UNIVERSITY OF GHANA

COLLEGE OF HUMANITIES

UNIVERSITY OF GHANA BUSINESS SCHOOL

DEPARTMENT OF ORGANISATION AND HUMAN RESOURCE MANAGEMENT

AN EXPLORATORY STUDY OF HUMAN RESOURCE (HR) ANALYTICS: IMPLICATIONS FOR HUMAN RESOURCE MANAGEMENT PRACTICE

BY

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THIS THESIS IS SUBMITTED TO THE UNIVERSITY OF GHANA, LEGON, IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE AWARD OF MASTER OF PHILOSOPHY HUMAN RESOURCE MANAGEMENT DEGREE

MAY, 2019

DECLARATION

I, **ALFRED BOAKYE,** do hereby declare that this work is the result of my own research and has not been presented by anyone for any academic award in this or any other university. All references used in the work have been fully acknowledged.

I bear sole responsibility for any shortcomings.

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CERTIFICATION

I hereby certify that this thesis was supervised in accordance with procedures laid down by the University.

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DR. YVONNE LAMPTEY **DATE**

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DEDICATION

I humbly dedicate this work to the Lord Almighty for his Faithfulness and Mercies towards me throughout my life and my studies.

I also dedicate this work to the two most important people in my life, Mr. Stephen Boakye and Rev. Kwaku Owusu-Boachie for their Immeasurable Love, Support and Encouragement throughout my work and education. I say, May the Good Lord continually bless and keep them.

This work is also dedicated to Mrs. Mercy Kwakye Boakye posthumously. God keep you safe till me meet again!!!!!

ACKNOWLEDGEMENT

My greatest gratitude goes to the Almighty God the Father, his son Jesus Christ and the Holy Spirit my guide for the wisdom and Grace throughout my academic journey. Elohim, May only your name be forever praised.

I owe it a great debt of gratitude to Dr. Yvonne Lamptey at the Department of Organisation and Human Resource Management at University of Ghana Business School, who supervised my work and gave her constructive criticism, guidance and tutoring to make this work a realization. God richly bless you!

I also want to appreciate Dr. Eric Afful-Dadzie of the Operations Department for his contribution towards my thesis. I say God bless you for the kind gestures. My appreciation also goes to my friends and all who contributed in diverse ways; encouragement when the going was tough, proof reading and offering their constructive criticism. You have been a blessing and God richly bless you All.

I wish to thank all the companies who granted me the go ahead to collect data for this work.

Finally, I would like to thank my family who have been my biggest supporters all the way through the entire process.

God Bless You All!

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LIST OF ABBREVIATIONS

HRM	Human Resource Management
HR	Human Resources
SHRM	Strategic Human Resource Management
ROI	Return on Investment
NPV	Net Present Value
LAMP	Logic, Analytics, Measures, Processes
IT	Information Technology
CIPD	Chartered Institute of Personnel and Development
BSc	Bachelor of Science
MSc	Master of Science
MBA	Master of Business Administration
EMBA	Executive Master of Business Administration
PhD	Doctor of Philosophy
MA	Master of Arts
MPhil	Master of Philosophy
Eng.	Engineering
IHRMP	Institute of Human Resource Management Practitioners
CPHR	Certified Professionals for Human Resources
SCP	Senior Certified Practitioners

ABSTRACT

Effectively managing human capital is very critical to organisations today. This has strategic implications for businesses that want to gain competitive advantage over others. HR analytics is gaining widespread attention in businesses with the goal of increasing their competitiveness. This study, therefore, sought to investigate the implications of HR analytics on human resource management practice in Ghana. Adopting a qualitative approach to research, twenty organisations were purposively sampled with ten each from public and private organisations. Data was collected in a span of two months with the appropriate institutional approvals. The interviews lasted for thirty (30) to forty (40) minutes where responses were audio recorded. The data collected were analysed using the thematic analysis. The findings showed that Microsoft Excel, Microsoft Power BI and regression and decision tree were the predominant tools and methodologies used in HR analytics. The study further found that the use of HR analytics use has brought great gains on how applicants are recruited in job roles, performance has increased both at the individual and organisational levels and the best talents retained for continuous growth and effectiveness. Finally, the study revealed that organisations that use HR analytics have faced several challenges as: lack of HR analytics competency, lack of management support and poor data and tools management in appropriately digging into their employee data. Through the study findings, it was recommended that, the Government of Ghana draft a policy document to promote the use of HR analytics in public organisations due to the benefits that comes with its usage. Also, educational and professional institutions need to review their course catalogues to include courses in HR analytics to train experts in the field. The Ghana Employers Association need to encourage their members to take advantage of HR analytics especially to member firms that are currently not using it and to recommend to other sister companies. Conducting further research into the field will help establish strong connections between HR analytics and other Human Resource Management practices. Value can be created by promoting the use of analytics in the HR unit or organisation to reap the enormous benefits.

CHAPTER ONE

INTRODUCTION

1.0 Introduction

The growing trend in businesses is the application of data analytics which is making a great impact in functional areas of firms. These areas are accounting (Earley, 2015) which has used analytics to mine data about customers and competitors to make decisions about their products and services by reducing errors and finding tax-saving opportunities to cut administrative costs; Supply chain (Souza, 2014) which has centred on the use of global positioning systems, radio frequency identification chips and data visualization tools to manage with real-time information regarding quality and location of goods in the supply chain and to better match supply and demand; and healthcare (Ward, Marsolo & Froehle, 2014) mainly focusing on well-established techniques as biostatistics to analyse patient data to improve health care and to generate accurate prescriptions from patient symptoms analysis. This goes to analyse how often patients visit the hospital and what it means and this enables the health facilities to reduce waiting time and potentially improve patient outcomes. The interest in the use of big data or data analytics increases by the day due to the fact that it helps understand a social phenomenon, a host of real-world applications (Raguseo, 2018) and plays a central role in decision-making (Power, Heavin, McDermott & Daly, 2018). Big data has been described by extant literature as complex data sets used in analysis and processes although it adds value to a firms productivity and operations (Manyika, Chui & Brown, 2011; Marr, 2015). For data-driven organisations (McAfee & Brynjolfsson, 2012), volume is an inherent property of big data aside other properties such as velocity, variety, and variability. Companies now have access to a growing volume of data to be able to derive insights for operational and strategic means (Brynjolfsson & Saunders, 2009; Laney, Lettong & Lapkin, 2013). According to literature, the introduction of technology has enabled the human resource function to gather, store and access a chunk of employee data (Heuval & Bondarouk, 2017) and insights generated through them for improved organisational processes (Carter & Sholler, 2015).

Although Human Resource Management is late in joining the data analytics trend (SHRM Foundation, 2016), HR professionals have recognized its potential for understanding and optimising the workforce (Edwards & Edwards, 2016; Sullivan, 2013). The interaction between HR analytics and human resource management is obvious as analytics help in optimising recruitment, assessment, promotion, retention, remuneration, turnover as well as other aspects related to human capital management. The continuous growth in the use of analytics has unlimited potential for organisational effectiveness and efficiency. This is as a result of the ease with which data is collected and analysed (Mclver, Lengnick-Hall, & Lengnick-Hall, 2018).

1.1 Background of Study

The introduction of information technology in recent years has had a significant impact on human resource management practices (Gueutal & Stone, 2005; Parry & Tyson, 2011; Kavanagh, Thite & Johnson, 2015). This has brought about a change in how firms recruit, select, motivate as well as retain their employees. Now, leading firms or companies are looking for a competitive advantage in their employees due to the importance of employees to organisations (Kalianna & Ajovu, 2015).

Human resource management has evolved over the last three decades to replace the traditional personnel management (Snell, 2011; Ulrich, & Dulebohn, 2015) and this evolution has been in its theory, research, and practices. The work of the personnel manager ranged from taking care of employee problems to administering labour contracts and being an administrative expert (Osei, 2017). Human resource management helps to improve on the quality of work life, ensure legal compliance and productivity (Kramar et. al., 1997) and this can be achieved through the effective operation of its functions (Osei, 2017).

Organisations are now using HR analytics in their recruitment and selection (Mohapatra, & Sahu, 2017) where employers are able to track, measure, gather and analyse their candidate data to make better hiring decisions (Koshy, 2016). Google through analytics has revolutionised Human Resources by building retention algorithms and has refined their recruitment processes (Mohapatra, & Sahu, 2017). The introduction of HR analytics enables firms to track the skill set of their employees in a database that will serve as a yardstick towards employee's continuous development in the organisation. This is to make informed decisions on when an employee will need a particular training and development program to suit the ever-changing market demands. In terms of performance, Google is able to use analytics to predict their employee performance (Craig, Harris, & Egan, 2011). The use of analytics or HR analytics is growing in the compensation literature (Mohapatra, & Sahu, 2017). Through this, there is effective oversight of the compensation and benefits programs within the organisation which are very important especially when it comes to organisational performance (Karia & Omari, 2015).

Although HR Analytics has been in existence since 1900, some researchers argue that it is a new concept in Human Resource Management (Johannink, 2015) and they believe, it can help businesses to be more effective and improve performance. HR analytics has been described as an indispensable HR tool (Boston Consulting Group, 2014). This has been noted by researchers on the powerful impact of HR analytics on organisational performance and a way for HR to contribute or add value to the organisation (Lawler III, Levenson & Boudreau, 2004). Examples are Google, Bestbuy, and Sysco that has improved on their competitive advantage through the use of HR analytics (Davenport, Harris & Shapiro, 2010).

The hype in the cycle today is HR analytics (Soundararajan, & Singh, 2017) and as the interest rises, organisations want to know more about it and how they can use them to improve organisational effectiveness and to make strategic decisions about their workforce (Kavanagh,

& Carlson, 2012). A LinkedIn report in 2018 has indicated that, the United Kingdom, Sweden, and Denmark are the top three countries that has adopted HR analytics fully. Also, there has been an increase in the volumes of professionals in these countries who have indicated HR analytics capability in conducting analysis on their human capital. This implies that, more countries including Ghana need to embrace this new trend in HR both in tools and capability to match up with other thriving economies like the ones indicated above.

In Ghana, the adoption and implementation of HR analytics has not been fully explored due to the high cost incurred in acquiring an HR analytics tool making it available to a few fraction of firms that can afford. Sierra-Cedar (2016) postulated that, about 45% and 51% of large and mid-sized organisations respectively are investing huge sums of money on HR analytics. With the complex nature of businesses in Ghana coupled with economic challenges such as weaker currency, low savings, and low productivity (Amposah-Tawiah & Dartey-Baah, 2011), makes it difficult for organisations especially public or indigenous ones to invest in HR analytics as other countries due to the high cost of purchasing an HR analytics software (Jensen-Eriksen, 2016).

1.2 Statement of Problem

Scholars of management have identified that organisational effectiveness is one of the most central topics when it comes to the study of organisations (Lee & Brower, 2006). Therefore, for organisations to be more competitive, frequent studies need to be carried out to identify deviations and to solve workplace problems. It is very essential to identify and develop ways of assessing organisational effectiveness rather than adding on to theories (Cameron & Whetten, 1983) as no one approach to effectiveness is inherently superior to another (Cameron & Whetten, 1983).

HR analytics is unknown in most business organisations (HR Analytics, 2017) making managers rely on their instincts rather than statistical and analytical approaches to data evaluation. There is a goal to create awareness about HR analytics as a discipline to aid business decision-making (HR Analytics, 2017). This study, therefore, seeks to contribute towards creating the awareness of HR analytics both in the domain of academia and organisations. It also seeks to find out if organisations use the HR analytic tool and if they do, to what extent this tool is used and how they can use it if they do not use it. Also, benefits, as well as challenges, will be identified to guide the analytics implementation process.

Since the emergence of HR analytics, HR functions seem to be under intense pressure to demonstrate its value (Holbeche, 2009) but the needed skills and competencies of those involved in HR analytics is important (Bassi, Carpenter, & McMurrer, 2012). The ability to carry out effective analytics to reap organisational benefits is not forthcoming as most individuals within the HR function lack the necessary skills, knowledge, and insight (CIPD, 2013). Organisations, therefore, need to measure the capabilities of the employees within the HR function to ascertain their readiness for HR analytics. The study seeks to explore how capable Ghanaian HR functions are towards the adoption and use of HR analytics in their organisational processes.

Empirical research into HR analytics is extremely limited (HR Analytics, 2017, Heuval & Bondarouk, 2017). Most of the HR analytics literature is either normative or industry-driven and therefore lacks scientific validity (Marler & Boudreau, 2017; Angrave et al. 2016). Academics have generally been absent with very few debating on the HR Analytics phenomenon and its scrutiny (Heuvel, 2016; Heuvel & Bondarouk, 2016). Since the interest in HR analytics is increasing considerably (Marler & Boudreau, 2017), and has received little attention from academic scholars (Marler & Broudreau, 2017), it is therefore important to build on the HR analytics literature because the field offers greater opportunities for academic contributions (Kapoor & Kabra, 2014). This study seeks to fill the gap in knowledge by adding to the already existing scientific papers published on HR analytics and to test its adaptability in businesses in the Ghanaian context. This will also set the pace for HR analytics study in Ghana as currently, studies conducted in Ghana on HR Analytics seems non-existent.

1.3 Research Purpose

This study sought to examine the implications of HR analytics on Human resource management practice. The purpose of this study was to provide an in-depth information on how to solve workplace problems in terms of employee management using HR analytics. Also, due to the low awareness of HR analytics in most businesses, this study sought to create awareness on HR analytics in Ghana outlining its benefits towards strategic decision making. Furthermore, the study intended to identify how ready HR professionals are to embrace the use of analytics within their various HR departments. This was to solve the capability gap issue hindering the full utilization of HR analytics in most firms in Ghana. The research problem indicated that, research on HR analytics have been dominant in other parts of the world with little or none in Ghana. The purpose of this study, therefore, was to provide extensive knowledge on HR analytics and its implication on HR practice, first, to bridge the existing gaps in literature on analytics in Ghana. Secondly, to provide insights to fill industry and contextual gaps on HR analytics and implications for both private and public businesses in Ghana.

1.4 Research Objectives

The aim of this study will be to investigate the implications of HR Analytics on Human Resource Management Practice. The above will be tested through the following specific objectives;

1. To describe how HR Analytics is conducted in private and public organisations in Ghana.

2. To identify the tools and methodologies used in HR Analytics among private and public organisations in Ghana.

3. To identify the benefits associated with HR Analytics use in private and public organisations in Ghana.

4. To determine the challenges associated with the use of HR Analytics in these organisations in Ghana.

1.5 Research Questions

The objectives of the study informed the following research questions of which the researcher sought to answer at the end of the study. They are;

1. How is HR Analytics conducted in private and public organisations in Ghana?

2. What tools and methodologies are used in HR Analytics among private and public organisations in Ghana?

3. What are the benefits associated with HR analytics use in private and public organisations in Ghana?

4. What are the challenges associated with the use of HR Analytics in these organisations in Ghana?

1.6 Methodology

The interpretivist research paradigm was adopted to gain a rich understanding on the nature of reality from a research participant's viewpoint. To gain a holistic understanding of how HR analytics is conducted, tools and methodologies used and the benefits, as well as, challenges, the qualitative research design was used. This was to enable the researcher to interact directly with research participants to take their views on HR analytics. The phenomenological study approach under the qualitative research approach was employed for the current study to understand the essence of the phenomenon from the research participant's perspective (Creswell, 2013). This was also to give the researcher first-hand descriptions about HR analytics and to examine the lived experiences of the research participants (Creswell & Poth, 2017). The study comprised of both private and public organisations in the Greater Accra Region of Ghana. Adopting a purposive sampling technique which is a non-probability sampling technique, twenty (20) Human Resource professionals, managers and employees working in private and public firms who operate an HR department and runs analytics were drawn for the study. A data collection procedure was followed to gather the responses from the research participants on the field. Employing both primary and secondary sources of data, thematic data analysis was used to gain insights from the data to draw patterns of meaning across the data set related to the research questions posed. In establishing the trustworthiness of the study, the credibility, transferability, dependability and confirmability criteria were adhered to. The current study was guided by some research ethics such as informed consent, institutional confidentiality, and anonymity. Respondents agreed without coercion to respond to the interview questions. Field data were kept under strict confidentiality and discarded after analysis.

1.7 Significance of the Study

The significance of this study can be looked at through the two major areas; practice and research. In practice, the findings that will be obtained from the data collected will create a term of reference which will help promote the use of HR Analytics in organisations as it will inform HR practitioners on its benefits to people management resulting in organisational effectiveness and increased performance resulting in high employee retention. The findings of the study would, therefore, inform management on the need to institute measures that are aimed at enhancing the effective use of HR Analytics thus instituting it in business processes at the workplace. The current study will go on to help organisational bodies such as Ghana Employer's Associations (GEA) to develop working strategies that will encourage the use of HR Analytics at the various workplaces and educated on the significance of it to their businesses and to set up systems for adoption and implementation.

For research significance, a review of past literature clearly indicates that little work has been done in the area of HR Analytics which are concentrated in other parts of the world with no work done in Ghana. This will set the pace for scientific research on HR Analytics studies in Ghana. That is, it will provide the various implications of HR analytics on HR outcomes from a Ghanaian perspective.

1.8 Scope & Limitations

This study covered twenty (20) organisations with ten (10) each from private and public firms within the Greater Accra Region. The present study was not without its own limitations like any other research work. The qualitative nature of the study resulted in collecting data from one respondent per organisation which may affect the transferability and dependability of the study as questions of bias may not be controlled. Also, this did not afford the researcher to observe and measure the impact of HR analytics across a period of time as data was collected within a particular point in time. In addition, the collection of data took a longer period of time as most of the respondents were seemingly busy and had to review the data collection appointments on each visit.

1.9 Chapter Disposition

The study is organised into five chapters which focused on different dimensions of the research. The first chapter will cover the introductory part of the study focusing on the broad overview, statement of the problem which will lead to the research purpose, objectives, questions, and significance of the study. The next chapter reviews the HR analytics framework and thorough review of related literature carried out on HR analytics. Chapter Three presents the research methodology used in the data collection and analysis for the study. It presents the research paradigm and design, population for the study, sample size, techniques, and data collection procedure, established validity and reliability and finally, ethical procedures for the study are presented. The analysis for the study which makes up the chapter Four, both from the descriptive and interview is captured in the penultimate chapter of the work with a detailed discussion on the objectives set out at the beginning of the study. Chapter Five focuses on the summary, and conclusions drawn from the study with implications and limitations subsuming the final chapter to ascertain if the research questions set out at the beginning of the study have been answered with directions for future research.

CHAPTER TWO

LITERATURE REVIEW

2.0 Introduction

The chapter focused on investigating the implications of HR analytics on Human Resource Management Practice. The chapter is introduced on how to add value to the organisation by measuring HR analytics. The decision making and processes on how analytics is conducted in HR practice using the LAMP Framework and the Decision-making Process model were the main conceptual models discussed under this chapter. The various tools and methodologies have been fully explored. Followed was the empirical literature of the study which was also discussed under this chapter. Lastly, the chapter reviewed the extant literature on HR analytics and technology, its applicability, usage and benefits and the challenges inhibiting the use of analytics within the HR function in firms.

2.1 Overview of Human Resource Analytics

Human Resource (HR) Analytics is not a new concept emerging today as it can be traced as far back as the early 1900s (Kaufman, 2014) when Jac Fritz-enz, a pioneer in Human Resource Management measurement published a book on "How to Measure Human Resources Management" in 1984 (Fritz-enz, 1995). HR analytics is an HR practice enabled by technology.

The perception that human resources as a function has no impact on organisational performance but creates cost or expenses must be addressed by Human Resource Practitioners. According to Fecheyr-Lippens, Schaninger, and Tanner (2015), some organisations are generating up to $10 million in savings and improving on employee productivity and engagement simultaneously thereby advancing the use of HR analytics in their firms. These misconceptions of HR not making an impact on organisational performance is as a result of HR Practitioners not being able to assess the real impact of human resources in an organisation (Muscalu &

Serban, 2014). Therefore, there is a need for Human Resource practitioners to learn to speak qualitatively and objectively using numbers (Fritz-Enz J., 2010).

HR has undergone a considerable transformation from a more administrative function to being a strategic business partner in organisations (Ulrich & Dulebohn, 2015). Now, HR is adopting methods to add value to organisations in terms of HR work as well as areas for HR investments including HR analytics. The HR analytics tool is a sector within the broader scope of analytics which involves the use of analytical processes such as Excel, SPSS, Python, R studio, Power BI, Tableau, SAP, amongst others within various Human Resource departments basically to improve on performance. This enables firms to realize a greater Return on Investment (RoI). HR analytics which tends to have a broader scope is helping Human Resource practitioners to gain insight into the process of gathering HR data to make decisions relevant to achieving an organisations objectives. HR analytics help to draw a causal relationship between the various activities carried out by Human Resource Departments and business outcomes. This relationship paves the way to assess the impact an HR department has on the organisation within which it is situated. Once Human Resource Practitioners are able to draw this causal link, they are able to devise and implement strategies that will augment the business to achieving its set goals and objectives for better outcomes.

Although it is important for Human Resource practitioners to contribute towards becoming a strategic partner to promote effectiveness (Jamrog & Overholt, 2004), they are not striving towards this goal (Lawler III & Mohrman, 2003). With the reasons for this low strive yet unknown, it is essential for Human Resource practitioners to develop better analytics if they want to achieve the goal of becoming strategic partners in organisations.

Human Resource Analytics is defined by Marler and Boudreau (2017) as an HR practice that is enabled by information technology to mine data using statistical, descriptive, and visual analyses related to HR processes, human capital, and organisational performance to establish business impact for decision-making that is data-driven. In simple terms, Human Resource analytics is a tool to help HR Practitioners make more informed decisions and to create value for organisations. According to Handa (2014), Human Resource Analytics refers to the use of both qualitative and quantitative data to gain insights and support people management through effective decision-making processes. HR analytics simply is collecting, manipulating, and reporting data through the use of information technology. Heuvel and Bondarouk (2016) also posit that HR analytics is about identifying and quantifying people drivers systematically for better decision making on business outcomes. This means that, being able to analyse data related to human resources to make decisions in a systematic way.

Analytics that target human resources according to Gustafsson (2012) has received a lot of names in the past including Talent analytics (Davenport, Harris & Shapiro, 2010), HR analytics (Mondore, Douthitt & Carson, 2011), Talent intelligence (Snell, 2011) or Workforce analytics (Hoffman, Lesser, & Ringo, 2012b).

Scientific articles have not been published in the field of HR Analytics as HR Metrics (Stone & Dulebohn, 2013) and e-HRM (Strohmeier, 2009). This has led to a lot of misconceptions within the HR arena with regards to HR analytics (Smeyers, 2012). The reason being that most of the articles written are practice-based or by consultancy firms (Johannink, 2015). Because HR analytics are used to make decisions to improve both individual and organisational performance, it should focus on the future rather than the past (Smeyers, 2012). It is evident that analytics are in different forms; descriptive, predictive and optimization or prescriptive (Watson, 2014). Although HR analytics is growing at a speed rate, some firms are still struggling to implement it due to the major capability gap found in today’s HR practice (Deloitte, 2015; 2016; 2017).

2.1.1 Types of HR Analytics

2.1.1.1 Descriptive Analysis.

Descriptive analysis is the first type of HR Analytics (Fitz-enz, 2010) and this is used to understand past behaviours and outcomes and also to help examine and describe the relationships and patterns that exist between them (Ulrich & Dulebohn, 2015). At this level, it is more of cost reduction and total process improvement (Fitz-enz & Mattox, 2014). It helps to answer the question, "What happened?" The descriptive analysis involves the use of published reports, dashboards/scorecards, data visualization and basic data mining (Fitz-enz & Mattox, 2014). Due to the nature of the descriptive level analysis, it does not attach meanings to patterns observed. This is more exploratory than predictive (Narula, 2015) and so HR Practitioners need to be careful not to make predictions into the future with this data as this may be risky to the organisation. This is because the main aim is to understand the present from the past.

2.1.1.2 Predictive Analysis.

The second level or type of HR Analytics is predictive analysis. At this level of analysis, the meaning is given to the data to make projections into the future. According to Fitz-enz (2009), with practice, there is the likelihood that, future occurrences to some degree can be made through the analysis of historical data. That is, the predictive analysis is more focused on probabilities and potential impact (Fitz-enz & Mattox, 2014) and answers the question, "Why did it happen?" According to Watson (2014), predictive analysis can be used to identify attributes that are required to increase job performance and is able to screen suitable applicants for the job. Simulation models can be used to evaluate job demand and supply using for example, "Java Developers" and as work conditions change, the models are rerun to update both hiring and retention plans (Narula, 2015). Some forms of predictive analysis are genetic algorithms, neural networks, decision trees (Watson, 2014; Narula, 2015). According to Bersin (2013) as cited in Narula 2015), only 4% of companies have been able to reach the level of performing predictive analytics on their workforce. According to Mishra, Lama, and Pal

(2016), predictive analytics has been able to provide organisations with insights into data to enhance future predictions. This level of analysis goes beyond mere data presentations on reports, tables or metrics but rather a proactive strategy to improve people-related decisions (Mishra, Lama, & Pal, 2016). Techniques such as data mining have become popular in this area as it seeks patterns from large organisational data set. It is able to answer the questions of "where will it happen again and in what magnitude".

2.1.1.3 Prescriptive Analysis.

The third and highest level of HR Analytics is prescriptive analysis. It focuses more on complex data that is used to make improved decisions. This form of analysis examines data and is able to answer the question "what should be done?" or "how can we make it happen?" The prescriptive analysis enables organisations to make accurate predictions about their workforce such as a possible employee resignation (Jensen-Eriksen, 2016). Mathematical programming and simulation are some examples of prescriptive analysis. It is worth emphasizing that, prescriptive analytics go beyond predictions as it uses high-quality statistics to make an influence on businesses.

