suggests that if companies use data analytics best practices, they are likely to attain a Compound Annual Growth Rate (CAGR) of 10.48%, and companies that implement data analytics have an opportunity to benefit from this growth (Navarro, 2023).

Based on the empirical research referenced in the study, it is evident that data analytics plays an important role in driving business financial performance, and it enables business leaders to make data driven and informed decisions related to the HR strategy, customer strategy and production and service design strategy. Researchers highlight that implementing data analytics and enhanced technology enables businesses to be competitive, operate more efficiently, and achieve good business financial results. Previous studies stated that JSE-listed companies compete in the local and global markets, and the companies need to implement data analytics to have a good competitive advantage.

2.3. Chapter 2 summary

The chapter describes the concept of data analytics, which is defined as a process that businesses use to extract, transform, and present big data for decision making. Data analytics has been evolving rapidly and requires businesses to move from traditional data analytics methods to modern and advanced techniques such as predictive analytics, Artificial Intelligence (AI), Machine Learning (ML), and the Internet of Things (IoT) to improve business efficiency and effectiveness. The chapter highlights technology and data infrastructure solutions that businesses need, and the agile mindset that business leaders need to adopt to successfully implement advanced data analytics practices within their business. The chapter further summarises how data analytics supports business drivers such as HR strategy, customer strategy, and production and service design strategy to achieve key strategic business objectives. For businesses to implement and execute HR strategy, customer strategy, and production and service design strategy there is a need for well-integrated and efficient systems, and Data Analytics professionals need to be upskilled and equipped with the right tools. The chapter closes by describing how South African JSE-listed companies leverage data analytics and technology to improve operation efficiency, increase market share, and achieve better business financial performance. The next chapter presents the research methodology that was followed to conduct this research.

CHAPTER 3: RESEARCH METHODOLOGY

3.1. Research philosophy

This section discusses the research philosophy that was adopted in this data analytics, human resource, customer, production and finance research. According to Lor (2011:57), philosophies can be defined as basic beliefs that guide the research and influence the researcher's choices of methods to be used throughout the research. Research philosophy consists of four levels, namely paradigm view, theoretical lens, methodological approach and data collection methods. A paradigm in an organisational or social theory is a philosophical view on how researchers position their study. Philosophical assumptions help researchers to articulate the basis and the foundation of research. Creswell and Plano Clark (2011:119) stated that paradigms assist in shaping the development of research. When a researcher can understand different paradigms, he gains the ability to answer research questions and resolve the research problem. A pragmatic philosophy will be used to answer the questions of this research, solve the research problem and integrate the findings of the study. This study will follow the four philosophical assumptions to answer the research questions, resolve the research problem and integrate the findings of the study.

This research follows the positivism paradigm, which is based on a logical positivism philosophical approach. According to Ryan *et al*. (2002:37), the positivism approach focuses on the natural science method in research that focuses on human behaviour, and it is limited to what people may observe and measure objectively. This method strives to formulate laws that apply to the studied population that are valid universally and that explain the causes of behaviours that can be objectively measured. The objective method in research implies that the population rather than the researcher should agree to what is being observed or the information that is collected. Furthermore, what is being observed, or the information that is being collected, should be used objectively for the purpose of the research. Positivism derives from natural science, and it includes testing of meaningful variance hypothesis developed from existing studies using the measurement of observable realities.

This study follows the positivism paradigm. The researcher works with an observable organisational reality and the product of the research is expected to be a law-like generalisation. In line with the objective of this study, the hypotheses were developed from previous empirical studies. The hypotheses were tested and confirmed. The methodology of this research was highly structured, and the emphasis was on quantifiable responses that will lead to statistical analysis.

3.2. Research approach

This study was conducted following a quantitative approach. The data was gathered from JSE-listed companies in South Africa, and the data was analysed using descriptive statistics. A quantitative research approach was used to gather greater knowledge and understanding of data analytics within the South African business context, particularly JSE-listed companies. According to Westerhaus *et al*. (2004:9), quantitative research includes testing the hypothesis and measuring the relationship within variables. It follows a process of collecting data objectively and analysing it to control and determine variables of interest. Westerhaus *et al*. (2004:9) highlighted that the result of quantitative research helps to determine if the proposed literature matches the findings of the study and if the results of the study and the literature help to resolve the research problem. In quantitative research, data is interpreted by using statistical analysis techniques, and it creates an ability to replicate the test and results of the study. The quantitative research approach helped the researcher to objectively collect and analyse data through statistical methods.

3.3. Research strategy

The research strategy that was followed for this study is a survey. Survey strategy refers to the collection of data from the sampled population through their response to an online questionnaire. This research strategy enabled the researcher to easily recruit respondents, collect data and analyse the data using relevant statistical methods. The survey strategy can use questionnaires that have numerically rated items. The survey strategy has been regarded as the best research strategy for large population-based research. The primary purpose of this strategy is to collect data describing the characteristics of a large sample (Westerhaus *et al*., 2004:9). The strategy is aligned with the objectives of this study, which requires the researcher to collect large amounts of data from a sizable population. The survey strategy allowed the researcher to collect and analyse quantitative data using inferential and descriptive statistics. The questionnaire was used as a data collection method in line with the survey strategy.

3.4. Time horizon

This study forms part of cross-functional studies, as it strives to establish the relationship between data analytics and financial business outcomes within JSE-listed companies in South Africa at the current moment in time.

3.5. Study population

The population of the study was data professionals in Human Resources, Customer or Production who use data analytics in their daily activities within their job. The professionals worked within JSE-listed companies in South Africa. The professionals were using Information Systems (HRIS) to carry out their daily activities, and they used data analytics and reporting to drive strategy within their departments. Permission was obtained from the employees or respondents who participated in the study by requesting them to read and sign a consent form. The respondents were informed that they were participating in the study voluntarily, and they could withdraw their participation at any point in time. The respondents were requested to share the informed consent form with the relevant manager or head of department to sign and approve that the researcher can conduct the study in their company. The informed consent clearly outlined the purpose of the study and stated that employees' responses and any organisational information included in the responses would be for the purpose of the study and will not be compromised. The researcher identified JSE-listed companies. Within the companies' employees who work with data analytics in HR, Customer and Production were identified. The researcher shared the objective of the study with the employees and management and informed them that only employees who work in HR, Customer and Production were requested to participate in the study.

3.6. Sampling

The convenience sampling method was used to conveniently select relevant respondents to participate in the study. According to Leedy and Ormrod (2016:184), the following guidelines need to be followed when selecting a sample size, with a simple "N":

- Populations not exceeding 100 are too small to be sampled, it is therefore appropriate to consider the whole population.
- If the population is around 500, 50% (250) is the appropriate sample.
- If the population is around 1500, 20% (300) is the appropriate sample.
- At a certain point, if the population is 5000 and above, a sample size of 400 may be appropriate.

According to Listcorp (2024), there are approximately 345 listed companies in South Africa, and each listed company is likely to have at least one data analytics professional in Human Resources, Customer or Production. As per the Leedy and Ormond (2016:184) guidelines, the population of this study is 345, therefore the sample was 50% of the population, (345 x 50% = 172,5). The sample size of the study is 173.

3.7. Designing the measuring instrument

A questionnaire was used as the data measuring instrument. The questionnaires were administered online for cost effectiveness and accessibility. The data gathered using online questionnaires was used for descriptive purposes. The questionnaires were re-tested, internal consistency was measured and alternative forms of questions were considered to ensure that they were reliable. The questionnaires were administered in a manner that abides with North-West University's code of ethics.

