The application of HR analytics to enable data-driven decision-making (DDDM) in Human Resource Management

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ABSTRACT

The growing interest in big data and data-driven decision-making (DDDM) by business has led to a bit of pressure on HR professionals to start engaging with it and make data-driven decisions that add value to their organisations. This would also help HR practitioners to play the strategic business partnering role that they have always aimed to execute. The literature reviewed revealed that although there has been an increase in interest and the adoption of HR analytics in organisations, the maturity or growth level has remained stagnant at level 1 (descriptive analytics) of the HR analytics maturity model. In addition, there is a research gap in guiding practitioners on the implementation of HR analytics and DDDM. The aim of this study was to explore and gain insights on how HR practitioners were using HR analytics to make data-driven decisions in their organisations. This will enable those HR practitioners lagging behind, and those that are stuck at level 1 of the maturity model to understand what they need to do to successfully adopt and utilise HR analytics to enable DDDM in their organisations. The study was conducted through exploratory qualitative research design. Data was gathered through conducting virtual semi-structured interviews with fifteen HR practitioners from different South African organisations and industries. The findings highlighted those factors, such as good quality data, HR capability, and technological analytical tools or systems needed to be in place for HR practitioners to effectively use HR analytics to enable DDDM. It also gave an indication of the type data-driven decisions HR practitioners made, as well as the barriers to effective implementation of HR analytics and DDDM.

Keywords:

Data-driven decision-making (DDDM), HR analytics, HR analytics maturity, Enablers, Data-driven decisions, HR capability

Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Philosophy in Corporate Strategy at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

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CHAPTER 1: INTRODUCTION

Using data-driven decision-making (DDDM) and Human Resource management in the same sentence was something that people were not used to. HR practitioners are experts in human or employee behaviour. Traditionally they never dealt with quantitative data, much less be associated with concepts such as big data. Thus, they were comfortable in working with words and making decisions using their intuition, knowledge, experience and expertise. However, the advent of digital transformation and a bit of pressure from business has led to interest and adoption of HR analytics and DDDM.

This chapter will discuss the rationale behind conducting this study. It will look at what is happening in the business environment, and its implications on the academic space. It will then briefly discuss the research aims, contribution, and scope.

1.1 Background of the research problem

Digital transformation, fourth industrial revolution, big data, data-driven decision-making (DDDM) are concepts that cannot be ignored by businesses and departments that want to remain in business. Those organisations that have embraced them have gained a competitive advantage against those that are lagging behind (Shamim et al., 2019; Kim et al., 2021). Human Resource departments, although comfortable working with human or employee behaviour and using their intuition, experience, and expertise to make decisions, can also not afford to ignore the changes happening in the business environment. Human Resource managers and practitioners have been forced to move out of their comfort zone and begin to embrace the use of data, innovative technological systems, HR analytics and DDDM in order to add value to their organisations (Huselid, 2018).

A survey conducted by PWC on 1000 senior executives indicated that they preferred and relied more on data when making decisions, as well as confirming their plan of action using the available data before implementation, than intuition (Stobierski, 2019). This is also in line with a study conducted by McKinsey & Company, which indicated that 70% of executives regard having reliable HR analytics as a top priority in their organisations (Ledet, et al., 2020).

Fortunately, there has been an increase in the uptake of HR analytics usage and DDDM by some HR practitioners (Davenport, 2019). This is also evident through the increase in the number of blogs and opinion papers from practitioners. However, the increase in interest has not really resulted in increase in the maturity levels or growth with regards to the utilisation of HR analytics and DDDM to impact business performance (Suresh, 2023). Hence, its impact is still internally focused and does not influence any business decisions or strategic execution (Gartner, 2023). In addition, Schroeder-O'Neal (2022) found that there was a misalignment between the existing practices of HR analytics and strategic objectives, lack of collaboration between line managers and HR practitioners due to differing priorities and interests, and HR data was always used reactively with lack of proactiveness from HR practitioners.

Consequently, HR practitioners are finding themselves being relegated out of the boardroom. They are threatened to be replaced by IT and Finance people who can easily use data to make decisions that have an impact on business (Boakye & Lamptey, 2020). It has therefore become imperative for HR practitioners to meet this business need. They have to fully adopt and utilise HR analytics to enable DDDM so that they can play a strategic business partnering role and avoid extinction.

1.2 Definition of research problem

Although there has been an increase in literature on HR analytics, DDDM appeared to be a fairly new concept in HR research. In a literature review study conducted by Cheng and Hackett (2021), they discovered about 22 academic articles from highly rated journals compared to 122 articles from blogs, popular press and trade journals written by practitioners. This indicated that scholars were trailing behind and needed to catch up with more academic research on DDDM in HR, as the practitioner-academic gap was growing bigger.

Unfortunately, scholars have not been fully able to offer guidance through science-based research on how practitioners could use HR analytics to make data-driven decisions that add value to the business (Cheng & Hackett, 2021; Marler & Boudreau, 2017). In addition, although research showed that HR analytics had a positive impact on organisational performance, there was still limited research on guiding practitioners on how to apply the knowledge (Álvarez-Gutiérrez et al., 2022; Mohammed, 2019), and which methods and procedures to use when analysing data (Levenson, 2018).

The majority of organisations were stuck at descriptive analytics, which is level 1 on the HR analytics maturity model (Mahommed, 2019). Practitioners argue that for these organisations to progress to the next maturity level, they needed new advanced statistical technologies through 4IR, machine learning and automation (Akter et al., 2019). However, Margherita (2022) contends that more research needs to be conducted to determine whether knowledge and the availability of more advanced technology positively contributes to the successful application of HR analytics within organisations. They maintain that there could be more that was hindering HR practitioners from applying HR analytics and DDDM. Zaitsava et al. (2022) add that further research also needed to be conducted to identify some of the challenges that were hindering organisations from fully adopting HR analytics and DDDM. Hence, the need for this study in order to explore what needs to be in place for HR practitioners to implement HR analytics and DDDM, as well as identify some of the challenges.

This study was a response to the invitation from Minbaeva (2018) and Huselid (2018) to close the gap between HR analytics theory and practice by exploring how HR practitioners were using HR analytics to enable DDDM in their organisations. This will be used as a research-based guide for practitioners who have not yet started using HR analytics and DDDM in their organisations. This research will contribute to academic discourse in HR Analytics and DDDM by exploring how HR practitioners in South African organisations are using HR analytics to make data-driven decisions that add value to business. It will further explore the factors that need to be in place for these organisations to fully implement HR analytics and DDDM.

1.3 Why is DDDM important.

Literature refers to data-driven decision-making (DDDM) as a practice of making decisions that are informed by data, instead of intuition (Akter et al, 2019). Business leaders believe that this is the right way to make decisions because it eliminates subjectivity, biasness, and judgement (Zaitsava et al., 2022). Due to digital transformation, businesses are bombarded with a lot of structured and unstructured data, called big data (Akter et al., 2019). DDDM enables businesses to use that data to make well-informed decisions, which gives them a competitive advantage (Kim et al., 2021).

HR as a department is also faced with similar big data challenges and opportunities. Apart from the structured data that is received from the traditional data sources, there is also a lot of unstructured data that can be mined from social media, and other electronic devices such as smart phones, body cameras, social badges and sensors (Cheng & Hackett, 2021). Through using DDDM, decisions associated with recruitment, performance management, workforce planning, and other people related processes become easier to make (Mohommed, 2019). Thus, HR practitioners are able to respond timeously to business requests with the confidence that they are providing the right decisions (Sousa et al., 2019). It is for that reason that HR practitioners need to familiarise themselves with DDDM so that they can start taking advantage of available data and use it for the benefit of their organisations (Akter et al., 2019).

1.4 Why is HR analytics important.

HR analytics is regarded as HR's ability to scientifically analyse and use employee data to produce reports that influence the performance of an organisation (Mohammed, 2019). Data quality, HR capability, IT infrastructure, a data-driven culture and support from management are some of the elements that need to be in place for organisations to fully adopt and use it for the benefit of the organisation (Shamim et al. 2019). Although there appears to be an increase in interest and uptake of utilising HR analytics, 80% of organisations were found to be stuck at level 1 (descriptive analysis) of the HR analytics maturity level (Peeters et al., 2020; Mohammed, 2019; Margherita, 2022). For these organisations to reap the full benefits of HR analytics, they need to mature to level 2 and 3 (predictive and prescriptive analysis) where HR practitioners are able to predict what will happen and prescribe any actions that will help mitigate future risks for their organisations (Mohammed, 2019; Margherita, 2022).

It is also important to note that HR analytics enable DDDM (Marr, 2018; Kim et al., 2021). Without the right analytical capabilities in place, HR practitioners will not be able to make data-driven decisions. It is for that reason that HR analytics is important for this study. Hence the main aim of this study was to explore how HR practitioners use HR analytics to make data-driven decisions.

1.5 Research aims

The main aim of this study was to explore how HR practitioners use HR analytics to make data-driven decisions. This was done by firstly exploring the extent at which organisations have adopted and utilised HR analytics to make data-driven decisions. Secondly, the study aimed to find out what kind of data-driven decisions that added value were made by the HR practitioners. Thirdly, the study also explored the kind of skills or capabilities HR practitioners needed to have in order to be effective in using HR analytics to make data-driven decisions. Finally, the barriers that were hindering HR practitioners from fully utilising HR analytics to make data-driven decisions were also investigated.

1.6 Research questions

The main research questions and the sub-questions are indicated below:

RQ: What is the extent of adoption and utilisation of HR analytics and DDDM?

Sub-Q1: What HR data-driven decisions have you made that were informed by HR analytics?

Sub-Q2: What kind of skills or capabilities do HR practitioners need in order to use HR analytics to enable DDDM?

Sub-Q3: What are the barriers that hinder HR practitioners from using HR analytics to make data-driven decisions?

1.7 Research contribution

This research was an exploratory study that would contribute to the Human Resource management literature. Although there has been an increase in research in HR analytics in the past few years, there still remains a gap in literature regarding how HR analytics add value to organisations (Minbeava, 2018). Álvarez-Gutiérrez et al. (2022) posit that there is low guidance from research to help practitioners in implementing HR analytics. This has led to the low adoption rate of HR analytics in organisations, specifically in South African organisations. Furthermore, DDDM in Human Resource management is a concept that still yet to be explored. There is low research on how HR practitioners use HR analytics to make data-driven decisions. The available literature focuses on HR analytics and does not show how this enables DDDM (Cheng & Hackett, 2021).

This research contributes by extending the literature on HR analytics to show how it enables DDDM and in turn, add value to the organisation. It further aims to expand the on the low research in the South African context. The research was conducted by interviewing 15 HR practitioners at middle and senior management in South African organisations whose role include HR reporting. It therefore contributes to understanding how SA organisations are using HR analytics to make data-driven decisions and also understand their adoption and utilisation of HR analytics.

1.8 Research scope

The scope of this research was focused on gaining more understanding and clarity on how HR analytics enable HR practitioners in South African organisations to make data-driven decisions that add value to their businesses. According to Marazanye (2017), although there has been a lot of interest in using HR analytics in organisations, there is low research that shows the adoption rate of HR analytics by South African organisations. This extends to how HR practitioners are using HR analytics to drive DDDM. From the literature perused, it can be deduced that South African organisations, like other organisations around the world, are lagging behind with regards to implementation of HR analytics and DDDM (Davenport, 2019; Vargas et al., 2018).

1.8 Roadmap or structure of the report

The research report is organized into seven chapters as depicted below.

Table 1: Roadmap/structure of the research report

Chapter 1: Introduction

Chapter 2: Literature review

Chapter 3: Research questions

Chapter 4: Research Methodology

Chapter 5: Presentation of findings

Chapter 6: Discussion of findings

Chapter 7: Conclusion and Recommendations

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter outlines and reviews the existing literature on HR analytics and DDDM. This will be done by discussing what DDDM is, what is DDDM in a Human Resource Management perspective and defining HR analytics.

Secondly, review literature on HR analytics by focusing on the difference and relationship between HR metrices and HR analytics, and the HR analytics maturity model.

Finally, the review will end by focusing on the factors that need to be in place for HR analytics to enable DDDM in organisations and the kind of data-driven decisions that are enabled by HR analytics will also be reviewed.

2.2 Understanding data-driven decision-making (DDDM)

The onset of the fourth industrial revolution, digital transformation, and the amount of data available data through different sources, has led to the shift from using intuition, which is regarded as putting an organisation at a competitive disadvantage (Kim et al., 2021), to data-driven decision making (DDDM) (Akter et al., 2019). Mikalef et al. (2019) refer to this period as the "age of data". It is a period where leaders rely on data as a cornerstone when making decisions as it gives more insights to business challenges (Akter et al, 2019; Shamim et al., 2019). As a consequence, leaders collect, analyse and interpret data from different internal and external sources to enhance the traditional way of decision-making.