The three types of Analytics by Fitz-enz & Mattox (2014) and Gartner (2011) have been summarised below:

Figure 2.1: Structure of the data analysis model adopted from Fritz- enz & Mattox, (2014)

2.2 Measuring Value through HR Analytics.

Firm's inability to sustain an above-average performance recorded over a long term period has been reported by researchers (Marler & Fisher, 2017). Ghemawat (2001) through a study described that through analysing 700 business units within a 10-year period noticed that, in a shorter term, the company was able to gain competitive advantage through the price and performance of their products. In the longer term, competitiveness was based on the core competencies available to sell even unanticipated new products (Prahalad & Hamel, 1990). Value has been conceptualised by the resource-based view theory to include resources and capabilities to reduce costs and to increase revenue (Barney & Hesterly, 2012). HR analytics as a tool for value measurement should be able to support the organisation's agility, innovation, and learning (Marler, 2009). In summary, companies create value by charging higher prices or operating efficiently than their competition (Marler & Fisher, 2017).

In making value-producing decisions within the HR function using employee data, is it necessary to invest in HR analytics? This section of the study explores the various ways of measuring value using HR analytics as an e-HRM technology. This is known as ROI decisions (Marler & Fisher, 2017). ROI is realise when a company's future cash flow generated by the investment is greater than the investment's required cash outflow. The HR function may realize ROI when greater efficiencies are achieved through HR data management, better talent management, and faster HRM processes to increase effectiveness (Marler & Fisher, 2017). The most frequently used methods explored to determine the ROI to make a business case are simple ROI, Net Present Value (NPV), Internal Rate of Return (IRR), and Payback.

2.2.1 Simple Return on Investment (ROI).

The simple ROI is a ratio that compares the net cash flows to the total cash outflows. This is written mathematically as

$$\frac{(\textbf{Total investment cash flows} - \textbf{Total investment cash outflows})}{\textbf{Total investment cash outflows}}$$

Using an example cited by Martin, Swift & Berkley (2002) as extracted from a white paper titled Workforce Analytics Return on Investment assumed workforce analytics IT investment about $ 4 million. With an employee strength of 25,000, 10.5 percent of which are managers and an assumed cash inflows from reduced IT and HR headcount, increased employee productivity and administration savings in 5 years is $7.1 million. In calculating the ROI where

Total investment cash inflows = $ 7.1 million

Total investment cash outflows = $ 4 million

Then the calculation is,

$$\frac{(\$\ 7{,}100{,}000 - \$\ 4{,}000{,}000)}{\$\ 4{,}000{,}000} = 0.78\ or\ 78\ percent$$

From the calculations above, it is obvious that, implementing HR analytics for the firm example above shows that, value is or will be created. This enables HR professionals who may be non-financial specialists to calculate the value of HR analytics without any complex analysis.

Citing another example by the researcher, an assumed firm has ten of its high performers leaving the organisation with an average annual salary of GHC 900,000. Due to their capabilities, the firm will lose twice its output costing the organisation GHC 18,000,000. If the firm is able to keep these high performers, it will save the firm an annual profit of 8,000,000. In order for the organisation to reduce turnover so as to help identify the factors leading to the turnover so as to stimulate HR solutions to curb this. Assuming the analytics tool will cost GHC 5,000,000. Using the simple ROI to calculate the investment of HR analytics in this area, Total investment cash flows = 8,000,000

Total investment cash outflows = 5,000,000,

Then the calculation is,

$$\frac{(\text{GHC } 8{,}000{,}000 - \text{GHC } 5{,}000{,}000)}{\text{GHC } 5{,}000{,}000} = 0.6 \textit{ or } 60 \textit{ percent}$$

From, the calculations above, the value will be created if the organisation should invest in the HR analytics tool or solution because turnover costs are as a result of employees leaving their organisation and reduces the organisation's revenue across the company.

2.2.2 Net Present Value (NPV).

The net present value (NPV) model helps to make more useful estimates in calculating ROI for HR analytics (Fisher & Marler, 2017). This model helps to calculate the worth of present cash inflows and outflows in future years. That is, investments made today should yield profits in the future. Explaining further, in calculating the NPV, the cost of capital is by discounting future cash flows in that, if the value of the cash today is invested, it would yield the same cash flow in the future (Marler & Fisher, 2017). This is calculated using the formula:

$$\boldsymbol{PV = \frac{FV}{(1+r)^n}}$$

where

PV is the Present Value

FV is the Future Value

R is the cost of capital as a decimal

N is the number of years in the future where the present value n= 0

Using the workforce analytics example to explain the above model, assume that the cash inflows and outflows over the life of the HR analytics tool purchase are as shown in the following table:

Table 2.2.1: **Cash flows of the Workforce Analytics Investment**

Year	**PV**	**Year 1**	**Year 2**	**Year 3**	**Year 4**
Software purchase	$4,000,000				
Cash inflows	$1,430,000	$1,230,000	$1,230,000	$1,230,000	$1,230,000
Net Cash flows (NCF)	$ (2,570,000)	$1,230,000	$1,230,000	$1,230,000	$1,230,000

Source: (Marler & Fisher, 2017)

These projected cash flows must be discounted so that, it can reflect the present value of the cash flows. That is, what is the worth of the various cash flows worth today? Using the previous formula, the present value factor is given below with formula 1÷ (1+cost of capital).

Table 2.2.2: Present Value Factor for calculating the NPV of the Analytic Investment

PV (Year 0)	**Year 1**	**Year 2**	**Year 3**	**Year 4**	
Present Value Factor	**1**	**0.909**	**0.826**	**0.751**	**0.683**

Source: (Marler & Fisher, 2017)

The above figures are then multiplied by each cash flow using the appropriate present value factor and finally totaling the cash flows to determine the Net Present Value for the HR analytic solution investment.

Table 2.2.3: The Net Present Value for the Workforce Analytic Investment

	PV	**Year 1**	**Year 2**	**Year 3**	**Year 4**
NCF	$ (2,570,000)	$1,230,000	$1,230,000	$1,230,000	$1,230,000
PV Factor	1	0.909	0.827	0.751	0.683

PV Cash Flow	$(2,570,000)	$1,118,070	$1,017,210	$923,730	$840,090
NPV	$1,329,100				

Source: (Marler & Fisher, 2017)

From the table above, the NPV for investing in the HR workforce analytics software is $ 1,329,100. This is how much or value the software solution adds to the firm at a 10 percent capital. If for example, from investing in HR analytics generates an NPV which is positive, it is a value-producing investment. The shortfall of this model is that it cannot be used to compare different HR analytics tools of different sizes and forms of analysis.

2.2.3 Internal Rate of Return.

This model helps to address the shortfalls of the NPV in that, the IRR estimates the rate where the discounted future cash flows to their present value are equated to the future cash inflows to present value cash outflows (Marler & Fisher, 2017). In simple terms, IRR is the rate of return on the cash invested in an investment. Thus, the benefits accrued or being earned when an organisation invests in HR analytics within their HR function. This model helps to evaluate how the HR analytics tool can be beneficial to the company and to compare it to other workforce analytics tools. The IRR for the analytics software is 20%. This model is disadvantaged as the number deduced from the IRR is not meaningful as it assumes that, cash flows generated from an investment can be reinvested at the IRR. That notwithstanding, much higher IRR compared to a company’s initial costs of capital is unlikely reasonable.

2.2.4 Payback.

The payback model being the final explains how long an investment costs takes to earn or yield benefits. (Marler & Fisher, 2017). The number of years it will take for an HR analytics tool invested in to earn back the cost of deploying such a tool. In another vein, the payback model gives an idea of how long a company’s investment is at risk. It also looks at how long the analytical tool will serve the needed purpose for the HR function. Using the workforce analytics example, the payback will happen between the second and third years. At this point, the HR analytics tool would have generated enough value for the organisation at least in covering the investment costs as this payback time period is reasonable should the analytics solution be useful for at least 5 years.

Table 2.2.4: Rates of the Workforce Analytics Investment in Years

Year	PV	Year 1	Year 2	Year 3	Year 4
Software purchase	$(4000,000)				
Cash inflows	$1,430,000	$1,230,000	$1,230,000	$1,230,000	$1,230,000
Cumulative NCF	$(2,750,000)	$(1340,000)	$(110,000)	$(1,120,000)	$2,350,000)

Source: (Marler & Fisher, 2017)

2.3 Making HR Analytics Decisions and Processes in HR Practice.

The use of analytics is increasing in organisations and HR is equally adopting it in their functional area with the purpose to make better decisions (Heuval & Bondarouk, 2017). A lot of issues in human resource management practices can be addressed using data mining techniques for effective and efficient decision making (Ranjan, 2008). This has called for how analytics is conducted in HR practice as there are a lot of failovers than success stories (Keerthi, 2018). The current study has adopted the five-step proccess model and the LAMP Framework to explain the decisions and how analytics is conducted in HR practice.

2.3.1 LAMP Framework (Boudreau & Ramstad, 2007).

A call to develop a new paradigm to ensure the continuous adoption of the strategy in human resource management has been triggered by Human resource researchers. This call is to introduce how human talent can enable firms to make a strategic impact (Boudreau & Ramstad, 2005; Cascio & Boudreau, 2011; Wright & McMahan, 2011). In order to create value through talents to improve decisions and for strategic impact (Cascio & Boudreau, 2011), supported by

Boudreau and Ramstad (2005) argue for a “decision science” approach. Thus, in making decisions about recruitment, selection, performance management, compensation and development, practitioners will be guided by pre-defined standards. These standards are what Boudreau and Ramstad (2007) call the LAMP Framework which stands for Logic, Analytics, Measures and Processes. According to Boudreau and Ramstad (2007), these four components are critical to a measurement system, first to uncover very important relationships through analysis and to also enhance decision making based on the analysis. To these authors, the framework will help draw causal relationships between the various Human Resource Management Processes and business or organisational outcomes. This framework creates a platform for HR practitioners to be able to conceptualise how HR analytics can be designed and to identify contributory factors for management decisions (Lydgate, 2018). Following to this, Boudreau and Ramstad (2007) are of the view that HR should focus on providing senior managers with measures that can guide them to make future decisions, one, about managing and secondly, for the deployment of employees within the organisation. The various components of the LAMP Framework are explained below.

2.3.1.1 Logic.

The logic component lays emphasis on how important it is to draw connections in order to explain the data collected, effects on business and the possible business outcomes (Lydgate, 2018). In simple terms, the logic element is the story behind these connections in the measurement system (Cascio & Boudreau, 2011). HR analytics is able to draw strategic connections between the numbers and the business outcomes. The vital or logical connections are anchored on the three points of strategic HR- impact, effectiveness, and efficiency framed as the Human Capital Bridge Framework. This guides strategic succession planning to derive HR practices implications and to make an investment at the bottom line.

The efficiency anchor point used in decision sciences is more focused on the resources necessary to deliver HR practices (Boudreau & Marler, 2005). Thus, in order to attain compliance, certain resources are needed to achieve the organisation's strategy. Typical efficiency indicators include time to fill vacancies and cost-per-hire, pay-per-employee and time-to-train. These indicators usually suggest resources such as time or costs and how they can be reduced at the same time increasing the volume of that HR activity. It explains how HR can increase their activity at a relatively cheaper cost (Boudreau & Ramstad, 2005). The effectiveness anchor point explains how the various HR policies and practices can affect an organisation's talent pool as well as its structures to which they are targeted (Boudreau & Marler, 2005). Once these areas are identified, it gives the green light to create capability, motivation, and opportunity for its employees. The capability involves creating knowledge about the organisation and its code of conduct. Motivation includes rewarding employee sustainability about organisational perceptions. Opportunity includes encouraging employees to engage in volunteering tasks both within and outside the organisation (Boudreau & Ramstad, 2005). The final anchor point known as impact elucidates whether the HR function is applying its programs and practices to where they will have the greatest effect to achieve strategic and organisational effectiveness (Boudreau & Marler, 2005; Magau & Roodt, 2010). This point helps management and HR professionals to improve on the availability, as well as, the quality of a particular workforce. This anchor point can reveal surprising results where initially an organisation thought their important employees were sales representatives simply because revenue was important to the organisation. Adopting the impact element revealed that, little could be gained from improving the sales representatives as they were highly performing (Boudreau & Ramstad, 2005).

HR professionals should be able to choose measurement systems whose focus is logically relevant and appropriate for performance. An example cited by Bailey et al. (2018) explains how Starbucks was able to measure the performance of their baristas to be able to capture key issues of trust and discretion as important clues because these elements would impact on their customer service. From this example, a logical connection is drawn between trust and discretion on customer service. This will inform Starbucks on the appropriate measures to run the analysis to track these dispositions of their Baristas. Once the connections are logically grounded, leaders who are not or outside the HR profession will be able to understand and use these measurement systems in order to enhance decision making.

2.3.1.2 Analytics.

Drawing logical connections without the appropriate analysis can flounder. That is to say, analytics is essential and needs critical attention of HR professionals to want to draw correlations between HR practices and business outcomes. Drawing the appropriate conclusions from HR data characterises the analytics component of the framework (Cascio & Boudreau, 2011). In correctly analysing and interpreting data to avoid any false assumptions, the right statistics, as well as, skills are needed to enable the HR professional to identify and articulate the key issues in the data. Analytics also involves sourcing for the right data both outside and within the HR function. It is equally important to build analytical competencies within the organisation to reveal insights. When data analysis is effective, it helps to correctly interpret the data (Bailey et al., 2018). This is plausible when there is a connection or balance between the various statistical methodologies used and its practical relevance (Cascio & Boudreau, 2011). This comes to educate that, a correlation between for example staff satisfaction and customer satisfaction does not signify a causal relationship as argued by Bailey et al. (2018). Thus, a customer can be satisfied based on location and not necessarily due to the satisfied staff who will provide excellent services to the customer. In another vein, we cannot say, a satisfied customer could possibly lead to a satisfied staff. The bottom line is, once HR professionals have more data at their disposal and are familiar with the analytical principles, it enables them to use HR data effectively and to make very important analyses.

2.3.1.3 Measures.

The third component as proposed by Boudreau and Ramstad (2007) posit that quality data is essential if HR professional want to drive organisational impact. High-quality metrics that focuses on what is important should be used for the analysis (Bailey, et al., 2018). For Boudreau and Ramstad (2007), focus in the past has been more on efficiency, therefore, recommending a shift towards effectiveness and impact which calls for context-specific measures. Looking at an example from Bailey et al. (2018), employee turnover can vary based on how important it is to the organisation with respect to who is leaving as well as the context. Organisations that competes based on quality will record serious talent gaps which will take a long time to recruit employees to replace those who have turned over. This is so especially when the employees are well trained, well-qualified and experienced. But if the focus of the firm is not quality but speed, then rapidly recruiting lower-skilled workers is important and easy to replace them when they turn over. Both scenarios will need to be tackled differently, therefore the need to focus on what matters.

This element of the framework has received the most attention in HR and this may be as a result of the various measures used in every area of HR (Cascio & Boudreau, 2011). Enhancing the quality of HR measures has received much attention and time with a timeliness, reliability, completeness and consistency criteria standards. Although these are important, lacking a context can result in little consequences when applied in areas that are not needed. As noted by Boudreau and Cascio (2008), much debate exists in how to accurately estimate turnover and its cost using the appropriate formulas. Although the various turnover-reporting systems can adequately measure turnover rates, the question is, ‘will every manager use the same criteria for calculating turnover?’ or each manager will calculate turnover based on what he/she feels matters?' This brings to light the essence of the logic element of the LAMP model so that, it can support a good measurement. Investing in the right measures where they will be needed has greater returns not just where improvements are feasible.

2.3.1.4 Process.

Once HR analytics is conceived as valuable and informative by management to their organisation, a change management process must occur. This is possible by aligning HR leaders' analytical initiatives with existing problems the firm is facing. This enables HR professionals to gain credibility and actively involved in management decisions (Cascio & Boudreau, 2011). When measuring HR outcomes, it is important to note that, it should be trailed down from a strategic change management process where line managers are educated that, HR measures is an essential component of the change process. The process is the final element of the LAMP Framework proposed by Boudreau and Ramstad (2007), explains how measurement can affect the decisions and behaviours of an organisation which occurs within complex webs of social structures, organisational cultural norms and knowledge frameworks (Cascio & Boudreau, 2011). It is imperative that these measurement systems must fit the change-management process. Throughout the process, managers must understand that HR analytics is informative and possible which does not necessarily need sophisticated analysis. Cascio and Boudreau (2011) intimate that simple measures and analysis which equally matches managers' mental models which are already in use are recommended. An example is cited by Cascio and Boudreau (2011) on how best to initiate a change process on how to reduce turnover cost without compromising on candidate quality. To these authors, the first step is to assess the turnover costs of the organisation and then create initial awareness using the same analytical logic as used in technological, financial and marketing investments. This then paves the way for managers to conduct more sophisticated analyses which goes beyond just the costs to its impact on the business. As mentioned earlier, education is very key in the process stage of the measurement assignment. That is, educating leaders or line managers on the various components of the financial decisions using the return-on-investment formula as a potent tool. It is believed that these HR measurements will be embedded within the organisation and its knowledge and learning frameworks where employees or constituents will increasingly be educated.

2.3.2 HR Analytics Process Model (Marler & Fisher, 2017).

Due to increased organisational competitiveness, it has become imperative for organisations or firms and especially the HR function to draw relationships between the various HRM Processes using HR analytics to achieve strategic business objectives (Marler & Fisher, 2017). A study by professors from MIT and the University of Pennsylvania as recorded by Brynjolfsson, Hitt, and Kim (2011) indicates that firms that invest in business and data analytics have five to six percent output and productivity. This can be realise when HR professionals have enough information in order to make smart decisions (Marler & Fisher, 2017) as smart decision-making companies perform better. In other to access and transform employee data into meaningful information for strategic decision making, software solutions called Corporate Performance Management (CPM) or Enterprise Performance Management (EPM) have been introduced (Ohata & Kumar, 2012). The system is able to integrate data sets from different sources which are stored in data warehouses, data marts to be retrieved easily (Marler & Fisher, 2017). The data is then transformed into actionable information in the form of dashboards and scorecards. To effectively transform employee data into information for strategic decision making requires capabilities both from IT and managers who will use the technology. Marler and Fisher (2017) therefore propose a five-step process demonstrated as a circular process. This explains how the HR function can add value to the organisation through the use of HR analytics. These steps can either be automated or performed by IT experts. According to Marler and Fisher (2017), being able to implement these five steps effectively is a sure way to build value in a way rivals cannot. The five steps are discussed below.

2.3.2.1 Create Scorecard Goals.

The first step to making better decisions using HR analytics is by establishing goals. Goal setting is a characteristic of effective managers as it enables them to achieve their vision and mission for their organisation considering the various opportunities as well as constraints of their environment (Marler & Fisher, 2017). Set goals are then translated into actionable objectives to guide line managers to achieve their vision and mission. This helps to build a strategic balanced scorecard (Kaplan & Norton, 2007). Kaplan and Norton (2007) explained score card as, expressing statements of vision and strategy as a set of objectives which is agreed upon by all stakeholders describing the long-term success drivers. Marler and Fisher (2017) further intimate that, understanding what the key drivers of an organisation are by managers has been a challenge. To these authors, the sure way to creating value through key drivers is by developing hypotheses that will operationally link HR activities of the organisation to financial outcomes. Thus, linking human resource processes to human resource outcomes which over time results in a financial effect. Scorecards are used to report key metrics. Scorecards have the ability to report actual results which are measured as customer, financial, learning and growth and internal operations established against short-and long-term goals. Predictions use more of historical trends to make projections into the future. An organisation can use employee performance and demographics to predict their turnover intentions. During recruitment and selection, a candidate’s skills, knowledge, and abilities can be used to predict their performance on the job. All these analysis and reporting are mostly outsourced to consultants as companies may not have the analytics capabilities in-built (Marler and Fisher, 2017). In creating value, it is essential that, HR professionals link the HR data such as data on employee skills to other organisational data using different statistical analyses.

Another way to effectively set goals that are in line with the corporate strategy is when HR professionals are knowledgeable about the business so they can equally share their insights (Marler & Fisher, 2017). In creating actionable goals, Groysberg, McLean, and Reavis (2006) recorded how a large telecommunications company developed an HR scorecard to answer questions from a strategic perspective; ‘Are the company’s people capabilities aligned with the future business needs?’; operations perspective, ‘where must HR excel to enable the business to meet their goals?’. The final perspective which is financial is ‘How can HR add financial value to the business?’ Identifying the most critical goals to achieve business outcomes such as increased profit margin, sales growth as well as reduced administrative cost in order to stay focused (Douthitt & Mondore, 2014) should be the concern of every professional.

2.3.2.2 Identify Metrics.

Identifying which methods to adopt in determining whether the causal model works is the next step once the HR professional is able to set the actionable goals and create the hypothesized causal model (Marler & Fisher, 2017). Organisations need to develop various processes that is able to measure operational outcomes associated with their respective causal models. HR professionals need to develop HR metrics that can track operational efficiency of the HR function so that, managers are privy to information to make efficiency decisions on the services the HR organisation is delivering. The core efficiency metrics which are mostly adopted (Marler & Fisher, 2017) although track significant HR expenditures, do not make any direct contribution to implementing the firm’s strategy. Becker, Ulrich, and Huselid (2001) lists some of the metrics as workers’ compensation costs per employee, percentage of payroll and percentage of correct entries into the HR information system. This form of metrics differ across companies in that, different companies have different strategies. That is, if a company see compensation and benefit as the surest way to attract, motivate and retain key talents, then benefit costs will be a more strategic metric to that company. Some metrics are developed based on HR department data, HR expense data, employment data, and compensation data. Yet, some are developed to manage the organisation labour costs in general such as turnover and salary and benefit information. Other HR metrics include the recruitment oriented metric with indices such as time to hire, cost per hire which is given as the budget for recruitment in a given period divided by the number of employees to be hired in a given period (Ulrich, 2019). Sickness absence is another example. This is the number of sick days over a period of time relating to a particular employee or employees. At the organisational level, it is the % of annual work days lost to sickness per employee/ total working days lost to sickness (Ulrich, 2019).

Performance-oriented metrics have certain indices used in the performance-oriented sphere including staff turnover, customer feedback, customer loyalty, engagement index, peer feedback, appraisal rating and behavioural rating (Ulrich, 2019).

Adapting the data-to-value cycle as discussed in the ROI of Human Capital by Fitz-enz (2009) is another way of explaining the HR efficiency metrics and this is very specific to the HR function. The data-to-value cycle tracks time, costs, volume as well as, errors associated with HR tasks and processes. Thus, the metrics should be able to measure the costs of the HR processes and tasks, the volume of the tasks, how long it will take to complete the tasks and the number of errors generated by the metrics. It is worth noting that, no single metrics are the best, therefore, companies must develop metrics that are aligned to their strategic goals by using analytics to create value. No generic efficiency metrics also exist but depend on the company's strategy. Finally, due to the unstandardized nature of metrics, vendors mass produce software applications, therefore HR professionals need to develop particular relevant and strategically important metrics for their analytics processes.

2.3.2.3 Capture and Integrate Relevant Data.

After the appropriate efficiency metric and the strategic performance drivers have been identified, HR professionals now need to know how to collect data to create the needed measures. The process of identifying and collecting accurate and timely data for analysis is where IT and people intersect. Once the process for creating, storing and sharing relevant data is managed, the HR analytics system executes the process to ensure consistency and access. It is important to gather initial data and get access to data (Niaksu, 2015). In capturing the relevant data the analyst needs to basically Familiarising himself with the data. Since data and its structures form the basis of analytics, knowledge in the available data is important (Mirski, Bernsteiner, & Radi, 2017). Data miners do this by mapping the available data and grade their quality (CIPD, 2018). This will enable the one running the analysis to assess whether the data is fit for its given purpose. As the data miner is able to identify data quality problems, they can also ascertain interesting subsets, discover insights into the data and identify hidden or missing data (Niaksu, 2015). That is, whether the employee data available is relevant in running the analysis. Data auditing will highlight the various gaps present in a data set so that, it can be filled for processing. For example, if HR practitioners want to run an analysis on the factors leading to high employee turnover but do not have data on their employee exit in a form of exit survey, it becomes difficult to run an analysis to discover patterns of these factors. Poor quality and missing data can also affect effective analysis. It is therefore important to mine data that is credible, reliable and of good quality so as to measure the effectiveness of the analysis on the business to achieve expected outcomes. This phase also focuses on the sources of data; whether structured or unstructured and which specific functional units they come from (IBM, 2011; Shearer, 2000). Whether the data is from internal or external sources, HR professionals and data scientists need to be careful which employee data to select (Keerthi, 2018). That is, HR practitioners need to know the data they are working with and be sure the right data is used for the right analysis. Data for analysis can be managed using seven aspects of data management identified by Davenport et al. (2010) which are structure, integration, uniqueness, quality, privacy, access and governance. The structure looks at the nature or the form in which the data exist such as unstructured text, cubes, structured data or arrays. Integration focuses on how data from different sources are stored in one central repository for analysis. Uniqueness explains how the data is exploited in such a way that, no one else has. This makes the data different and stands out. In terms of quality, the data must be one that can be relied on to conduct the analytics for decision making. Privacy looks at how to effectively safeguard the data so that, external sources do not get access to the data. For HR professionals to analyse data, they need to gain access to the data for specific analytics solutions so they can manipulate and create information from the acquired data. Finally, governance has to do with the various means through which people ensure the usefulness of data for analysis. This can be done when HR professionals know what information is needed and how this information is managed across functions in the organisation.