3.8. Data collection

Employees who work with data analytics in HR, customer and production within JSE-listed companies in South Africa were identified and recruited to participate in the study with consent. The researcher contacted employees who work in JSE-listed companies on LinkedIn, telephonically or through email to request them to participate in the study. A response rate of 69% was achieved, the questionnaire was distributed to 45 employees who consented to participate in the study, and only 31 employees completed the questionnaire. The researcher shared the NWU ethics letter with the employees to show them that the research has been approved by the NWU ethics committee. The respondents of the study were requested to share the letter with the management of the company for approval.

The questionnaires were administered via a website, and the respondents received a link to complete the questionnaires. Relevant strategies such as length, content or appearance of the questionnaires were considered in order to motivate respondents to complete the questionnaires to increase the response rate. Respondents were asked for consent to participate in the study. The actual privacy and perception of acceptable by respondents were considered. The researcher ensured that the data collection tool was structured in a way that was not intrusive. Sensitive data such as demographics was only used to profile respondents, it will not be used for further statistical analysis or to compare groups of respondents. Demographic information was collected for the purpose of understanding the population's representation. Demographics were not used to inform the results of the study. Respondents were informed of their right to participate in the study. The questionnaire consisted of two sections, Section A and Section B. Section A included questions related to the respondents' demographics, respondents were asked to mark their answer with "X" close to each related question, and if the answer did not reflect on the questionnaire, the respondents were allowed to provide their answer in "others (please specify)" section. In Section B, respondents were given a statement with answers that ranged from - Strongly Agree = 5, Agree = 4, Neutral = 3, Disagree = 2 to Strongly Disagree = 1, then the respondents were requested to circle the number about the statement.

Table 2: Data Management Procedure

Phase	Procedure	Product
1. Qualitative data collection	Web based questionnaire (N = 173)	Numeric data
2. Quantitative data analysis	SPSS quantitative software	Descriptive statistics
3. Integration of results	Interpretation and explanation of quantitative results	Discussion, developing a framework, implications, and future research

3.9. Statistical analysis

Statistical analysis for this study was conducted using SPSS (Statistical Package for the Social Science) software. The analysis was conducted with the assistance of North-West University's recommended research consultant team.

Ordinal data was collected from the questionnaires for statistical analysis. The data was collected and automatically recorded on an online platform as respondents complete the questionnaires. A simplified data layout of the questionnaire was considered for smooth data transformation or coding. The data was coded using numeric codes to make the recording process quicker and to make re-coding straightforward. The data was assessed in order to check if there are errors and to ensure that the errors are cleared before the data is analysed.

Exploratory data analysis (EDA) was used at the initial stage to explore and understand the data. The EDA approach was followed in line with the objectives of the study. The approach helped to introduce unplanned analysis in order to respond to any new findings. The EDA approach helped to explore and present individual variables in the form of tables and charts. The EDA approach was also used to profile demographic data.

Descriptive statistics were used to describe and compare variables numerically in line with the objectives of the study. The central tendency was used to describe the sample and population quantitatively. The mode was calculated to identify values that occur more frequently in the dataset. The median was calculated to identify the middle value in the dataset. The mean was calculated to analyse all included data values. The range was calculated to get a quick impression of how the data values were distributed. A visual or formal test was conducted to determine the normal distribution of the data. Analysis of variance (ANOVA) was conducted to analyse the variance and to test the statistical significance. A correlation coefficient was calculated to quantify the strength of the relationship between the two variables of the study: variable 1: data analytics and variable 2: HR strategy. The correlation coefficient helped to determine whether there was a positive or negative relationship between the two variables. 3.10. Reliability and validity

To ensure that the results of the study are reliable, data collection techniques and the analysis process were designed in a way that yields the same results on all occasions. There was transparency on how the researcher made sense of the data. Respondents' errors and biases were considered throughout the study. Validity was taken into consideration when conducting the study. Validity threats such as history, testing, instrumentation, mortality, maturation and ambiguity were taken into consideration when conducting the study. The correlation coefficient was used to test the correlation between the two variables of the study. Cronbach's alpha was used to measure internal consistency on how variables are closely related.

3.11. Ethical consideration

The study followed ethical considerations and practices outlined in North-West University ethics guidelines. According to De Vos *et al.* (2011:441), the researcher must ensure that the research meets ethical standards for the research to conform to the required standards of research and to value the collaboration of research participants or respondents and all other stakeholders involved in the research. The researcher needs to show values of accountability to promote social and moral values. Ethics needs to cover important factors, including avoidance of harm to participants, respondents, and stakeholders. Ethical principles require the researcher to ensure that participants or respondents are informed of their consent, and they are encouraged to participate voluntarily. The researcher must ensure that respondents' or participants' privacy and confidentiality are not violated or compromised. Lastly, the researcher must inform respondents or participants of the objectives of the study and their contribution as well as their rights to withdraw their responses or participation from the study.

3.12. Publication of findings

The findings of the study will be published as they are and there will be no deception or misappropriation to people and there was no data manipulation in the study.

3.13. Chapter 3 summary

The study followed a positive paradigm based on a logical positivism philosophical approach. A quantitative research approach was followed to collect and analyse data. The targeted population of the study was data analytics professionals who work in Human

Resources (HR), Customer, and Production or Service Design departments within South African JSE-listed companies. Convenience sampling was used to conveniently select respondents who qualified to participate in the study. The sample size of the study was 173. The measuring instrument used for the study was an online questionnaire that consisted of a Likert scale questionnaire ranging from 1 = Agree to 5 = Strongly Agree, and the questionnaire had the following sections; (A) demographics, (B) qualifications and experience, (C) roles and responsibilities, (D) company technology and analytics tools, (E) skills and knowledge, (F) data analytics techniques or approaches, (G) HR strategy, (H) customer strategy, (I) production and service design strategy, and (J) business financial performance. Demographic data was only collected to profile respondents and not to compare their responses. SPSS tool was used to conduct inferential statistics and PowerBI was used to conduct descriptive statistics. A reliability test was conducted to measure whether the results of the study are reliable, and a correlation coefficient was conducted to analyse the relationship between the variables. The study followed ethical practices outlined by the North-West University's ethics guideline. The researcher ensured that respondents were informed of their consent, that they participated voluntarily, and that their confidentiality and privacy were not compromised. POPI Act was followed throughout the study and the researcher asked for approval from the management of the companies before conducting the study.

CHAPTER 4: DATA ANALYSIS AND INTERPRETATION OF RESULTS

4.1. Introduction

This chapter focuses on data analysis and interpretation of results from the data that was collected from data analysts or data professionals who work in the HR, Customer and Production departments within JSE-listed companies in South Africa. The data was collected using an online survey tool (Google Forms) and it was analysed using PowerBI for descriptive statistics and SPSS for inferential statistics. The distributions of descriptive statistics findings on demographics, role, experience and qualifications were analysed using frequencies, then the results were transformed into graphs.