DDDM is linked to data analytics, which transforms raw data into information and intelligence that can be used in decision-making (Klee et al., 2020). Data analytics enable DDDM. It is a field of study that uses fields of engineering, computer science, decision-making and statistical methods to collect, organise, manipulate and interpret data (Mortesen et al., 2015 cited in Angrave et al., 2016). Russom (2011) cited in Ghasemaghaei et al. (2017, p. 101) describe it as "a combination of processes and tools, including those based on predictive analytics, statistics, data mining, artificial intelligence, and natural language processing, often applied to large and possibly disperse datasets for gaining invaluable insights to improve firm decision making". Shamim et al. (2019) argue that this also include the ability to communicate actionable decisions through storytelling. Hence, data on its own, although valuable, without manipulation by technological interventions and interpretation by individuals to give new insights into decision-making, it may be rendered useless (Shollo & Galliers, 2016 cited in Klee et al., 2021).

Garcia-Arroyo and Osca (2021) posit that although the process of decision-making may sound easy, the challenge is in obtaining useful insights from the data. To that end, Triguero et al. (2018) maintain that data has to be smart. Meaning that the data collected and used to make decisions has to be of great quality. Garcia-Arroyo and Osca (2021) recommend that before data could be collected; there should be a plan in place on how it will be organised, stored and interpreted. As a consequence, the success of DDDM is dependent on the sophisticated data collection and analytical tools, having the right people with the right skills, leadership, talent management and culture (Shamim et al. 2019). In addition, although the DDDM process is important, what is critical to its success is the outcome, which is the impact of the decisions made on an organisation's performance. Hence, quality decisions are evaluated on the basis of their effectiveness or attentiveness, which is the impact of the decision made, and efficiency, the use of the available resources (Lofgren & Nordblom, 2020).

Zaitsava et al. (2022) posit that DDDM is an algorithm that help leaders make and improve their decision-making processes through analysing data, predicting situations and recommending mitigating actions against any future risks. Being an algorithm, it means DDDM is unambiguous and complies to the following criteria, namely, "1) each step in the algorithm is clearly defined; 2) inputs and outputs of the algorithm are clearly defined; and 3) the algorithm has a guaranteed endpoint that produces the right results" (Cheng & Hackette, 2021, p. 2). Hence, the reliability of the results and the positive impact it will have on organisational performance.

Although the science or technology behind the algorithm is important, leaders still play a critical role in ensuring that the right decisions are made (Zaitsava et al., 2022). They need to be competent in analysing and interpreting the data and relationships between the data sets in order to gather insights to make well-informed and impactful decisions. Hence, to be good in analytics, leaders need to have high cognitive and reasoning powers (Ghasemaghaei et al., 2017). This challenges leaders to harness their thinking capabilities beyond their knowledge and experiences. On the other hand, without proper sophisticated analytical tools, leaders are fallible human beings, and their decisions can be blurred by their biases and judgements (Zaitsava et al., 2022).

Ghasemaghaei et al. (2017) argue that in order to make data-driven quality decisions, leaders and organisations need to improve their data analytics competency. This includes data quality, bigness of data, analytical skills, domain knowledge and tools sophistication.

Hence, organisations need to be prepared to invest money and resources to ensure that the competency levels are improved (Klee et al., 2021). Akter et al. (2019) posit that there is an increase in demand of data analysts with statistics and machine learning capabilities in the market. It was predicted that between 140 000 and 190 000 people with advanced data analytical skills will be required in the USA by 2018. They have therefore been added onto the list of critical skills.

Consequently, when DDDM is effective and efficient, it leads to a data driven culture where leaders' beliefs, attitudes and practices encourage the use of data insights to make decisions that contribute to an organisation's success (Chatterjee et al., 2020). Such cultures motivate leaders and employees to be innovative and to actively participate in the whole process of data management and decision-making. Shamim et al. (2019) posit that inflexible cultures where change is resisted have found it difficult to evolve to the fourth industrial revolution and adopting DDDM. In addition to a culture that resist change, although available literature indicates that DDDM adds value to business, some organisations have been slow in its adoption due to the high levels of IT and educated employees needed, management practices, an organisation's learning agility and the availability of reliable data (Brynjolfsson & McElheran, 2016), as well as using incorrect statistical techniques and tools (Klee et al., 2020). Out of the reasons mentioned, Klee et al. (2020) argue that employee competencies at all levels of the organisation are crucial in the success of data analytics and DDDM. Usually, small organisations do not have people with the necessary analytical and technical skills needed (Garcia-Arroyo & Osca, 2021).

The extant literature on DDDM leaves no doubt that being able to make data-driven decisions gives organisations a competitive advantage (Kim et al., 2021), however Zaitsava et al. (2022) argue that more research needs to be conducted to ascertain why organisations are reluctant to invest in data technology that will make HR analytics and DDDM more effective and efficient. To that point, HR is one of the functions that has been flagged as lagging behind with regards to using DDDM whilst other functional departments such as marketing, finance, and supply chain have already started using it successfully (Davenport, 2019; Vargas et al., 2018). Hence, the need to conduct a study on how DDDM can be applied in Human Resource Management.

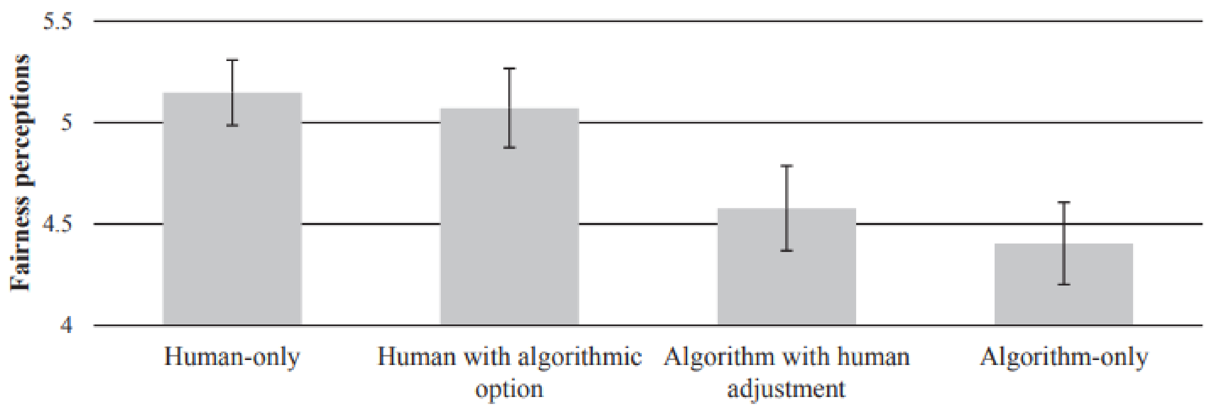
2.3 Data-driven decision-making in Human Resources

Human Resources is a function that deals with people issues with no mention of numbers or statistics (Marr, 2018). However, the increase in interest in business data analysis, and the use of DDDM by other functional departments has led to increased pressure in using HR analytics to make data-driven HR decisions (Margherita, 2022). With businesses spending approximately 70% of their income on human resources, more is expected from HR (Huselid, 2018). HR practitioners are challenged and encouraged to use HR data analytics in making evidence-based or data driven decisions that create value in the organisation (Margherita, 2022). Thus, decreasing subjectivity and biasness in the recruitment, performance and other HR decisions (Kim et al., 2021). In addition, people trust the use of algorithm more than decisions made by human beings. This is because human beings are judgmental in nature (Raveendhran & Fast, 2021). As a consequence, DDDM enables HR departments to be dynamic and flexible, allowing them to quickly explore opportunities within and outside the organisation in order to create adaptable strategies.

In order to meet the demands as set by business leaders on providing data-driven decisions, HR practitioners must be able to 1) identify good quality data that will answer the business' question; 2) use statistical methods to analyse the data; 3) apply systems thinking to connect the dots between two or more different systems or data; 4) interpret the data and produce actionable reports for leaders (Kryscynski et al., 2018). However, due to the amount of data, they are faced with, HR practitioners may find it difficult to mine useful data (Garcia-Arroyo & Osca, 2021).

Baesens et al. (2017) caution against viewing HR data analytics as the only way of making decisions. The scholars argue that data analytical tools are always changing and need to be constantly updated, they may at times be unavailable when HR practitioners need to use them. Gal et al. (2020, p. 2) refer to it as "a fallible companion technology", which can impose and influence people's behaviour. Thus, the HR practitioner's knowledge, experience and intuition still remain critical in making decisions. Furthermore, although there is no doubt that using data to make hiring decisions or identifying top talent is more accurate than using intuition, it also important to consider whether employees regard this process as fair (Newman et al., 2020). For example, the engineers at Google rejected the use of DDDM when management used it to make hiring decisions (Newman et al., 2020). **Error! Reference source not found.** below depict employees' perception of fairness when human or algorithm only or used in combination in making HR decisions.

Figure 1: Fairness of various decision processes.



Source : Newman et al. (2020, p. 157)

The figure above shows that relying on algorithm or DDDM only, reduces employees' perception of fairness in the decision-making processes. Newman et al. (2020) posit that this is caused by employees' perceptions that relying only on data removes the qualitative part of the story and does not give enough context of the situation under review. Thus, preventing employees from identifying and meaningfully engaging with the results from the analysis (Gal et al., 2020). This backs up the point that although DDDM may be the best way to remove bias and subjectivity and for business leaders to improve their reliability on HR insights, and has also worked in organisations such as Google, Microsoft, LinkedIn and IBM (Cheng & Hackett, 2021); human intervention through their cognitive skills is a necessary evil in ensuring that employees' perception of fairness is maintained (Ghasemaghaei et al., 2017).

Furthermore, since HR decisions always affect people's lives and careers, it is important to ensure that all processes followed are errorless. Importantly, if not used properly, DDDM in HR may indeed turn into a management fad as cautioned by Angrave et al. (2016) cited in Cheng and Hackett (2021). Hence, it should be closely aligned to relevant HR questions such as recruitment, selection, learning, performance, and employee engagement that need to be answered to influence the organisation's strategy and its performance.

There are different tools such as sensors, analytics, machine learning and artificial intelligence that can be used to enable DDDM (Marr, 2018). Kim et al. (2021) posit that further studies should be conducted on the different technological tools that could be used to enable DDDM in HR processes and practices. This research paper has however only focused on HR analytics as an enabler to DDDM.

2.4 Defining Human Resource Analytics (HR Analytics)

Although it is sometimes referred to as talent analytics, workforce analytics, human analytics or people analytics, HR analytics involves analysing human resource data to help HR practitioners make data-driven decisions (McIver, et al., 2018; Margherita, 2022). Different scholars define HR analytics differently, however, the common theme in all the definitions studied pointed to the use of HR data analytics in making data-driven decisions.

Mohammed (2019) views HR analytics as HR's ability to scientifically analyse and use employee data to produce reports that influence the performance of an organisation. It is a tool that gives depth to leaders' data-driven decision-making processes in relation to HR data. Gurusinghe et al. (2021) assert that it is a scientific solution that allows leaders to make workforce and business-related decisions. Margherita (2022) refers to it as a fact-based approach of combining employee data with business data in order to make decisions that have a meaningful impact in the execution of an organisation's strategy. Thus, HR analytics enable HR practitioners and line managers to make data-driven and fact-based business decisions informed by insights gained from HR processes such as performance management, learning and development, employee engagement surveys and culture a (Boudreau & Cascio, 2017). HR analytics should therefore be aligned to the organisation's HR strategy that is informed by the organisation's strategy (McIver, et al., 2018; Wang & Cotton, 2018).

Nocker and Sena (2019) posit that the ultimate goal of HR analytics is to assist HR practitioners in identifying HR trends and predict different scenarios that will impact the organisation's strategy and performance. It helps answer questions such as "what the relationship between learning and development (L&D) and organisational performance is, how can organisations retain employees, whether the organisation's employee wellness program contributes to performance". It helps HR from making errors and challenges them to think beyond the current metrices they are measuring, knowledge and experience (Kim et al., 2021). Thus, HR analytics in HR introduces a dynamic or constructs that the practitioners may not be familiar with.

Huselid (2018, p. 690) defines it as "the process involved with understanding, quantifying, managing and improving the role of talent in the execution of strategy and the creation of value. It includes not only focusing on metrics (e.g., what do we need to measure about the workforce?), but also the analytics (e.g., how do we manage and improve the metrics we deem to be critical for business success?)". To that end, Nocker and Sena (2019) & Marler and Boudreau (2017), caution against confusing HR metrices with HR analytics. They argue that metrices measure the effectiveness and impact of current HR processes, whilst HR analytics uses innovative statistical techniques to provide insights and show the impact of HR on business decisions and performance. Due to its innovativeness, HR analytics is not static, nor a destination. Hence, it requires HR practitioners to continuously learn about their business and techniques to apply in gathering insights that will solve the business challenges (McIver et al. 2018).