2.3.2.4 Analyse and Report Information.

The penultimate step focuses on how to analyse the HR data stored in the data warehouse and data marts to produce information for decision making. After selecting the modelling technique, the analyst needs to test the quality and validity of the chosen model (Shearer, 2000). Once the analysis is done, it needs to be meaningfully communicated. The analytical procedures can be automated with the aid of IT. This helps with standardization, consistency, and timeliness. The degree to which the HR processes are automated according to Marler and Fisher (2017) is referred to as business decision. At this stage of the decision-making process, HR professionals need to decide and describe to what extent they want to automate the actual decision rather than the information output derived and presented (Davenport et al. 2010). The degree of automation can be seen in three spheres. The first is fully automated, where all decisions, analysis, and actions are automatically automated. Citing an example for Marler and Fisher (2017), a firm can eliminate a candidate from its recruiting pool based on how the candidate answers certain biographical questions. Since the decision is automated, it automatically eliminated the candidate once the answers do not match what the employer is looking for and has been coded. This approach is able to create very consistent and fast decisions. The second, automated with overrides require extra expertise and judgment in exceptional cases although the decisions are made automatically. For this, the decision maker is prompted that, action is required. The third approach which is assisted is used for more complex and unpredictable variables such as employee performance. To make decisions about employee performance may need a review of key people such as the employee's manager and the Human resource professional. Now, the analyst runs the model using the prepared data set by manipulating the available data in different ways using the appropriate technique or approach (Keerthi, 2018). Firms either perform descriptive, diagnostic, predictive or prescriptive analysis (Fitz-enz, 2010) depending on what they seek to achieve.

Reporting information involves organizing and presenting the knowledge gained in a way to be easily used by the HR professional (Shearer, 2000). Deployment refers to the process whereby new insights gained from the results of the analytical model is used to improve the organisation (IBM, 2011). Final results are then communicated in a report to all stakeholders such as management to make decisions on the workforce (IBM, 2011). Verbal presentations or results are usually given during meetings by HR Professionals or analysts to management or related departments or functions through charts and graphs (IBM, 2011; Shearer, 2000). Dashboards, predictions, and scorecards have been identified for typical automated analyses and for reporting (Marler & Fisher, 2017). The dashboard is an interactive interface designed to deliver personalized graphical displays of key HR metrics to the end user or HR professional. The reported information in a dashboard can be updated daily due to its dynamic nature. Dashboards are essential as it affords HR professionals and business executives the opportunity to analyse trends and conduct root-cause analysis of the various HR processes. The data takes the form of graphs, ratios, trend lines, and colour coding as it is presented graphically. For example, a dashboard could provide an HR professional on trainings done each day, weekly and monthly and the impact of such pieces of training on employee and the associated costs involved.

HR analytics vendors are able to deliver prebuilt dashboards where the analytical information is predetermined. An example cited by Martin (2011) indicates how an early version of Oracle HR Analytics has seven prebuilt dashboards including compensation, HR performance, recruiting, workforce profile, absence, learning enrolment and U.S Statutory compliance. According to Boudreau (2017), people analytics should be made more user-friendly by HR. Guenole et al. (2017) further support the argument raised by Boudreau that, statistical findings should be translated into stories inspired by insights gained from the data. To Kennedy and Hill (2017), data visualization is a way of garnering audience engagement. In order not to turn people off with complex statistical information, data visualization tends to be a more useful and powerful tool to get a message across to an audience.

Reporting should be simple, clear and illustrate a possible solution to the identified business problem emanating from the business understanding (CIPD, 2018).

2.3.2.5 Make Decisions and Monitor Results.

Once the analysis is conducted and the information is reported, it is now time to make decisions out of the generated information and then monitors the results. This is characteristic of the final step of the decision-making process. HR professionals need to cross-check to see if they have the right data and information needed to be able to make the decisions (Marler & Fisher, 2017). Once HR professionals are able to take decisions with management, HR professionals need to monitor to ascertain if the decisions made from the data is having an impact. This is done by comparing the before and after information. For example, as cited in Marler and Fisher (2017), trying to compare the average employee turnover before implementation and what happens after the implementation. Deployment refers to the process whereby new insights gained from the results of the analytical model is used to improve the organisation (IBM, 2011). In other words, deployment is eliciting change from the data mined through integration into the organisation's daily activities or practices. Implementation is done by HR professionals who manage the function and to make decisions evident from the results of the analytics (Keerthi, 2018). It is therefore important for HR professionals to gain access to historical data to serve as the basis for establishing impact. Monitoring the results reveals certain trends that influence whether the scorecard goals at the financial stage of the process have been achieved. If there are uncertainties or goals are not achieved due to certain inconsistencies, the HR professional can go back to set or review the goals. These analytical processes are essential for building tools for company improvements as they invest in information systems, especially HR analytics. It is essential that HR professionals gain access to HR data if they can transform them into relevant decision making information. In so doing, they need to ensure that, it adds value but to the HR function and the organisation and this is when the various HR activities are aligned to the corporate objectives.

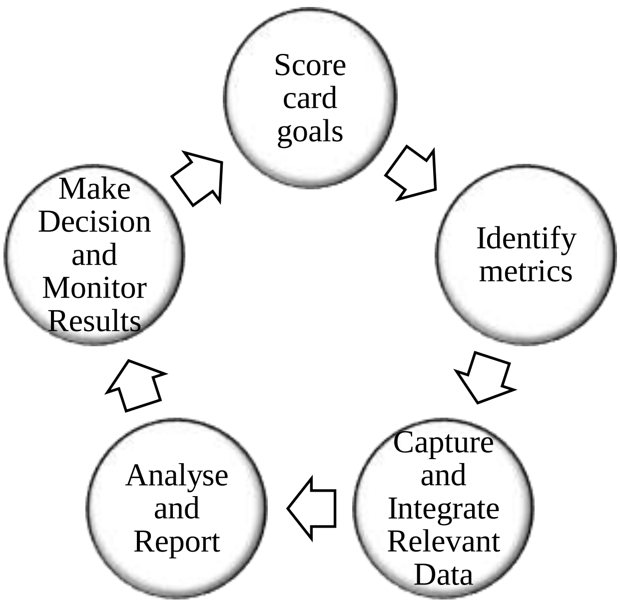

Figure 2.2: Decision-Making Process Model (Marler & Fisher, 2017)

2.4 HR Analytics Technology (Analytical Tools).

Enhancing a country's economy for competitive advantage has been fuelled by information technology. The best utilization of the advancement in technology is making Human resource management more efficient, from hiring the right talent to retaining the best ones and this has made Human resource management more evidence-based with the power to make accurate decisions. Technologies available in the HR functions within organisation is expanding and continues to advance in sophistication (Davenport, et al., 2010). The adoption of technology within the HR function has increased in the last five years from static HR management solutions to dynamic, mobile-based tools, real-time cloud systems, and platforms to increase the efficiency and effectiveness of the HR function in recruiting and retaining the right talent and to identify key result areas to make future investments. According to Sierra-Cedar (2016), about 45% of large organisations and about 51% of midsized organisations are investing huge sums of money on HR technology. It is therefore important organisation adopt technology to better manage their employees just like other physical or financial assets because it is not only inadequate but reckless to manage the human capital based on intuition or instincts (Bassi & McMurrer, 2007; Dery, Grant & Wiblen, 2012).

Gathering data on employees does not only help in ensuring employee efficiency but also to make relevant decisions on how to improve the processes (Oracle, 2011). HR analytics software has the potential of revolutionizing the HR function to increase organisational performance (Bersin, 2015a, 2015b; Oracle, 2011). Huge vendors have emerged on the scene to deliver best HR analytics software as a service to organisation (Choudhury & Barman, 2016). Oracle, SAP, IBM, SAS, Tableau, Python and Microsoft are leading in the area of Business Intelligence with data analytics competencies rooted in them (Kapoor & Sherif, 2012). These software's apply both mathematical and statistical models to predict, optimize and discover purpose. Google has joined the HR analytics field and has contributed immensely by introducing the people analytics function (Davenport, Hams, & Shapiro, 2010). Analytical competencies that range from basic data analysis to more advanced multivariate models are required to run effective HR analysis (Narula, 2015). Inferential statistics such as regression, correlation, Analysis of Variance (ANOVA), multivariate choice models, factor analysis, and hierarchical linear models can be used to forecast the performance of an organisation. According to Kapoor and Sherif (2010), HR Practitioners are able to gather intelligent insights, make predictive changes and informed decisions both at the operational and strategic levels of the organisation through the application of advanced analytical techniques.

Decision makers within the information era, have been exposed to enormous data available on hand (Elgendy & Elragal, 2014; Oussous, Benjelloun, Lahcen, & Belfkih, 2018). As technology continues to evolve, there will be multitudes of data flow within organisations on a daily basis. There is the need to find more efficient and faster ways to analyse such data which cannot be analysed using traditional data analysis techniques and infrastructures (Elgendy & Elragal, 2014). Analytical tools have been beneficial and extensively used by computer science, statistics and operations disciplines (Karkhanis & Dumbre, 2015; Keleş, 2017). Thousands of analytics tools exist today for big data management. Thus, from data acquisition through to data visualization (Praveena & Bharathi, 2017).

2.4.1 R Programming.

R programming which is an open source data tool is a free software widely used by data miners and among statisticians for statistical computation and graphics. Open source data tools or software is defined as software whose development and source code are available for public use where nobody can exploit it (Laurent, 2004). In other words, open source data tools are software applications that are generally free and openly available. Open source data tools have become synonymous to free software in the minds of many (Walters, 2007). R programming software is used to develop statistical software for data analysis (Praveena & Bharathi, 2017). This tool has a well-developed language component, effective and simple functionalities as well as input and output facilities (Team, 2000). Oracle, one of the big data distributions uses R to perform analytics (Oussous et al. 2018). R has become an accepted open source library especially for statistics (Zupan & Demsar, 2008). R studio, which is a free and available open source tool is integrated into R to provide a graphical user interface (Wimmer & Powell, 2015). This programming software performs tasks such as regression, clustering, text mining, time series analysis and statistical modelling (Wimmer & Powell, 2015). A drawback of R is the fact that it has a limited capacity to store large datasets as a result of its one node memory. Also, because R is executed in a single thread, the data should be stored in no larger than 10 – 20 percent of a computer's RAM. (Oussous et al. 2018). The Teradata Aster R has been introduced to aid the distribution of data analysis thereby minimizing the one-node memory limitation (Brown, 2014). Despite the shortfalls, R has been the leading analytics tool and widely used by statisticians and data analysts for data mining.

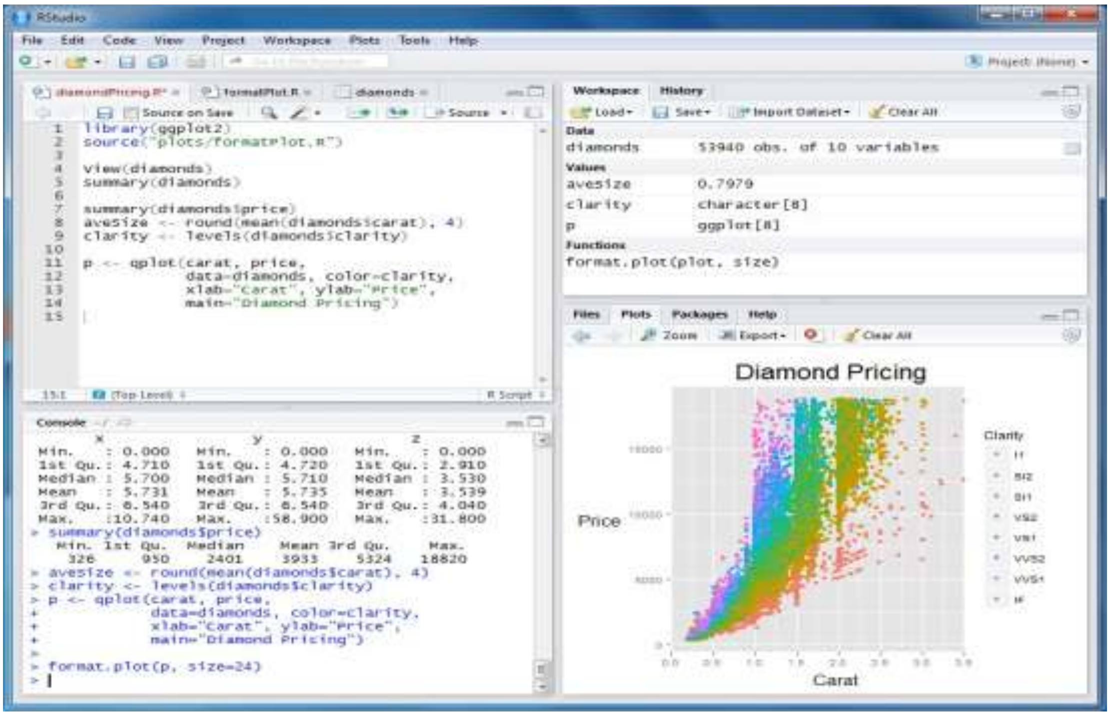

Figure 2.3: The R studio Programming Interface

2.4.2. Orange.

Orange, another open source data mining tool has the visualization, analytics and scripting components. Widgets are the main building blocks to creating workflows in Orange. These widgets are classified as data, visualize, regression, classify, evaluate, associate and unsupervised (Wimmer & Powell, 2015). Orange is used for scripting in Python and has the ability to write meaningful extensions in C++ (Wimmer & Powell, 2015; Zupan & Demsar, 2015). Orange, aside from its simplicity of use, has different visualizations of models and data incorporated in them (Zupan & Demsar, 2008). These visualizations ranges from bar charts, scatter plots, networks, trees, dendrograms and heat maps. Linking widgets in orange can create workflows to support a data science process (Wimmer & Powell, 2015). In classical statistics, orange is weak because it is unable to provide widgets to support statistical testing (Zupan & Demsar, 2015). Thus, it is limited in reporting capabilities for visual exportations.

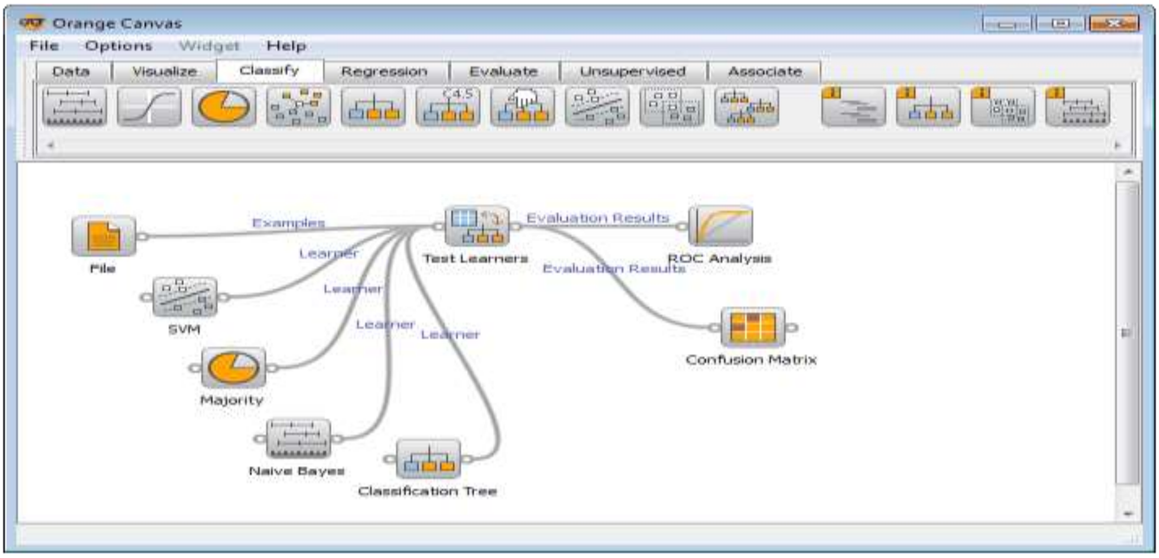

Figure 2.4: The Orange Programming Interface

2.4.3 Tableau.

Tableau as a data visualization tool is a corporate tool that is highly familiarized for data visualization which allows for the creation of graphs, charts, maps and other graphics

(Caldarola & Rinaldi, 2017; Fahad & Yahya, 2018). Data visualization tools which are software, enable users to interact through intuitive means in order to explore and analyse available data to identify patterns, draw causalities and support decision making (Bikakis, 2018). As a business intelligence software, tableau has an in-memory data engine that is able to accelerate visualizations (Wang, Wang, & Alexander, 2015). This analytics tool comes in three different products for large scale data processing. These are Tableau desktop, tableau, server and tableau public. Tableau desktop as a design tool is used to create dashboards and visual analytics (Murray, 2013). It only connects to MS Access, Excel or text files. Tableau server produces large workbooks which gives people the opportunity to interact with other people's work via a web browser (Murray, 2013). Users are able to find, Organise and comment in reports with improved security. Tableau Public is a free web service used to publish reports online. This avenue enables bloggers to interact with visualizations via the web despite the small storage space approximately for each user. Novice can learn how to use and analyse data using Tableau public. Tableau as a data visualization tool is not only time saving but also enables decision makers through the dashboard, gain access to any information from the database.

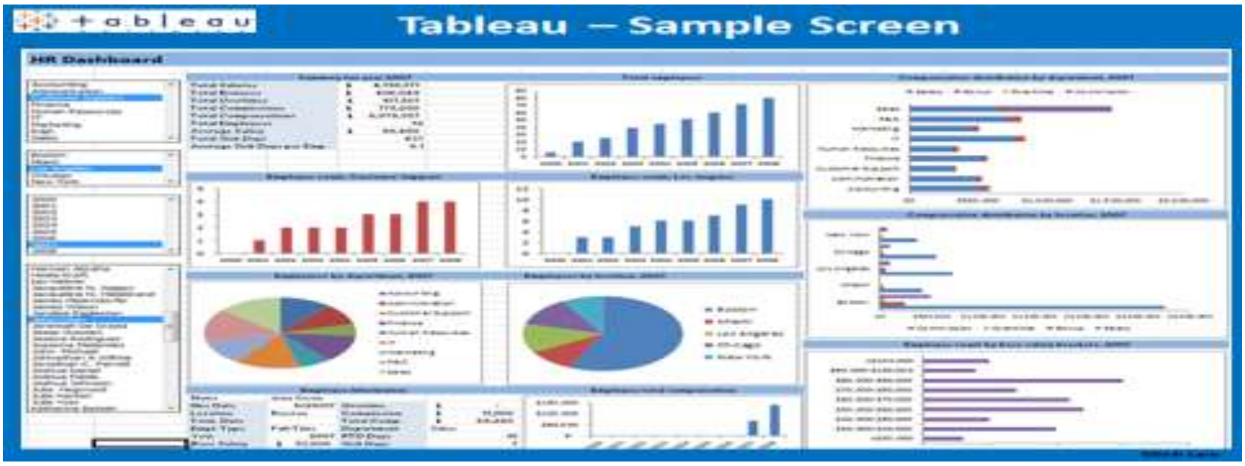

Figure 2.5: The Tableau Programming Interface

2.4.4 Microsoft Excel

Excel has been described by literature as one of the most widely used spreadsheets within the computing environment with diverse statistical functions for analysis (Laverty, Miket, & Kelly, 2002). This data visualization tool also has powerful graphical capabilities which gives a deeper understanding to data (Laverty, et al., 2002). Creating visual simulations is made easier with Excel as well as computations (Orvis, 1996) not forgetting data forecasting and results presented in an attractive manner (Rusu & Rusu, 1998). Although Excel is integrated into Microsoft Office Suite, it can be used independently (Rusu & Rusu, 1998). Excel is able to provide its own programming language and visual basic applications for visual programming (Rusu & Rusus, 1998). This makes it easier to generate real-time reports at very cost effective prices.

Figure 2.6: The Microsoft Excel Programming Interface

2.4.5 Microsoft Power BI.

Microsoft Power BI is one of the analytical tools integrated into the Microsoft Business Intelligence Suite (Microsoft, 2016). Power BI has been very instrumental in data visualization (Petrovski, 2016). Power BI has the capability of uploading excel workbooks into the cloud which enables recipients to share reports at a go without being limited by distance (Aspin, 2014). Stirrup (2016) is of the view that, inaccurate data representation in the form of dashboards, makes it difficult for people to make informed decisions. In view of that, Power BI plays a critical role in providing a clear picture of what a particular organisational data means and this helps in making informed decisions (Petrovski, 2016). Following the argument of Borup (2015), a good data visualization must quickly expose the meaning of a data set particularly the trends, patterns, and status at a glance which might take time using traditional methods.

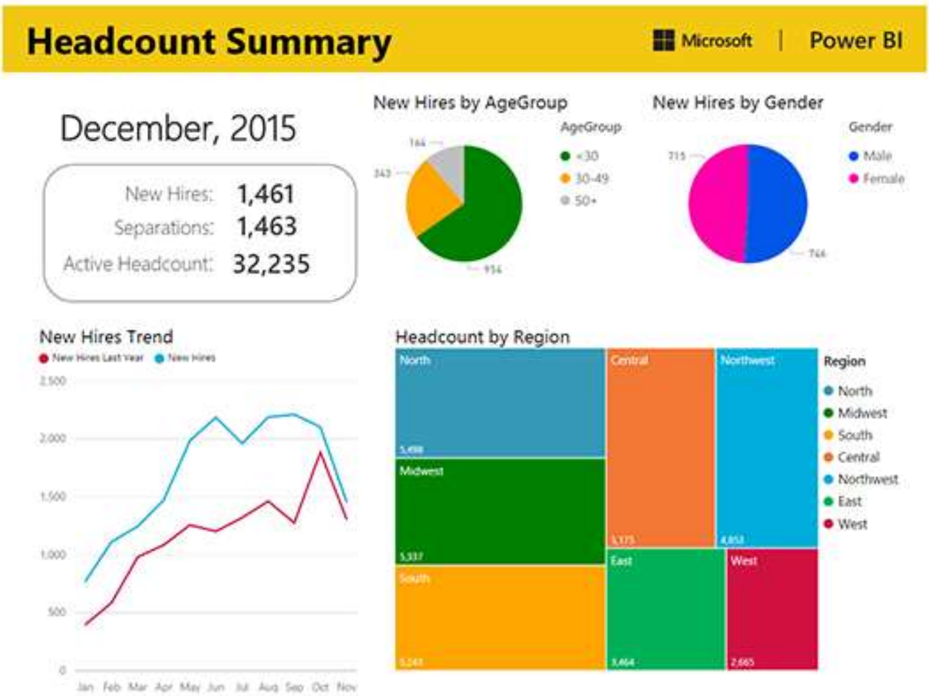

Figure 2.7: The Power BI Programming Interface

2.5 HR Analytics Technology (Methodologies).

The humongous amount of data within the human resource management domain has attracted data mining research in this area (Strohmeier & Piazza, 2013). Certain methodologies have been adopted to explain how data is mined to predict certain behaviours (Kirimi & Moturi, 2016). Analytical methodologies in HR systems is essential because, it helps discover and extract meaningful patterns from large data sets in HR (Kirimi & Moturi, 2016). These models are explained below.

2.5.1 Decision Tree.

Decision Tree is one of the most popular classification techniques (Jantan, Hamdan, & Othman, 2010) and rules generated can be used to make future predictions (Kirimi & Moturi, 2016). As a tool to make predictions, it can produce models with rules which are human-readable and can be interpreted (Jantan, et al., 2010). The decision tree has been known for its popularity because it does not require any expert knowledge (Jantan, et al., 2010). Many studies have employed decision tree techniques such as personnel selection (Chien & Chen, 2008), job attitudes (Tung, Huang, Chen, & Shih, 2005) among others. The decision tree operates by a drop down of a tree connected from the root node to certain leaf nodes. These nodes which are branched based, work on the if-then condition (Milovic & Milovic, 2012). Some variants of the decision tree are ID3, C4.5, CART, SPRINT and SLIQ (Hemalatha & Megala, 2011). A data mining framework was developed by Hein and Chen (2008) to generate meaningful rules for employee selection. Thus, to find out which talents are most suitable to an organisation so they can design effective strategies to ensure that, right employees are always recruited. Yet another study by Jantan at al. (2010) revealed how C4.5 decision tree classification algorithms were used to forecast talent performance using past experience knowledge (Jantan, et al., 2011).

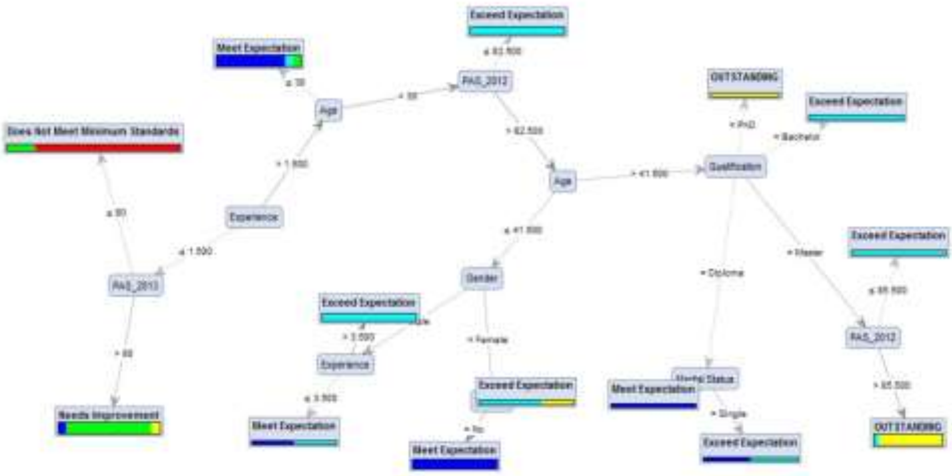

Figure 2.8: Decision Tree to illustrate the effect of Experience on Performance (Kirimi & Moturi, 2016).