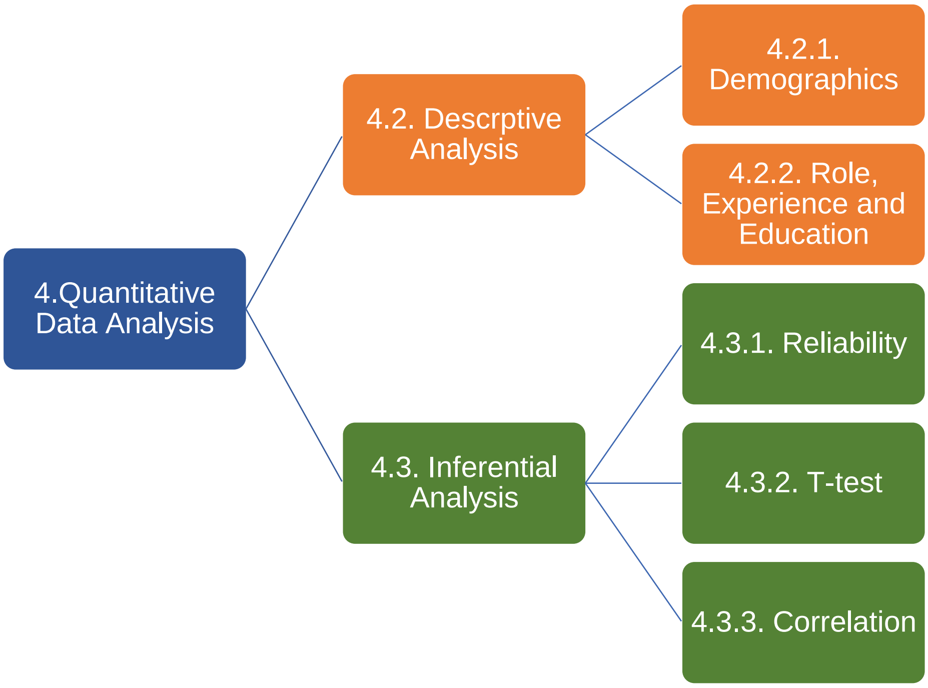

Figure 6: Quantitative Data Analysis

4.2. Descriptive analysis

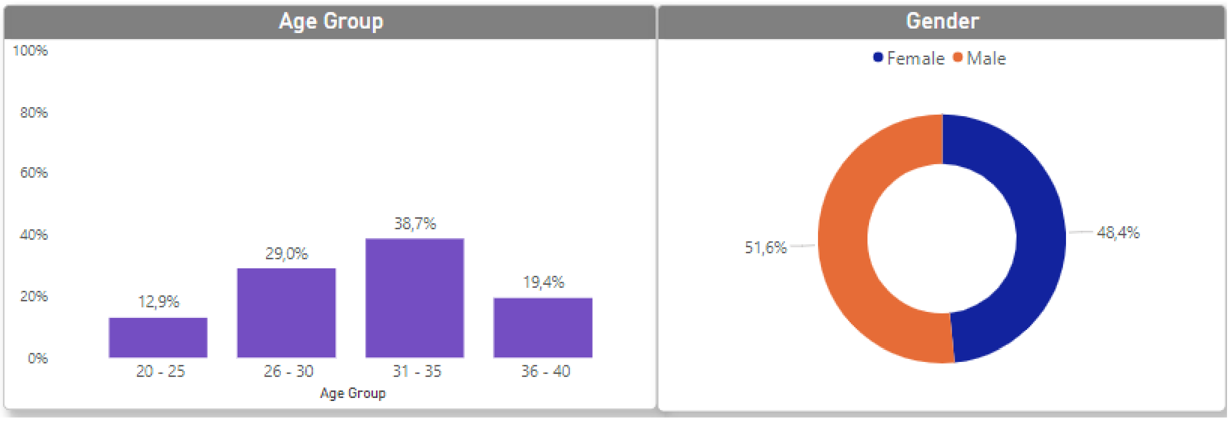

Figure 7: Demographics of the study

4.2.1. Demographics (age and gender)

Figure 7 indicates that the total number of data analysts or professionals who participated in the study is 31. As illustrated above, the age group that participated in the study ranges between 20 and 40 years, and they can be regarded as young professionals. 12.9% of participants are between the ages of 20-25 years, 29.0% of participants are between the ages of 26-30 years, 38.7% were between the ages of 31-35 years, and lastly, 19.4% of the participants are between the ages of 36-40 years. A further analysis conducted was the gender of the respondents, and, as illustrated in the visuals above 51.6% of the respondents are females and 48.4% of respondents are females.

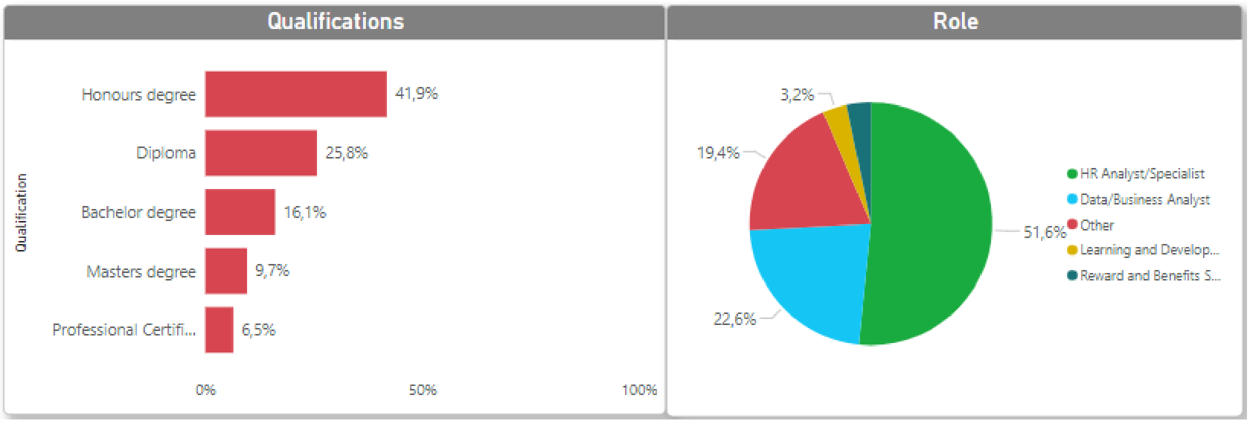

Figure 8: Role, experience and education factors

4.2.2. Role, experience and education factors

Role, experience and education factors were taken into consideration when analysing descriptive statistics, in order to understand the knowledge and skills fit of respondents in line with the objectives of the study. As illustrated in figure 8, the overall qualifications that the candidates have and the roles that they occupy into account, it confirms that the respondents were eligible to participate in the study because they met the requirements of the targeted population. A breakdown into categories of qualifications that the respondents hold shows that the majority of the respondents (41%) have an honours degree, followed by 25.8% of the respondents who have a diploma, 16.1% of the respondents have a bachelor's degree, 9.7% of the respondents have master's degrees and 6.5% of participants have a professional certificate. A further analysis was conducted to establish the role that the respondents hold. As illustrated in the visuals above, 51.6% of respondents are HR Analysts or Specialists, 22.6% of the respondents are Data or Business Analysts, 19.4% of the respondents hold other roles such as Customer Analysts, Finance Analysts or Production Analysts, 3.2% of the respondents are Learning and Development Specialists and lastly 3.2% of the respondents are Reward and Benefits Specialists.