In their study of different HR analytics definitions, Marler and Boudreau (2017, p. 15) summarises it as "An HR practice enabled by information technology that uses descriptive, visual, and statistical analysis of data related to HR processes, human capital, organisational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making". This definition comprises all the elements articulated in all the other definitions, including looking at other factors outside the organisation that will help it to adjust to changes. Accordingly, HR analytics therefore serves as a link between HR and organisational performance (Bahuguna et al., 2018). This definition shows that HR should play a strategic role to influence business decisions through using HR analytics instead of being inward focused and only interested in improving HR processes (Minbeava, 2018).

The definitions indicate that there is consensus amongst researchers regarding the role and importance of HR analytics in influencing business decisions. However, although there is a common theme in using data to make data-driven or evidence-based decisions, there is no generally accepted definition of what HR analytics is, and more research needs to be conducted to define the different constructs (Bhuguna et al., 2022). This will also assist HR practitioners to remove the current confusion between HR metrices, HR analytics and DDDM.

2.4.1 HR metrices and HR Analytics

As indicated above, Nocker and Sena (2019) & Marler and Boudreau (2017), caution against confusing HR metrices with HR analytics. HR metrices measure internal current processes, whilst HR analytics focuses on strategic measures that enable leaders to make decisions that impact organisational strategy and performance (Marr, 2018). McIver et al.

(2018) contend that previously, HR's success was based on their ability to report on the HR activities measured through the HR metrices, and not on how these numbers impact the business. To that end, HR metrices are numbers on the HR scorecard or dashboard that show what has happened in the business with regards to adherence to HR processes. HR analytics use the numbers from the metrices to answer the "so what" question for the organisation, which enables HR practitioners to make data-driven decisions (McIver et al., 2018).

Huselid (2018) posit that when developing HR metrices, it is important to consider what those KPIs will be measuring, the data-driven decisions that need to be made, and how those decisions will impact the organisation's strategy. This can only be possible when HR practitioners understand the challenges faced by business and how they can contribute in solutioning for those challenges (Levenson, 2018). To that end, they should be interested in understanding the root cause of the problem by asking the right questions (Mclever et al., 2018) posit that for HR analytics to be able to help organisations answer their business challenges, for an example, before designing an HR metrics on measuring a learning and development intervention, it is important to understand the importance and contribution of that intervention to the organisation's strategy and performance. HR metrices will therefore show how many employees have attended a specific learning and development intervention; HR analytics will show how the intervention has improved individual and organisational performance (McIver et al., 2018). The insights gathered from the analytics will then influence the decisions to be taken on whether the organisation is able to solve the challenge it was faced with. Hence, HR analytics is able to link the metrices to DDDM and the execution of strategy and organisational performance (Huselid, 2018). As a result, HR is able transition from only performing transactional activities, to being a strategic partner of the business. The different questions or measures are depicted below:

Table 2: The difference between HR metrices and HR Analytics measures

HR metrices	**HR Analytics Questions/Measures**
Number of new hires Vacancy rate Number of employees attending training Number of resignations	Strategic workforce planning – what is the number of employees and skills needed now and in the future in order to achieve the organisation's strategy?

Absenteeism Leave balances Overtime worked Number of employees who completed compliance training	Are the recruitment strategies used enabling the organisation to get the right candidates at the right time? What is the relationship between training and productivity? How does an organisation retain employees? Does an organisation's wellbeing program contribute to an organisational performance? Are employees with specific degrees more productive than others? Are permanent employees a better investment than temporary employees?

Adapted from: Nocker and Sena (2019); Marr (2018); McIver et al. (2018)

The move to being a strategic partner also means that HR practitioners must grow and mature in the use of HR analytics to enable DDDM. The different HR analytics maturity models are discussed below.

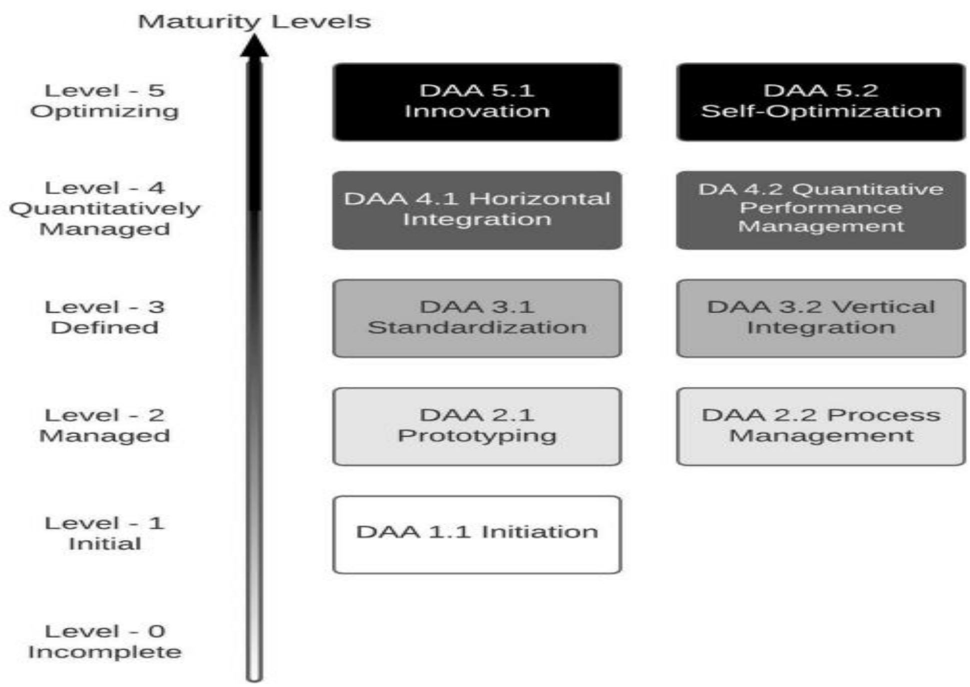
2.5 The maturity models of HR analytics

Different organisations are at different maturity levels with regards to their implementation of HR analytics (Nocker & Sena, 2019). It is the aim of progressive organisations to grow and improve their maturity levels (Gökalp et al., 2021). They use different data analytics maturity models to assess their data analytics maturity. Krol and Zdonek (2020) posit that there are about eleven known data analytics models. However, it is noted that there could be more. The majority of these models were developed by consultants and vendors and were not scientifically researched and do not guide organisations on how to improve their data analytics maturity levels (Gokalp et al., 2021). For the sake of this study, only two models; the data analytics maturity assessment framework (DAMAF) and the HR analytics model will be discussed.

2.3.1.1 The data analytics maturity assessment framework (DAMAF)

The DAMAF was developed by Gokalp et al. (2021) and is comprised of data analytics attributes (DAAs) and six maturity levels (MLs). It allows organisations to measure the extent in which they consistently apply data analytics in their processes and practices. The MLs range from ML0 – incomplete to ML5 – optimizing. The framework is depicted below.

Figure 2: The data analytics maturity assessment framework (DAMAF)



Source: Gokalp et al. (2021, p. 4)

Each of the MLs are explained as follows:

I. ML0 – Incomplete – the organisation does not have any intention to be data-driven. They rely wholly on knowledge, expertise and intuition to make decisions.

II. ML1 – Initial – there are plans to become a data-driven organisation. The vision and strategy have been developed. However, it has not been fully implemented. Data analytics is used in a reactive mode and the data analytics results are unreliable and unpredictable. There is no structured management of data. Hence, data integrity is a challenge.

III. ML2 – Managed – organisations start to see and appreciate the value that is added by using data analytics. They start to develop frameworks and models to use in the organisation. They pilot the model in the different departments by developing goals and track progress through using data analytics.

IV. ML3 – Defined – organisations start incorporating data analytics in all other processes in the different departments. A standardieed approach to data analytics is followed by all the departments.

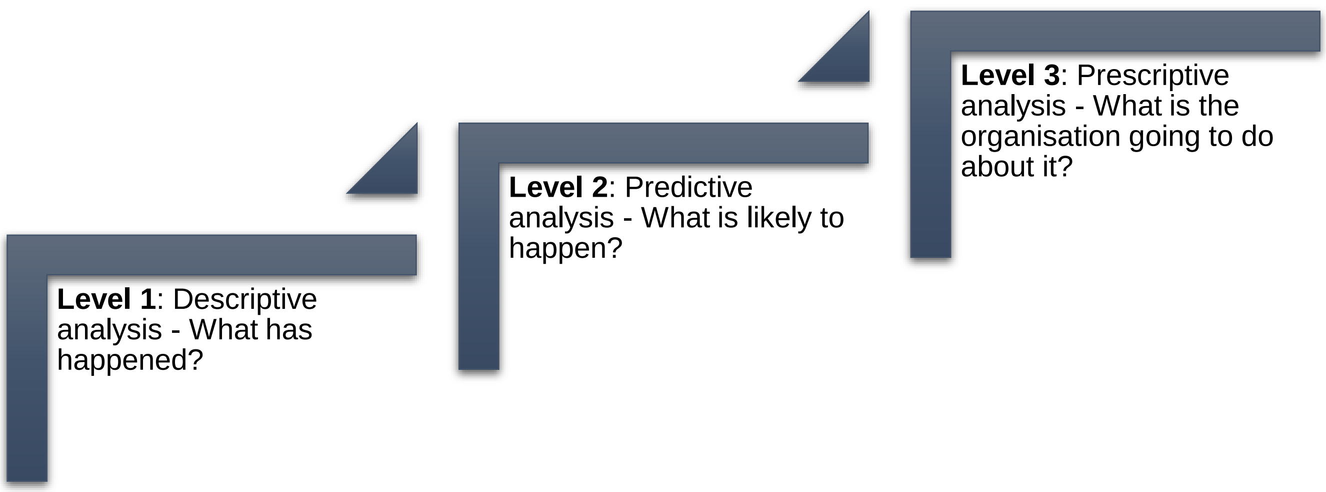
V. ML4 – Quantitively managed - organisations start to manage projects and report progress in a quantitative manner. Reports are prepared using statistical analysis and reported quantitatively. The data-driven organisational culture is embedded within the organisation and external stakeholders are properly inducted to the manner in which projects are managed and reported.

VI. ML5 – Optimising – at this stage, organisations are continuously learning and improving the data analytics approaches and practices. They become more innovative and more advanced data analytical technology is used to analyse data.

2.3.1.2 The HR analytics maturity level

Mohammed (2019) and Margherita (2022) have identified three types or maturity levels of HR analytics: descriptive, predictive and optimisation or prescriptive analytics depicted below in Figure 3

Figure 3: HR analytics maturity model

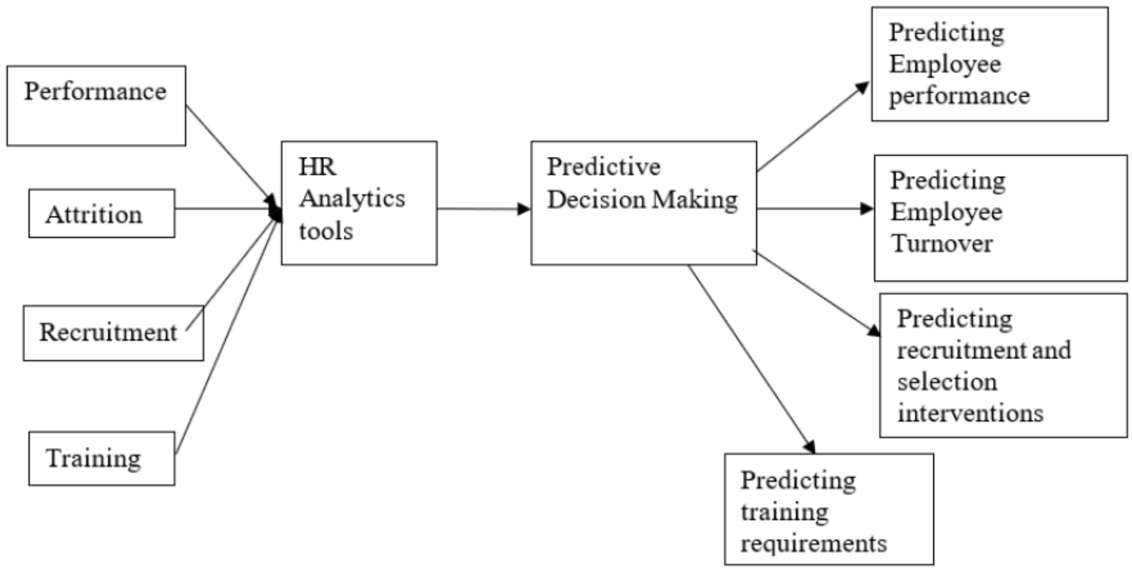


Source: Author’s work adapted from Mohammed (2019); Margherita (2022); Gartner (2023)

Level 1: Descriptive analysis – at this level, HR practitioners report on what has happened in the previous period under review. The reporting focuses on information gathered within and outside the organisation from different data sources to explain or describe the past (Margherita, 2022). The focus is on reporting on the HR dashboard/scorecard that shows how HR has achieved its metrices by using different charts and diagrams that may be depicted by using Excel spreadsheets or PowerPoint (Mohammed, 2019). Examples of this reporting include reporting on HR KPIs such as the number of learners who attended training, costs-per-hire, vacancy rate, employee engagement (McIver et al., 2018; Margherita, 2022)

Level 2: Predictive analysis - involves the use of advance algorithm to make sense of information and to predict future scenarios (Margherita, 2022). This involves showing unseen trends, relationships, risks and the ability to predict or forecast the future based on the organisation's past performance and the relationships of the constructs under review (Mohammed, 2019). Hence, HR analytics help HR practitioners to develop trends and patterns of certain constructs such as employee and team performance, that will enable the organisation to predict the future (Edwards & Edwards, 2019). For example, the results of an employee engagement survey can be used to predict the turnover rate of an organisation. Mohammed (2019) developed a model that shows how level 2 HR analytics (predictive analytics) are performed and predict the different HR outcomes as depicted in Figure 4 below.