2.5.2 Regression Models.

Regression models play an essential role in predictive analytics. It is focused on establishing relationships between variables understudy (Bhattacharyya, 2018). Different businesses use different regression models (Bhattacharyya, 2018). Linear regression, a type of regression is used to analyse relationships that exist between response and predictor variables. Another regression model is known as logistic regression. It is used to predict categorical dependent variables (Punnoose & Ajit, 2016). This model was used to predict the relationship that exists between withdrawal behaviours such as lateness, tenure, job content, absenteeism and demographics and employee turnover (Punnoose & Ajit, 2016). Another study by Saradhi and Palshikar (2011) employed the use of logistic regression to predict employee churn against other data mining techniques.

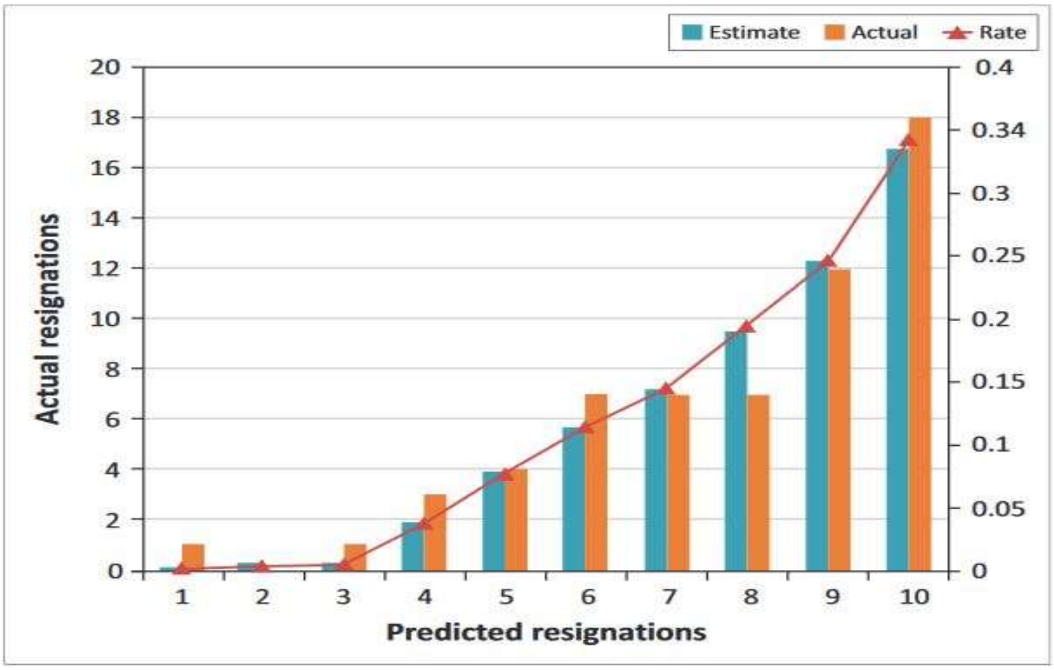

Figure 2.9: Demographic characteristics to predict Voluntary Turnover using Regression. (Schlechter, Syce, & Bussin, 2016).

2.5.3 K Means.

K Means is a popular clustering algorithm which is mostly used in the industrial world (Novaliendy, Hendriyani, Yang, & Hamimi, 2017). This clustering algorithm was developed by MacQueen (1967) and further improved on by Hartigan and Wong (1975). This methodology is used to partition ***N*** observations into clusters, ***k*** so that, each observation will belong to a particular cluster with almost the same or close mean (Kakushadze & Yu, 2017). That is, points on a data are clustered on the basis of similarities that exist between the data (Sarker, Shamim, Zama, & Rahman, 2018). This is instrumental in evaluating employees so as to maintain a motivated and skilled workforce within an organisation (Sarker et al. 2018). The K means as a clustering algorithm was adapted by Sarker et al. (2018) to group employees based on their performance to design training programs for those who were not productive. This was done by gathering the data set of employees spanning four years from the employee database. Codes were generated for the performance rating scale and analysis conducted. From the analyses which were recommendations to the organisation, management will be able to predict the performance of its employees in the next year as well as take necessary steps on how to manage the qualified and inexpert employees (Sarker et al. 2018). It is refreshing to note that, this kind of algorithm, K means, can be developed to predict employee performance in any organisation (Sarker et al. 2018).

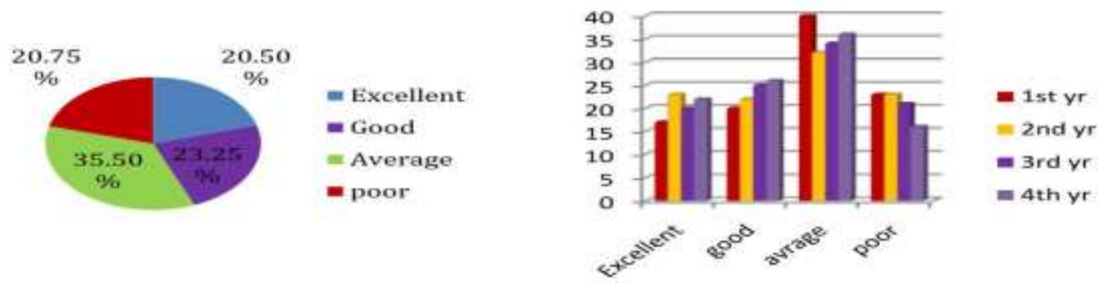

Figure 2.10: Using *k*-means to evaluate Employee Performance (Sarker et al. 2018)

2.5.4 Association Rule Mining.

In data mining processes, discovering associations has become very vital (Hussain & Srivatsa, 2014). This helps to improve the quality of decisions made by businesses. This is made possible through the frequent patterns, causal structures, interesting correlations as well as associations identified within a database (Hussain & Srivatsa, 2014). Association rule mining has been described by Nuntawut, Kittisak & Nittaya (2014) as a data mining technique used in identifying familiar relationships between data in different ways. As the best-known data mining technique, the association algorithm detects patterns based on relationships between items in a similar transaction (Kalyani, 2012). The relationship or association generates results based on ***if/then*** pattern for decision making (Kumbhare & Chobe, 2014). Association rule mining has been used effectively to predict the right talent into the right jobs in organisation by identifying patterns and rules that are related to employee performance (Jantan, Hamdan, &

Othman, 2009). Also, the association mining technique can be used to detect patterns between employee performances within a time frame which will inform the appropriate developmental strategies to improve on their performance at work (Jantan, et al., 2009). If HR professionals detect that, particular employees are underperforming, then specific goal-oriented trainings will be rolled out for them to be equipped and become productive. In another vein, if certain conditions are available to the employee, then job performance will increase.

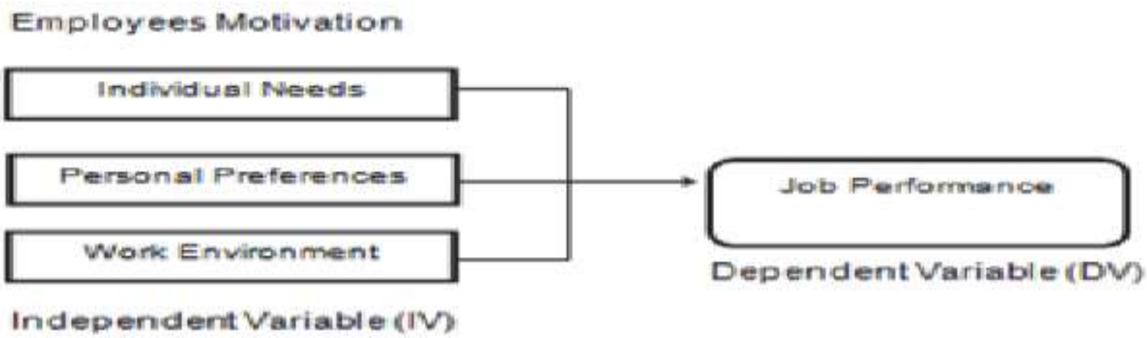

Figure 2.11: The Association rule drawing on the *if/then* relationship between Motivation and Job Performance (Said, Zahari, Zaidee, Ali, & Salleh, 2015)

2.6 Application of HR Analytics.

The Human resource management practices have reached some level of maturity in almost all organisation and the application of HR analytics to that effect justifies what the actual business case is for those practices (Reddy, Lakshmikeerthi, 2017). Analytics presents an incredible opportunity to aid businesses to understand what they are yet to know and this is possible when HR professionals are able to identify patterns and trends for better strategic decisions about future workforce challenges (Huselid, 2014). Analytics systems that support decision-making are a growing source of value for organisations and increasing competitive advantage (LaValle et al. 2011). According to Davenport and Harris (2007), analytics technologies have matured over the past years, and are widely used in various businesses. The United Parcel Services aside using IT to provide transparency on the shipment status of their customers, they use analytics to track their customer's usage patterns, complaints and customer attrition (Davenport, 2006).

Applying analytics can create a business opportunity thereby creating a sense of urgency for adoption and implementation in the HR function (Deloitte, 2015). This is as a result of the advancement in technology, economic flux, global competition for talent, skills shortages and demographic shifts (Huselid, 2015). Research has indicated that, more than 87% of business leaders worry about engagement and retention (Bersin, 2015) which calls for using more evidence-based methods to make decisions about a firm's human resources. HR Analytics application may be a one-time effort to inspire organisational change and so the purpose behind this effort should not be underestimated. Understanding the data and the context for which it is collected will provide insights that are meaningful to determine which resources will be needed and the form of analysis to undertake (Angrave, Charlwood, Kirkpatrick & Stuart, 2016).

HR Professionals and management must understand the contribution of human capital towards organisational success prior to the adoption of HR Analytics (King, 2016). For the purposes of adding value to the organisation through the use of analytical tools, the nature of the issue to be tackled needs to be explicitly defined (King, 2016). It is necessary to establish a cause-effect relationship behind an issue and understand its implications on business outcomes before shooting solutions at the perceived issue (Fitz-enz & Mattox, 2014).

The purpose to which analytical efforts are adapted to solving an identified problem in an organisation is very important and once this is realise and information on how the human capital may contribute meaningfully to organisational success is obtained, it is, therefore, expedient to consider the data to be used in the analysis. Data comes in different forms today; HTML, XML, text, SPSS, MS Excel, SQL, MA Access to name a few. Although the variety is overwhelming, it increases the chances of accessing the data format needed. Gathering information has now become relatively faster and easier as data is now stored in a common place (Fitz-enz & Mattox, 2014). Data quality should not be overlooked in terms of missing data and data entry errors as this may cause the old adage, “garbage in, garbage out”. The data must be one that can describe, explain, predict and optimize performance.

In all, management support is crucial to achieving success. Top management needs to provide the required resources to those driving the analytical efforts towards its implementation (King, 2016) and to assist in data accessibility as well as support during resistance from employees. Resources should include building the analytics capabilities of the HR function. A LinkedIn report in 2018 indicates that the United Kingdom, Sweden, and Denmark are the top three countries that have adopted HR analytics with volumes of professionals who have indicated HR analytics capability.

2.7 Benefits of HR Analytics among Firms.

Human resource departments are exposed to a humungous amount of data on employees and the business every day. Analytics is able to combine all this information to improve the effectiveness of the organisation, impact on the bottom line (Soumyasanto, 2016) and to achieve competitive advantage (Davenport, et al., 2010). The use of analytics within HR has increased the scope of making HR a strategic partner in organisation according to a study by Boudreau and Lawler III (2009) and researchers have posited that, the use of analytics to understand HR practices and its impact on organisational performance is a powerful way for the HR function to be able to add value to their business (Boudreau, Lawler III & Levenson, 2004). To effectively use talents to drive business results is by investing in analytics during the recruitment process so as to get access to an enduring database about job applicants. This will help hire passionate and qualified people within a short time. The business is then able to achieve a competitive advantage through their workforce.

Bersin (2013) in a survey with 480 large organisations reported that, more than 60% of firms are currently investing in analytics to make their HR department more data-driven to gain the power to change the future of HR to become more evidence-based. The use of analytics in firms is increasing (Deloitte, 2105; 2016; 2017) with CEOs pressuring their HR departments to adopt these practices (Deloitte, 2016) despite its slow rate of diffusion in businesses. Through the use of analytics, Maersk Drilling, an offshore drilling company as reported by Rasmussen and Ulrich (2015) decided to double the resource allocation towards their trainee program due to the strategic implications of the program as it increased their return on investment. Analytics was used as a change management process that helped to achieve those results for business impact. Also, Google through their People and Innovations Lab (PiLab) used analytics to identify four segments of managers and how their behaviour characteristics affected the organisation's management practices.

Fiocco (2017) in studying the use of analytics in HR practices in Epsilon, found that analytics were used to analyse pay structures of employees which was useful during negotiations with trade unions. The use of analytics also helped Epsilon to detect that most of their employees were exposed to high risks of eye damage accounting for 30% of the company's accidents and so decided to provide glasses for all employees to reduce the number of accidents and eye defects. The analytic tool has enabled them to consistently track and reduce health and safety related issues and accidents among their workers, the causes as well as policies to help prevent those accidents.

Toward an evidence-based HR, Togt and Rasmussen (2017) shared through their research, the current value, challenges as well as the future of HR analytics from a Fortune 500 company with the aim of expanding both the academic and practical aspects of HR analytics. Using practical findings to discuss this issue, HR analytics even though may be a hype today, clearly adds value to an organisation and this value extends beyond just talent outcomes. Using practical findings, the study established a moderate positive relationship between HR analytics and Human resource management on organisational outcomes such as productivity and profit. From the study, it cannot be overemphasized that, HR analytics is a necessary tool toward evidence-based HR.

To effectively manage challenges associated with HR outcomes in the areas of work performance, and competitive advantage, recruitment, and selection activities need to be done analytically (Ejo-Orusa & Okwakpam, 2018). These researchers go further and found that there exists a positive relationship between predictive analytics and some selected human resource management practices such as recruitment and selection, performance management and succession planning amongst Human Resource Practitioners in Port Harcourt in Nigeria. Analysing data generated from 159 respondents using a survey questionnaire, a significant positive relationship existed between predictive analytics and human resource management practices understudy. Conclusions were then made on the importance of predictive analytics and its impact on the human resource management practices outcomes. The study is an eye-opener to the direct impact of analytics on some Human resource practices and outcomes such as increased productivity, increased profit, better employee acquisition procedures, and employee retention.

Building on the literature on how predictive analytics can help Human Resource Professionals in Human Resource management, a study was conducted by Malisetty, Archana, and Kumari (2017). Certain key areas were identified with human resource management where value could be created using predictive analytics. Some of the key areas are recruitment and selection, attrition, talent management and learning, and development. Predictive analytics can be used to forecast HR capacity to help in resource utilization. Attrition can be reduced or eradicated through predictive analytics by analysing employee data and attrition records. Critical analysis of the HR data through predictive analytics is a way to respond to organisational objectives.

Ruohonen (2015) further states that, there is a need to leverage predictive analytics in the human resource management domain to identify the possible benefits. Using a qualitative approach to data collection where semi-structured interviews backed up by a questionnaire and multiple case studies were utilised, interesting findings were observed. Although the findings were company specific, general implications for businesses can be deduced. The benefits were enhanced individual and organisational performance, increased employee engagement and satisfaction, customer satisfaction, increased profitability and sales, and cost reductions. These benefits were identified in areas valuable to these organisations within the Human Resource domain. The findings of the study reveal the need to leverage predictive analytics if the organisation wants to be strategic partners in the business. Although the findings are relevant, using firms that are matured in the use of predictive analytics could have elicited quite different evaluations other than young ones as was the case in this study. A bigger sample could have also increased the definitive trends as well as credibility to some of the questions posed compared to the smaller sample of five.

Being able to get the most out of HR analytics is by drawing a connection between Human Resource data and the strategic objectives of the company. Based on this, Waxer (2013) outlines some strategic implication of adopting HR analytics in organisations. She postulates that reduction in attrition, increased performance, efficiency in compensation and enhanced employee morale are some of the implications associated with HR analytics which can improve businesses to gain competitive advantage. Despite these strategic implications for organisations to benefit from, Waxer goes on to outline some of the challenges encountered by organisation who wants to implement analytics in their business processes. Some of them are; the inability to find the right talent to run HR analytics, huge cost implications as well as poor data quality for analysis. These findings are significant in the sense that, these strategic implications are what will make businesses effective and in the end increase return on investments. The challenges outlined will motivate an organisation to invest resources to realize the full benefits of HR analytics.

In the quest to increase the competitive advantage of companies who use analytics in decision making because the interest in HR analytics is growing, Narula (2015) conducted a study to give insights on the usage, techniques, and impacts of HR analytics. Using qualitative surveys, to report empirical findings from the study, key implications of HR analytics on the bottom line were explored. Critical talent retention, enhanced recruiting cycles and costs, improved workforce planning and forecasting and improved decision making are the end products of HR analytics. The study highlights how to assess the effect of HR activities to evaluate business performance and strategy and these are efficiency, effectiveness, and impact as anchored by Boudreau and Ramstad (2005) to draw the connection between resources and organisational effectiveness. The study further explored the applicability of HR analytics using two firms that have made business value out of analytics; Motorola and Hewlette-Packard.

Investigating how the use of human resource analytics can affect an employees' willingness to improve their performance, Sharma and Sharma (2017) focused on the role of performance appraisal systems to measure the causal link between HR analytics and performance. A conceptual model was developed to explain the relationship between HR analytics and performance appraisals on employee performance. In the end, HR analytics was found to be the solution to increasing the objectivity and accuracy in the appraisal process as robust data analysis tools were utilised as against the initial subjective bias in the performance appraisal systems that existed.

There is a noticeable take-up and increased investments in the area of HR analytics in the next few years to come as most HR Professionals are working hard to ensure the use of analytics in their companies (Craig, Harris, & Egan, 2010). This is evident in the study by Hueval and Bondarouk (2017) who explored what the future of HR analytics might look like, through an exploratory study on the rise (and fall?) of HR analytics, delving into the future application, value, structure and system support. With a sample of twenty (20) HR analytics Practitioners, from eleven large Dutch firms, they investigated the future of HR analytics come 2025. Their study gives hope that the future of HR analytics is bright as it will become an established discipline that will impact positively on businesses as well as in strategic business decision making processes. Also, the future of HR analytics is projecting an integration among the HR function and other functions within the organisation like Information Technology which will later assume a central analytics function.

There still exist some misunderstandings of how an organisation can use workforce analytics in order to achieve essential organisational outcomes. Although workforce analytics is now the emerging trend in the Human resource management field, that opens an opportunity for HR as a key driver in businesses. In view of this, Mclever, et al. (2018) researched on how an organisation can overcome this dilemma through the use of examples from companies to improve business outcomes. The study drew a link between workforce analytics and organisational outcomes. The assertion was that HR activities in the past were counted but measures of its effectiveness were deficient. The study reveals that, analytics is focused on results and how these results are achieved. Therefore, in measuring the number of employees hired by an organisation, analytics should be able to provide evidence that, investing in such hires will lead to increased productivity. Better still, rather than measuring the number of training provided, analytics is able to provide evidence on how the training will increase customer satisfaction which will in turn increase sales and profitability.

As to whether HR analytics will be able to predict future organisational success, combat attrition and hire high performers by some researches, Marler and Boudreau (2017) conducted a study to address this question. Using the integrative synthesis approach, the study focused on evidence-based review of peer-reviews published on Human resource analytics. With only fourteen (14) articles published in quality peer-reviewed journals, Marler and Boudreau addressed five questions; what HR analytics is, how it works, why it works, what HR analytics produce and the requirements for HR analytics to succeed in an organisation. Using the theory of Diffusion of innovation by Rogers (2003), the findings indicated that, the level of HR analytics adoption is very low accounting for only 16% amongst organisations. This study is very critical to the HR analytics study as it identifies that, no explicit theoretical framework exists to explain why or the importance of HR analytics as a majority of the articles have used non-quantitative empirical research. It has also established a cause-effect relationship between HR analytics and financial performance and has gone further to identify the shortage of HR professionals with analytical skills as the main reason for the low level of HR analytics adoption.

Taking a snapshot view on analytics in HR, Mukundan (2017) conducted research in India to discuss briefly analytics in HR, the analytics continuum and its current state in organisations.

The study goes on to explore the leadership skills, HR skills and how aligning HR activities to a firm will yield potential benefits from analytics. The author believes that, despite the introduction of measurement in HR over the past years, businesses can utilise huge data sets within the HR department to add value to the business. The drive for deep analytics has rocketed over the past few years, the reason being that, employee retention and engagement is now a top priority for organisations. Firms are able to study the trends of employee experience and optimize them so they can continuously retain their best talent. Mukundan is of the view that, although HR analytics is a hot topic today, organisation using advanced analytics globally still remains small. That is, about 86% of the analysis is descriptive and diagnostic for reporting purposes with just 4% using predictive analytics. The study further gives insights on this disparity to be that, companies' use of tools that are unrelated in managing talents makes it impossible to get accurate data for predictive and prescriptive analytics. In predicting the way forward, Mukundan is of the view that acquiring the right capabilities both in technology and skills is essential so that HR professionals are able to understand the nature and form of data, detect relationships and predict outcomes. This is because technology and analytics take the centre stage in organisations and so firms that are slow in enhancing their capabilities are bound to lag behind in a competitive market. Also, knowing the value of using analytics enables HR professionals to understand "what types of analytics" to use, "when to use them" and "how to use them". This will help firms identify where efforts, time and investments are needed to produce desired outcomes.

In enhancing the competitive advantage of firms, leading-edge companies are adopting sophisticated methods to analyse their employee data. They are able to measure high productivity, retain top talent and engage their employees. Harrah, an entertainment company as reported by Davenport, et al. (2010) is noted for using analytics in customer selection, refine pricing and also promotions targeted at particular segments. They have also been able to gain insights from data to make people decisions by matching the right employee capabilities to the right jobs. The health and wellness program by Harrah has also been evaluated using analytics and this has led to an increase in preventive-care visits in on-site clinics. This has lowered the urgent-care costs of the firm by millions of dollars.

King (2010) reports through a study on how analytics was used to identify the likelihood of individuals leaving their companies. A project sponsorship by a consultancy firm to a participating university in the mid-Atlantic region of the United States of America, the project team was expected to evaluate attrition in an organisation. The team gathered 5 years of HR data on employees from the company which was moved to R and manipulated for analysis. Performing different statistical analysis through various modelling techniques such as logistic regression, gradient-boosted machines, decision trees, and *K*-means clustering, interesting findings were observed. The team was able to identify the main reason for the high attrition level in the organisation to be "time in position". That is, the more years an employee occupied in a particular position without promotion, the more likely such an employee were to leave the company. Fitz-enz and Mattox (2014) have also reported the same findings that "staying too long in one job" is correlated with employee disengagement. In calculating the monetary value, it was estimated by the team that, averagely, about US $ 3.1 to US $ 9.3 million dollars can be saved each year if attrition is reduced or eradicated in organisations.

Extant literature and reports from consultancy firms have discussed extensively on the benefits and usage of analytics in businesses and especially the HR department to add value to the firm by understanding how the various HR practices impact on the organisation performance. Since the existence of analytics, how has HR professionals accepted this challenge to their advantage? Lije and Kamalanabhan (2016) in their study discussed the various factors that influence the level of acceptance of analytics among HR professionals. Adopting the unified theory of acceptance and use of technology through a qualitative study, individual, organisational and technological factors were identified to influence the acceptance of HR analytics in organisations. For individual factors, the author identified that, analytical skills; readiness to change, thus adopting new technology; understanding the importance of analytics, opportunities to use and performance expectancy affect how HR professionals accepted analytics in their organisation (Venkatesh, Morris, Davis & Davis, 2003). Gaining the right analytical skills was found to be the dominating factor affecting this acceptance. Organisational factors included training; management support; a vision for using analytics, resources, data availability, business type, organisational size, and analytical culture. The study identified that management support and training was critical to the acceptance of analytics by HR professionals. Analytical culture also played a role in the acceptance relationship where organisations that are hungry for data analytics are more likely to accept the HR analytics tool than firms that are not. The last factor discussed was technological which identified effort expectancy as the factor influencing the acceptance of analytics in firms. Tools and software used in analytics that are easy to use and user-friendly are more likely to be accepted than technologies that are not. Providing the needed technical support to HR professionals have been found to help increase the level of acceptance of analytics in organisations.

Some firms have used data to develop initiatives to improve employee recruitment and selection. About 55 percent of organisations in India believe that predictive analytics can help in securing quality hires (Press Trust of India, 2015). Biogen, which is an American global biotechnology company based in Cambridge with an analytics team are able to understand the recruitment of its employees through the use of a predictive methodology. The introduction of

Predictive analytics has helped to make improved hiring decisions in terms of speed of hire and quality of hire (Naasz & Nada, 2015). The traditional method where HR experts used their subjective estimations or judgments to determine a candidate's skills and competency on a job has been reduced considerably (Naasz & Nadel, 2015).

Employee performance is increasingly impacting the bottom line of any organisation because human capital forms the very foundation of such organisations. A manufacturing firm in India according to an article published in The Times of India was able to track ten employees who had very low morale due to issues they had with their manager. This helped management to quickly take steps to solve the situation to avoid employee performance deteriorating (SHRM, 2018). Amway, a multi-level marketing company was able to promote an employee who was two levels below in the organisational hierarchy of the firm. This was possible through the use of predictive analytics when the performance indicators clearly proved the suitability of this employee. HR analytics in the area of performance management has helped organisations to anticipate the performance outcomes of their employees to increase revenue and improve employee engagement (SHRM, 2018) and reduced attrition among employees. Predictive analytics have been used by firms to structure performance reviews as well as employee satisfaction surveys so as to make strategic decisions for the firm. The firm is able to build the core competencies of its workforce to deliver exactly what its customers want. This is one area high performing companies are using to differentiate themselves from their competitors (Anschober, Bailon, Matzler, & Richardson, 2010). The overall company performance has been improved through the use of HR analytics.