Table 3: Respondents Work Experience

Work Experience	**Percentage**
Less than 2 years	6.5
2 to 5 years	45.2
6 to 10 years	22.6
11 to 15 years	22.6
More than 16 years	3.2
Total	**100.0**

A further analysis was conducted to understand and categorise the work experience of the respondents. Based on the results reflected in table 3, 6.5% of the respondents have less than 2 years of work experience, 45.2% of the respondents have 2 to 5 years of work experience, 22.6% of the respondents have 6 to 10 years of work experience, another

22.6% of the respondents have 11 to 15 years of work experience and lastly 3.2% of the respondents have more than 16 years of work experience.

4.3. Inferential analysis

Table 4: Reliability

Variable	Factor	Cronbach's Alpha	Mean inter-item correlation	Mean	Std. Deviation
Data analyst roles and responsibilities	C	0.706	0.230	3.824	0.355
Company technology and analytics tools	D	0.847	0.497	3.559	0.315
Skills and knowledge	E	0.852	0.500	4.171	0.222
Data analytics techniques/approach	F	0.943	0.680	3.649	0.242
HR strategy	G	0.948	0.594	3.908	0.139
Customer strategy	H	0.917	0.689	4.077	0.074
Production and service design strategy	I	0.860	0.451	4.009	0.113
Business financial performance	J	0.843	0.580	4.202	0.125

4.3.1. Reliability

The Cronbach's alpha coefficient was analysed to assess the reliability of each scale of the instrument and the results are reflected in the above table. The general threshold for Cronbach's alpha is when the measure is greater than 0.9 it is excellently reliable, when the measure is between 0.8 and 0.9 the reliability is good, when the measure is between 0.7 and 0.8 the reliability is acceptable, and any measure that is less than 0.7 it has low reliability which indicates that the measuring instrument and the concepts measures might need to be improved (Field, 2022:311).

The results in table 4 indicate that Cronbach's alpha for all variables; data analysts' roles and responsibilities, company technology and analytics tools, skills and knowledge, data analytics techniques or approaches, HR strategy, customer strategy, production and service design strategy and business financial performance are between 0.706 to 0.948, which is evident that the items measure the same underlying concept reliably. HR strategy (0.948) and data analytics techniques or approaches (0.943) have excellent internal consistency, this indicates that the factors have a similar underlying concept of reliability. Data analysts' roles and responsibilities (0.706), business financial performance (0.843), and company technology and analytics tools (0.847) have a relatively lower consistency but show good reliability.

When variables have a higher mean inter-item correlation, it indicates that they are measuring the same concept and have a strong correlation. The mean helps to assess the relative performance across the variables, while the standard deviation helps to show how the responses are spread across each variable. Variables that have a higher standard deviation indicate that the responses have a greater variability (Field, 2022:318). Skills and knowledge of data analysts (0.4995) and production and service design strategy (0.4508) have a moderate correlation because the mean inter-item of the variables falls within an ideal range. Customer strategy (0.689) and Data analytics approaches or techniques (0.680) have a high degree of similarity because their mean inter-item correlation is relatively high compared to other variables. Business financial performance (4.202) and skills and knowledge of data analysts (4.171) have the highest mean score, which is the highest among other variables. This indicates that the variables have a positive rating on average. Data analysts' roles and responsibilities have the highest standard deviation (0.355), which suggests that this variable has more variation in responses.

Table 5: T-test

			Point	95% Confidence interval	
		Standardizer[a]	Estimate	Lower	Upper
Data analyst roles and responsibilities	Cohen's d	0.51345	1.384	0.558	2.191
	Hedges' correction	0.52723	1.348	0.543	2.134
	Glass's delta	0.59045	1.203	0.363	2.019
Company technology and analytics tools	Cohen's d	0.87480	0.486	-0.264	1.228
	Hedges' correction	0.89827	0.473	-0.258	1.196
	Glass's delta	0.83329	0.510	-0.249	1.257
Skills and knowledge	Cohen's d	0.50562	1.468	0.632	2.284

	Hedges' correction	0.51918	1.430	0.615	2.224
	Glass's delta	0.54895	1.352	0.488	2.189
Data analytics Techniques/Approach	Cohen's d	0.70547	1.295	0.479	2.093
	Hedges' correction	0.72439	1.261	0.466	2.038
	Glass's delta	0.78157	1.169	0.334	1.980
HR strategy	Cohen's d	0.70238	0.388	-0.358	1.127
	Hedges' correction	0.72122	0.378	-0.349	1.097
	Glass's delta	0.60645	0.449	-0.306	1.193
Customer strategy	Cohen's d	0.75814	0.213	-0.526	0.949
	Hedges' correction	0.77847	0.208	-0.512	0.925
	Glass's delta	0.59081	0.274	-0.470	1.011
Production and service design Strategy	Cohen's d	0.68200	0.304	-0.439	1.041
	Hedges' correction	0.70030	0.296	-0.427	1.014
	Glass's delta	0.62093	0.334	-0.414	1.073
Business financial performance	Cohen's d	0.54446	0.397	-0.349	1.136
	Hedges' correction	0.55906	0.386	-0.340	1.106
	Glass's delta	0.44795	0.482	-0.275	1.227

4.3.2. T-test

The T-test results in table 5 indicate that data analysts' roles and responsibilities have an effect size of 0.513, which is a medium effect size. The variable has a point estimate of 1.384 with a confidence interval of 0.558 to 2.191, which indicates a statistical significance with moderate effect between the groups. Company technology and analytics tools have an effect size of 0.875, which is a large effect size. The variable has a point estimate of 0.875 with a confidence interval of -0.264 to 1.228, which indicates that the difference is not statistically significant regardless of the variable's large effect size. Skills and knowledge have an effect size of 0.506, which is a medium effect size. The variable has a point estimate of 1.486 with a confidence interval of 0.632 to 2.284, which indicates statistical significance with a moderate effect size. Data analytics techniques or approaches have an effect size of 0.705, which is a large effect size, The variable has a point estimate of 1.295 with a confidence interval of 0.479 to 2.093, which indicates statistical significance and strong difference between the groups. HR strategy has an effect size of 0.702, which is a large effect size. The variable has a point estimate of 0.338 with a confidence interval of -0.358 and 1.127, which suggests that the significant difference of this variable cannot be concluded confidently. Customer strategy has an effect size of 0.758, which is a large effect size. The variable has a point estimate of 0.213 with a confidence interval of -0.526 and 0.949, which suggests that the significant difference of this variable cannot be concluded confidently**.** Production and service design strategy have an effect size of 0.682, which is a medium to large effect size. The variable has a point estimate of 0.304 with a confidence interval of -0.439 to 1.041, which suggests that the significant difference of this variable cannot be confidently concluded. Business financial performance has an effect size of 0.544, which is a medium sized effect. The variable has a point estimate of 0.397 with a confidence interval of -0.349 and 1.136, which suggests that the significant difference of this variable cannot be confidently concluded.

4.3.3. Correlation coefficient

According to Field (2022:342), Spearman's rank correlation coefficient was used to test the relationship between multiple variables in line with the objective of the study. This method of correlation analysis uses a monotonic function to test how well two variables are related to each other, looking at a range of positive to negative monotonic relationships. In Spearman's rank correlation, correlation coefficient = 1 indicates a perfect positive relationship between two variables. In this instance, when one variable increases the other variable relatively increases as well. A correlation coefficient = -1 indicates a perfect negative relationship between two variables and in this instance, when one variable decreases, the other variable decrease as well. When the correlation coefficient = 0 it indicates that there is no relationship between two variables. When the correlation coefficient is 2-tailed, ** it indicates that the relationship between the two variables is statistically significant at 99%, and when it is 1-tailed *, it indicates that the relationship between the two variables is statistically significant at 95%.