Figure 4: HR analytics and predictive decision-making



Source: Mohammed (2019, p. 61): HR Analytics and Predictive Decision-making model

Level 3: Prescriptive or optimisation analytics - is the HR analytics' ability to produce different alternatives for HR practitioners that will help an organisation to be more effective and probably change or improve its decisions (Margherita, 2022). For example, after predicting what would happen with employee turnover through predictive analysis, HR practitioners are able to use that information to plan and implement different interventions that will mitigate the risks of employees, especially top performers, from leaving.

In order to add value to business, HR analysis need to evolve and mature through the different stages. However, most are still stuck in using descriptive analysis (Margherita, 2022). They should be able to use HR analytics to assess organisational priorities, predict and forecast different scenarios for the future (Margherita, 2022). As a result, they are unable to mature from using descriptive to predictive and even prescriptive analysis mainly due to HR practitioners' lack of the necessary analytical skills (Álvarez-Gutiérrez et al., 2022).

Although scholars would like to see organisations mature to using predictive and prescriptive analysis, about 80% of organisations surveyed indicated that descriptive analysis added more value to them than the other analytics (Peeters et al., 2020). This could be caused by the size, agility and maturity of the organisations, and the fact that HR practitioners may not know the kind of insights and value that predictive and prescriptive analysis might bring. Margherita (2022) posit that further studies should be conducted to determine whether predictive and prescriptive HR analytics would be of great value in organisations that are mature with regards to data analytics and business intelligence.

Based on the models above, it is clear that HR departments who wish to implement data-driven decision making in their organisations should strive to be operating at level 3 and 4: predictive and prescriptive analytics or ML3: defined (Mohammed, 2019; Gokalp et al., 2021). It should however be noted that models can only serve as a guide regarding the level and value add of HR analytics to organisational performance by HR practitioners. Peeters et al. (2020) argue that the assumption that the higher the level of data analytics maturity in the organisation, the more impactful it is in an organisation is a misconception. HR practitioners are challenged to move beyond taking an inside-out approach where the focus is only on achieving their KPIs, and theorizing the analytical models to putting them in practice so that they can influence organisational performance (Margherita, 2022).

2.6 Enablers of effective application of HR analytics and DDDM

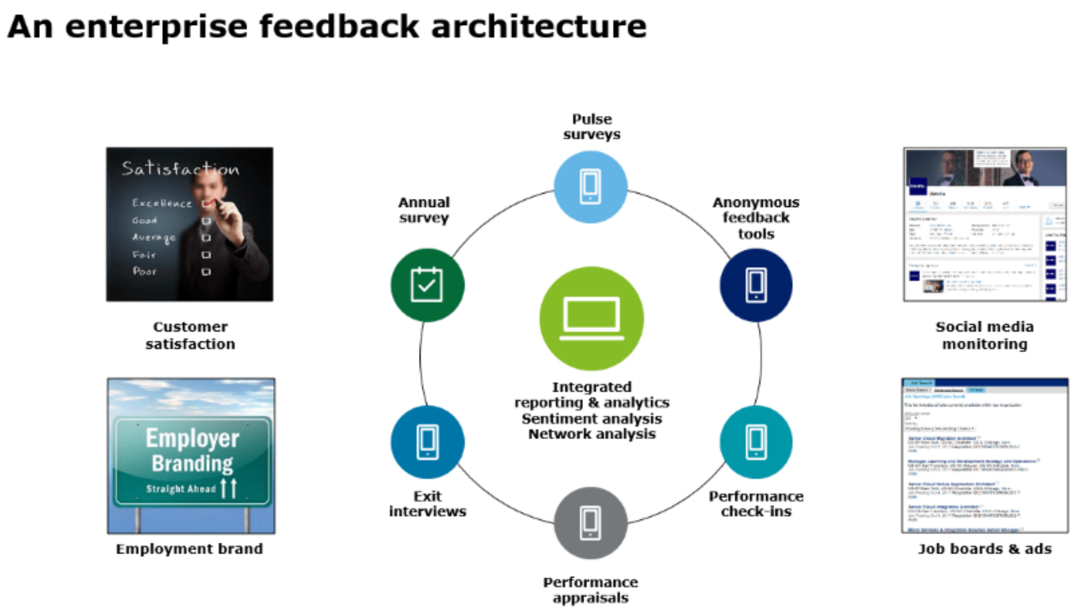
Fernandez and Gallardo-Gallardo (2020, p. 172) have identified four themes that need to be in place for HR practitioners to use HR analytics to make data-driven decisions. These are quality of data, HR capability, software and technology, people, and management". These are discussed below.

2.6.1 Data quality

The notion of "garbage in, garbage out", which means that the quality of data captured in the system will result in the same quality of the report, remains true to HR analytics (Andersen, 2017). It is one of the reasons HR analytics is lagging behind. The quality of data that is used and manipulated through technology is critical in producing reliable reports with practical and applicable recommendations to influence organisational performance (Minbaeva, 2018). Tambe et al. (2019) admit that HR data is complex and not easy to work with. The ability to produce valid and reliable intelligence that can be successfully applied in making business decisions increases the credibility of the HR professionals (Mohammed, 2019). One of the biggest challenges faced by HR practitioners is understanding which data to collect and use (Álvarez-Gutiérrez et al., 2022). Some of the data may be true, some useless and some useful. HR practitioners need to ensure that the data they use is of good quality, and credible (Schiemann et al., 2018).

The question on whether to use simple data that is collected from structured internal HR sources such as employees' salaries, performance, and training attended; or big data, which comprise of unstructured data from sources such as emails and external sources from social media comes into play (Akter et al., 2019). Bersin (2017, p. 1) posit that in addition to the traditional employee or HR data sources, data can be sourced from six different sources such as "pulse surveys, annual surveys, exit interviews, performance appraisals, performance check-ins and anonymous feedback tools" as depicted below:

Figure 5: Bersin's sources of data



Source: Bersin (2017, p.1) an enterprise feedback architecture

Error! Reference source not found.above shows that HR practitioners are using some of their listening strategies to gather data about employees. Raveendhran and Fast (2021) assert that there is an increase in the uptake of using non-traditional ways of gathering data. Production information from the operating floor, social media, videos and sensors are some of the non-traditional data sources that are being used to gather HR data (Hamilton & Sodeman, 2020). Case in point, organisations have started using behaviour tracking tools to gather data on their employees. With the increase in remote working due the Covid pandemic, organisations have also started looking at different ways of tracking employees. Hence, the collection, rules applied, merging of data from the different data sources, usage and storage of data are some of the aspects that HR practitioners should pay special attention to ensure the credibility of data (Minbaeva, 2018).

Accordingly, this includes HR data governance to ensure that the data is collected and used in an ethical manner (Mohammed, 2019). Care should therefore be taken not to infringe on any legal prescripts or personal confidential information. Multinational organisations are also faced with the challenge of different legislation where information is not shared freely (Nocker & Sena, 2019).

Nocker and Sena (2019), identified three challenges to the collection and use of data in making impactful decisions, referred to as data silos. These challenges include data being held in old systems that cannot be easily accessed, HR not having access to organisational or operational data as there could be no single source or data storage for the whole organisation, large organisations producing different reports to different stakeholders with varying requirements and expectations. In addition, data is collected and captured by human beings which makes it susceptible to human error, and different concepts used and interpreted differently in the organisation (Peeters et al., 2020). As a consequence, more time is spent on cleaning the data before it can be used.

2.6.2 HR capabilities

The number of job adverts for HR analytics in the job market indicates that there is an increase in demand for such skills (Huselid, 2018). Vargas, et al. (2018) posit that analytics is complex and requires different skills in each of its steps of collecting, sifting, manipulating and interpreting the reports. This means that at each step (gathering data, developing analytical methods, analysing and interpreting data) in HR analytics, specific competencies are required from the practitioners (Vargas, et al., 2018). It is therefore difficult to find one person with all these skills. Most organisations do not have these competencies and are battling to build capacity and capability (Minbaeva, 2018; Tambe, et al., 2019; Edwards, et al., 2022). It is for that reason that Green (2017) recommended to have a team comprised of people with the different skills.

Álvarez-Gutiérrez et al., (2022, p. 130) identified five HR Analytics competencies: “1) technical knowledge, 2) consultations, 3) data fluency and analysis, 4) storytelling, and 5) communication”. Peeters et al. (2020) assert that business acumen should be added to the list. Green (2017) maintains that HR practitioners need the seven competencies as per the model that was designed by Mortem Kemp Anderson.

Table 3: Seven competencies of a world-class people analytics team

SEVEN COMPETENCIES OF A WORLD-CLASS PEOPLE ANALYTICS TEAM

HAVE	BE GOOD AT	HAVE	MASTER TECHNIQUES OF	HAVE STRONG	MASTER	HAVE EXPERTISE IN	
GOOD DATA	STORY TELLING	BUSINESS ACUMEN	VISUALISATION	PSYCHOLOGY SKILLS	NUMBERS AND STATISTICS	CHANGE MANAGEMENT	= MAXIMUM IMPACT
X	STORY TELLING	BUSINESS ACUMEN	VISUALISATION	PSYCHOLOGY SKILLS	NUMBERS AND STATISTICS	CHANGE MANAGEMENT	= Unable to perform analytics
GOOD DATA	X	BUSINESS ACUMEN	VISUALISATION	PSYCHOLOGY SKILLS	NUMBERS AND STATISTICS	CHANGE MANAGEMENT	= Unable to get the message across
GOOD DATA	STORY TELLING	X	VISUALISATION	PSYCHOLOGY SKILLS	NUMBERS AND STATISTICS	CHANGE MANAGEMENT	= Focus on the wrong problems
GOOD DATA	STORY TELLING	BUSINESS ACUMEN	X	PSYCHOLOGY SKILLS	NUMBERS AND STATISTICS	CHANGE MANAGEMENT	= Boring and confusing output
GOOD DATA	STORY TELLING	BUSINESS ACUMEN	VISUALISATION	X	NUMBERS AND STATISTICS	CHANGE MANAGEMENT	= Bias and unable to interpret results
GOOD DATA	STORY TELLING	BUSINESS ACUMEN	VISUALISATION	PSYCHOLOGY SKILLS	X	CHANGE MANAGEMENT	= Poor analysis
GOOD DATA	STORY TELLING	BUSINESS ACUMEN	VISUALISATION	PSYCHOLOGY SKILLS	NUMBERS AND STATISTICS	X	= Unable to turn insights into outcomes

Source: Green (2017, p. 138) Seven core competencies of a world-class people analytics

Considering the challenge to find one employee with all the competencies recommended; HR analytics should have a team with balanced resources, knowledge and expertise (Green, 2017). The model above shows that the team needs to 1) have good data, 2) be good at storytelling, 3) understand the business, 4) are experts at visualisation, 5) have strong psychology background, 6) knowledge of statistics and numbers, and 7) change management (Green, 2017). Accordingly, a team that has all the seven competencies is able to make a huge impact in the organisation. Meaning that if it lacks either one of the competencies, it will never be able to use HR analytics to make data-driven decisions.

Since HR data may include employee engagement, performance, or other behaviour-related information that the team has been requested to answer, there should also be a team member with a psychology background or qualification (Green, 2017). As indicated previously, data analytics is a field of study that includes statistics. Hence, the importance of having someone who can do statistics in order to perform the necessary statistics (Angrave et al., 2016). Finally, a change management person is needed to ensure that the identified stakeholders buy-in and understand the role of the HR analytics team, the research, or services they provide, and action the insights that have been generated through the analysis (Green, 2017).