Today, it is easier for some organisations to track the rate of attrition within its workforce. Predictive analytics are used by HR practitioners in determining the rate and probability of an employee leaving the organisation within a specific period (Grillo & Hackett, 2015) through the use of attrition scores from the analysis. Knowledge gained from the analysis informs HR practitioners especially when it comes to taking decisions on succession planning. According to Oehler and Falletta (2015), a transportation company was able to reduce employee turnover and to increase its annual productivity level by $1.7 million due to the extensive use of analytics. They analysed employee's performance ratings to predict their performance outcomes and this informed them to take measures to create equitable reward systems leading to increased employee retention. There is a negative effect of employee turnover on an organisations performance because when an employee turns over, his skills and knowledge go with him (Shaw, 2011), therefore continuous analysis is needed to determine such rates and strategic decisions taken to retain such employees as they increase productivity.

2.8 Challenges associated with the use of HR Analytics in Firms.

The increasing development in Enterprise systems has compelled organisations to pay attention to the use of data and analytics as a tool for measurement (Deloitte, 2013; Boudreau & Ramstad, 2005). Due to the promising future of HR analytics (Green, 2016), organisations are ready and willing to implement HR analytics within the HR function to make effective decisions. Although some organisations have been successful in the HR analytics implementation, some are still struggling to even start (Deloitte, 2013). In the implementation, technical as well as professional skills have become a top priority (Deloitte, 2015) although most HR departments find it difficult to combine "data" and "business" to achieve business results (Narula, 2015). Several authors have made suggestions regarding what could be the possible challenges inhibiting the adoption of HR analytics in an organisation.

HR data whether sources within or outside the organisation should be error-free if the HR professionals want to describe, explain, predict and in the end optimize performance. It is essential that HR professionals understand the context for which the data is collected (Angrave, et al., 2016). This helps to generate meaningful insights into the data. According to Davenport, et al. (2010), data credibility is one key challenge where organisations are not able to centralize their databases with quality data for analysis. If the data for analysis is not of quality, there is the fear that expected outcomes will not be achieved.

The inability to develop capabilities such as systems, skills, technology, and resources has raised red flags to the adoption of analytics in firms (Fitz-enz, Phillips & Ray, 2012). Getting the right competencies especially in the mathematical and statistical techniques is very crucial in the analysis of HR data to make decisions. The challenge HR face in implementing HR analytics has been explored by Chahtalkhi (2016) and has identified six categories of challenges based on a qualitative study amongst three companies. Lack of management or business support was the first to be recorded where the business did not recognize the essence of implementing HR analytics due to the fact that, the added value and benefits of HR analytics have not been fully explored by management. Following is the availability and accessibility of data and tools. How to get knowledge on the tools suitable for which kind of analytic techniques and analysis has been a problem. How and where to get data has equally been a challenge to HR analytics implementation.

Other categories have been legal and compliance, training and skills, communication and finally roles needed in setting up an analytics team. Mukundan (2017) beliefs that, lack of capability and competence in terms of technology and skills inhibits HR professionals from moving to the expected level in analysing HR data. Due to the shortage of HR professional with the required analytical skills, the dream of wide adoption of analytics in organisations may not see the light of day. Bassi (2011) makes a prediction that, the absence of the required IT acumen on how the analytics software will be used coupled with the financial skills of the business may compel the HR function to cede responsibility for analytics to the finance and IT function in the organisation.

In trying to investigate how employees perceived the usage of predictive analytics and how it affected their commitment to work, Khan and Tang (2017) conducted a study with organisations representing diverse industries in Tianjin, China, and using news reports, official organisation websites, annual reports and firms with formal HR departments they collected data on the issue. With five organisations out of twelve agreeing to participate in the study, theoretical and managerial implications were worth exploring. Firms were not able to extract and analyse the greater chunk of HR data due to the capability gap that existed with using the HR analytic tool. Another challenge explored was the inability of management involving the employees through the HR analytics process.

Adding to the existing challenges decelerating the diffusion of HR analytics in businesses, Long, et al. (2016) identified six of these. To them, the common barriers are economic, looking at the costs and benefits involved, uncertain results and too high initial investments; Institutional or regulatory where there is low institutional support or the absence of a regulatory framework to guide the use of analytics; Behavioural or Psychological were the lack of support from management, conflict with traditional methods of analysis, overly complex technologies and lack of acceptance; Organisational included lack of required skills and competencies, poor information, poor accessibility to technologies and habitual routines; Market where there are individual uncertainties as well as consumer motivation and finally social where there is peer pressure.

Fiocco (2017) further identifies that, the mind-set of HR professionals is another potential hindrance to the use of HR analytics. He asserts from his findings that, HR professionals are not ready or do not want to work with figures and numbers due to how they view HR analytics as involving more mathematical and statistical analysis. For this, Ramussen and Ulrich (2015) strongly recommend that, HR analytics is taken outside of the HR department and assigned to Line Managers until the HR function matures in the use of analytics.

Further expanding on the assertions accounting for the underutilization of HR analytics in businesses, Deloitte (2015) conducted a study to find out why companies were struggling to move into the analytics arena. The findings indicated that, the main reason for this underutilization is due to what they refer to as “capability gap”. This capability gap entails the poor data quality for analysis, weak business case for introducing analytics change and lack of needed analytical skills. In bridging this capability gap will mean a company investing in expensive solutions from external vendors and building this capability internally.

In running effective human capital analytics, it is critical that managers focus and address three interrelated facts that can cause a hindrance to this analysis. To Minbaeva (2018), data quality, strategic ability to act and analytical competencies are needed to design and implement measures towards organisational capability. Therefore, interventions at the individual, structural and process levels of analysis will help drive improvements at these levels.

2.9 Chapter Conclusion.

Information technology has proved its ability to fuelling a country’s economy for competitive advantage from the discussions so far. Therefore, investing resources in HR technology is essential to better manage the workforce. The literature on analytics has revealed that implementing analytics in firms has great benefits especially in decision-making with the aim to add value to the business. Gaining an understanding of how these innovations work is essential in realizing its relative advantage. Despite the great benefits of using HR analytics, it has challenges such as lack of management support and right analytical skills to run analysis as key determinants making it difficult to realize the full potential of analytics by HR professionals. Building the right capabilities is essential in driving the adoption and implementation decision not forgetting the management support which serves as a catalyst to HR analytics implementation.

CHAPTER THREE

METHODOLOGY

3.0 Introduction

The study sought to investigate the concept of HR analytics and its implications on Human Resource Management Practice. This chapter covered the methodology of the study which comprised of the research paradigm and design, population, sample and sampling techniques. The instruments for collecting data and procedures were also captured. The chapter further discussed the sources of data, its validity and reliability, and the method of analysis. The chapter closes with some ethical considerations necessary for the current study.

3.1 Research Paradigm

Once a researcher sets out to investigate a phenomenon, the approach is dependent on how they think about the issue to be studied so that, the findings will be reliable. The thoughts, beliefs, and assumptions about society are shaped by what the researcher perceives as constituting knowledge and this frames the way they view the world. This is known to social scientists as a paradigm (Schwandt, 2001). A paradigm according to Schwandt (2001) represents the values and beliefs within a discipline shared about the world which guides how problems will be solved. Paradigm which has its aetiology from Greek, "paradeigma" meaning pattern was first used by an American Philosopher, Thomas Kuhn in 1962 (Kivunja & Kuyini, 2017). This word was used to describe a philosophical way of thinking. A paradigm explains what and how a phenomenon should be studied and how to interpret the results. Some characteristics or elements are used to explain a research paradigm. These are ontology (nature of reality), epistemology (nature of knowledge) and methodology (nature of approach) (TerreBlanche, Durrheim, & Painter, 2006; Tuli, 2010). That is, each research paradigm adopted has its own ontological, epistemological and methodological assumptions, beliefs, values and norms which acts as the structure to differentiate one paradigm from another (Creswell, 2007).

Ontology refers to how the nature of social reality is perceived by a researcher. Ontology as a branch of philosophy refers to how we make sense of a social phenomenon under investigation (Scotland, 2012). It helps to conceptualise the nature of reality and this is crucial to how meaning is made from data gathered. Ontology examines the underlying belief system and the assumptions of the researcher. This helps to orient how the researcher thinks about the research problem, how significant it is, and the possible approach to answer the research question so that the researcher can contribute towards its solution (Kivunja & Kuyini, 2017).

Epistemology which means knowledge comes from a Greek aetiology, "episteme" (Krauss, 2005). This refers to how something is known in reality or how knowledge comes about within the world (Cooksey & Mc Donald, 2011). It focuses on the nature and form of knowledge, how it is acquired and communicated to other people to deepen our understanding of the world. The underlying question under this element is "How we know what we know?" (Kivunja & Kuyini, 2017). Epistemology is essential in research because it helps establish the truth you put in a data and this affects the way knowledge will be uncovered in the social context understudy.

Methodology refers to the logical flow of systematic processes in conducting research (Boateng, 2014). It is how evidence can be collected to help understand or explain a phenomenon. They are the design, approaches, methods, and procedures used in gaining knowledge about something. How to collect the desired data to gain knowledge which will help understand a phenomenon and answer the research question is what constitutes the epistemological element of a research paradigm.

Researchers have proposed different paradigms to help deepen our understanding of a phenomenon. Candy (1989) is of the view that all these paradigms can be grouped into three taxonomies; Positivist, Interpretivist or Constructivism and Critical paradigms. Tashakkori and Teddlie (2003a; 2003b) further propose a fourth one known as the Pragmatic paradigm which borrows elements from the first three.

Positivist paradigm which was first proposed by a French Philosopher, Auguste Comte defines a worldview of research as a scientific method of investigation (Kivunja & Kuyini, 2017). It uses experimentation to explore observations and to answer questions based on facts (Fadhel, 2002). Due to its fact-based assumptions, researchers who adopt this paradigm should be able to generalise the occurrences they observe due to the objective nature of the research process (Creswell, 2008). For the researcher to be precise in describing the data gathered, analysed and interpreted, quantitative methods are central (Boateng, 2014). Positive ontology is objectivity where reality is seen as single, objective and tangible. The epistemology focuses on the researcher distancing him/herself from the phenomenon and measuring reality as it is. In terms of axiology, the data gathered should be free from the researcher's personal values or feelings to ensure impartiality (Chilisa, & Kawulich, 2012).

The critical paradigm postulates that, social justice issues which most often lead to conflicts, oppression, power structures, and struggles need critical attention (Taylor & Medina, 2013). These issues according to Kincheloe and McLaren (2000) can be addressed by practicing deep democracy by identifying socially unjust structures, beliefs, policies, and practices. The researcher constructs a moral vision through his/her own critical consciousness (Brookfield, 2000) to make a better society. This can be executed individually or in a group. This paradigm operates on a transactional epistemology (Kivunja & Kuyini, 2017) with its ontological assumptions based on historical realism. The best methodology is dialogic and its axiology places much respect on cultural norms. This paradigm is sometimes known as the Transformative paradigm (Taylor & Medina, 2013).

The interpretivist or constructivist paradigm which is described as a relatively new paradigm (Taylor & Medina, 2013) upholds that, the world is socially constructed (Wilson, 2004). This enables the researcher to gain a rich understanding of how reality looks like from a participant's point of view. These social constructions are documents, observations, tools, shared meanings, and a language which are expressed through participant's activities, beliefs as well as their behaviour (Goede, 2005; Klien, & Myers, 1999). As a key part in process inquiry, this research approach places importance on the researcher's subjectivity in data interpretation (Taylor & Medina, 2013). In explaining its ontology, individuals lived experiences play a key role. The best way to know about the phenomenon is to inquire from the people who experience the phenomenon (Boateng, 2014). Interpretivist or constructivist methods include qualitative approaches such as interviews, participant observation, and ethnography. This paradigm is more value-laden due to the individual's perception (Chilisa, & Kawulich, 2012).

The current study has adopted the Interpretivist paradigm to explore the use of HR analytics among private and public organisations in Ghana to gain a deeper understanding of the phenomenon and further find out the benefits and challenges associated with its use. More precisely, in examining the implications of human resource management practice and whether HR analytics use will elicit different opinions and views based on the experiences and practice of the HR managers and professionals. With these expectations coupled with the qualitative research design, influenced the adoption of this research paradigm. Further studies should use a quantitative approach to research to explain the concept and its use amongst private and public organisations in Ghana.

3.2 Research Design

The structure or blueprint of any research is what is termed as a research design. That is, it serves as the "glue" that combines and holds all the parts in research together (Akhtar, 2016). In other words, research design clearly specifies the various methods and procedures needed to collect and analyse the needed data or information which is reliable and trustworthy (Cooper & Schindler, 2011; Churchill & Lacobucci, 2009). The most classified research designs are Quantitative and Qualitative. Quantitative research designs gather data through the use of questionnaires, experiments, and surveys which are tabulated in numbers, and analysed with statistical tools (Hittleman & Simon, 1997). Qualitative research design, on the other hand, employs interviews, documents and texts, observation and researcher's reactions to issues (Myer, 2009). This approach to data collection attempts to interpret a phenomenon based on the meaning people attach to them (Denzin & Lincoln, 2003).

The study adopted the qualitative approach which fits within the Interpretivist research paradigm. This helps to gain a holistic understanding of people's lived experiences within a specific setting (Rahman, 2017). Miles and Huberman (2013) agree with the assertion that, qualitative approach to research provides rich descriptive as well as explanations of processes within a local context. Thus, the researcher will be able to discover the inner experiences of the population under study and how culture shapes their meaning (Corbin & Strauss, 2008). This research design will make it possible to study how analytics is used in HR practice, the benefits as well as the challenges in implementing analytical tools within the HR function.

In critically examining the lived experiences of the research participants, the current study adopted the phenomenological approach to research (Creswell & Poth, 2017). This will allow the researcher to interact directly with the participants to elicit their individual feelings and perceptions of HR analytics. This will also go a long way to give the researcher first-hand descriptions about HR analytics. Finally, it will help the researcher to understand the essence of the phenomenon from the perspective of the research participants (Creswell, 2013). Data gathering techniques such as interviews, observations, personal and official documents are used in such a study approach. The research questions are usually open-ended, descriptive and nondirectional (Creswell, 2003). This approach is appropriate for the study because the researcher wants to live in the world of his participants.

3.3 Population of the Study

A research population refers to all the elements which meet the criteria to be included in a study (Burns & Grove, 2003). The population for this study will comprise private and public organisations within the Greater Accra Region. Greater Accra Region is the best choice for the study due to the fact that it is the capital of Ghana with the diverse nature of employees. Greater Accra is also, according to a survey conducted by the Integrated Business Establishment Survey (IBES) under the Ghana Statistical Service has revealed that, over 70% of generated revenue is concentrated within this region. The survey further explored that, more than two-thirds of employment are centred within this region (Ghana Statistical Service, 2017). Due to the increasing nature of activities within the capital, this has attracted most firms, businesses, companies, corporate institutions as well as other organisations either profit or non-profit as compared to the other regions lacking the resources; both human and physical for operation. Owing to the fact that most firms have their head offices and decision-making units located in Greater Accra has made it necessary to select organisations in Accra and Tema as the study population (Abor, Adjasi, & Hasford, 2008). This population was also an added advantage to the researcher which helped to reduce cost and for timely collection of data for the research. Employees from Multi-National and Domestic firms which are private and public in nature respectively were considered in this present study. This is because human capital plays an important role in streamlining the development of both sectors. (Popa, Dobrin, Popescu, & Draghici, 2011).

3.4 Sampling Technique and Sample Size

Sampling technique refers to sampling scheme a researcher adopts in selecting a sample based on certain probabilities attached to them (Showkat & Parveen, 2017). Two main types of sampling techniques exist; probability and non-probability sampling.

Probability sampling technique is an approach to sampling where every unit has an equal chance of being selected (Alvi, 2016; Etikan & Bala, 2017; Rahi, 2017). In other words, it is an approach where each sample stand the chance or probability of being chosen. Some probability sampling methods are; simple random sampling, stratified random sampling, systematic random sampling, cluster sampling and multi-stage sampling (Rahi, 2017). Simple random sampling is the simplest where each element of the population stand a chance of equally being selected into a sample (Alvi, 2016; Rahi, 2017). This can be done by throwing a dice, tossing a coin and lottery method (Showkat, 2017). The complete frame which lists all the various units of the population is needed and this can create cost of the units which are widely scattered geographically (Ghauri & Gronhaug, 2005). This has been the shortfall of this sampling technique. The systematic random sampling is when an initial sampling point is randomly selected proceeded by a selection of cases at a regular interval (Rahi, 2017). Thus, only the initial unit is selected and the others selected based on an interval size (Showkat, 2017). In other words, a random order should be listed where every element will be chosen from that sequence framed (Showkat, 2017). Although a lot of effort is needed for larger populations, it ensures that, the sample is extended to the whole population (Alvi, 2016). Stratified random sampling is an improvement on the systematic random sampling (Showkat, 2017). This is where a strata is formed from the population based on certain characteristics (Showkat, 2017). The strata is the subgroup selected from the population, this type is ideal because it ensures a representative sample that captures the diversity of the population although it is costly and needs a lot of effort making it time-consuming (Alvi, 2016). Last but not least is the cluster sampling where a population is sampled into clusters (Alvi, 2016). It is more of creating aggregations of a population that are geographically dispersed (Rahi, 2017) and may not be accessed at a time. In other words, cluster sampling is when a researcher divides a population into groups known as clusters. This technique is more economical and saves time (Alvi, 2016; Etikan & Bala, 2017). If there is no homogeneity among the clusters, the sample may not be representative of the entire population (Alvi, 2016). Multi-stage sampling is the final probability sampling method. It is when sampling is done across hierarchical levels (Battaglia, 2011), usually involving a sequence of stages (Rahi, 2017). Random sample selection is the first stage in random sampling, followed by specific regions and then relevant objects into the sample size. The sample may not be representative of the entire population if it does not capture the diverse characteristics of the population making generalizability difficult (Alvi, 2016).

Non-probability sampling technique is usually associated with qualitative research (Taherdoost, 2016). This sampling technique is used to examine real-life occurrences and not to make statistical inferences (Yin, 2003). Research participants are selected due to the ease to which they are accessed (Showkat, 2017). Aside from this technique being less complicated, less expensive and easy to apply, it is mainly used to study cases or a particular phenomenon to gain insight (Alvi, 2016; Showkat, 2017). Prominent amongst them are convenience sampling, purposive sampling, quota sampling, and snowball sampling. Convenience sampling is used to sample research participants who are readily available. Also known as accidental sampling, research participants who are convenient and easy to approach are included in the sample (Alvi, 2016; Rahi, 2017). Researchers are able to gather interview responses in a more cost-effective way as whoever gets in contact with the researcher qualifies to be sampled (Showkat, 2017; Rahi, 2017). This creates subjective biases on the part of the researcher (Alvi, 2016). Quota sampling is used for heterogeneous populations, where the element of the population does not meet all the predefined criteria (Alvi, 2016). In view of that, any individual who possesses some or all the characteristics the researcher is looking for is sampled for the study (Etikan & Bala, 2017). The issue with this type is that the sample is not representative of the population causing the problem of generalizability (Alvi, 2016). Purposive or judgemental sampling is the last but not least. It is the most widely described in qualitative literature (Gentles, Charles, Ploeg, & McKibbon, 2015). Purposive sampling is selecting research respondents with a prior purpose in mind (Alvi, 2016). Yin (2011) also intimated that, purposive sampling is more of selecting research participants or sources of data that, because of its richness in information, can answer the study's research questions. This is based on the researcher's judgment as to who will provide the appropriate information to answer the research questions (Etikan & Bala, 2017). According to Patton (2015), purposive sampling has the aim of gathering rich-information cases for in-depth analysis and insight. Snowball sampling is a non-probability sampling technique also known as chain referral sampling (Alvi, 2016; Showkat, 2017) used to study few cases as a result of the small population to which they were sampled (Taherdoost, 2016). This approach works in populations that are difficult to access as a result of its closed nature (Breweton & Millward, 2001). In order words, an initial contract group that are relevant to the study is used as referrals to gain access to others (Rahi, 2017). When the population is unknown or difficult to secure, the snowball technique is most useful (Daniel, 2012). This subjects the sampling to biases and systematic errors from the researcher and network connection (Alvi, 2016).

The purposive sampling technique which is a non-probability sampling technique was used to select the respondents for the study. Purposive sampling makes it easier for the researcher to select cases that will answer the research questions to achieve the research objectives (Saunders, Lewis, & Thornhill, 2007; Yin, 2011). This sampling technique is used to gain insights from information-rich cases for in-depth understanding (Patton, 2015). Also known as judgment or subjective sampling, the researcher has the luxury to select the respondents due to certain characteristics the respondents possess which is useful to the study (Boateng, 2014; Latham, 2007). The study targeted HR professionals and managers who use analytics in their everyday practice to enable the researcher to collect rich information about HR analytics and its implications towards HR practice. Convenience sampling was also used to select available and willing respondents for the study. The interviewees that participated in the study were at least one HR professional, manager or employee from the HR department or an analytics practitioner who works closely with the HR unit with knowledge in HR Analytics and HR's role in becoming a strategic business partner. Also, firms that use any of the levels of analysis from descriptive analytics through to prescriptive analytics were allowed to participate in the current study as Fitz-enz (2010) indicates that, real analytics starts at the descriptive level and therefore are potential study samples.

In order to generalise research findings to a larger population, it is important to work with a sample of respondents who are characteristic of the population (Creswell, 2003). A sample is a portion of a population chosen by a researcher to stand for the larger population (Polit & Beck, 2010; Tailor, 2005). Bryman and Bell (2003) believe that, a research sample is a portion of the target population for investigation. Probing further, Hanlon and Larget (2011) also postulate that, a research sample is a subgroup of a larger population. This implies that a sample is a fraction of the whole population selected to take part in a study. Selecting the right sample size in a qualitative study is a tedious task as there are no particular criteria for sample size determination (Terra-Blanch, Durheim, & Painter, 2006). That notwithstanding, it is important to draw an appreciable sample so that, the research findings can be generalised. In qualitative research, Marshall, Tobin, Marshall, Gooch, and Hobday (2013) intimate that, a sample size that ranges between fifteen (15) to thirty (30) is needed to inspire confidence in data collection. Qualitative research uses a smaller sample size due to the quest for an in-depth understanding of a phenomenon (Dworkin, 2012). The sample for qualitative studies should at most be 30 because data saturation becomes evident at this stage (Boddy, 2016; Dworkin, 2012). Data saturation is a point in the data collection process where no new or relevant information is offered (Mason, 2010).

A sample of 20 Human Resource professionals, managers, and employees who work within private and public firms that operate HR units and run analytics with diverse socio-economic backgrounds were drawn for the study. These firms were selected based on referrals whiles the researcher also visited organisations and if they used HR analytics qualified to take part in the study. Following the conditions of ethics and in order to ensure anonymity and high level of data confidentiality, the names of participants as well as firms nor their sectors of operation were not to be identified in this study. Therefore, research participants were coded as "Respondents" although it was indicated whether they worked for a private or public firm.

3.5 Sources of Data

Data collection has become an integral part of every research to answer the research questions and in gathering information for this purpose, two methods have emerged; primary and secondary data (Douglas, 2015). Primary data is the factual first-hand information collected by a researcher (Mesly, 2015). This includes observations, surveys, experiments, interviews, and questionnaires. Secondary data refers to data collected by a researcher earlier for a purpose other than the one at hand (Johnston, 2014; Mohajan, 2017; Mesly, 2015) and this includes books, journal articles, publication, and internal records. Secondary data can also mean data that has already been interpreted and recorded by a researcher (William, 2011). Primary data were the main source of data for this study. The primary data were mainly the responses from the research respondents which were analysed and interpreted. The secondary data which consisted of documents from the companies under study, journals and books and also reviewed literature were used to augment the primary data source to provide supporting evidence towards the outcome of the study.

3.6 Data Collection Instruments

The current study employed the qualitative method approach to research where structured interviews were conducted and responses analysed. Since the literature on HR Analytics is still limited, employing this approach will help expand the scope of the study. Interviews are necessary when collecting in-depth information about a phenomenon based on people's feelings. Dornyei (2007) posits that most often used method in collecting qualitative data is through interviews and is more powerful when the researcher wants to investigate people to elicit their views in greater depth (Kvale, 2003). Berg (2007) also agrees to the assertion that interviews are not just for analysing words or reports of informants but to allow them to speak in their own voice and to express their thoughts and feelings themselves.

An interview is a conversation with the purpose of gathering descriptions of interviewee's world life and how they interpret the meaning of a phenomenon (Kvale, 2003). Schostak (2006) also adds that, an interview is an extended conversation between parties with the aim of collecting in-depth information about a particular topic or issue. Boateng (2016) further posits that an interview is a way for interviewers to elicit new and in-depth information from participants. Interviews are designed to obtain thick and rich data from an investigational perspective (Creswell. 2007).

Research has identified four main types of interviews frequently used in the social sciences. The first which is referred to as structure interviews requires an immediate and mostly 'yes' or 'no' response giving both the interviewer and interviewee little freedom (Berg, 2007). This is because such interviews are organised based on predetermined questions. An open-ended or unstructured interview is the second type which is more of an open situation where flexibility is given to both sides (Alshenqeeti, 2014). This allows the researcher to pay keen attention to the development of the conversation and to give room for the interviewee to throw more light on the issue (Dornyei, 2007). Last but not least is the semi-structured interview which due to its more flexible nature, provides an opportunity for the researcher to probe further and expand the participant's responses (Rubin & Rubin, 2005). Such interviews require a checklist or interview guide (Berg, 2007) to help cover all relevant research questions. For the purpose of this study, the researcher will employ the semi-structured type of interview because it will allow the researcher to cover various areas and issues that concern this study. Last is focus group interviewing which according to Barbour and Schostak (2006) is a technique where participants are selected due to their purposive nature although they are not representative of a population but focused on a particular topic or an issue. Despite its suitability for complex behaviour investigation, it can be time consuming and effortful (Alshenqeeti, 2014).