The strength of the correlation can be verbally described using the guide for the absolute values below:

Table 6: Correlation strength

Correlation coefficient	Description
0.00 - 0.19	Very weak
0.20 - 0.39	Weak
0.40 - 0.59	Moderate
0.60 – 0.79	Strong
0.80 – 1.00	Very strong
**	2–tailed (99% statistical significance)
*	1–tailed (95% statistical significance)

Table 7: Data analytics and business financial performance correlation coefficient

	Data Analytics		
Variables	**Company Technology and Analytics Tools**	**Skills and Knowledge**	**Data Analytics Techniques/Approach**
Business financial performance	0.566**	0.414*	0.214

Primary objective: Understanding the relationship between data analytics and business financial performance

The primary objective of the study is to explore the role of data analytics in enhancing business financial performance within JSE-listed companies in South Africa. The elements of data analytics include several components, such as the technology of the company and analytics tools which are important for completing data analytics tasks such as data storage, data cleaning, data transformation and data presentation. Skills and knowledge of data analysts are other important elements of data analytics, because they help to ensure that the professional has the capability and is competent enough to complete the required task. The skills include domain knowledge, data manipulation, data transformation, data visualisation and data interpretation. The other important element of data analytics is techniques or approaches followed when carrying out data analytics tasks, which guides on best practices to be followed when analysing data (Ridge *et al.,* 2015:689).

The results in table 7 show that the relationship between the first element of data analytics, which is technology and analytics tools against business financial performance is < 0.566**. The results suggest that there is a moderate positive relationship between data analytics and business financial performance when looking at technology and analytics tools as an element of data analytics. A further observation is that the relationship between these two variables is 2-tailed, which suggests that there is a strong level of significance at 99% between the two variables.

The results in table 7 show that the relationship between the second element of data analytics, which is skills and knowledge of data analysts against business financial performance is < 0.414*. This suggests that there is a moderate positive relationship between data analytics and business financial performance when looking at skills and knowledge of data analysts as an element of data analytics. A further observation is that the relationship between the two variables is 1-tailed, which suggests that there is a strong level of significance between the two variables.

Lastly, when testing the primary objective of the study, the results in table 7 show that the relationship between the third element of data analytics. data analytics techniques or approaches. against business financial performance is < 0.214. This suggests that there is a weak positive relationship between the two variables.

Table 8: Data analytics, HR strategy, customer strategy and production and service design strategy correlation coefficient

	Data Analytics		
Variables	Company Technology and Analytics Tools	Skills and Knowledge	Data Analytics Techniques/Approach
HR strategy	0.356*	0.349	0.254
Customer strategy	0.312	0.272	0.067
Production and service design strategy	0.411*	0.254	0.072

Secondary objective 1: Understanding the relationship between data analytics and HR strategy

The results in table 8 indicate that there is a weak positive relationship between HR strategy and data analytics (company technology and analytics tools) at < 0.356*, and the relationship is statistically significant at 95%. The results further indicate that there is a weak positive relationship between HR strategy and data analytics (skills and knowledge of data analysts) at < 0.349, with no statistical significance. Lastly, the results indicate that there is a weak positive relationship between HR metrics and data analytics (approaches and techniques) at < 0.254.

Secondary objective 2: Understanding the relationship between data analytics and customer strategy

The results in table 8 indicate that there is a weak positive relationship between customer strategy and data analytics (company technology and analytics tools) < 0.312, with no statistical significance. The results further indicate that there is a weak positive relationship between customer strategy and data analytics (skills and knowledge of data analysts) at < 0.272, with no statistical significance. Lastly, the results indicate that there is a very weak positive relationship between customer strategy and data analytics (approaches and techniques) at < 0.067, which can be considered a negligible correlation.

Secondary objective 3: Understanding the relationship between data analytics and production strategy

The results in table indicate that there is a moderate positive correlation between production strategy and data analytics (company technology and analytics tools) at < 0.411*, and the relationship is statistically significant at 95%. When analysing the relationship between data analytics and production strategy, the results indicate that there is a weak positive relationship between production strategy and data analytics (skills and knowledge of data analysts) at < 0.254, with no statistical significance. Lastly, the results indicate that there is a very weak positive relationship between production strategy and data analytics (approaches and techniques) at < 0072, which can be considered as a negligible positive correlation.

4.4. Chapter 4 Summary

The total number of data analytics professionals who participated in the study was 31, and out of 31, (51.6%) of the respondents were males and (48.4%) were females. Their ages ranged between 20 to 40 years. The respondents' qualifications included a professional certificate, diploma, bachelor's degree, honours degree, and master's degree, and their work experience ranged from 0 to more than 16 years. The reliability test of the study indicated that the results were reliable by having Cronbach's alpha that ranges between 0.706 to 0.948. The correlation coefficient linked to the primary objective of the study indicated a positive relationship between data analytics and business financial performance. The first element of data analytics which is technology and data analytics tools indicated a correlation coefficient of < 0.566** with a strong level of statistical significance at 99%. The second element of data analytics, which is the skills and knowledge of data analysts indicated a correlation coefficient of < 0.414* with a statistical significance of 95%. The third element of data analytics, which is data analytics approaches or techniques indicated a correlation coefficient of < 0.214 with no statistical significance. The data analytics approaches or techniques is the only element of data analytics that has a weak positive relationship with business financial performance. It can be concluded that technology and data analytics tools, and skills and knowledge of data analysts are essential elements of data analytics that can assist companies achieve positive business financial results. Data analytics approaches or techniques do not carry much weight in enhancing business financial performance. Companies need to invest more in technology, data analytics tools, and upskilling data analysts.

CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

5.1. Introduction

Chapter 5 provides the conclusion and recommendations based on the findings of the study in relation to the study objectives. The chapter closes the study with areas for future research and the conclusion of the overall study.

5.2. Primary objective: Conclusion and recommendations:

Empirical research conducted in the literature review supports the view that data analytics have an impact on the business financial performance of many companies, including South African JSE-listed companies. Studies show that data analytics has become an important factor for companies that aim to optimise resources and improve operational efficiency to drive positive business financial performance. Grover *et al.* (2018:392), stated that companies that use data effectively can improve their decision making through data analytics, trend analysis and forecasting of financial and operational data. Studies suggest that, when businesses leverage data analytics, they position themselves better to drive production, customer and Human Resources (HR) strategies to improve business efficiency, minimise risks, gain better market share and attract, engage and retain the best talent. In line with the review of the literature of this study, it can be stated that companies use data driven insights to better understand their employees' behaviour regarding the organisational objectives. In order to make better decisions related to talent. When companies understand customer behaviour, they can tailor-make products and services to meet the needs of a customer and penetrate the market by understanding the needs of potential customers. According to Angrave *et al.* (2016:4), customers are at the centre of each business. It is therefore essential for companies to know their loyal customers' behaviour and reward them for their loyalty in repeat business. Companies can improve their internal operations by leveraging data analytics. This can be achieved through automation and streamlining processes and production. Research shows that companies that use data analytics effectively can increase sales and profitability.