These teams may include data scientists who may not possess an HR qualification or background (Huselid, 2018), but are complemented by other members with psychology skills (Green, 2017). King (2016) (as cited in Mohammed, 2019) recommends the use of external service providers to assist HR practitioners with their HR analytics. However, this can only be a temporary solution. Kryscynski et al. (2018) recommend the following two interventions: (i) upskilling the current HR practitioners on HR analytical skills, which includes the use of HR systems, performing basic statistics to generate reports, interpreting the reports as well as performing predictive and prescriptive analysis; and (ii) recruiting employees with strong analytical skills.

The need for skills outside HR leads to the argument about where HR analysts should be housed in the organisation's structure. Nocker and Sena (2019) are of the opinion that if HR analytics are taken out of HR into the business, then the HR technical knowledge that is needed for HR insight in making business decisions will be lost. On the other hand, Peeters et al. (2020) argue that housing HR analytics in HR puts it at a disadvantage as it will not have access to the data analytics skills in the organisation. Furthermore, it will not have access to other business data that is required to indicate whether HR analytics is contributing to organisational performance.

Some of the other competencies are discussed below.

(a) Analytical skills

Ghasemaghaei et al. (2017) assert that people who want to work with data must be good in analytics, they need to have high cognitive and reasoning abilities. Hence, analytical skills or abilities include having a sense or logic to be able to work with data by collecting, cleaning it, analysing it by using statistical tools and interpreting it to make sense of it (Kryscynski et al., 2019). Part of working with data is the ability to gather data through observations, surveys, interviews or reading secondary documents. HR practitioners with good analytical skills are able to 1) make well-informed, evidence-based and data-driven decisions that help solve business challenges, 2) use the insights gathered from the analysis to initiate actions, 3) see connections and relationships that may not be visible to other people, and 4) able to interact better and create relationships with employees from other departments who work with data (Kryscynski et al., 2019).

As a result, HR practitioners that do not have these analytical skills end up being excluded from strategic discussions and decisions (Álvarez-Gutiérrez et al., 2022). Unfortunately, HR practitioners have been known to be afraid of dealing with numbers (Boakye and Lamptey, 2020). They have been flagged as people who are unable to make data-driven decisions because they lack basic analytical skills. They are unable to engage with line managers to find out their challenges, as well as using basic statistical tools to analyse data (Minbeava, 2018). This prevents them from fully adopting and utilising HR analytics to enable DDDM in organisations (Angrave et al., 2016). In certain areas, the HR analytics role has been taken over by IT and statisticians because the HR practitioners are seen not to be playing a strategic role (Boakye & Lamptey, 2020; Marler & Boudreau, 2017).

(b) Technical or HRIS knowledge

Kryscynski et al. (2019) maintain that part of being able to analyse data is the ability to use the available HRIS and different statistical tools. Unfortunately, the majority of HR practitioners use simple statistical analysis that do not provide the depth needed to make value-adding, evidence-based organisational decisions (Minbaeva, 2018; Kryscynski et al., 2018). They are not competent nor comfortable to use more sophisticated analytical tools that will enable them to move from descriptive to predictive analysis (Vargas et al., 2018). Thus, some leaders undermine the strategic role played by HR.

McCartney et al. (2021) assert that HR analysts should have deeper knowledge and understanding of the HRIS as well as applications such as advanced Excel to conduct predictive modelling and Power BI. They should be able to use statistical tools and techniques to manipulate the data and transform it into HR intelligence that can be applied for the organisation's benefit (Peeters et al., 2020). This include using professional visuals such as graphs and charts that are appealing to the end use. To that end, organisations have been undertaking to upskill their HR practitioners to familiarise them with all the functionalities the system has to offer (McCartney et al. 2021).

(c) Communication skills

HR analysts are also expected to have good communication skills because analytical skills are not only about the knowledge of statistics, but they include story-telling skills. (Minbaeva, 2018; Fu et al., 2022). When data has been analysed and turned into HR intelligence, it needs to be communicated to the line managers for them to action some of the predictions and prescription that will impact business positively (Peeters et al., 2020; McCartney et al. 2021). To that end, organisations need HR analysts who are able to communicate the results of the analysis to line managers in a manner that makes sense to line managers (Marler & Boudreau, 2017). Meaning that the HR analysts should be able to tell a good and compelling story. Without good story-telling skills, the team will never be able to communicate the insights and actions to be taken to the line managers (Peeters et al., 2020).

(d) Consulting skills

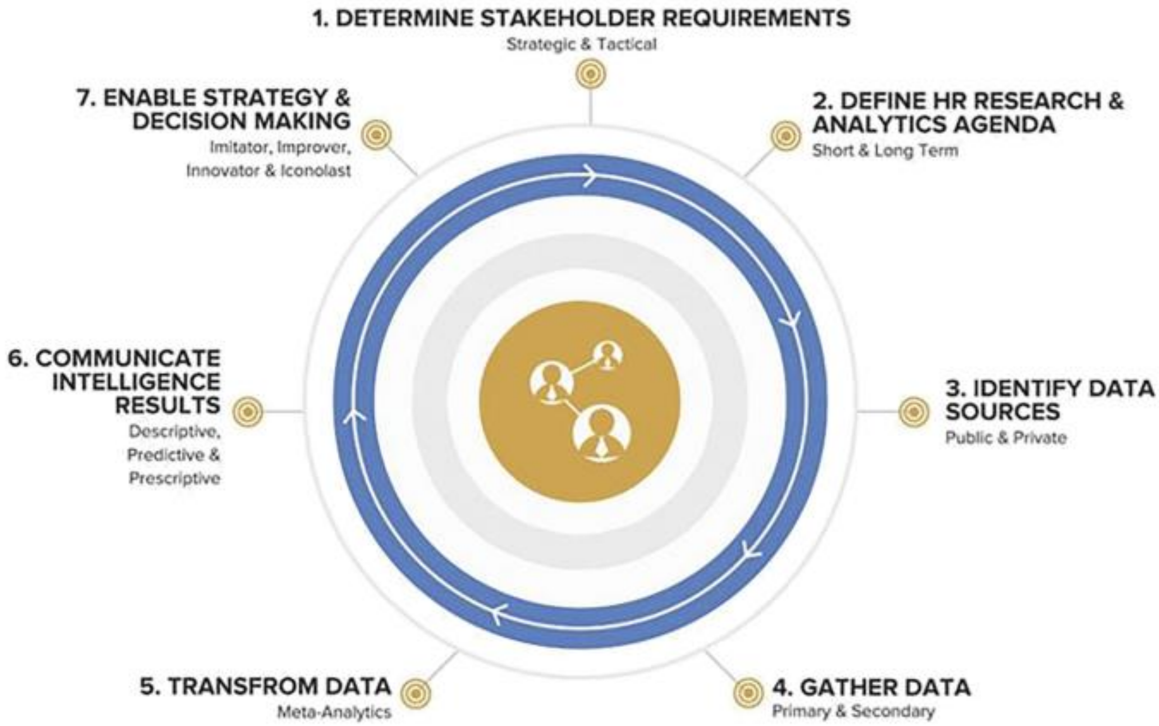
According to Peeters et al. (2020) HR analysts need to understand who their critical stakeholders are. They posit that senior managers, line managers, HR managers, other analytics teams and employees have been identified as stakeholders. Before trying to implement any HR solution or intervention, it is important to clarify and understand what the stakeholders need (McCartney et al., 2021). HR analysts need to be curious to ask questions until they understand which analytics to use and what they will be solving for (Huselid, 2018). They need to be confident in who they are and act like subject matter experts who are able to advise line managers accordingly. This also includes the ability to coach line managers and provide them with solutions that are well-informed and based on data analytics. As a result, HR analysts will be able to avoid using a linear, narrow and inward focused analysis of HR data as cautioned by Levenson (2018). This will also enable them to add value to the business and influence organisational performance.

Part of being an internal consultant is understanding how business operates. Hence, HR practitioners should familiarise themselves with their organisations' business operating models, understand the whole operations value chain and how the business make its revenue (Levison, 2018). This will enable them to speak the business language and gain respect and credibility from line managers.

2.6.2.1 The HR Analytics capability process/cycle

Since the biggest contention in HR analytics research is that there is no framework or process that guides HR practitioners on how to implement HR analytics that will have an impact on business, Falletta and Combs (2020) developed the seven-step process depicted below in Figure 6. The purpose of the cycle is to help build HR capability in line with the research deliverable expected from HR practitioners (Peeters et al., 2020).

Figure 6: HR Analytics cycle



Source: Falletta and Combs (2020, p. 54) HR analytics cycle

1) *Determine stakeholder requirements:* Peeters et al. (2020) senior managers, line managers, HR managers, other analytics teams and employees have been identified as stakeholders. Before trying to implement any HR solution or intervention, it is important to clarify and understand what the stakeholders need. HR practitioners need to be confident and curious to ask questions until they understand which analytics to use and what they will be solving for (Huselid, 2018). As a result, HR practitioners will be able to avoid using a linear, narrow and inward focused analysis of HR data as cautioned by Levenson (2018). This will also enable them to add value to the business and influence organisational performance. Hence the importance of having commercial acumen skills and understanding the business of the organisation (Green, 2017).
2) *Define HR research and analytics agenda:* since a research approach is followed in conducting HR analytics, this step involves crystalising the research question and objectives. This step also determines which HR interventions to prioritise in order to solve current and future business challenges (Levenson, 2018).

3) *Identify data sources:* with the advent of big data, there are lots of data sources that HR can use to gather data from, as indicated in **Error! Reference source not found.** (Bersin, 2017).
4) *Gather data:* after identifying the kind of data required in order to solve the research question, HR practitioners will start gathering data through observations, surveys, interviews or reading secondary documents. Triguero et al. (2018) maintain that data collected has to be of great quality. Hence, HR practitioners should also spend time cleaning up the data to avoid "garbage in, garbage out" principle (Anderson, 2017).
5) *Transform data:* this step involves using statistical tools and techniques to manipulate the data and transform it into HR intelligence that can be applied for the organisation's benefit.
6) *Communicate intelligence results:* when the data has been analysed and turned into HR intelligence, it needs to be communicated to the relevant stakeholders for them to action some of the predictions and prescription. Hence, the importance of communication and storytelling skills that HR practitioners need to have Fu et al. (2022). These skills help HR practitioners to connect the dots and tell a story that can be easily understood from a business perspective (Kryscynski et al., 2018).
7) *Enable strategy and decision-making:* the report from the analysis should be able to provide direction with regards to the actions that need to be taken. Such actions should lead to the execution of the organisation's strategy and improve organisational performance. This step supports HR analytics not to be seen only as an HR capability, but an organisational capability, which is connected and critical to the achievement organisation's strategy and its performance (Samson & Bhanugopan, 2022).

The process above shows the importance of having an HR analytics team or HR practitioners who have the necessary HR analytics capability as outlined in the seven-competencies model as illustrated in **Error! Reference source not found.** (Green, 2017).

2.6.3 HR Information infrastructure

HR analytics is a novel and innovative statistical way of analysing and using HR data to make well-informed business decisions (Minbeava, 2018). Hence, HR systems and technology plays a pivotal role in making HR analytics a success (Mohammed, 2019). HR analytics need to be enabled by digital technology in order to add value to people and organisational decisions (Margherita, 2022). Knowing that it is impossible for data analytics to be free of error (Mohammed, 2019), technology becomes a critical enabler and accelerator in making HR successful. It helps in manipulating and reporting on the data to make sense of what has happened and possible predict and prescribe accurately what needs to happen (Vargas et al., 2018). Organisations must therefore provide the right infrastructure and HR practitioners need to be competent in the use of such technology.

McIver et al., (2018, p. 398) refer to workforce analysis as a “techno-centric and research-oriented field”. To that point, HR practitioners need to be able to use technological systems in their research. The system should be able to collect data from different sources such as the Human Resource Information System (HRIS), the organisation’s performance scorecard or dashboard, and social media, and use statistical analysis methods to produce intelligence for the leaders to act on (Mohammed, 2019). Accordingly, the data must be stored in an integrated infrastructure where integration and interpretation of such will be easier for the HR practitioners (Belizón & Kieran, 2021).

Most HR practitioners are reluctant to use HR analysis because they do not have the right resources – skills and infrastructure – in order to execute their deliverables. Furthermore, due to its high costs, most organisations are reluctant to spend money on the technology required since HR is usually one of the functions that receives low budget (Belizón & Kieran, 2021). Although technology plays a critical role in enabling HR analytics, Margherita (2022) suggests that more research be conducted to determine whether more advanced technology positively contributes to the successful application of HR analytics within organisations.

According to Aral et al. (2012) in Marler and Boudreau (2017), organisations that have initially adopted the use of HR analytics but not having the right HR systems in place have failed. This means that HR needs to get out of its shell and start engaging with IT systems and understand data analysis. The lack of understanding of IT systems and failure of HR systems to produce the necessary insight hinders HR practitioners from fully utilising HR analytics (Angrave et al., 2018). HR practitioners are therefore encouraged engage with different stakeholders who do not necessarily have an HR background but would assist in analysing data (Marler & Boudreau, 2017).