An interview guide was adopted to aid in the data collection. This was to enable the researcher to collect information on the same general areas from each interviewee (McNamara, 2009). This allows for flexibility in getting the needed information from the respondents (Rubin, & Rubin, 2005). The interview guide contained a list of all the questions that were explored during the interview and had not more than 15 main questions (Boyce & Neale, 2006). The interview guide was in two parts; A and B. Part A sought to obtain responses about the participants' demographics such as highest educational qualification, professional certification if any, job position, tenure, approximate number of employees and kind of organisation the respondent worked for since these variables are deemed necessary for the current study. Part B presented questions that probed into the HR professional's familiarity with the HR analytic tools, how and why it is used, benefits and possible challenges associated with its use.

3.7 Data Collection Procedure

One aspect of a research methodology is the procedure for data collection. The procedure is the step by step way of doing things. Data collection started from Mid-February through to

Mid-April, 2019. This was preceded by obtaining an introductory letter from the Department of Organisation and Human Resource Management of the University of Ghana Business School. The introductory letter was then sent to all the institutions with a copy of the interview guide for appointment booking based on the day and time favourable for the respondents attributing it to the fact that these employees have very busy schedules. Contacts were mainly made through Human Resource Managers of the various organisations and sometimes Directors where they were seen as ones to give final approval. Some firms demanded a hand-written letter before approval was given. Follow up calls and visits were made to organisations that could not schedule an interview date to fast track the process of data collection. An interview schedule was drawn with dates and times for the interview based on approval from organisations. On the day of the interview, respondents were asked to fill a consent form following an explanation of their rights as research participants and ethical issues involved in the research. A face-to-face interview using an interview guide was then conducted for all the respondents to reflect on the issues under discussion without documenting them. The interviewees were taken through a 30 - 40 minutes interview although some extended to 50 minutes on the open-ended questions developed purposely for the study based on the study objectives. Referrals were recommended by the respondents after the interview to organisations that also use analytics within their HR departments. Permission was sought from first the organisation sampled for the study as well as participants and with permission from respondents which were granted, and their responses were recorded using a recording device. The data were then transcribed and saved on a computer. The transcribed data were printed and sent back to some of the respondents for corrections and omissions before the final analysis was carried out.

3.8 Data Analysis

Data analysis in qualitative research is one of the important steps in the research process to enable researchers makes sense of qualitative data (Ngulube, 2015). To obtain usable and useful information to identify relationships between variables and to forecast outcomes, data analysis utilises the method of studying, sorting, translating and displaying the data (Miles, Huberman, & Saldana, 2014). Creswell (2007) postulated that, data analysis in qualitative research should include preparing and organizing the data, coding and presenting the data in the form of text, tables or figures.

The most widely used method for data analysis is the thematic data analysis tool (Braun & Clarke, 2006). It is considered as the foundational approach to analyzing data qualitatively (Guest, MacQueen, & Namey, 2012). Thematic data analysis was adopted for the current study. This analysis tool was ideal because it helped to identify themes and patterns of meaning especially across a data set related to the research questions (Braun & Clark, 2006) and to examine the different perspectives of the respondents. In preparing and organizing the data as hypothesized by Creswell (2007), the data collected was reduced by selecting, simplifying and transforming the available data (Miles, & Huberman, 1994). Initial codes were generated after thoroughly reviewing the reduced data. Identified themes were organised, reviewed and thoroughly discussed in order to answer the research questions. In achieving this, the procedure for analysis qualitative data which are the six steps outlined by Braun and Clark (2006) was adopted. The first stage is to familiarize with the data; second, generate initial codes; third, search for themes; four, review themes; penultimate, define and name themes; and finally, report the findings.

3.9 Validity and Reliability using the Trust Worthiness Criteria

It is without a doubt that, validity and reliability are of great importance to scientific research towards finding knowledge (Alshenqeeti, 2014). Every researcher, either quantitative or qualitative need credibility in their research and this can be attained through the validity and reliability of the research methods (Pandey & Patnaik, 2014). The trustworthiness of a study helps to evaluate its worth which may lead to generalizability (Pandey & Patnaik, 2014; Golafshani, 2003). In a qualitative study, Lincoln and Guba (1985) have recommended some trustworthiness criteria for ensure validity and reliability. The criteria for establishing trustworthiness involves credibility, transferability, dependability, and confirmability.

3.9.1 Credibility.

Credibility as a trustworthiness criterion is similar to internal validity in quantitative research (Lincoln & Guba, 1985; Simon, 2011; Shenton, 2003). It is about building confidence in the truth established from the findings (Lincoln & Guba, 1985; Holloway & Wheeler, 2002; Macnee & McCabe, 2008). That is, being able to match up the participant's responses and the research instrument. Using prolonged engagement as a technique for ensuring credibility, the researcher is able to build relationships with members of the organisation and to know various aspects of the research setting. This cultivates a relationship of trust between the researcher and the respondents (Creswell & Miller, 2000; Lincoln & Guba, 1985; Pandey & Patnaik, 2014). Before the main questions on the interview guide were asked, the researcher engaged the respondents in informal discussions to establish rapport and build trust in the respondents. The researcher later inquired more about the organisations before the day of the interview to make the discussion more interactive. Another technique for ensuring credibility is persistent observation. Through persistent observation, the researcher is able to discover characteristics of research participants and setting that is unusual but relevant to the issue under focus (Anney, 2014; Lincoln & Guba, 1985; Simon, 2011). The researcher through careful observation was on the lookout for any unusual characteristics about the setting or respondents that might be relevant to the study's discussion. Triangulation as another technique is used for the purposes of improving the reliability of research findings (Golafshani, 2003). Triangulation is done by combining different and multiple methods, sources, investigations, and theories to obtain evidence that are corroborating (Onwuegbuzie & Leech, 2007). This helps reduce bias, re-examines the integrity of the research responses (Anney, 2014) and deepens understanding (Lincoln & Guba, 1985). Denzine (1978) postulates that, if the type of data collected, sources of data and theoretical frameworks conclude the same, then credibility is achieved. The current study in ensuring triangulation of the qualitative data gathered combined both primary and secondary data to answer the research questions. Member checks were also adopted in the current study. Pandey and Patnaik (2014) argue that this technique is important to strengthening the credibility of the study. This can be achieved by summarizing the participant's responses to ensure that, their words match up to what they intend to communicate (Lincoln & Guba, 1985; Pandey & Patnaik, 2014). Also, the final report in the form of themes must be taken back to the respondents (Creswell, 2009) so they can provide alternative and context interpretation (Patton, 2002). This will give the respondents the opportunity to cross-check the interpretations of their responses and whether they are true (Anney, 2014; Merriam, 1995; Lincoln & Guba, 1985). The study also provided thick descriptions by providing enough details or information to readers (Tracy, 2010). This involved giving a detailed account of responses and account of the study to enable other researchers to replicate the study (Anney, 2014).

3.9.2 Transferability.

Transferability is the extent to which research findings can be extended to other contexts with other participants (Anney, 2014; Lincoln & Guba, 1985). To be able to achieve this, enough contextual information about the setting should be provided (Pandey & Patnaik, 2014) through a technique known as thick description. With thick descriptions and purposive sampling, research findings should be transferable to similar settings (Bitsch, 2015; Lincoln & Guba, 1985). The current study adopted the purposive sampling technique (Teddlie & Yu, 2007) to sample the research participants so that, findings can be transferred to other similar organisations. This helped to ensure that, if the same methods are employed in similar settings, the outcomes should be the same (Pandey & Patnaik, 2014).

3.9.3 Dependability.

Bitsch (2005) has defined dependability as the stability of research findings over a period of time. That is, evaluating the responses, interpretation, and recommendations to ensure they are supported by data received from the research participants (Anney, 2014; Cohen, Manion, & Morrison, 2011; Tobin & Begley, 2004). In ensuring dependability, the research procedure for example, how the raw data is collected, how the data is analysed and what interpretations are given to the data must be considered (Anney, 2014; Lincoln & Guba, 1985; Merriam, 1995; Shenton, 2004). In other words, it involves all the activities of the study on how the researcher collected data, recorded and analysed the data (Bowen, 2009; Li, 2004). This is known as an audit inquiry (Pandey & Patnaik, 2014; Lincoln & Guba, 1985). In ensuring dependability in the current study, the research methodology was discussed in detail outlining all the components of the data collection and analysis.

3.9.4 Confirmability.

This concept is comparable to objectivity in a quantitative study (Pandey & Patnaik, 2014; Lincoln & Guba, 1985). This is to ensure that, findings are not based on the researcher's imaginations but solely from the data gathered (Tobin & Begley, 2004). That is, the findings should be the results of the respondent's experiences and ideas rather than that of the researcher (Pandey & Patnaik, 2014). The concept of confirmability can be achieved through audit trials and reflexivity. Audit trails are conducted to ensure that, all the necessary steps are taken throughout the development of research activity (Pandey & Patnaik, 2014; Lincoln & Guba, 1985). This includes all raw data collected field notes, process notes, instrument development information, how data is condensed and methods of analysis. This provides evidence of the rigor to which the researcher arrived at the end of the research activity (Bowen, 2009). Because this study is a scientific one, all the elements of scientific research were adhered to. Reflexivity, on the other hand, is systematically adhering to how knowledge is constructed. That is the step by step process of arriving at a research finding. The researcher needs to keep a reflexive journal or keep a record to help plan data collection and to take note of all happenings on the field (Koch, 2006; Wallendorf & Belk, 1989). The researcher kept a book to record all activities pertaining to this current study.

3.10 Ethical consideration

Every research needs to be guided by ethics. Ethics in research is very important because it is set to protect the rights of both the researcher and participants (Fouka & Mantzorou, 2011). Ethics are codes of conduct or rules that guide research or study. The researcher will adhere to all ethical standards to meet academic research where issues of confidentiality, privacy, and anonymity of respondents will not be compromised.

Informed consent is the first step to be taken in any research. Informed consent goes beyond just the potential participant saying “Yes” to take part in research. They need to know exactly what they are agreeing to. Therefore, the researcher will explain in detail the procedure of the study and then seek their consent (McLeod, 2015). This was fully deployed where respondents willingly agreed without coercion to respond to questions asked by the researcher and signed an informed consent form to that effect.

Confidentiality and anonymity are very essential in any research. By the very nature of the qualitative research, participants are often asked to disclose their thoughts, attitudes, and experiences (Nunn, 1998). Therefore, participants' confidentiality and anonymity will not be undermined. Anonymity is concealing the research participant's identity (Saunders, Kitzinger, & Kitzinger, 2015) because it protects them from harm (Vainio, 2013). Once the anonymity of research participants is assured, they give authentic responses (Taylor, 2015) which are critical to the study's results (Vainio, 2013). Their responses were used for the sole purpose of the research and under no circumstances were their demographics and responses used if not for the sole aim of analysis and discussions. Due to the nature of the study, actual company names were not used but were represented with codes in the form of letters of alphabets. Also, responses in the form of recordings were saved under a password to avoid others gaining access to it. The password combined numbers and letters, upper and lower case characters and sufficiently long characters. All recordings were deleted after the transcription and data analysis. Paper-based data were destroyed immediately after transcription. Research participants were also allowed to decide the extent to which they want to be anonymous (Surmiak, 2018).

The participants were also given the freedom to withdraw from the interview at any point of the interview process without any explanations from the respondents. Their withdrawal may be due to personal reasons and that cannot be underestimated. Therefore, if participants are uncomfortable with the study, they should be allowed to leave as well as withdraw their data if they so wish (McLeod, 2015).

3.11 Chapter Conclusion

The research methodology was extensively discussed in this chapter. A detailed description of the research paradigm, as well as design, population, sampling and sampling techniques, were provided. Adding to that, the sources of data, as well as the instruments for data collection and procedures were further explored. Data analysis procedures, validity, and reliability of the study were also explained. The chapter ends with the ethical considerations adhered to throughout the entire study to make it scientific and to make it possible for generalisation.

CHAPTER FOUR

DATA PRESENTATION AND DISCUSSION OF FINDINGS

4.0 Introduction

This chapter of the current study explains the analysis of the data collected using a semi-structured interview and goes on to discuss these findings in light of the literature reviewed for the study. The research questions which emanated from the research objectives are explained through the data analysis. The initial part of this chapter focused on the demographic characteristics of the interviewees. The study further presents the findings from the qualitative data collected which focuses on the understanding of HR analytics, how HR analytics is conducted, some tools and methodologies employed in conducting analytics, some benefits as well as challenges. This chapter ends with some views from the research participants on the prospects of HR analytics and practice in Ghana.

4.1 Socio-Demographic Characteristics of Interviewees

The current study gathered raw data on the demographic characteristics of the interviewees who are either HR professionals, HR Managers or HR persons who use and are familiar with HR analytics within the HR function. This comprised of their highest educational qualification, professional affiliation, job position, tenure, the average number of employees and the type of organisation they work for. In ensuring that the responses of the interviewees were in consonance as presented in the study, their demographics were essential (Creswell, 2014).

Below are the socio-demographic characteristics of the interviewees:

Table 4.1 Socio-Demographic Characteristics of Interviewees

Respondent code	Educational Qualification	Professional Affiliation	Job Position	Tenure	Firm Size	Type of Organisation
Respondent 1	MSc Service Mgt	IHRMP	Manager, HR strategy	7years	700	Private/MNC
Respondent 2	MBA HRM	IHRMP	Principal HR Officer	16 years	2505	Public/Domestic
Respondent 3	MBA HRM	SCP, SHRM	HR Business Partner	6years	1600	Private/MNC
Respondent 4	PhD Law	None	Country HR Director	7years	502	Private/MNC
Respondent 5	EMBA HRM	IHRMP	Human Capital Manager	12 years	152	Private/MNC
Respondent 6	MPhil HRM	IHRMP	Dir. HR, Admin & Org	7.5years	194	Public/Domestic
Respondent 7	MSc HRM	CPHR, SHRM, CIPD, IHRMP	Lead, HR Shared Services	10years	525	Public/Domestic
Respondent 8	Bsc HRM	IHRMP	HR Assistant	3years	179	Private/Domestic
Respondent 9	MBA HRM	IHRMP	Deputy HR Manager	16years	8000	Public/Domestic
Respondent 10	MA Public Admin.	IHRMP	Director, HR	25years	3,000	Public/Domestic
Respondent 11	Bsc Mechanical Eng.	None	HR Business Partner	3.5years	500	Private/MNC
Respondent 12	MA Public Admin	IHRMP	HR Programs Officer	8years	404	Public/Domestic
Respondent 13	Msc HRM & Training	CIPD	Talent Acquisition Partner	8.10years	600	Private/MNC
Respondent 14	Bsc HRM	None	HR Analyst	2years	675	Private/MNC
Respondent 15	Bsc Business Studies	SHRM	HR Supervisor	5years	280	Public/Domestic
Respondent 16	MBA International Business	None	HR, Assistant Director I	7years	34	Public/Domestic
Respondent 17	BA Sociology & English	None	HR Officer	8years	2000	Public/Domestic
Respondent 18	BA Theatre Arts	CIPD	HR Analyst, West Africa Cluster	4.8years	2000	Private/Domestic
Respondent 19	MBA HRM	IHRMP	Mgr. Talent & Transformation	18 years	500	Private/MNC
Respondent 20	MBA HRM	SHRM	Groupe HR Manager	12years	7000	Public/Domestic

Source: Field Data (2019)

4.1.1. Educational Qualification of Interviewees

From the data presented in Table 4.1 clearly indicates that majority of the respondents are Master Degree holders, 13 constituting 65%. This is followed by first degree holders who constitute 30%, with 1 respondent with a Ph.D. constituting 5%. It is clearly evident that the sample for this study comprises of highly educated respondents. It is also evident that almost all the respondents have some working knowledge in Human Resource Management.

4.1.2 Professional Affiliation of Interviewees

It is indicative from Table 4.1 that half of the respondents are Professional HR Practitioners having joined the Institute for Human Resource Management Practitioners, 10 accounting for 50 %. 5 respondents accounting for 25% have joined other professional bodies like the CIPD with 5 of the respondents, 25% not part of any professional body. Once the respondents are able to run the basic form of analytics which is descriptive in nature, they are included in the research study.

4.1.3 Job Position of Interviewees

Most of the respondents are in managerial roles within the HR function accounting for 60%. That notwithstanding, about 40% are into non-managerial roles within the function. The diverse job positions give rich explanations to the research questions as different viewpoints are expressed in different contexts. These job roles throw more light on the competency levels and skills of the respondents in the management of the various HR processes and its impact on the bottom line as well as organisational performance.

4.1.4 Firm size of Interviewees

Table 4.1 presents the number of employees of the various interviewees. It can, therefore, be said that, 8 accounting for 40% of the total respondents belong to an organization with firm size within 1 – 500, followed by 1000+ which is 7 accounting for 35% of the total respondents. The third following group which is 501 – 1000 are accounting for 25% of the total respondents.

The impact of firm size on innovation adoption and implementation has been studied although there is no conclusive link on this relationship. According to Barker (2012), larger organizations are more likely to adopt and implement innovations such as HR analytics than smaller organizations generally. However, the findings of the study indicated that analytics use in either private or public organisations is not influenced by firm size. From the socio-demographic characteristics of interviewees, firms with as low as 34 and as high as 8000 employees are using HR analytics in their HR departments. That comes to say that irrespective of the size of firm, HR analytics is still useful and relevant to mine employee data.

4.1.5 Tenure of Interviewees

Table 4.1 illustrates the number of years of work experience or tenure of the respondents. Majority of the respondents thus 13, fall within 1 – 10 years of continuous service in the HR function accounting for 70%, followed by 11 – 20 years, 5 respondents accounting for 25% and 1 respondent with 25 years of experience in the function accounting for 5% of the overall percentage. This shows the rich hands-on experience of the respondents and the in-depth knowledge accrued over the years about the HR function and the management of the organisation’s human capital and its contribution towards organisational performance and competitiveness. This is also indicative of the fact that, these respondents are aware of the changing trends of the function over a period and how the HR department must position itself towards achieving organisational excellence.

4.1.6 Type of Organisation

Table 4.1 gives an equal distribution of the organisation between private or public and multinational and domestic firms. 50% of the interviewees are from private firms with 50% coming from public firms. This was to enable the researcher to draw diverging lines or differences between the private and public to measure the effectiveness and benefits as well as outcomes of HR analytics in practice in these firms.

4.2 Conceptualization of HR Analytics

Over the years, the Human Resource function has undergone an enormous transformation, moving from an administrative phase to a more strategic and value-adding phase in organisations (Ulrich & Dulebohn, 2015). This has involved the investment and use of innovations or technology to ensure that organisations are managed effectively and efficiently. In an attempt to achieve strategy as well as add value to organisations, HR analytics has been introduced as an indispensable tool (Boston Consulting Group, 2014) for the HR function to increase performance and to meet the strategic and value-adding agenda (Lawler, III, et al., 2004). HR analytics is a tool used to develop concepts and ideas in solving HR-related business problems through the use of mathematical, statistical and data mining techniques. This enables HR practitioners and managers to make informed decisions to create value for their organisation. In simple terms, HR analytics refers to the process of gaining insights and meanings into HR data for decision-making which results in adding value for an organisation. Adding value to an organisation means using the resources and capabilities of an organisation to increase revenue and to decrease cost (Barney & Hesterly, 2012) and once HR analytics is utilised effectively, this goal of supporting organisation agility, innovation and learning will be achieved (Marler, 2009).

All the research respondents conceptualised HR analytics in the context in which they operated and these were the definitions they gave to it. This is presented in the table below.

Table 4.2 Understanding of HR Analytics by Respondents in both Private and Public Firms

Respondent 1: *HR analytics looks at how the HR function can enable the business to perform very well by exposing them to a lot of the contribution or how HR itself will contribute to the business. This is to make basic HR decisions based on empirical data from within the organisation and outside the organisation where the data exists.*

Respondent 2: *HR analytics is about using systems to be able to manage HR information. After gathering this information, reports are generated to be able to make informed decisions about the workforce and workforce plans.*

Respondent 3: *HR analytics is a tool that helps to find the link between HR practices and organisational performance. It helps to quantify the cost and impact of an employee on the bottom line as a key tool towards achieving competitive advantage.*

Respondent 4: *HR analytics is basically how data is used to make decisions that affect people in the workplace by taking accurate decisions that will affect the lives of people within the business.*

Respondent 5: *Putting simply, HR analytics is collating raw data and making meaning out of it to address strategic people management issues.*

Respondent 6: *HR analytics is using data to manage employees and also to take strategic decisions.*

Respondent 7: *HR analytics basically is a discipline of HR that deals with taking HR decisions using empirical data. It's building a business case rather than use your gut feelings or predictions based on one's own experience or that of others.*

Respondent 8: *For every business, the sole aim is to make a profit and HR analytics basically tries to find the right solution towards talent management to achieve organisational goals.*

Respondent 9: *HR analytics basically has to do with planning. Thus knowing and understanding the workforce to be able to assess the needs of the workforce at any time.*

Respondent 10: *HR Analytics is more of the segregation of the various domains of HR studies. It involves the use of HR information to manage the workforce.*

Respondent 11: *HR analytics is about using data and trends to trigger business decisions. HR analytics is actually using HR data, insights from data to trigger critical decisions in service of business performance.*

Respondent 12: *HR analytics is having data on staff, and being able to analyse the data to make decisions for the organisation.*

Respondent 13: *HR Analytics is about using systems and structures usually IT systems that can extract data for analysis to make decisions. It's just having data about people, behaviour, structure and making meaning from the data.*

Respondent 14: *HR Analytics is about identifying people-related issues in an organisation through business-related drivers to make decisions.*

Respondent 15: *HR analytics is using HR data which is critically analysed to make informed decisions out of it.*

Respondent 16: *HR analytics has got to do with understanding the HR processes, the trends in work, and how it plays on productivity or output.*

Respondent 17: *HR Analytics is a kind of tool used to predict, forecast and resolve HR problems.*

Respondent 18: *HR analytics is about gathering raw data from employees for processing to make meaningful analyses to inform management decisions for strategic positioning.*

Respondent 19: *HR analytics is the practice of analysing HR data to find out any underlying reasons for causes of performance or non-performance and to investigate any issue of HR concern.*

Respondent 20: *HR analytics is about gathering data from employees and further analysing to make decisions for the organisation which is strategic in nature and to make recommendations to management.*

Source: Field data (2019).

4.3 HR Analytics Process in Ghanaian Firms

According to Marler and Fisher (2017), it has become imperative that organisations and especially the HR function draw relationships between the various HRM processes to achieve strategic business objectives using analytics. This can be realised when the HR unit has enough information to perform better. Field data from the current study revealed that, to run analytics effectively to gain insights for strategic decision making, a five-stage criteria need to be adopted. These are; understanding the business goals, identifying the appropriate measurement tools, capturing relevant employee data, analysing and reporting on employee data and taking decisions on analysed employee data which are congruent to create scorecard goals, identify metrics, capture and integrate relevant data, analyse and report information and finally make decisions and monitor results respectively as expounded by Marler and Fisher (2017). The steps identified from the field fits well in all the steps explained by the authors above and the issues discussed in the subsequent paragraphs.

4.3.1 Understanding the business goals.

According to Kaplan and Norton (2007), scorecard is expressive statements of strategy where objectives are set and further agreed upon by stakeholders to describe their long term success drivers. Goal setting has been a characteristic of effective managers where they are able to translate set objectives into actions to guide them in delivering the organisation vision and mission. From the responses gathered from the interviewees, all of them engage in creating scorecard goals or understand their organisations set goals and target as the first and important step to running analytics within the HR function. Some initial codes that emanated from the field data to support understanding the business goals included business strategy, trends, KPIs. An interviewee had this to say to buttress this theme which is presented below;

…so we derive our goals from the main strategy through which obviously, our managing director gets his strategy and is cascaded down to every individual and that is the basis on which are goals and our KPIs are set for the year. ***(Respondent 3)***

Another interviewee who has 7 years of working experience in HR strategy had this to say;

> *...for us, every year, every employee has a KPI that is derived from the business KPI. So KPIs are cascaded from the overall business strategy right from the CEO to the very last person in the organisation. For instance, one of our goals as HR is to grow our internal employees and this is in line with the business strategy.* ***(Respondent 1)***

Creating scorecard goals in the analytics process cannot be underestimated. Organisations should be able to draw connections between the various HR activities in the organisation which feeds directly into their financials (Marler & Fisher, 2017). Once HR Professionals in organisations set goals, it directs what they should be doing as a function stemming from the corporate strategy to drive the various HR processes so that, they are able to measure value added to the business and the function as a whole. Typically, when HR units create scorecards as the first step in the analytics process, they are able to develop actionable goals and these focus on answering questions from the strategic, operations and financial perspectives of the firm (Groysberg, McLean & Reavis, 2006).

4.3.2 Identifying the appropriate measurement tool.

Once the goals are set in motion, there is the need for HR to be able to measure the various HRM outcomes in the light of value creation. A lot of metrics or measurement tools have been developed for the HR function to increase the efficiency, effectiveness, and impact of the various HR activities on organisational outcomes (Marler & Fisher, 2017; Ulrich, 2019). There are recruitment oriented metrics such as time to hire, cost per hire, quality of hire amongst others (Ulrich, 2019). Time to hire is the total number of days of opened jobs to the total number of jobs. Cost per hire is the cost of recruitment in a given period to the total number of hires in a given period of time. Performance-oriented metrics include a turnover index, net promoter score and sickness absence (Ulrich, 2019). A Turnover index is the total number of employees who leaves in a year to the average number of staff in posts during the year multiplied by 100. The net promoter score is the difference in the number of promoters and detractors to the number of respondents multiplied by 100. Sickness absence is the workdays missed to the total workdays schedule multiplied by 100. Finally is the revenue oriented metrics which involves Return on Investment (ROI) and labour cost as a percentage of sales. ROI is given as the difference in the total investment cash flows and total investment cash flows to the total investment cash outflows. The labour cost as a percentage focuses on the total payroll and benefits to the total revenue multiplied by 100.