Companies can build data driven business environments and achieve better business financial results if they invest in good technology, build strong analytical capabilities and refine analytical techniques. The results of this study indicate that, if companies invest in technology and data analytics tools as part of their data strategy, they will be able to positively impact the business's financial performance. According to Khanzode and Sarode (2020: 32), JSE-listed companies in South Africa are competing for talent and market share, and companies that invest in improving operations by leveraging data analytics are likely to be at a good competitive edge. Companies can invest in technology by enhancing their data infrastructure, which includes well integrated systems, data warehouses, real-time data processing tools, cloud data solutions and data analytics platforms that are user-friendly. Douthit & Mandore (2014:18) stated that, for companies to enhance their data infrastructure, they need to allocate dedicated resources that will focus on modernising the data infrastructure. Companies need to invest in enhanced data analytics practices such as Artificial Intelligence (AI), Machine Learning (ML) and predictive analytics for better automation of processes and to predict what the future will look like for better planning and to mitigate future risks. Technology is constantly evolving; therefore, companies need to regularly update their technology to remain relevant and to maintain competitive advantage.

The results of the study indicate that the skills or knowledge of data analysts or data professionals are positively related to business financial performance. It is therefore important for companies to have skilled data professionals who have the skills, knowledge and experience to effectively use the technology for better business value. Companies can attract and hire skilled data analysts who can effectively use advanced technology and data analytics tools and upskill data analysts who are already in the business through training. Data analysts need to stay abreast with the latest developments and tools in their field and continuously improve their skills such as data analytics, statistical analysis and coding. The other important factor related to the skills or knowledge of data analysts is their ability to help the business to drive a data driven culture by encouraging data literacy and data decision making across the organisation.

The results of the study indicate that the use of sophisticated data analytics techniques might be beneficial to data analysts, as it influences how they efficiently complete tasks but does not have a significant impact on the business financial performance of the company. Data analysts need to prioritise analysing data and recommending decisions that are aligned with the strategic objectives of the business not just learning every new analytics technique that might not add value to the business. Data analysts need to acknowledge that, at times, simple data analytics techniques can add more value and save the business time. It is important for data analysts to continuously evaluate the effectiveness of analytics techniques and ensure that they are aligned with business financial performance goals and adjust the techniques where necessary to maintain relevance.

5.3. Secondary objective 1: Conclusion and recommendations

Research shows that data analytics is increasingly becoming important in the Human Resource (HR) function of South African JSE-listed companies, as it helps to drive the HR strategy. Gallardo-Gallardo (2021:173) stated that data analytics in HR enables professionals to improve talent attraction and retention by being able to use data to identify ideal candidates, use best practices and benchmarks to attract the candidates and further analyse factors that drive attrition, in order to put measures in place to retain the best talent. Studies show that many companies measure attrition and overlay it with the total cost of replacing employees who have left, to measure the cost that a company will sustain due to high attrition. In the South African business context, data analytics is widely used to measure Diversity, Equity and Inclusion (DIE) to comply with legislative regulations and to improve engagement and inclusivity (Qin et al., 2024:34). Research shows that JSE-listed companies in South Africa make use of data and analytics to track performance, to improve performance of employees and the business. This helps companies to foster high performance, anticipate skills that the company needs currently and in future and to identify training opportunities to ensure that the company remains competitive in the market. HR executives use data and analytics to measure the achievement of HR strategic objectives.

The results of this study show that the HR strategy is positively related to the use of good technology and advanced data analytics tools as elements of data analytics. Business leaders need to invest in HR related technology and HR analytics tools to improve data driven decision making related to workforce analysis, talent management, learning and leadership development and compliance. The HR data infrastructure enhancements should be included in the scope of the company wide data infrastructural developments to enable the HR function to leverage existing technology and data solutions. The study shows that HR professionals need to be trained in data literacy so, that they can be able to effectively interpret data insights and make data driven decisions to improve the value of the HR function. When HR professionals understand the principles of data analytics, they will be able to collaborate with cross-functional teams on data initiatives that impact HR across the company.

5.4. Secondary objective 2: Conclusion and recommendations

As highlighted by Olson (2023), data analytics has become increasingly important in driving customer strategy, because it helps companies to derive data driven insights from their customer data and design an effective strategy to meet customer needs. Olson (2023) stipulated that, when a company has a clearly defined customer strategy and metrics to measure the company's effort in attracting and retaining customers, it can increase its customer base and market share. Data analytics helps companies to be able to analyse and interpret customer preferences, behaviour and trends to make informed business decisions related to the customer base.

When customer strategy is well aligned with data analytics best practices, JSE-listed companies can improve their business financial performance through increased market share and customer base. In the study of He (2021:6), it is stated that data analytics enable companies to personalise their customers' needs and market segmentation through effective customer metrics. Many companies use data from their e-commerce- and social media platforms to understand their customers' demographics and behaviours, such as purchasing preferences and patterns. Based on Joel and Oguanobi (2024:40), it can be concluded that companies that effectively segment their market and customers can personalise their products and services to cater for the needs of their customers. They can also communicate effectively with their customers to keep them engaged and interested in the products and service offering. According to Joel and Oguanobi (2024:41), companies use data analytics to measure customer behaviour, such as repeat purchases, and reward these customers as loyal customers to drive repeat purchases. Companies need to have well integrated customer technology to understand the full customer cycle and collect customer feedback for continuous improvement. Predictive analytics is an important data analytics factor that companies need to invest in to proactively engage with customers' future needs and to better anticipate the needs of future generations of customers.

The results of the study suggest that, while company technology and analytics tools are important to drive customer strategy, companies should also invest in putting best practices and policies in place to create both customer centric approaches and a framework to ensure that they can contribute to the effectiveness of a successful customer strategy. A clear customer framework can help companies to ensure that there is standardisation and consistency around customer principles, and this will enable companies to provide high quality products or services. The results of the study also indicate that the customer technology and analytics tools in place at JSE-listed companies might not necessarily translate actionable insights into customer strategy decision making This implies that there is a disconnect between company technology, analytics tools and the strategic application. The results of the study further suggest that the skills and knowledge of data analysts are important to drive customer strategy, but they are not used to their full potential. The results further indicate that the data analytics approaches and techniques do not play a huge role in driving customer strategy. JSE-listed companies need to invest in aligning their technology, analytics tools skills and knowledge of their analysts with the customer strategy to get full value. Companies need to further invest in empowering their employees and aligning with customer best practices to improve customer experience.

5.5. Secondary objective 3: Conclusion and recommendations

Das (2022) highlighted that, when companies effectively use data analytics in production and service design, they can improve their production and service design quality and efficiency. Data analytics assists companies to have a greater understanding of whether they are using their resources to their full potential to achieve the production and service design strategy (Das, 2022). In line with the study of Zafari *et al.* (2019:2570), companies use data analytics to improve operational efficiencies, reduce costs and drive positive business financial outcomes. According to Olawale *et al.* (2024:671), many companies invest in data analytics factors such as the Internet of Things (IoT), Artificial Intelligence (AI) and Machine Learning (ML) to understand the effectiveness of production machinery to improve quality and efficiency. They also use these factors to predict machinery maintenance to avoid breakdown and downtime. Companies also use AI and ML to understand whether the service that they are providing meets the needs of the customers. Data analytics can help companies to drive production and service design strategies through inventory management and demand forecasting. This helps to manage risks related to storage costs, shortage of stock and overproduction. Companies can use data analytics to plan and improve their production.