2.6.4 Support from stakeholders

HR analytics have different stakeholders such as HR professionals, line managers, analytics teams from other departments and all employees. The HR analytics team need to understand the needs and expectation of each stakeholder in order to satisfy and influence them to use the insights gathered from HR analytics when making decisions.

Senior or top management: these are critical stakeholders in the implementation of any initiative in an organisation (Hamilton & Sodeman, 2020). They can act as ambassadors for the process through developing and approving policies, procedures, and practices. They also use the insights to make important decisions for the organisation. Without their support, line mangers will not implement some of the interventions that would have been designed based on the HR analytics conducted. Hamilton and Sodeman (2020) further argue that HR executives should have a higher-level of understanding of how HR analytics work. This will enable them to convince their peers in the executive c-suite to buy into and encourage their line managers to implement data-driven decisions brought by HR.

HR professionals: since the analytics team may not necessarily be made up by only HR practitioners, it is important to develop and maintain good relationships with HR colleagues as they will provide the HR data for analysis. On the other hand, HR professionals may benefit from the analytics done as the HR insights gathered will put them in good stead with line managers who will use it to make data-driven decisions that influence organisational performance. Senior HR managers must also have an understanding of HR analytics so that they can be able to make the right decisions (Hamilton & Sodeman, 2020).

Line managers: execute the policies, processes and practices that have been approved by senior management. They are expected to implement decisions that will be taken through the use of the insights from the analytics. It is therefore important to understand the issues that they are struggling with to ensure that the analytics provided help them solve a real problem. They are therefore able to give feedback on whether the analytics provided add value to the business. Line managers also need to understand that the results from the analysis are there to enhance their decision-making capabilities, and not to take over their role. Resistance from these stakeholders will lead to a failure of the initiative.

Other analytics teams: organisations may have different analytics team in various departments throughout the organisation. For HR analytics to influence organisational performance, the data they have should be analysed in line or together with other organisational performance data from other departments. This means that the teams must work together, whether they are housed in one central area or different areas in their respective departments.

Employees: employees are also expected to provide the data that is used for analysis. Without trust and not knowing what the data will be used for, employees may refuse the organisation access to the data. Unfortunately, the process followed in HR analytics does not allow for transparency in the data collected and how it was manipulated. Employees and the organisation get to see the results only (Gal et al., 2020). This may lead to employees questioning the data that was collected and challenging the results, which then impact negatively on the credibility of the HR analytics. Baessen et al. (2017) contend that it is also important to manage the dynamics associated with employees' connections as the interaction between them such as emails and social media posts (LinkedIn or X) can be leveraged as data sources.

2.7 Decisions enabled by HR analytics.

Steps 5 of the HR analytics cycle mentioned above, refers to analysing data and turning it into intelligence in order to make decisions that benefit the organisations (Falletta & Combs, 2020). Margherita (2022) posit that HR analytics has the potential to make decisions that contribute to the organisation's performance and outcomes. Some of the outcomes include, but not limited to sales performance, profitability, customer satisfaction, innovation, and efficiency (Nocker & Sena, 2019). However, because it has focused more on its internal processes and achieving its KPIs, it is sometimes difficult for business to see its' value-add. Hence, it is important for HR practitioners to clearly articulate the data-driven decisions. This will also enable them to measure its success by evaluating whether they were able to interpret the analytics and make decisions based on the insights gathered (Baesens et al., 2017).

2.7.1 Cost containment decisions

In determining the HR analytics that have an impact on business performance, Harris et al. (2011) (as cited in Marler & Boudreau, 2017) argue that although HR analytics may help organisations in identifying and saving costs, those savings were too little to have an impact on the business. They maintained that HR costs were only administrative in nature. However, Boakye and Lamptey (2020) posit that HR analytics assist organisations in saving more money than just administration costs. They argue that HR analytics, specifically predictive analysis, have the ability to help organisations in determining the chances of employees leaving the organisation (Mohammed, 2019).

Sousa et al. (2019) posit that HR functions are given the responsibility of saving costs by managing the spend on employee salaries, training expenditures, workforce planning, and any other people related costs they may have agreed upon. In addition, organisations save on huge amounts of money associated with recruitment costs, onboarding and training new employees, who would be replacing those that have resigned (Mohammed, 2019).

2.7.2 Recruitment decisions

HR analytics is critical in helping HR managers to use data when making decisions associated with workforce planning, recruitment, selection, training, and retention (Mohammed, 2019). Boakye and Lamptey (2020) assert that by using HR analytics to make recruitment decisions, a lot of mistakes have been removed from the process. They maintain that HR analytics enable the recruitment team to be objective and appoint the right people for the right positions at the right level. This is also made possible through the use of predictive modelling, which is level 2 on the HR analytics maturity model (Mohammed, 2019).

In addition, advanced technologies such as AI and machine learning also help improve the rate at which recruitment decisions are made. These tools extract and highlight information from a CV for the HR practitioners to zoom in, analyse and profile the candidates against the advertised position, transcribe the interview and analyse the transcription, as well as predict the right candidate to appoint (Álvarez-Gutierrez et al., 2022; Ben-gal, 2018). As a result, HR analytics show return on investment of the statistical tools and systems used (Ben-gal, 2018). Hence organisations are moving towards digitilising their recruitment processes (Minbaeva, 2018).

2.7.3 HR interventions

According to McIver et al. (2018) HR analytics is a research-based field. Peeters et al. (2020) also maintain that apart from only analysing data, HR practitioners should be able to conduct research to find out alternative ways of solving an organisation’s specific challenge that is aligned to its strategy. The findings should not only benefit the organisation, but the employees as well. They should be able to improve job satisfaction and employee engagement, contribute positively to employee wellbeing and allow opportunities for employees to grow and develop within the organisation (Gal et al., 2020). For example, Google’s Aristotle project was conducted to determine whether performance, collaboration and team satisfaction had an impact on organisational performance.

The insights gathered from the research led to Google implementing initiatives such as providing employees with free meals, offering them places to nap when they are tired in order to improve employee satisfaction. Consequently, leading to high employee retention rate (Marr, 2018). Hence, HR analytics should move beyond identifying organisational challenges, and provide research-based solutions that will allow the organisation to achieve its strategic objectives in an ever-changing business environment (McIver et al., 2018).

Marler and Boudreau (2017) posit that through HR analytics, organisations were able to identify what was causing the employees to be disengaged. The results of employee engagement surveys enable HR to design interventions that improved their employee engagement rating.

The data gathered through exit interviews enable organisations to design interventions that will ensure retention of employees (Boakye & Lamptey, 2020). In addition, some of the interventions that could be informed by HR analysis include compensation and reward programs, learning and development, and leadership development programmes (Hamilton & Sodeman, 2020).

2.8 Summary of the literature review

The literature reviewed show that DDDM, although it may be a fairly new concept to HR, has been around for a while (Cheng and Hackette, 2021). Digital transformation and big data have shifted the way leaders used to make decisions by depending on intuition only, to making data-driven decisions (Akter et al., 2019). This move has also compelled HR practitioners to move out of their comfort zone and to start embracing DDDM. This can only be done through analytical tools such as HR analytics (Minbeava, 2018; Huselid, 2018, Levenson, 2018). It can also assist in making sure that the HR practitioners play a strategic partnership role in their organisations (Boakye & Lamptey, 2020). Literature has also revealed that there was a practitioner-academic gap in that more practitioners have written more on DDDM than academics (Cheng and Hackette, 2021).

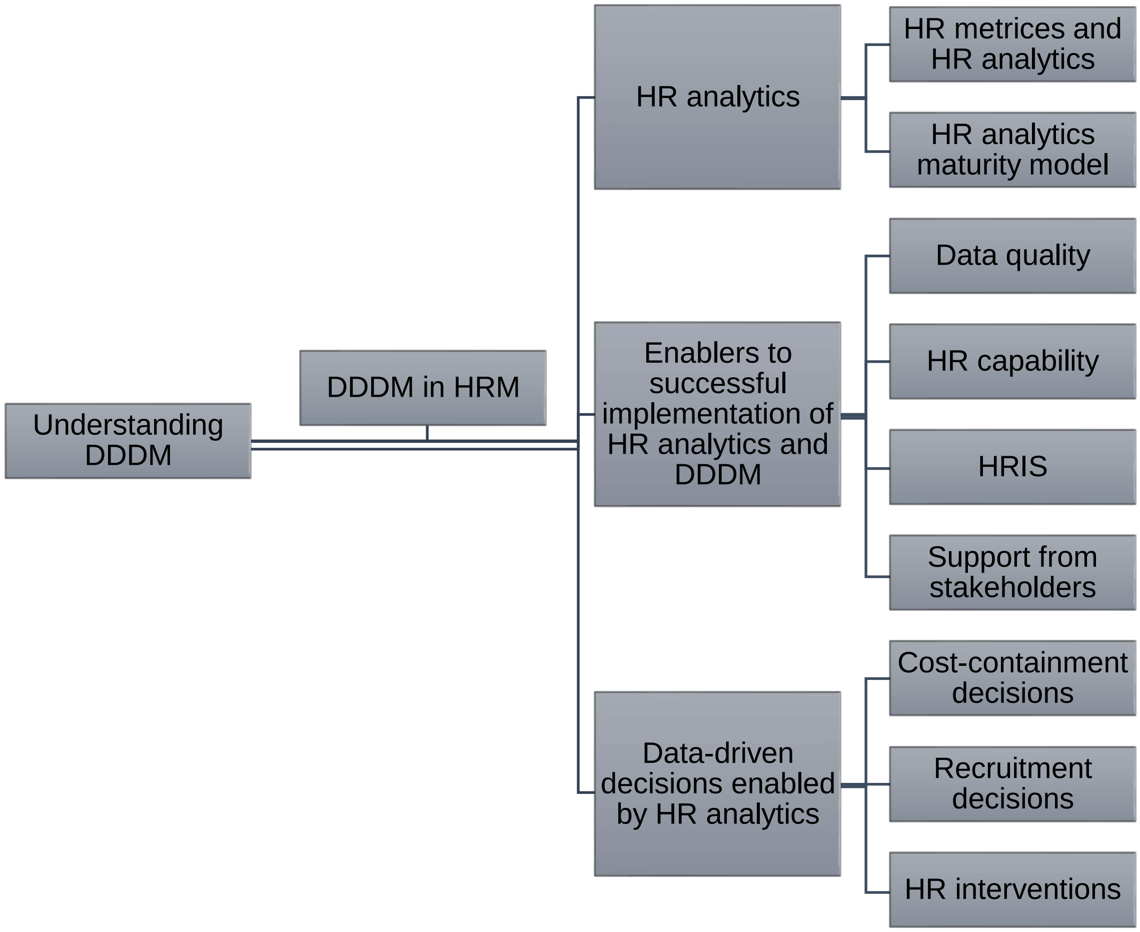
HR analytics, as an enabler for DDDM has received an increase in attention from scholars and practitioners (Davenport, 2019). This has led to an increase in the number of organisations that are utilising to make data-driven decisions. However, the majority of the organisations, about 80%, are stuck at level 1 (descriptive analysis) of the HR analytics maturity model (Peeters et al., 2020). Margherita (2022) posits that further research needs to be conducted to ascertain whether advance technological tools will help in progressing the organisations to level 2 and 3 of the HR analytics maturity model.

The extant literature reviewed also indicate that factors such as the quality of data, HR practitioners/analysts' skills and capabilities, the availability of a well-integrated system, and stakeholder support, are some of the conditions that need to be in place for HR practitioners to successfully use HR analytics to enable DDDM (Vargas et al., 2018; Álvarez-Gutiérrez et al., 2022, Huselid, 2018, Levenson, 2018; Kryscynski et al., 2018). The absence of all these factors will therefore be flagged as barriers that hinder the application of HR analytics and DDDM.

The literature also revealed that for HR analytics and DDDM to be regarded as effective, the decisions made by HR practitioners must add value to the business (Lofgren & Nordblom, 2020). These decisions have an impact on organisational outcomes such as sales, innovation, customer satisfaction and efficiency (Nocker & Sena, 2019).

Based on the literature reviewed, the study aims to explore how HR practitioners are using HR analytics to enable DDDM, thus closing the research gap on DDDM in HR. This will be done by looking at the extent at which organisations have adopted and utilising HR analytics and DDDM, and exploring the data-driven decisions that HR practitioners make for the benefit of their organisations. This will be followed by investigating the different skills that HR practitioners need to have to effectively use HR analytics for DDDM, and finally looking at some of the barriers that hinder HR practitioners from successfully applying HR analytics and DDDM. Below is the conceptual framework of the literature reviewed.