One respondent had this to say to support the recruitment oriented metrics;

…another is the number of days to fill critical roles. This metric is important because a critical role is a role that, if you leave vacant beyond a certain number of days depending on your company, you expose the business to risk. So for example, in my organisation, if you leave the supply chain director role vacant for 45 days, you expose the business to risk. We will not have any product to sell. ***(Respondent 11)***

Another respondent said this to buttress the performance-oriented metrics;

So here, we use the supervision cost metric. So the supervision cost has got to do with the number of people who directly report to a manager and the cost involved in their operations. So I sum up their salary and divide by his salary. It should not exceed a particular number and if it exceeds that means the company is not being efficient or that department is not being efficient and so it will have a negative impact on the revenue or financials of the company. ***(Respondent 14)***

The findings of the study reveal that adding value to an organisation is about being able to measure various HR activities and their outcomes on the organisation. Thus, practitioners need to be guided by pre-defined standards of measurements (Boudreau & Ramstad, 2005; Casio & Boudreau, 2010). This falls in line with the views of Boudreau and Ramstad (2007) on the critical role of these measurement systems. This is to unravel very important relationships between HR activities and decision-making. This also enables HR professionals to design better HR analytics systems and to find factors that can contribute to management decisions (Lydgate, 2018). The focus needs to be on HR Professionals designing high-quality metrics to run analytics (Bailey, et al., 2018) to drive organisational impact (Boudreau & Ramstad, 2007).

Furthermore, identifying the right and quality metrics for analytics increases the efficiency, effectiveness, and impact although the focus has largely been on efficiency in the past. The analyst can develop initial hypotheses which will guide what to look out for or measure (Bosnjak, et al., 2009). The outcomes of the metrics would have emanated from the corporate strategy and are relevant to performance. Firms that invest in the right measures and where they are needed gain greater returns and not just where improvements are feasible.

4.3.3 Capture relevant employee data.

In capturing relevant employee data, it is important to create, store and share the data that is managed to ensure consistency and access. Familiarising oneself with the data is important because it forms the basis of analytics and the knowledge from the data is equally important (Miriski, Bernsteiner, & Radi, 2017). The analyst needs to assess the quality of the data (CIPD, 2018) and whether they are for the given purpose. Data analyst or miners are able to identify problems with the data as well as identify hidden or missing data (Niaksu, 2015). Merging all data sets due to the different sources they may come from, are all done in this phase (Brown, 2018). HR practitioners also need a central point to capture all relevant data on employees to ensure effective error-free analysis and appropriate reporting for decision-making.

A respondent said;

So we have a big data repository centre which we call a business warehouse which is the system we use to capture our employee data. ***(Respondent 13)***

Another respondent had this to say;

Lately, we have worked on software that is helping us. We call it Human Resource Information Management Systems and we use it to capture employee data. ***(Respondent 9)***

It is undisputed that gathering the right data for analytics is the ideal thing to do. This is consistent with Davenport et al. (2010) assertion of ensuring that data for analytics should be of quality, unique, should be cleaned and useful for analysis. In data preparation, analysts need to ensure that, the data is based on the analytical tool requirement before particular data sets are selected (Pajek, 2017).

A respondent with 10 years of working experience in HR analytics and a practitioner exclaimed;

In capturing the data, you have to capture the right data. Also, the data will always be raw, so you need to clean it up and dress it for analysis without of course being biased and all that. You have to clean your data, run it into the structures of the schemas then run your analysis, and report on them. ***(Respondent 7)***

Data and especially HR data need to be safeguarded to prevent external sources from getting access to them as they can manipulate the information rendering it not useful for analysis. Therefore HR practitioners or managers need to ensure that data on employees who are an organisation human capital is kept private and until legally requested for, it should not be readily available to external sources. A certified CIPD respondent explained;

…we have the data processor, the data subjects, and then the data owner. So if there hasn't been a request from the data owner to run attrition data for example 2017 – 2018, the one requesting for the data needs to have a valid reason for that? ***(Respondent 18)***

4.3.4 Analyse and report on employee data to Management

This phase of the analytics decision-making process focuses on how employee data stored in warehouses are produced for decision making. Drawing the appropriate conclusions for the gathered HR data is what characterises this stage (Cascio & Boudreau, 2011). This involves selecting the right tools and methodologies (Shearer, 2000). The analysis is run using the prepared employee data set through manipulations (Keerthi, 2018) using appropriate techniques as descriptive, diagnostic, predictive or prescriptive (Fitz-enz, 2010) depending on what the organisation seeks to achieve. The analytics process can be automated, automated with overrides or automated with an assisted approach or technique as postulated by Marler and Fisher (2017).

A respondent commented;

...so after the data has been captured, you manipulate the data to know the number of males and females in the system, which departments they belong to, the number of management staff we have, the junior staff we have and then the officers we have in the system. So at each level, there is a different report that we come up with through the analysis based on the information captured. ***(Respondent 2)***

Another respondent had this to say;

The thing is that our system takes in a lot of data and you should be able to manipulate the system to be able to obtain the information that you need. So if it is a monthly headcount report that you want, you should be able to get that. ***(Respondent 4)***

These analytical outcomes are reported using dashboards. The dashboard is an interactive interface designed to deliver personalized graphical displays of Key metrics to the end user (Marler & Fisher, 2017). This brings out the trends which come in the form of graphs, ratios, colour coding as it is presented graphically. These dashboards can provide HR professionals with information of training, its costs and the impact on employee and organisational performance.

A respondent opined;

For us here, we use dashboards. Dashboards are used for displaying the outcome of the analysis. We use that of SPSS, Tableau, and Excel. That's what we use mostly but there are other tools depending on the data set you are looking at. ***(Respondent 7)***

Another respondent commented;

There are a lot of formats we use in reporting. There are graphs and tables. We use traffic lights where if you are off track you are red and so on. We also use scoreboards like trend analysis. ***(Respondent 11)***

One other respondent is of the view that;

...the information is reported through pie charts and a little bit of writing. ***(Respondent 17)***

Once the analytics is run, the output needs to be communicated in ways that can easily be comprehended by the target audience irrespective. This is in consonance with what Shearer (2000) postulate as knowledge gained should be presented in a way to be easily used by the HR professional. Final results should then be communicated in a report to all stakeholders such as management to make decisions on the workforce (IBM, 2011). Verbal presentations or results need to be given during meetings with related departments or functions through charts and graphs (IBM, 2011; Shearer, 2000). Reporting should be simple, clear and illustrate a possible solution to the identified business problem emanating from the business objectives (CIPD, 2018). In order not to turn people off with complex statistical information, Kennedy and Hill (2017) are of the view that data visualization tends to be a more useful and powerful tool to get a message across to an audience.

A respondent expounded;

There's no better way to convey compelling information than to use maybe a graph, charts or whatever might be used. ***(Respondent 1)***

4.3.5 Take decisions on analysed employee data.

Once the analytics is run on the various HR practices, decisions need to be taken as well as monitor the results or decisions. This is to improve the HR function and the organisation as a whole. IBM (2011) augment this viewpoint by arguing that, the new insights gained from the results of the analytical model should be used to improve the organisation. Results from analytics should not just be generated but critical decisions about the workforce and how they can add value to the organisation should be taken by making them more efficient and effective.

In the end, the function is able to impact the organisation to achieve its set objectives. Implementing change actions out of the analytics outcome and monitoring the results to ensure the output is critical to the analytics process. A respondent made this statement;

*"… all our analytics are geared towards decision making to know how many categories or employees we have, what they are doing, where they are placed and the kind of productivity the organisation is getting from their activity and through this as HR people we know how to recruit, how we promote people, how we plan the exit of people through retirement or vacation of post". **(Respondent 2)***

HR analytics outcomes used in organisational change should be integrated formally into the function daily activities or processes. This is essential in workforce planning and decision making especially in the management of high performers. HR professionals should own the analytics process as they are the implementers of the analytics outcomes (Keerthi, 2018). If the decisions taken are not reflecting the corporate strategy, the HR professional or manager needs to review the objectives set at the beginning of the analytics process and recreate the scorecard goals. The areas of improvement once assessed may bring to light some approaches that are possible hints to running effective analytics or misleading ones for better maintenance and restructuring (Shearer, 2000).

The data gathered from the respondents from the field has established the fact that, taking decisions and monitoring results has lifted the face of the function into the limelight. Management now recognizes the contribution of the function towards the growth of the organisation because the function backs all their recommendations with facts and figures. Taking decisions and monitoring the results have changed how management perceived the HR function to be more data-driven and fact-based. A comment made in that light by a respondent interviewed include;

*"Because we present our observations with hard fact data, management believes what we say as the figures speak for themselves. Indeed this has raised the function to another level and so we have management's full support in what we do now". **(Respondent 20)***

The resultant effect of the decisions taken by the HR function after the analytics output determines how the firm will achieve a greater return on investment. That is to say, the effectiveness and how efficient the HR services have an impact on the bottom line will determine how the financials of the organisation will look like and this is in consonance with what Marler and Fisher (2017) postulated. Nonetheless, some respondents were of the view that, although they present the facts after running the analysis, management does not agree with the figures and facts presented to them. The respondents attributed this to gut feelings of management, the HR functions ability to comprehend numerically and their personal bias towards employee management. Also, the respondents believe that management is very pessimistic when they present insights about the workforce to them. This demotivates them to make critical decisions as they are afraid of possible turn downs. One respondent said this to confirm the above assertion;

…when we present our findings during management meetings, they sometimes do not believe us. They tell us we don't know anything about numbers. This goes to affect our subsequent decisions… ***(Respondent 20)***

4.4 HR Analytics Tools and Methodologies

The introduction of technology has made the human resource function more efficient and more evidence-based in making accurate decisions about the workforce. The introduction of analytics in the HR function has revolutionised the function thereby increasing the performance of the organisation to increase the firms return on investment (Bersin, 2015a; 2015b; Oracle, 2011). There has been the introduction of software as a service to firms (Choudhury & Barman, 2016) with mathematical and statistical models built in them (Kapoor & Sherif, 2012) to discover, predict and optimize the various HR processes. With the enormous data available to HR professionals and managers on employees, these technologies will help in efficiently analysing these data in faster ways which traditional data techniques and infrastructure cannot do (Elegendy & Elragal, 2014).

In explaining data mining and how it can support behaviour predictions, Kirimi and Moturi (2016) introduced the adoption of certain analytical methodologies. These methodologies as used in HR systems have helped to discover and extract patterns from HR data with meaning (Kirimi & Moturi, 2016).

4.4.1 Microsoft Excel.

Microsoft Excel as a data visualization tool has been noted to give a deeper understanding to data and analysis according to Laverty, Miket, and Kelly (2002). These features have made visual simulations of data easier and outputs of it presented in an attractive manner (Orvis, 1996; Rusu & Rusu, 1998) making it one of the tools highly patronized. This data analysis and visualization tool are the most widely used with functions for various statistical analysis (Laverty, et al., 2002). An interviewee made this comment to support this standpoint;

"Microsoft Excel is one of the best tools on the market. They give you the information you want, simple, and very easy to understand. Excel is user-friendly and very easy to interpret and understand the reports they produce. So I want to believe that's why the company purchased this software." ***(Respondent 3)***

About 90% of the interviewees said they used Microsoft Excel in running their analysis with the benefits postulated by one of the respondents above. Microsoft Excel has been noted to be the most widely used software in the analytics space and this is because it is able to provide its own programming language and basic visual applications. This is in consonance with Rusu and Rusu (1998) as the software makes the generation of real-time reports much easier and cost effective. Some respondents, however, are stacked to Microsoft Excel due to the unavailability of other software within their organisation to analyse their HR data. To the respondent;

"We are using excel for now because that is what we have readily available to us."

(Respondent 5)

Research respondents have expressed their satisfaction with the use of Microsoft Excel due to the flexibility to which they are able to manipulate their HR data and to present in a more attractive and appealing format to management for decision making. The respondents are of the view that it is easy to use, easy to understand, simple, user-friendly, readily available and accessible and flexible. No wonder it is the most widely used spreadsheet in the computer space for analysis and data visualization (Laverty, Miket & Kelly, 2002). This validates the acceptance of this tool in the analytics space and its increased use in the HR function for analysing HR data for effective decision making.

4.4.2 Microsoft Power BI.

Microsoft Power BI deeply integrated into the Microsoft Business Intelligence Suite (Microsoft, 2016) has played key roles in data visualization (Petrovski, 2016). This has given more meaning to data in recognizing trends, status and patterns in quicker ways than the traditional methods (Borup, 2015). Inaccurate data representation has made people decision making difficult. With the introduction of Microsoft Power BI, HR professionals and managers are able to critically provide clear pictures of what particularly is happening to their HR data and bottom line. In the end, it facilitates decision making (Petrovski, 2016) and puts the HR function in the limelight. Its flexibility and fit for purpose is gradually increasing its usage in the Human resource management space. A respondent agrees with this assertion in the comment below;

I think Power BI is one of the software we use which is very flexible. For me, every software, flexibility, and fitness for purpose is the big thing for me. I've used two software and I've seen that Power BI is very simple to use. You can change scenarios and you can use it to simulate and not lose the base data. ***(Respondent 11)***

From the interviewee's responses gathered from the field, Microsoft Power BI is the second widely used analytical tool constituting 10% of the total responses which are adopted to manipulate HR data for strategic decision making. These respondents believe that this software or analytical tool are business tools not for IT people which can be used to gain insights into HR data. Microsoft Power BI just like Microsoft Excel has been described as flexible, has a good visual appeal and fit for purpose. This is in congruence with Borup (2015) who is of the view that, an analytical tool with good visualization quickly exposes or extracts the meaning from an HR data for effective decision making. A respondent said;

...the Power BI gives us a better pictorial view which is also appealing to the eye, usually when you presenting to high-level managers. ***(Respondent 13)***

Organisations are investing in Microsoft Power BI due to its ability to load huge workbooks in Excel into the cloud without being limited by distance (Aspin, 2014). Also, organisations are investing in this analytical tool because it comes with other Microsoft applications making it cheaper as compared to purchasing different tools from different vendors. The newness of the Microsoft Power BI in the business arena may account for the low patronage. Its usage is expected to shoot up in the near future due to the advanced functionalities and proper reporting options. That is;

...Power BI is actually new in this organisation and most HR departments, so not many people will use it. Just about 20% may use it compared to about 80% using Excel. ***(Respondent 13)***

4.4.3 Regression Models.

The aim of running analytics within the HR function is to draw causal relationships between the various HR practices and organisational outcomes. Regression models either linear or logistic has been identified to establish this relationship between the HR variables

(Bhattacharyya, 2018). This model has enabled the HR function within firms to draw correlations between HR activities and their outcomes. An interviewee exclaimed;

"We use regression to always draw relationships between occurrences and the results. For example, we did a staff survey on trying to measure engagement. We did it twice in that year, so April and of course around the end of the year and it was interesting that, some of the comments that were coming up had to do with performance. Management was of the view that because we increased salaries, the performance was going up. But we did a regression analysis and we realise it wasn't salaries. After this, we increased salaries and performance was still the same" ***(Respondent 7)***

Data from the field indicated that, 90% of the respondents used regression models as their analytical methodology. This has enabled them to predict their workforce and to find interventions for solving some of their HR problems. Regression models used in analysis has enabled organisations to identify causal trends in their HR practices on performance and to establish clear cut impacts on the organisation. HR professionals or managers are able to make suggestions on the kind of interventions required. This is as a result of the causal link or correlations they draw through the use of regression models. A respondent said;

…we have been using regression because it tries to draw a cause and effect relationship between the HR processes we have here. For example, we had a challenge with our nurses and the services they render to our external customers who are patients. After running a regression analysis we realise that they had a customer relations skill gap which was affecting their performance. Management then took a decision to train our nurses. So every Thursday of every week unless it's a holiday, there is a CPE (Continuous Performance Evaluation) training for them to improve on their contact with our patients and to boost their performance. ***(Respondent 8)***

4.4.4 Decision Tree Models.

The decision tree as an analytical methodology has been noted to generate rules used for making future predictions (Kirimi & Moturi, 2016). This analytical methodology has enabled firms immensely in their personnel selection (Hein & Chen, 2008) roles and predicting job attitudes of employees (Tung, Huang, Chen & Shih, 2005). To a respondent;

I think the decision tree is very good. The model helps you to match even your employee demographics and how it impacts their performance and the company as a whole. This insight helps you to plan your workforce and effectively manage them. I think decision trees should be the way to go for organisations who really want the best workforce to work with. Personally, I love using this model but I don't know how many organisation know about it and investing in it. ***(Respondent 19)***

The field data revealed that, decision tree is the next most used methodology in analytics within the HR function. This has enabled the firms to match up employee job attitudes to performance levels in the organisation. Specific trainings are then designed for those employees underperforming. Also, the decision tree has enabled firms to recruit suitable job applicants for various job roles. After running the decision tree analysis, HR professionals and managers are able to map employee's competencies to their various job roles to which they identify some skills gaps thereby affecting the type of candidates to recruit for a job role and the competencies they possess. This assertion is in congruence with Hein and Chen (2008) noting that, to be able to recruit the right people into an organisation, meaningful rules should be mapped on employee competencies and attitudes towards organisational performance. The decision tree model is gradually growing in its usage and becoming more popular because it requires no expert knowledge thereby making it more user-friendly and easy to use (Janthan, Hamdan & Othman, 2010). One respondent exclaimed;

...through the decision tree, we as a department are able to see the kind of employees and the skills they possess in the work they do. The insights shapes how we recruit our talents and we make sure we are getting the skill set our current employees were lacking. ***(Respondent 10)***

4.5 Benefits of HR Analytics among Firms

The advent of analytics has increased the scope of making the HR function as a strategic partner (Boudreau & Lawler III, 2009). This is as a result of the HR departments being able to combine the humungous data on employees extracted to improve on the bottom line (Soumyasanto,

2016) and to achieve competitive advantage (Davenport, et al., 2010) and enabled the HR function to add value to businesses (Boudreau, Lawler III & Levenson, 2004). The resultant effect has been increased organisational outcomes measured as customer, financial, learning and growth, and internal operations as established against short-term and long-term goals (Kaplan & Norton, 2007). HR professionals and managers are now better able to provide HR solutions and services to employees that are in line with the organisation's set goals and objectives.

4.5.1 Employee Acquisition.

In responding to the challenges associated with overall employee work performance and attitudes, analytics has effectively managed how employees are hired and placed in job roles (Ejo-Orusa & Okwakpam, 2018). Analytics has reduced the errors associated with recruitment and selection drastically by engaging the right people for the right jobs (Ejo-Orusa & Okwakpam, 2018). Naasz and Nadel (2015) have also argued that HR analytics has improved hiring decisions in terms of speed and quality of hire. This has become expedient because if the subjective estimates or judgments HR experts make in determining how a candidate skills and competencies influence employee performance (Naasz & Nadel, 2015). Some initial codes that emanated from the field data to support the positive impact of analytics on employee acquisition are to search for the best talents who will add value to the organisation. Also, analytics has made it possible to improve the quality of hiring processes. A respondent had this to say to buttress the theme which is presented in the quote below;

"…we use something called the Cultural Assessment Test. So what that does is, there are series of questions which are system based where the new hire has to go into that system and take the test. And that in itself will filter out a lot of the applicants and the qualified ones invited for an interview. This has saved us a lot of time and has increased our efficiency."
(Respondent 4)

Another interviewee added this;

...there are series of assessment like cognitive and behavioural. Even when we are dealing internal candidates thus doing internal recruitment. The applicants do about three assessments before and analytics has helped us to whittle down until we finally get the shortlisted number to interview. This has improved the quality of people we bring into the organisation. ***(Respondent 10)***

With the positive impact of analytics in acquiring the right talent to add value and increase competitive advantage among firms, CEOs are pressuring their HR departments according to a report by Deloitte (2016) to adopt the use of analytics. A study by Ejo-Orusa and Okwakpam (2018) has confirmed the positive relationship analytics has on recruitment and selection of employees in some selected banks in Nigeria. From the study, increased productivity, better employee acquisition, increased profit and employee retention has been recorded as the benefits of analytics on employee acquisition. It is important to critically assess and improve on the acquisition or recruitment and selection of employees if an organisation wants value both to the HR function and the firm as a whole. Effective and efficient organisation always outsmart and perform better than ones that are not. In effect, there is increased profitability for the sustenance of the business and increased employee retention. Businesses are also able to attain business objectives if they use analytics to manage their recruitment and selection processes. A senior certified practitioners and an affiliate of the strategic human resource management practitioners with 6 years of working experience exclaimed;

I think HR analytics has helped us as much as possible and continue to enable us to get people that are closely matched to our culture, our organisation and can help us to attain our objectives. ***(Respondent 12)***

Some respondents having recognized the benefits of analytics in attracting and retaining the right talents have not benefitted from it as an organisation. This is as a result of the heavy political nature of their organisation and how it influences how candidates are posted into job roles with the needed competencies to perform. Nevertheless, these HR practitioners have started the deployment of analytics in their talent acquisition through graduate internships with the hope that this will transcend to permanent job roles. Deploying analytics in this area is to assess how these graduates' value systems can be synchronized with the organisation value to drive business goals and objectives. A respondent from a public organisation expressed this concern in the statement below;

…analytics is fully deployed in recruiting our graduate into internships by trying to assess their value systems to see if it will synchronize well with our culture. We put the link on our website where our recruitment modules are linked to our website. So you log in, take a test, you upload your CV. Analytics help us to streamline the applications...so even before you come in we know who meets the mark and how fit the person is to work with us.
(Respondent 16)

The positive outcomes of employing analytics in how talents are recruited into an organisation is enormous and so HR professionals and managers need to invest heavily in this area. This will make the HR function more evidence-based. Secondly, the value will be added to the business where the employee's outcomes in the form of performance are increased because the right talents will be in the right jobs. These findings echoe in the argument raised by Davenport, et al. (2010) that, organisations that are investing in analytics to match the right employee capabilities to the right job is increasing their productivity as well as retaining their top talent.

4.5.2 Increased Performance.

Literature has consistently proven the significant impact of performance in the bottom line and organisational outcomes. According to Jain and Gautam (2014), organisation has used performance to outwit their competitors where employee outputs are aligned to the overall business objectives. Analytics has enabled HR professionals and managers to contribute to the strategic plans of the business. They have been able to identify the strong leadership qualities of their employees through the analysis of their performance appraisal systems (Waxer, 2013).

Management through these analyses has devised strategies to avoid the performance of employees from deteriorating (SHRM, 2018). Further to this is the anticipation of this performance of their employees to increase the firm's revenue and improvements in employee engagement (SHRM, 2018). Key codes identified form the responses from the interviewees indicate that, for an organisation to thrive and add value, the HR function should be able to meet set targets or key performance indicators, match efforts to rewards and increased productivity. A respondent had this to say;

"So yes, at the end of every year, we use the performance management tool, which helps us to do our KPIs. We feed it into the system, run the analysis, at the end of the year, we churn out our reports. The people that are not performing are put on performance improvement plans so I think that is pretty clear cut. At the end of the year, the reports are available to help us make a decision as to who are the high performers because performance must be linked to rewards." ***(Respondent 3)***

All the research respondents were of the opinion that, through their performance appraisal analysis, they were able to discover certain trends in their employee capabilities of which the HR function capitalizes on to improve the performance of the human resource and the impact on the business. At the organisational level, businesses are able to maximize profit and gain competitive advantage through the bottom line. Another dimension in measuring the performance of an organisation is the ability of the HR function to reduce cost. Once the HR function is able to optimize their processes by becoming effective and efficient, they are able to reduce huge expenses the function incurs (Fitz-enz & Mattox, 2014). HR professionals and managers through analytics are able to keep an eye on where revenue is going, where cost is going, and how the function can optimize the resources or cost linked to productivity. One respondent purported;

Through HR analytics, we've reduced 3 million pounds of cost this year. This 3 million is on overheads alone. ***(Respondent 11)***

This assertion is consistent with the findings of Ruohenen (2015) who observed that, HR analytics enhance organisational performance and reduces costs, and these are areas valuable to organisations. On how the HR function reduced cost in the quest to add value to their business, one respondent had this to say;

> *We've never been able to exhaust our budget, not even training. For example, we were running our training programs with third party companies and that's what most of us do and in hotels. We run a report on the cost of the hotel bills as against if we had our own place. We matched it and we ended up with the company buying a property for us to do all our local trainings instead of the hotels. Clearly when you see the cost we just reduce, you will be amazed. Yes it was influenced by HR analytics.* ***(Respondent 7)***

One interesting finding from the field worth mentioning is the subjective nature of traditional methods of performance appraisals and the sudden transformation or outlook it has taken since the introduction of analytics in the performance management domain. This comes to confirm the study by Sharma and Sharma (2017) to draw a causal link between HR analytics and performance using appraisal systems. It was purported that, there is increased objectivity and accuracy in the appraisal process. This robust data analysis tools utilised are reducing the subjective bias that comes with traditional performance systems that existed. More objectivity, fairness and not feel they have been treated unfairly because discussions on performance will be based on performance management data.