The results of the study indicate that there is a positive relationship between data analytics and production and service design strategy. Company technology and data analytics tools positively shape the production and service design strategy by helping JSE-listed companies to improve their service delivery, optimise production and improve efficiency to achieve the company's production and service delivery objectives. The results of the study indicate that the latest technology and analytics tools can help JSE-listed companies automate and streamline production and service design processes for better efficiency. The results of the study further suggest that JSE-listed companies must invest in the technology and data analytics skills of their employees to build capability and operate more efficiently. Data analytics approaches and techniques don't play a huge role in improving production, the most important factor is investing in the right technology, upskilling employees to be ready to use the technology and aligning the data analytics strategy with the right production and service design metrics.

5.6. Areas for future research

Future researchers must do a deep dive into understanding the investment needed to implement data analytics and technology within businesses and investigate the actual Return on Investment (ROI) that businesses will achieve by implementing data analytics solutions. Data analytics solutions are expensive to implement and companies might prioritise other investments, it will be important for future researchers to further investigate the feasibility of South African JSE-listed companies to implement data analytics solutions, taking into consideration the current economic landscape. Future researchers need to continuously explore how constant changes in technology and data analytics have an impact on the result of this study.

5.7. Conclusion

It can be concluded that data analytics is an important factor, and it can enable South African JSE-listed companies to improve their business financial performance. When companies integrate data analytical practices across Human Resources, customer management, production and service design, business leaders can have an opportunity to analyse business operations in line with the company's strategic objectives to improve operational efficiency and business financial results. Companies that leverage data analytics and build a data driven culture can make important business decisions faster and can position themselves better in the market against their competitors. The study highlights that companies value investing in technology and data analytics tools, but the challenge is acquiring and retaining skilled and experienced data analysts for each business stream i.e., HR, customer, production and service design. Companies need to align their data strategy with business objectives to realise the full potential of data analytics. When companies invest in innovative and creative solutions, they can stay competitive in the market by attracting and retaining the best talent, increasing their customer base, improving customer share, optimising production and designing tailored services that meet customers' needs.

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APPENDIX A: QUESTIONNAIRE

QUESTIONNAIRE

To be completed by a data analytics professional in HR, Customer or Production department in JSE-listed company within South Africa.

SECTION 1

Respondents Demographic Information

Demographic information will only be used for profiling purposes, not for comparison. In line with POPI Act, you are not obligated to complete demographic information and there will no negative consequences if you decide not to provide demographic information. You can request to access your personal information at any time to change the information.

For each of the questions below please put an "X" in the brackets on the right-hand side of your answer. If your answer to the question is not provided as an option below, write in the space provided to the right of "Other (*Please specify*)".

Part A

1.1 Gender Male [ ] Female [ ] Prefer not to say [ ]

Other (*Please specify*)_________

1.2 Age group 18 – 30 years [ ] 31 – 40 years [ ] 41 – 50 years [ ]

51 – 60 years [ ] 61 years + [ ]

Part B

1.3 Employment status Permanent [ ] Fixed Term Contractor [ ]

1.4 Please state your highest qualification

Professional Certificate [ ]

Diploma [ ]

Bachelor's degree [ ]

Honours degree [ ]

Master's degree [ ]

Doctoral degree [ ]

Other (*Please specify*)_________

1.5 Please specify your role

Human Resource Administrator [ ] Human Resource Officer [ ] Human Resource Specialist [ ] Human Resource Manager [ ] Human Resource Analyst [ ] Human Resource Systems Specialist [ ] Learning and Development Specialist [ ] Reward and Benefits Specialist [ ] Human Resource Generalist [ ] Data or Business Analyst [ ] Customer Analyst [ ] Production Analyst [ ] Manufacturing Analyst [ ]

Other (*Please specify*)_________

1.6 **Number of years worked** Less than 2 years [ ] 2– 5 years [ ] 6 –10 years [ ] 11–15 years [ ] Greater than 16 years [ ]

1.7 **Is your company listed**? Yes [ ] No [ ]

1.8. **In your role, do you work with systems and data?** Yes [ ] No [ ]

1.9. **Do you have systems or data analytics qualification (including recognised certificates)?** Yes [ ] No [ ]

1.10. **Have you been trained on how to use systems and data analytics tools?** Yes [ ] No [ ]

To what extent would you agree or disagree with each of the following statements on a scale ranging from Strongly Agree = 5, Agree = 4, Neutral = 3, Disagree = 2 to Strongly Disagree = 1. (Please simply put a "circle" on a number representing your preferred answer. If you make a mistake, put an "X" across the circle and choose another answer.)					
Part C: My role involves the following systems and data analytics tasks					
1. Data capturing	1	2	3	4	5
2. Data cleaning	1	2	3	4	5
3. Maintaining and updating system data	1	2	3	4	5
4. Maintaining systems functionality	1	2	3	4	5
5. Creating data solutions and creating data storage platforms	1	2	3	4	5
6. Bringing data together from multiple platforms to provide accurate, complete and up to date dataset	1	2	3	4	5
7. Generating and submitting business reports	1	2	3	4	5
8. Drawing insights, trends and storytelling from data	1	2	3	4	5
9. Presenting reports and solutions to stakeholders	1	2	3	4	5
Part D: The company that I work for have the right technology and tools that enables me to perform my work					
1. Information systems that stores data in one platform	1	2	3	4	5
2. Software applications that helps to collect, clean, analyse and visualise data	1	2	3	4	5
3. Software applications that uses artificial intelligence algorithms to automatically perform specific tasks and solve problems	1	2	3	4	5
4. Software applications that allows systems to be more accurate in predicting business outcomes using existing business rules and processes.	1	2	3	4	5
5. Enterprise system used for the analysis and reporting of structured and semi-structured data from multiple sources i.e., HR, customer, marketing, production etc.	1	2	3	4	5
6. A database built to run in a hybrid cloud environment to help organise, store, and manage data	1	2	3	4	5
Part E: I have the following skills and knowledge to perform my work					
1. Identifying business problems, collecting and analysing data to resolve the problem	1	2	3	4	5
2. Setting internal standards for data and drafting data policies	1	2	3	4	5
3. Creating a simplified diagram of a software system and data elements by using text, and symbols to represent data and how it flows	1	2	3	4	5
4. Creating the representation of data through use of common graphics, such as charts, plots, infographics and animations	1	2	3	4	5
5. Building a compelling narrative based on data and analytics that help tell the story and influence and inform a particular audience	1	2	3	4	5