Table 4: Conceptual framework of the literature review



CHAPTER 3: RESEARCH QUESTION

Research questions are critical to any study as they guide and determine whether the study is going to be good or bad (Agee, 2009). It therefore becomes necessary to review and interrogate the research questions after the literature review to ensure that the right questions are asked to answer the aim and purpose of the research. One main research question and three sub-questions were developed after the literature on HR analytics and DDDM was reviewed.

3.1 Research Question 1: What is the extent of the adoption and utilisation of HR analytics and DDDM in your organisation?

The purpose of this question was to ascertain the extent and depth at which HR practitioners have adopted and utilising HR analytics and DDDM in their organisations? Mohammed (2019) and Margherita (2022) posit that organisations that have fully adopted the use of HR analytics and DDDM have transitioned from level 1 (descriptive) analytics to level 2 (predictive), and in some areas to level 3 (prescriptive) analytics. In addition, organisation's utilisation of analytics and DDDM can range from those that use only intuition up to those who use it as a competitive advantage (Davernport, 2019). An important part of this question was to determine whether HR practitioners were using descriptive analysis or have matured through the levels to use predictive and/or prescriptive analysis to inform DDDM.

3.3 Sub-question 1: What HR data-driven decisions have you made that were informed by HR analytics?

The literature reviewed indicate that HR analytics provide HR practitioners with insights that enable them to make data-driven decisions that add value to the organisation (Falletta & Combs, 2020). With the main aim of the research being to explore how HR practitioners use HR analytics to make data-driven decisions, the aim of this question was to find out what kind of data-driven decisions have HR practitioners made.

3.4 Sub-question 2: What kind of skills or capabilities do HR practitioners need in order to use HR analytics to enable DDDM?

HR capability has been identified as one of the important factors that will enable HR practitioners to effectively apply HR analytics to make data-driven decisions (Minbeava, 2018; Huselid, 2018; Kryscynski et al., 2018). This question sought to understand the type of skills HR practitioners should have in order to use HR analytics to make data driven decisions.

3.5 Sub-question 3: What are the barriers that hinder HR practitioners from using HR analytics to make data-driven decisions?

Literature revealed that some organisations have not yet fully started using HR analytics to make data-driven decisions, whilst the majority are stuck at level 1 (descriptive analytics) of the HR analytics maturity model (Mohammed, 2019). Fernandez and Gallardo-Gallardo (2020) posit that there are certain factors that are hindering these organisations from effectively and fully applying HR analytics for DDDM. The aim of this question was to find out from the participants what were some of the barriers that were hindering them from applying HR analytics in order to make data-driven decisions that add value to their organisations.

CHAPTER 4: RESEARCH METHODOLOGY

This chapter describes the research methods and methodology that was used in answering the research question: “How is HR making use of HR analytics to enable data-driven decision-making in their organisation?”. It describes the approach followed in answering the research questions mentioned in Chapter 3. It outlines the research methodology, the research design, and show how the research methodology was applied in answering the research questions.

4.1 Choice of methodology

4.1.1 Research paradigm

Andersen (2004) asserts that when thinking of conducting research, it is important to consider what the best way of approaching it will be. Accordingly, two paradigms, the positivist and interpretivist could be chosen to approach the study. These paradigms inform the research design that will be followed and depend on the type of study that the researcher wants to conduct (Given, 2008). If the researcher wanted to gather scientific and objective facts, the positivistic approach would be the best approach to use. This approach is for researchers who believe that there are objective facts to be gathered from the research that may not be influenced by the researcher (Given, 2008).

However, if the researcher wanted to conduct a subjective study where the feelings and thoughts of the research subject were considered, then the interpretivist approach would be used. Based on previous research from the literature in chapter 2, the majority of the research was conducted through systemic review of literature and quantitative studies (Mohammed, 2019; Huselid, 2018, Kryscynski et al., 2018), the researcher believed that the interpretivist approach will assist in gaining deeper understanding of how HR practitioners implement DDDM from a different perspective.

4.1.2 Underlying assumptions of interpretive paradigm

The interpretivist paradigm is based on the phenomenological assumption that the research subject cannot be separated from their environment (Sandberg, 2000). Since the researcher sought to explore and understand the perceptions and experiences of the research subjects in their natural setting, the interpretivist approach was used (Andersen, 2004; Sandberg, 2000). Bell et al. (2019) posit that interpretivism is aimed at answering the “how” and “why” questions, which allowed the researcher to explore, gain clarity and create meaning of the people’s lived experiences.

This study was a response to the invitation from Minbaeva (2018) and Huselid (2018) to close the gap between HR analytics theory and practice by exploring how HR practitioners were using HR analytics to enable DDDM in their organisations. Hence, an interpretivism approach was chosen as the best research approach to answer the research question as it would also help understand how people behave (Bell et al., 2019). It allowed the researcher to understand how they applied HR analytics in their different environments.

4.1.3 Research strategy

This study used a qualitative research approach. A qualitative approach focuses on words as opposed to interpreting numbers (Bell et al., 2019). Gupta et al., (2019, p.1) define it as "a field of study that deals with exploring, describing and interpreting the innate quality of entities and social processes". This approach allowed the researcher to probe and explore the perceptions of the research subjects in order to gain a deeper understanding of the research problem, and how they experience the constructs identified (Gupta et al., 2019). It therefore exposed information about what was happening within an organisation's context without having to measure the number of times certain things happened. This study aimed to explore and gain more in-depth understanding of how HR practitioners use HR analytics to make data-driven decisions in their organisations. Hence, qualitative approach was regarded as relevant and allowed the researcher to gather the participants' perceptions and understanding (Creswell, 2007).

4.2 Research design

Research design provides a guide on how data will be collected and analysed (Bell et al., 2019). It is regarded as the way researchers approach the study to be conducted, thus ensuring that it answers the research question and meets its aims and objectives (Creswell et al., 2007). Due to the limited time taken to conduct the study, a cross-sectional design, which refers to the collection of data at a specific point in time was followed (Bell et al. 2019). An exploratory qualitative research design was used in this study as the purpose was to find out how HR practitioners are using HR analytics to make data-driven decisions (Saunders, 2019 cited in Makri & Neely, 2021). This approach enabled the researcher to study phenomena in its natural habitat, further allowing the researcher to gain new insight into what was currently happening regarding HR analytics and DDDM within the different organisations (Creswell, 2007).

An exploratory qualitative study approach gave the researcher an opportunity to ask the "how" and "why" questions as it uses words rather than numbers, in contrast to quantitative research (Bell et al., 2019; Yin (2018). And since the procedure followed was inductive in nature, the researcher was able to build on information that was also shaped by their experiences throughout the study from the ground up, instead of using only available theory (Creswell, 2007). One of the advantages of a qualitative study as postulated in Creswell (2007) is that it gives the researcher an opportunity to adjust questions during the study, allowing the researcher to explore and gather more insights on the questions being asked. The researcher was also able to adjust some of the questions to fit the organisation's context and the respondent's understanding of the constructs (Bell et al., 2019). The researcher was therefore able to review the current available model and develop a new one that could be used to help practitioners understand the extent in which they were applying HR analytics to make data-driven decisions.

4.2.1 Population

A research population is a group of people with the same characteristics that the researcher will draw a sample of participants from (Asiamah et al.,2017). Creswell (2007) warns against identifying a population with different characteristics as it will be difficult to find common themes to be used during coding for data analysis. For this study, the population was the HR practitioners at senior and middle management who have been in their positions for a period of more than a year, as well as HR practitioners whose title reads as HR analyst from different South African organisations.

4.2.2 Sampling

A sample is chosen from the population on which the focus of the research study will be (Bell et al., 2019). The participants in this study were selected using a purposive sampling method, which is a "non-random ways of ensuring that particular categories of cases within a sampling universe are represented in the final sample of a project" (Robinson, 2014, p. 32). The participants were selected based on their knowledge, experience, and expertise on the research question. A snowball sampling, which includes referrals or recommendations by the respondents about other people who are subject matter experts on the research question was also used (Creswell, 2007).

The sample for this study comprised of HR managers at middle and senior management level who work closely with HR analytics and whose responsibility includes HR reporting to management teams. Furthermore, they have been in their role for a period of not less than a year. The sample was obtained from the researcher's personal and professional network of HR professionals on LinkedIn as well as ex-colleagues from different organisations in varying industries. This study excluded HR consultants at junior level whose role does not include reporting to business management teams, as well as those HR practitioners who have been in the organisation for less than a year. The criteria for inclusion in the sample included having HR reporting as a responsibility in their job profile. The study was not discriminate any age, race, gender, size of the organisation or industry. This did not have an influence in the achievement of the research objectives and aims.

Saturation, which is a measure of whether the sample size or number of interviews is sufficient for the study, was taken into consideration (Guest et al. 2020). This is also important in ensuring rigour and reliability of the study (Guest et al. 2020; Buckley, 2022). Guest et al. (2020) posit that 12 interviews are enough to reach saturation point. Hennik and Kaiser (2022) maintain that this point can be achieved by conducting between 9 – 17 interviews. Beyond this point, no new insight is gathered from the data collected. For this study, the researcher targeted to conduct a minimum of 10 and maximum of 15 interviews to ensure that saturation was reached. The researcher was able to conduct 15 interviews with the suitable HR practitioners from different industries such as government departments, telecommunication, mining, engineering, petrochemical, financial, management consultation and fast-moving consumer goods (FMCG).

4.2.3 Research instrument

Research instruments are tools used by researchers to gather data that will enable them to answer their research question (Wilkinson & Birmingham, 2003). One on one in depth semi-structured interviews through virtual meetings were used to collect data from the participants (Gupta et al., 2019). Wilkinson and Birmingham (2003) posit that semi-structured interviews are less flexible than the unstructured, but more flexible than the structured interviews. The semi-structured interviews allowed the researcher to guide the interview, whilst also giving the interviewees an opportunity to control the direction of the conversation.

Interview questions were prepared beforehand. The attached interview protocol (Appendix A) was followed to ensure consistency, reliability, and validity of the instrument (Schoch, 2020). The interview protocol was comprised of one main research question and three sub-questions as outlined in Chapter 3. The questions asked were open-ended and the researcher avoided asking leading and loaded questions (Bell et al., 2019). The necessary interview ethical considerations, seeking permission, interpersonal and communications skills were followed to ensure consistency during the interviews (Bourgeault et al., 2010).

4.2.4 Piloting

Piloting is an important step in research. It refers to testing the interview questions designed with a few participants to ensure that there is no confusion, and the intention of the study is clearly answered (Kumar, 2011). Conducting a pilot allowed the researcher to identify and correct any mistakes in the way the questions were asked in order to ensure that there was no ambiguity; the questions were clear and concise (Wilkinson & Birmingham, 2003). Malmqvist et al. (2019) maintain that a properly conducted pilot increases the quality of the research and is able to inform and improve the research. It must also be independent of the main research study. The researcher tested the interview questionnaire with two HR practitioners who possess the same characteristics as the sample population. The first interview was conducted using the first draft of the interview protocol. Feedback was noted and some questions adjusted to ensure that there was no ambiguity. The second pilot interview was conducted on the reviewed and updated interview protocol. These two HR practitioners did not form part of the main research study.

4.2.5 Data Collection

Glette and Wiig (2022) posit that the credibility and quality of the research outcomes hinges on the quality of data collected. Consequently, data that is collected in an unplanned and unstructured manner stands the risk of being difficult to analyse and interpret. Hence, it is important to use a systematic data collection approach in order to ensure rigour. It enables the researcher to produce good quality research (Olsen, 2012). The researcher used semi-structured interviews for this study. The interview questions were used to guide the discussions, and more follow-up questions were used to explore the phenomena under investigation (Makro & Neely, 2021). Consent to record the interviews was sought from the participants in order to ensure that the interviews were recorded and transcribed to avoid loss of critical information.

4.2.6 Data Analysis

After the systematic collection of data, it was analysed and interpreted accordingly in order to make sense of the information (Kumar, 2011). The analysis was started soon after the first interview to ensure that the information was recorded whilst still fresh (Charmaz, 2006 cited in Makri & Neely 2021). Burnard and Morrison, 1994 cited in Hougton et al. (2015) posit that data analysis is conducted to ensure that it is properly studied and tested to identify common themes. The authors further allude to the importance of knowing data intimately by studying it repeatedly. This is the first step in data analysis. It also includes highlighting and noting words that are relevant to the questions being asked (Makri & Neely, 2021). However, due to the amount of data collected, the process was not as linear as indicated by Hougton et al. (2015). It was non-linear and often going back and forth between the data collected and analysis in order to develop codes and themes that are well-informed by the data.