4.5.3 Employee Retention.

Organisations have improved on how to retain their talents or top performers because HR practitioners and managers are able to determine the rate and probability of an employee leaving the organisation within a specific period of time (Grillo & Hackett, 2015). This has become possible through the attrition scores generated from the analytics run within the HR function. Firms have been able to design equitable reward systems after analysing employee's performance ratings with the resultant effect of increased employee retention. Considerable attention has been paid to employee turnover and how to retain key talents because of what the organisation loses in terms of skills and competence shortage within a particular period. Organisation that analyse their attrition data are better able to gather information about why people leave the firm and find ways of dealing with the issues to retain other top performers from turning over. With this, the attrition rate is always kept at bay. A respondent intimated;

We have something we call the employee engagement survey done every November. We have a lot of questions which is about 67 questions and different indexes, including engagement, performance, diversity, innovation, safety, work life balance, work environment. Last year for instance, we had 98% participation, almost like every single person in the organisation took part in the survey. The results are out and again this is when we use analytics. So we go in, analyse our results and based on that we come out with action plans and the purpose of that is to help us make the work environment the best that it can be and in doing so we hope to retain our employees. ***(Respondent 4)***

The finding is in line with the study conducted by Malisetty, Archana and Kumari (2017) that found that, attrition can be reduced using analytics by analysing an organisation employee data as well as attrition records. It was expounded that, monitoring and controlling attrition is one of the key areas the human resource function can add value. Organisation in curtailing employee attrition are running employee surveys once in a year or twice a year to solicit for employees view on how the firm’s culture is impacting their performance. The analysed data has revealed insights on the salary, development opportunities such as learning and growth, and job ethics and values which is used to improve on the job environment and to make the employee more engaged. This indirectly motivates them to stay. As employee retention and engagement has become a topmost priority in organisations today has called for deep analytics in these areas to study employee experience trends for optimization and to continuously retain the best talent (Mukundan, 2017; Waxer, 2013; Ruohenen, 2015). Fitz-enz and Mattox (2014) have also reported similar findings to say that, if attrition is kept at bay or eradicated, firms are sure to save millions of dollars averagely.

Comment to support this was;

...over the past three years, the average attrition rate annually is just below 2% and it might be one of the best. ***(Respondent 1)***

HR professionals and managers have the sole responsibility of ensuring that, top talents are not turning over by consistently checking and analysing the attrition data and employee data to gain insights on the rates and who is likely to leave the organisation. As employee's leave their organisation for another, they leave with their skills and knowledge which would have contributed to the firm's productivity (Shaw, 2011). Such insights are then translated into actionable strategies to keep these top talents who contribute immensely towards the organisation's return on investment and overall organisational performance.

4.6 Challenges associated with the use of HR Analytics in Firms

The readiness and willingness of organisations to make effective decisions and especially within the HR function is a result of the promising future of HR analytics as a measurement tool (Boudreau & Ramstad, 2005; Deloitte, 2013; Green, 2016). Despite the promising nature of HR analytics use in organisations, some are still struggling to implement it (Deloitte, 2013). Most HR departments are not able to combine data and business to achieve organisational results (Deloitte, 2015; Narula, 2015). These shortfalls come in the form of lack of HR analytics competency, lack of management support and poor data and tools management.

4.6.1 Lack of HR Analytics Competency.

HR function's inability to utilise the data at their disposal to add value to the firm is termed as a capability gap (Deloitte, 2015). Once HR professionals and managers lack the analytical skills, they are unable to dive deep into the HR data available to make strategic decisions for the organisation (Mukundan, 2017). The major themes emerging from the responses from the field are HR professional's inability to interpret analytical results and lack of working knowledge in statistics or numeric. A respondent with 12 years of continuous working experience in the HR function had this to say;

"I think that HR people, in general, are not numerical. And so if you want to run analytics, you need some level of statistical mind and even the interpretation of it. Even when the data is run for you, you should be able to interpret it cos that's another level and if you are not able to interpret, then how do you know how the result is going to impact on decision making." ***(Respondent 20)***

Another respondent said this;

At the moment we don't have any HR analytics experts, we don't, not here not even at the group office. ***(Respondent 5)***

All the respondents submitted that HR professionals and managers are not numeric, and this affects how they run deep analytics. Literature on HR analytics has some points indicated the inability on the part of HR professionals and managers to conduct statistical analysis using employee data. This has made some researchers like Ramussen and Ulrich (2015) propose that analytics be taken out of HR departments to line managers until these departments gain the competence to run analytics. Long, Blok and Coninx (2016) have also mentioned that, lack of required skills and competence are some of the organisational challenges inhibiting the use and implementation of HR analytics in businesses. This comes to say that, if the organisation does not make the skills and competence readily available to managers in the HR function through training, then they will lack it. A respondent said this to support this argument;

If the organisation is not analytics-driven, the HR function will lack that skill. The HR has to find a way to fit in otherwise they will lose their relevance. ***(Respondent 19)***

Minbaeva (2018) strongly believes that, gaining the right analytical competence can enable managers to design and implement better solutions for increased organisational performance and value creation but these professionals are not ready to work with figures and numbers. They see HR analytics as involving statistics and mathematical equations which is greatly limiting the use of analytics within the HR function (Fiocco, 2017). Management needs to focus on building the analytical competence of their HR function to gain the best out of them towards creating value for the organisation which translates into increased performance and increased competitive advantage. People in HR departments should pull data and analyse it themselves. They need to be analytics savvy to thrive in people management.

4.6.2 Lack of Management Support.

Every HR function is expected to add value first to the function and then translated to the organisation as a whole. This is possible if management is ready to support the function by understanding and recognizing the essence of analytics and the enormous benefits it presents to the firm. The support may come in the form of providing the analytics technologies and acquiring the skills and competence to drive its implementation (King, 2016; Long, et al., 2016). Most of the interviewees are of the opposing view that, management support has been low in the implementation of analytics in their firms. A respondent made this statement to maintain that, management support has been low;

"The major challenge is really getting management support to invest in some of the analytic tools. For instance, if I proposed this to a manager to invest in an analytic system whereby when new hires come into the organisation we can key in some data so we can analyse and track them, management will say, why do we have to invest in this, can't we just do it manually? They are not looking at how this will sort of optimize our services and make us work smarter." ***(Respondent 18)***

Despite this finding, about 20 % of respondents reported that, they have received support from management on HR analytics implementation within the HR department ranging from training to acquiring the analytical tools to ensure effective analyses of employee data. This insight contrasts the findings of Chahtalkhi (2016) who identified a lack of management support as the first to be recorded from emerging categories of challenges faced in the implementation of HR analytics during a qualitative study among three companies. It is postulated that firms are not able to recognize the essence of HR analytics attributing it to the fact that, the added value and benefits from HR analytics has not been explored fully by management. A respondent in countering this assertion said;

Management has really supported us since we started running analytics in this organisation. We are constantly going for training on analytics. ***(Respondent 17)***

Management needs to rally behind the HR unit by providing all the analytical resources needed for running deep analytics on employee data. This will compel management to make available the tools or software, skills and competencies for HR professionals and managers to add value to the organisation. This support is also coming in the form of training the HR professionals and managers on how to do deep analysis on employee data using HR analytics. A professional with 16 years of progressive working experience in the human resource function had this to say;

...management is supporting by giving training and retraining us on analytics use. ***(Respondent 2)***

4.6.3 Poor Data and Tools Management.

HR data whether sources within or outside the organisation should be error-free if the HR professional wants to describe, explain, predict and optimize performance. That is to say, the context for which the data are collected needs to be understood well enough so that, the right data is used for the right analysis (Angrave, et al., 2016). Also, gaining the right data and how to get the data has been a challenge to HR professionals and managers. Accessibility to analytics tools or technologies has equally been a challenge (Chahtalkhi, 2016) despite the expansion of these tools and its maturity in the past years (Davenport & Harris, 2010). The main codes identified from the field to buttress on poor data and tools management as a challenge towards the use of analytics in firms are inaccurate employee data, poor data quality, unavailability of tools and data and lack of data completeness. This respondent had this to say concerning inaccurate employee data for analysis;

"The problem is getting the right or accurate data set. It had to take 2 years especially performance data and we still struggling through it" ***(Respondent 7)***

A respondent with 25 years of working experience said;

…the challenge is making sure that the data is accurate. ***(Respondent 10)***

These findings from the field is congruent to the assertion raised by Chahtalkhi (2016) on why the availability and accessibility of data and tools have become a challenge. Access to the right data and tools and its availability for creating information has become essential (Davenport, et al., 2010) and should be invested in just as in financial assets of organisations. If the analytical tools and data are difficult to access and are unavailable, HR professionals and managers are unable to explore the data on their employees to gain insights for strategic decision making which will impact the bottom line and the overall firm improvement. It will also make the HR function more effective and efficient. A respondent said;

"Well, we don't have the tools except the Excel we have which is not enough"

(Respondent 6)

Again, available and accessible data for analysis need to be of quality and credible if expected analytics outcomes are to be achieved (Davenport, et al., 2010). It is essential to always ensure that, data captured on employees are fit for purpose. Once data quality problems are identified, then they can be corrected before running the analysis. Data quality cannot be underestimated in the process of making strategic decisions and so HR professionals and managers need to grade the quality of their employee data (CIPD, 2018; Niaksu, 2015) before analysis. An interviewee opined;

Data quality has been a challenge for us. Data from different people at various levels are presented in forms that are convenient to them and that may not be what they present. Even if you give them standard ways of presenting them, they come to you with the data in a form you do not desire, so it affects the quality of work that you do. ***(Respondent 9)***

Data completeness also affects the analytics conducted within the HR function. Some responses from the field data indicated that, because most of the time, the data at their disposal for analysis is not complete, it derails the quality of work they do. The possibility of this challenge occurring is when employees present data in forms convenient to them and not the expected format which is standardized. The HR function then loses part or most of the information for processing. Another respondent raised a point on data completeness and how it affects their analytical outcomes;

…the completeness sometimes is also a challenge. Completeness of the data that we collect, so once it's not complete, it affects the analytics. ***(Respondent 9)***

4.7 Prospects of HR Analytics in Human Resource Management Practice in Ghana

The Human resource function and human resource management have taken a whole new leap over the years. From a more traditional way of delivering HR services and solutions, the function has moved to being more technology oriented to add value to the practices and processes of how the human resource of the organisation will be effectively and efficiently managed. Trending now is how HR professionals and managers can gain insights into employee data to make strategic people decisions to make an impact on businesses. This introduced HR analytics and how insights and trends can be revealed through meaning derived from employee data. There has been increased investment in HR analytics as more HR professionals and managers are pushing for its introduction and implementation in their companies (Craig, et al., 2010). The future of HR analytics in human resource management practice in Ghana is bright when people begin to look at figures and take decisions to have an impact on the bottom line and the business as a whole. This falls in line with the assertion raised by Heuval and Bondarouk (2017) who explored what the future of HR analytics might look like come 2025. The outcome reports a bright future where HR analytics will become an established discipline to impact positively on the human resources of businesses. The HR department needs to work effortlessly on the challenges to fully maximize the benefits of HR analytics. Below are the views presented by some respondents from the field on how they see the future of HR analytics in human resource management practice here in Ghana? One respondent said;

The future of HR Analytics I think is still very bright. I think HR has come a long way from just being personnel management and administering payroll to now being strategic partners who now has a seat in the board room. This is very objective, facts and data-driven so it's easy to get the buy in of the people that matter to make those decisions. ***(Respondent 3)***

Another respondent added;

The prospects are great. I've been doing a lot of research, and HR analytics keeps coming up. If HR wants to be recognized as a strategic partner then it cannot but make analytics are priority. For me, it is the future for HR. ***(Respondent 5)***

One further intimated;

...there is a huge potential for HR analytics in Ghana. We are not in the past anymore. Whether we like it or not we have to catch up. We can't continue doing the normal absent, present, am healthy, am sick HR. No, we have to grow as HR analysts. If we don't, we lose our jobs in the next couple of years. All we need to do is to show our worth. ***(Respondent 7)***

One other respondent believes that;

The future of HR analytics in Ghana is very bright. People are now beginning to understand the use of HR analytics and systems. Now, people are developing analytical software that is able to help especially with information technology. For me, the future of HR analytics is very bright. And then management is beginning to appreciate the use of analytics too. HR analytics has become essential in decision making. ***(Respondent 9)***

Finally, a respondent made this comment in that light;

I think that it's going to be bright if we should get serious. Multi-National Companies are very serious in running analytics, not just in HR but everywhere. But our local companies are just working blindly. We need to change our attitude. I think there is a big gap we need to close. People should begin to look at figures and take actions. HR analytics is here with us. I think that our institutions like IHRMP should begin to study trends and start running courses in analytics and begin to train people specialized because they know that, that is where it is going. ***(Respondent 11)***

4.8 Differences in HR analytics adoption, implementation and usage in Private and Public Firms in Ghana

Twenty firms with a respondent each from these firms were interviewed for this study. Ten were from private and ten from Public organisations. This section of the study outlines some observed differences between those two groups of firms or organisation. Clear cut differences were observed on how HR analytics is adopted, implemented and used in private and public firms in Ghana. A glaring difference identified from both firms was the culture of the organisation. It was evident that the private firms used more data and are analytics-driven and this reflected on how they operated. These private firms are manipulating their employee data now and then and these insights are reflecting on how they carry out their HR services. The level of competitiveness has risen among private firms than between private and public firms. This has compelled private firms to always devise strategies and invest heavily on HR analytics to manage their workforce to be efficient, effective and impact the business to maximize profit. The adoption of analytics within their function has spread throughout the organisation because of their understanding and impact of data on their return on investment. Almost all departments in the private firms understudy are running some form of analytics to boost their various functions to collectively contribute to the success of the organisation. The Public sector, on the other hand, employs a lot of the workforce in Ghana and HR analytics use in these areas are quite non-existent.

Also, the researcher identified that the private organisation invested heavily on acquiring the analytics competency who will run these analyses on employee data to make critical decisions for the firm. Due to the importance attached to the implementation of HR analytics, CEOs or management of private firms have recruited data analysts and people who are numeric and can interpret analytic results. The firms that do not have the human resource to run analytics have outsourced this service to consultancy firms who run the analysis for them at a fee. Almost all Public organisations interviewed mentioned that, they lacked the competence to run analytics. The only competence they have in stock is the basic knowledge in Microsoft Excel to gain insights that are very limited. Employees who run analytics within the private organisation have job titles as Human Resource Business Partner (HRBP), Talent Acquisition Partner, HR services Lead, HR Analysts and Talent & Transformation and analytics forms a core part of what they do in the HR unit.

Another divergence observed between the private and public organisation understudy was the availability of analytical tools in the HR function for data mining. The absence of analytical tools in public organisation has crippled the HR function to run deep analysis on the human resource. Apart from the two public organisations who has other analytical tools in addition to Microsoft Excel, the eight others depended solely on Microsoft Excel for their analysis. This inhibits them from digging deep into their employee data to gain impactful insights to manage their workforce. Private organisations, on the other hand, has acquired other sophisticated or advanced analytical tools with some coded internally to run most of their analysis. Due to the data-driven nature of their organisation, investing in such tools is relatively easier. Possibly due to the positive implication of these tools on their business.

The final difference found in the study is the awareness of HR analytics presence in organisation. Throughout the study, it looked obvious that about 90% of the public organisation interviewed did not know they were conducting some form of analytics in their HR function.

This is due in part to the fact that they do not have a well-structured infrastructure for running analytics like data analyst or experts specifically employed to do the analytics. Also, this could be possible because of the non-existence of the tools or software to run the analysis. For them, using Excel to analyse employee data did not seem like analytics to them. This was contrasted in the private organisation who were sampled for this study. Table 4.3 below presents the divergence or differences found between private and public organisations on their adoption, implementation, and usage of HR analytics in Ghana.

Table 4.3 Differences between Private and Public Organisation in HR Analytics adoption, implementation, and usage

Differences between HR Analytics Adoption, Implementation, and Usage in Private and Public Firms	
Private Organisation	**Public Organisation**
1. Exhibits a data and analytics-driven culture.	1. Data and analytics-driven culture not evident in public organisations.
2. Required statistical skills and competencies to conduct HR analytics are available.	2. Lack of required statistical skills and competencies to conduct HR analytics.
3. Availability of HR analytics tools and methodologies for analysis.	3. Insufficient HR analytics tools and methodologies for analysis.
4. Increased awareness of HR analytics presence in the organisation.	4. Awareness of HR analytics presence in the public organisation seems non-existent.

Source: Field Data (2019)

4.8 Chapter Conclusion

This chapter presented the analysis of the field data collected using a semi-structured interview guide. The findings were discussed in light of the research objectives set out at the beginning of the study together with the literature reviewed. The first part focused on the demography of the research respondents which was followed with the presentation of results and discussions of the key findings related to the HR analytics process, tools and methodologies adopted, benefits and challenges associated with HR analytics within the HR function. Ending this section, some views on the prospects of HR analytics in human resource management practice in Ghana and some divergent observations identified between public and private organisations during the study were presented.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.0 Introduction

This chapter presented a summary of the findings of the study which were discussed extensively in the previous chapter. This is then followed by the conclusions drawn from the study influenced mainly by the objectives and outcomes of the study. The final chapter ends with key recommendations that were drawn from the study to inform research, policy, and practice.

5.1 Summary of Findings

The purpose of this research study was to investigate the implications of HR analytics on human resource management practice. The objectives were; one, to describe how HR analytics is conducted in organisations; two, to identify the tools and methodologies used in HR analytics; three, to identify the benefits of HR analytics among firms; and finally, to determine the challenges associated with the use of HR analytics among firms. The study used twenty organisations; ten public and ten private organisations where HR managers and employees who work in the HR departments were interviewed. Respondent's demographic characteristics indicated that about (55%) of the interviewees had gained formal education in human resource management and those without this educational qualification had gained some professional qualification in human resource management. The demographics also showed that all the respondents were working within the HR department with years of working experience ranging from two to twenty-five years.

5.1.1 HR Analytics Process in Ghanaian Firms.

The first objective of the study which sought to describe how HR analytics is conducted in organisation revealed that all the organisations go through various processes to gain insights from their employee data. In understanding the business goals, it was revealed that the HR professionals and managers developed their actionable goals which stem from their corporate strategy to drive their HR processes to enable them to measure its value towards their businesses. They move on to identify the various measurement tools specific to their organisation to increase the efficiency, effectiveness, and impact of the various HR practices. Relevant data is then captured on their employees to assess its quality as well as missing or hidden data to run meaningful analyses. The last but one process is to analyse the captured employee information. Employee data after manipulation to gain insights is then presented using dashboards which display statistical information into simple graphical representations. Critical business decisions are then taken to make a strategic business impact. Through this, the HR function adds value to the services they deliver towards making the organisation more productive by aligning the various HR activities with the business objectives.

5.1.2. HR Analytics Tools and Methodologies.

The second objective of the study sought to identify the analytical tools and methodologies used in HR analytics implementation. Extant literature has identified various tools and methodologies used to run analytics in HR departments. The findings from the field indicated that about 90% of the respondents reported their use of Microsoft Excel as the analytical tool used in gaining insights from their employee data. This was followed by Microsoft Power BI (10%). These tools were adopted because of the deeper understanding it gives to data. Flexibility, availability and accessibility, its visual appeal, ease of use, simplicity, and fitness for a purpose were some of the benefits which made the adoption of these tools ideal. These tools were the most used in organisations within the Ghanaian context. The regression model was the dominant (80%) followed by the decision tree (20%). These two were predominantly used because it helps draws correlations between the various HR activities and its outcomes. The established correlations help in drawing intervention programs for effective management of the workforce which emanates from matching up employee job attitudes with performance levels in the organisation.

5.1.3 Benefits of HR analytics among Firms.

The third objective sought to identify the benefits associated with the use of HR analytics among firms. These benefits can be seen in employee acquisition, performance, and employee retention. HR analytics has improved the search for best talents through improvement on the quality of hiring processes in firms that have adopted HR analytics to analyse their employee data. In terms of performance, firms are now able to match efforts to rewards and this has increased productivity tremendously. The HR function in increasing the performance of employees has also reduced HR cost to the barest minimum while being effective, efficient and making an impact. Grey areas have been identified and change plans successfully implemented to ensure effective organisations. The right employees have been retained through the introduction of HR analytics. Scores from analysed employee satisfaction surveys have enlightened HR professionals and managers on the areas of the workforce to focus on to keep a healthy environment for employees.

5.1.4 Challenges associated with the use of HR analytics in Firms.

Despite the acceptance of HR analytics in firms for strategic decision making, the HR function has faced some challenges in its usage in their organisation. The final objective sought out to determine the challenges associated with analytics use in firms. It was revealed that lack of HR analytics competency, lack of management support and poor data and tools management were the major challenges inhibiting the use of HR analytics within the HR function. Some HR professionals and managers (20%) are not able to interpret analytical outputs with little or no working knowledge in statistics or numeric which has created a competency gap in running analytics in the HR function. Management support has been evident in some organisation while non-existent in others. The necessary tools or software, skills, and competencies have not been fully utilised for the full implementation of analytics in firms. Further examination showed that inaccurate employee data, poor data quality, unavailability of tools, unavailability of data and lack of data completeness characterised poor data and tools management.

5.2 Conclusions of the Study

The enormous benefits associated with HR analytics has increased its use to gain insights into employee data to make strategic decisions for organisational effectiveness (Lee & Brower, 2006). This has made HR analytics an indispensable tool for HR professionals and managers to add value to businesses. In the end, it was revealed that HR analytics has contributed significant positive contributions in the areas of employee acquisition, increased performance and employee retention. Again, the study revealed the various tools and methodologies available to run effective analytics for the HR function and some shortfalls that cripple the full implementation and use of analytics in organisations.

5.3 Recommendations

From the findings of this study, the researcher makes the following recommendations towards future research, policy, and practice;

5.3.1 Recommendations for Practice and Policy.

First and foremost, given the benefits of HR analytics and its contribution towards building effective organisations to increase competitive advantage, it is imperative for the Government of Ghana and policymakers to put in place a policy document to manage and direct the use of HR analytics in public organisation. This recommendation has become necessary as it was observed during the data collection process that, most public organisation had not heard of HR analytics and its use in such organisation were non-existent.

In addition, recommendations are made by the researcher to Employers' Associations i.e. Ghana Employers Association (GEA) and other organisational bodies to educate its members on the benefits HR analytics can bring to their businesses to make them more effective, efficient and value driven. Members from firms who are already using analytics can share their experiences to encourage the firms not using analytics in their HR function to start implementing them in their firms.

Also, the researcher through this study makes recommendations to HR professional institutions such as the Institute for Human Resource Management Practitioners (IHRMP) to begin a search into the trends in the market and places where HR professionals or practitioners can add value through the adoption of HR analytics and begin training HR managers through specialized courses in analytics to become specialized experts.

5.3.2. Recommendation for Future Studies.

The current study has laid the foundation for further empirical research to be conducted on the implications of HR analytics in human resource management practice within businesses in the Ghanaian context. Future studies can consider a comparative study between public and private organisations that has adopted HR analytics using the quantitative approach. Also, the study focused on all the various HR activities as a composite one and HR analytics' influence on them. With this, future studies can examine the implications of HR analytics focusing on the individual processes to evaluate its effect on the bottom line and business performance.

Furthermore, future studies can consider testing the findings of through a longitudinal approach to explore the meanings and values associated with HR analytics and HR practice. This will also afford the researcher the opportunity to increase the scope of the study to include more respondents to elicit their responses on the subject matter. That notwithstanding, the findings of the current study are great insights towards the scientific development of research and practice of HR analytics in Ghana.

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APPENDICES

APPENDIX A: INFORMED CONSENT (RESEARCH RESPONDENTS)

UNIVERSITY OF GHANA

DEPARTMENT OF ORGANISATION AND HUMAN RESOURCE MANAGEMENT

INFORMED CONSENT

Dear Respondent,

I am a Part II student offering an Mphil in Human Resource Management at the University of Ghana Business School (UGBS) from the aforementioned institution. As part of the requirement for the award of an Mphil Degree, I am conducting a research on **"An Exploratory Study of Human Resource (HR) Analytics: Implications for Human Resource Management Practice.**

Participation in this research is Voluntary and responses are for academic purposes only.

In ensuring outmost anonymity and confidentiality, and as a condition of ethics approval, names of participants and firms, nor their sectors of operation will be identified in this study.

I therefore seek your support and cooperation in this regard.

Please endeavour to respond to all questions on the interview guide.

Signature of Respondent: **Date:**

………………………………… ……………………………………

Thank you very much for your acceptance to take part in this research!!!!

APPENDIX B: INTERVIEW GUIDE (RESEARCH RESPONDENTS)

UNIVERSITY OF GHANA

DEPARTMENT OF ORGANISATION AND HUMAN RESOURCE MANAGEMENT

INTERVIEW GUIDE

Dear Sir/Madam

Thank you very much for your time to have this interview. This interview guide is to serve the sole purpose of an academic research on the title, *"An Exploratory Study of Human Resource (HR) Analytics: Implications for HR Practice."* This is in partial fulfilment for the award of an MPhil Human Resource Management degree at University of Ghana. This guide is in two sections. Your responses will remain completely confidential and anonymous.

SECTION A

1. Please provide me with the following details
   a. What is your highest educational qualification? Is it in HRM?
   b. Do you hold any professional certification in HRM? eg. SHRM
   c. What is your Job Position?
   d. How long have you been working in the HR function?
   e. What is the approximate number of employees of your organisation?
   f. What kind of organisation do you work for? MNC, GH Private etc.

SECTION B

1. What is your understanding of HR analytics?
2. How do you use HR analytics? Do you use it daily?
3. Which type of analytics is performed in your HR function?

- Why this type or types?

4. What specific tools and methodologies do you adopt in your analysis?

5. Why do you use these tools and methodologies?

6. How has HR analytics been beneficial to your organisation in the areas of

   a. Employee Acquisition

   b. Performance

   c. Employee Retention

7. What are the challenges you face using HR analytics?

8. What are the prospects of HR analytics in Human Resource Management practice in Ghana?

9. Any general comments on anything I need to know for this research?

Thank you very much for your time. Your responses are much appreciated!!