6. Creating reports to present data to evaluate business strategies and performance	1	2	3	4	5
7. Using data trends and insights for decision making	1	2	3	4	5
Part F: I use the following data analytics approach to analyse, interpret and make data driven decisions in my role					
1. Statistical interpretation to analyse historical data to identify patterns and relationships	1	2	3	4	5
2. Analysing a sequence of data points collected over an interval of time	1	2	3	4	5
3. Exploring the naturally occurring data groups within a data set					
4. Examining data to understand the root causes of events, behaviors, and outcomes	1	2	3	4	5
5. Forecasting data to predict future outcomes	1	2	3	4	5
6. Visually outlining the potential outcomes, costs, and consequences of a complex data decision	1	2	3	4	5
7. Using data to identify which data points have an impact on a specific business outcomes	1	2	3	4	5
8. Using statistical techniques to reduces a set of variables by extracting all their commonalities into a smaller number of factors for focused analysis	1	2	3	4	5
Part G: I use data to drive the following HR (people) metrics to achieve financial business outcomes of the company that I work for					
1. Identifying talented employees and attracting them to fill key positions within the company	1	2	3	4	5
2. Identifying employees' level of engagement and motivation to drive business financial performance	1	2	3	4	5
3. Understanding why employees are voluntarily leaving the company and creating retention strategies to reduce rehiring expenses	1	2	3	4	5
4. Identifying ways to improve employee benefits offering to enhance employee experience and performance	1	2	3	4	5
5. Identifying key leadership skills that employees need to improve leadership capability and decision making within the company	1	2	3	4	5
6. Tracking the training spend against budget	1	2	3	4	5
7. Measuring the financial benefit that the company receives compared to the cost of running employee training programs	1	2	3	4	5
8. Measuring employee and departmental performance and ensuring that the performance is aligned to business performance goals	1	2	3	4	5
9. Identifying talented employees that will succeed executive and critical roles in the company and developing them for the roles to protect business knowledge and to build business continuity	1	2	3	4	5
10. Measuring that employees are strategically allocated to the right department and ensuring that they have the right tools to optimise productivity	1	2	3	4	5
11. Measuring HR operational efficiency (budget, leave provision, overtime cost management etc.) to manage business costs effectively	1	2	3	4	5
12. Measuring if the company hires, develop and retain diversified talent to drive innovation and to enhance business financial performance	1	2	3	4	5

13. Measuring if the company complies with legislative requirement such as Employment Equity (EE), Black Economic Empowerment (BEE) etc., to avoid penalties, to improve business competitiveness and contribute to inclusive and equitable economy.	1	2	3	4	5
Part H: I use the following customer metrics to achieve financial business outcomes of the company that I work for					
1. Identifying if customers continue using company's products or services over a given period to measure the value of product or service offering	1	2	3	4	5
2. Measuring the net profit that the company is likely to generate from the customers throughout the customer and business relationship	1	2	3	4	5
3. Identifying if customers are likely to make repeat purchases of the same product to measure customer loyalty and to predict business financial performance as a result of repeat purchases	1	2	3	4	5
4. Identifying how happy customers are with the business offering and improving customer services where needed to drive business financial performance	1	2	3	4	5
5. Identifying how likely customers will refer the business to other potential customers to help the business improve its market share	1	2	3	4	5
Part I: I use the following production metrics to achieve financial business outcomes of the company that I work for					
1. Measuring the number of products that the company produce to ensure that the right quantity of products is produced	1	2	3	4	5
2. Measuring the period of time when a machine is not in production and its impact on business financial performance	1	2	3	4	5
3. Measuring the direct or indirect cost that the business incurs for producing products and ensuring that the costs are within budget	1	2	3	4	5
4. Measuring the availability of factory operations from the beginning to the end of production process to get detailed perspective of production performance and to categorise major production losses and poor performance.	1	2	3	4	5
5. Identifying the percentage of manufacturing time that is truly effective to improve production efficiency and quality	1	2	3	4	5
6. Measuring the efficiency of production equipment to make strategic decisions to optimise equipment efficiency	1	2	3	4	5
7. Measuring if the production resources are being used to generate output to assess current operation efficiency	1	2	3	4	5
Part J: Data analytics enables me to directly or indirectly achieve the following financial business outcomes					
1. Profitability	1	2	3	4	5
2. Increase in customers	1	2	3	4	5
3. Increase in sales volume	1	2	3	4	5
4. Cash conversion	1	2	3	4	5

ANNEXURE B: LANGUAGE EDITOR'S LETTER

DECLARATION

This is to declare that I, Casper JH du Plessis, qualified language editor and proofreader, have language-edited the dissertation by

KV Monyela

orcid.org/0009-0003-6005-6815

with the title

Exploring the role of data analytics in enhancing business financial performance within JSE-listed companies in South Africa

CJH du Plessis

Casper JH du Plessis

Qualified language editor and proofreader at the New Zealand Institute of Business Studies

Date: 25 November 2024

Tel: 084 838 7921

ANNEXURE C: ETHICAL CLEARANCE

NWU®
NORTH-WEST UNIVERSITY
NOORDWES-UNIVERSITEIT
YUNIBESITI YA BOKONE-BOPHIRIMA

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Fezlwe.Mseleni@nwu.ac.za

12 June 2024

ETHICS APPROVAL LETTER OF STUDY

Based on approval by the **Economic and Management Sciences Research Ethics Committee (EMS-REC)** on, 12/06/2024 the Economic and Management Sciences Research Ethics Committee hereby approves your study as indicated below. This implies that the North-West University Senate Committee for Research Ethics (NWU-REC) grants its permission that, provided the special conditions specified below are met and pending any other authorisation that may be necessary, the study may be initiated, using the ethics number below.

Study title: Exploring the role of data analytics in enhancing business financial performance within JSE listed companies in South Africa.

Study Leader/Supervisor (Principal Investigator)/Researcher): Prof. Wedzerai Musvoto

Student: K Monyela (24006793)

N	W	U	-	0	0	6	0	6	-	2	4	-	A	4
Institution				Study Number						Year			Status	

Status: S = Submission; R = Re-Submission; P = Provisional Authorisation; A = Authorisation

Application Type:
Commencement date: 12/06/2024 **Risk:** **Minimal**
Expiry date: 12/06/2025

Approval of the study is initially provided for a year, after which continuation of the study is dependent on receipt and review of the annual (or as otherwise stipulated) monitoring report and the concomitant issuing of a letter of continuation.

Special in process conditions of the research for approval (if applicable):

- None.

General conditions:

While this ethics approval is subject to all declarations, undertakings and agreements incorporated and signed in the application form, the following general terms and conditions will apply:

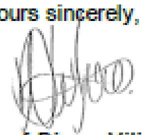
- *The study leader/supervisor (principle investigator)/researcher must report in the prescribed format to the EMS-REC:*
  - *annually (or as otherwise requested) on the monitoring of the study, whereby a letter of continuation will be provided, and upon completion of the study; and*
  - *without any delay in case of any adverse event or incident (or any matter that interrupts sound ethical principles) during the course of the study.*
- *The approval applies strictly to the proposal as stipulated in the application form. Should any amendments to the proposal be deemed necessary during the course of the study, the study leader/researcher must apply for approval of these amendments at the EMS-REC, prior to implementation. Should there be any deviations from the study proposal without the necessary approval of such amendments, the ethics approval is immediately and automatically forfeited.*
- *Annually a number of studies may be randomly selected for an external audit.*
- *The date of approval indicates the first date that the study may be started.*

n the interest of ethical responsibility, the NWU-SCRE and EMS-REC reserves the right to:

- *request access to any information or data at any time during the course or after completion of the study;*
- *to ask further questions, seek additional information, require further modification or monitor the conduct of your research or the informed consent process;*
- *withdraw or postpone approval if:*
  - *any unethical principles or practices of the study are revealed or suspected;*
  - *it becomes apparent that any relevant information was withheld from the EMS-REC or that information has been false or misrepresented;*
  - *submission of the annual (or otherwise stipulated) monitoring report, the required amendments, or reporting of adverse events or incidents was not done in a timely manner and accurately; and / or*
  - *new institutional rules, national legislation or international conventions deem it necessary.*

The EMS-REC would like to remain at your service as scientist and researcher, and wishes you well with your study. Please do not hesitate to contact the EMS-REC or the NWU-SCRE for any further enquiries or requests for assistance.

Yours sincerely,



Prof Diana Viljoen-Bezuidenhout
Chairperson: NWU Economic and Management Sciences Research Ethics Committee