Grounded theory was applied to analyse the data collected. Thomas and James (2006) contend that grounded theory is relevant for studies that are conducted, and theories developed in natural settings. Thus, being able to create meaning out of the data. This approach was found to be relevant to the current study in that the respondents interviewed were asked to respond to questions that they are experts in and work with daily. The data received was also used to build on identify nuances and possible modification of the current model that could be used by practitioners (Bell et al., 2019; Tie et al., 2019).

In order to ensure that the data collected was properly analysed, the researcher followed the thematic analysis as outlined in Braun and Clarke (2006). Thematic analysis, an analytical method used to identify and group together data with common words, meaning patterns into different themes, was applied to analyse the data gathered (Kiger & Varpio, 2020). It allowed the researcher to unearth data that was not overtly articulated, and the researcher remains objective when analysing the data (Gupta et al., 2019).

The researcher performed the analysis by first reading the transcripts to gather insights. The transcripts were then loaded on Atlas.ti to begin the coding process, which refers to closely studying the huge amount of data gathered in order to develop concepts (Makri & Neely, 2021). The researcher developed codes that were informed by the similarity of words and meaning from the data gathered. The codes were then grouped into group codes and later into themes (Bell et al., 2019). The themes were further reviewed, analysed, and synthesised in chapter 5 and 6 in order to produce the final report and recommendations in chapter 7 (Braun & Clarke, 2006; Makri & Neely, 2021).

Throughout the analysis process, the researcher continuously used the three questions data analysis framework that comprised of the following questions: “1) what are the data telling me; 2) what is it that I want to know; and 3) what is the dialectical relationship between what the data are telling me and what I want to know?” (Srivastava & Hopwood, 2009, p. 78).

4.2.7 Research quality and rigour

The researcher acknowledged the fact that qualitative research is complex and proving the validity and rigour of the study might be difficult due to the risk of bias and subjectivity applied in the data gathering and analysis (Klenke et al., 2016). In order to address the criticism regarding qualitative research on trustworthiness, which are linked to validity and reliability, the researcher considered Guba's four criteria of credibility, transferability, dependability, and confirmability (Shenton, 2004). This was done by ensuring that there is transparency about the context of the research and the manner in which data was gathered and analysed.

The use of a standard interview protocol while interviewing all the participants ensured reliability of the study. The interview documents or transcripts are also stored on Atlas.ti for transparency reasons. The interviews were recorded and transcribed later to ensure accuracy in the evidence or quotes used. The use of an exploratory semi-structured interview allowed the researcher to repeat or paraphrase any questions that were not clearly understood by the interviewee (Bell et al., 2019). Answers that were deemed not to be relevant in answering the research question were not included in the analysis, however left in the transcript.

4.9 Limitations of the research methodology

Although qualitative research has its own advantages, qualitative research has the following limitations: 1) it can be too subjective – since data was gathered through semi-structured interviews, the researcher still remains the main instrument and may allow their own personal biases to influence the data gathered. In addition, the findings depend on what the researcher may choose to include or exclude in their interpretation of the data; 2) the research cannot be repeated anywhere else – each study is based on its own unique context, culture and circumstances. This study was conducted in the context of the chosen South African organisations, which may not be representative of all organisations in South Africa; 3) the findings can therefore not be generalised, especially in cases where the sample for interviews has not been chosen through probability sampling (Bell et al., 2019; Creswell, 2007).

4.10 Ethical considerations

Ethical considerations refer to the researcher's responsibility to ensure that research ethical standards are met (Bell et al., 2019). Ethical clearance was therefore sought from the research committee before data was gathered from the chosen sample of respondents. The ethical clearance was provided and ensured that the researcher had consent from the institution and the participants to conduct the research. The signed consent form was emailed to the participants a week before the interview outlining the purpose of the research and the fact that the interview will be recorded and transcribed later. This ensured that the participants knew what the research was about, how they will be expected to participate and what the data collected will be used for (Kumar, 2011). The collected data was stored on the researcher’s laptop, which has a password to ensure that no one except the researcher had access to it.

CHAPTER 5: PRESENTATION OF FINDINGS

5.1 Introduction

The purpose of this research was to explore how HR practitioners in South African organisations use HR analytics to make data-driven decisions. This chapter describes the findings from the 15 semi-structured interviews conducted. It comprises a brief description of the interviewees, the coding process followed, an analysis of the findings and a conceptual framework that emerged from the data. The findings will be presented as themes grouped per research question.

5.2 Description of the interviews

Fifteen semi-structured interviews were held with HR practitioners who were identified as senior and middle managers from different South African organisations. The participants were drawn from multiple sectors, including the mining, fast-moving consumer goods (FMCG), financial services, public sector, telecommunications and management consulting sectors. These virtual interviews were conducted through MS Teams and Zoom took between 45 minutes to an hour. All interviews were recorded as agreed through the letter of consent that was sent before the interviews stipulated. The transcripts were later transcribed by the researcher using the Sonix App.

Out of the 15 interviewees, 2 held the position of HR data analyst at middle management level, 5 were at middle management comprised of 3 learning and development managers, 1 leadership development manager and 1 organisational effectiveness manager, and 8 senior managers comprised of 4 in HR operations, 1 in employee wellness and benefits, 1 in talent management and 1 in diversity and inclusion. The findings from the interviews with the HR practitioners and data analysts were analysed together. However, in instances where the researcher found the views of the HR data analysts highlighting important aspects that were slightly different to those of the other HR practitioners, these insights were examined separately.

In addition, when analysing the data, the researcher found that in certain instances the participants highlighted two separate ideas in one question. The two ideas from the same participant were classified as participant number (a) and (b). The details of the participants are depicted below:

Table 5: List of participants

Participant	Role	Management level	Industry
Participant #1	Learning and Development Manager	Middle management	Management Consultation
Participant #2	Senior Manager: Human Resource Operations	Senior management	Public Sector
Participant #3	Leadership Development Manager	Middle management	Management Consultation
Participant #4	Organisational Effectiveness Manager	Middle management	Mining
Participant #6	Employee Wellness and Benefits	Senior management	Financial services
Participant #7	Learning and Development Manager	Middle management	Public Sector
Participant #8	Senior Manager: Human Resource Operations	Senior management	Fast Moving Consumer Goods
Participant #9	Senior Manage: Talent management	Senior management	Telecommunications
Participant #10	Learning and Development manager	Middle management	Mining
Participant #12	Senior Manager: Human Resource Operations	Senior management	Mining
Participant #13	Senior Manager: Human Resource Operations	Senior management	Mining
Participant #14	Senior Manager: Diversity and Inclusion	Senior management	Financial services
Participant #15	Senior Manager: Organisational Effectiveness	Senior management	Fast Moving Consumer Goods
Participant #5	Data analyst	Middle management	Fast Moving Consumer Goods
Participant #11	Data analyst	Middle management	Mining

5.3 The coding process

The qualitative analysis software, Atlas.ti was used to analyse the transcribed interviews through a three-step coding process. The transcripts were uploaded at different times after the interviews took place. Before coding the transcribed interviews, the researcher read through the transcripts, taking into consideration the literature that was reviewed in Chapter 2. The whole document was coded based on the key words identified in the responses. The codes were reviewed, and duplicates removed. Those with similar meaning were grouped into code groups. The code groups were then clustered into themes based on the research questions. The researcher then followed the process depicted below in coding and analysing the data.

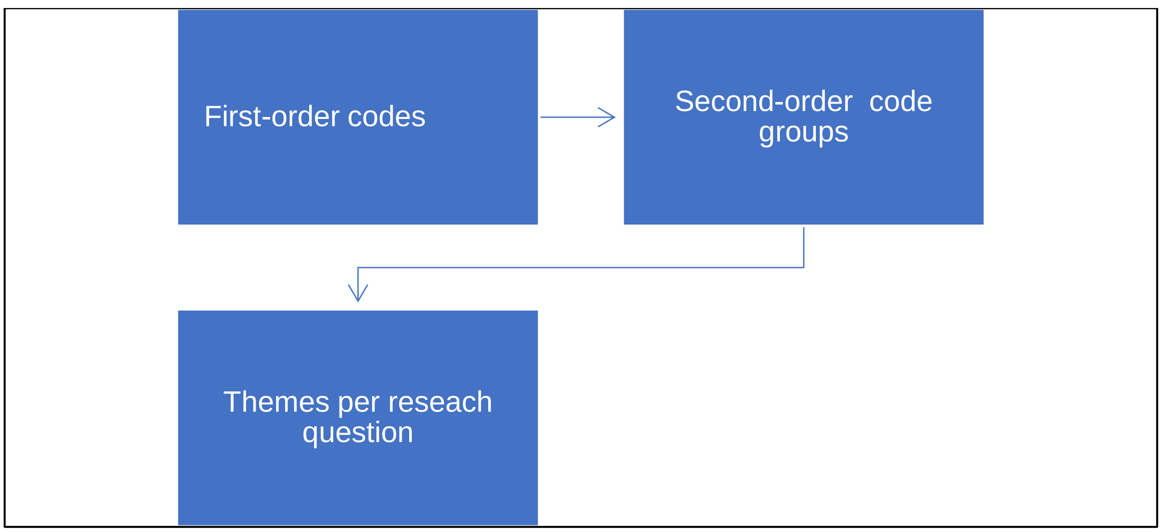


Figure 7: Coding process.

The first-order codes found were initially 285. These were revised and down to 130 codes and then grouped into 14 code groups. On further analysis, the code groups were clustered into themes that aligned with the research question and sub-questions. 11 themes were found as depicted in the summary below. Guided by the objectives of the study, 10 themes were identified to highlight the key findings and give deep insight on the research topic.

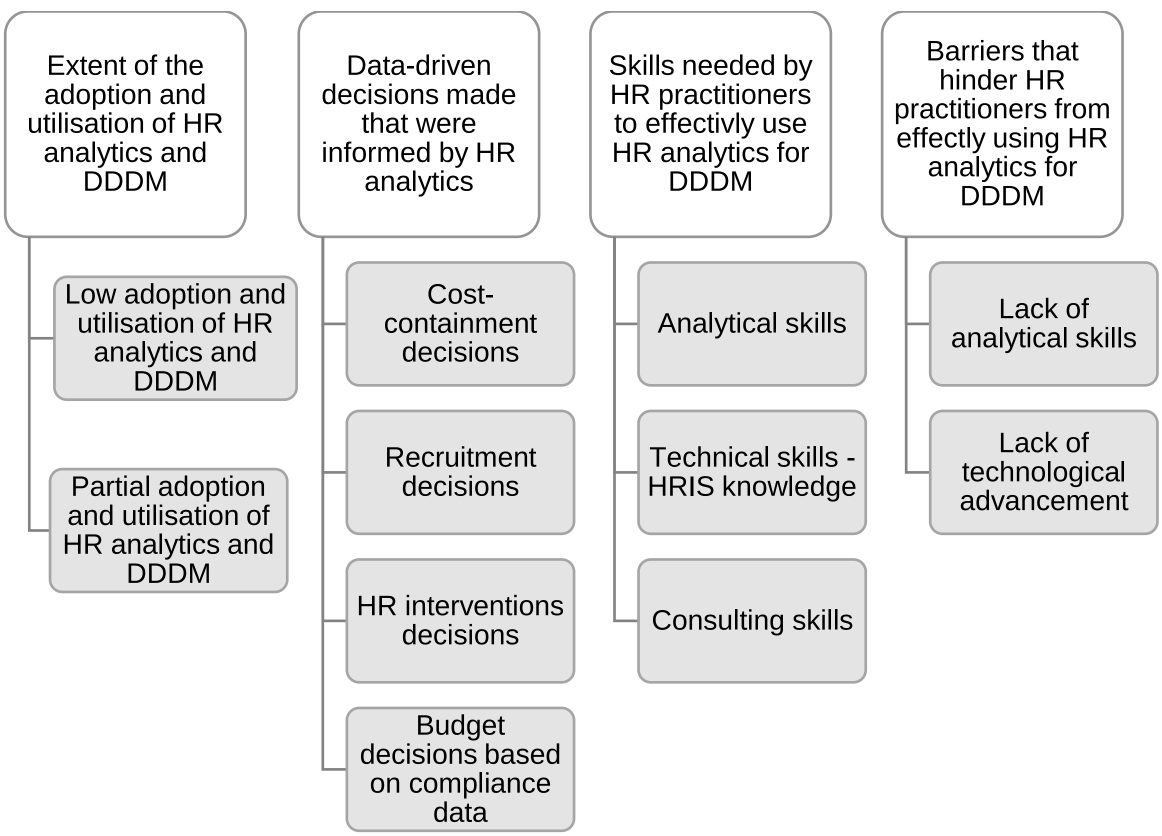
Figure 8: Summary of the number of codes, code groups and themes

First-order codes	285
Revised codes	130
Code groups	14
Themes	11

5.4 Presentation of findings

The findings from the data gathered are presented in themes per research question and the sub-questions. The themes were assigned in line with the research questions. The findings are presented in line with the conceptual framework presented in **Error! Reference source not found.**.

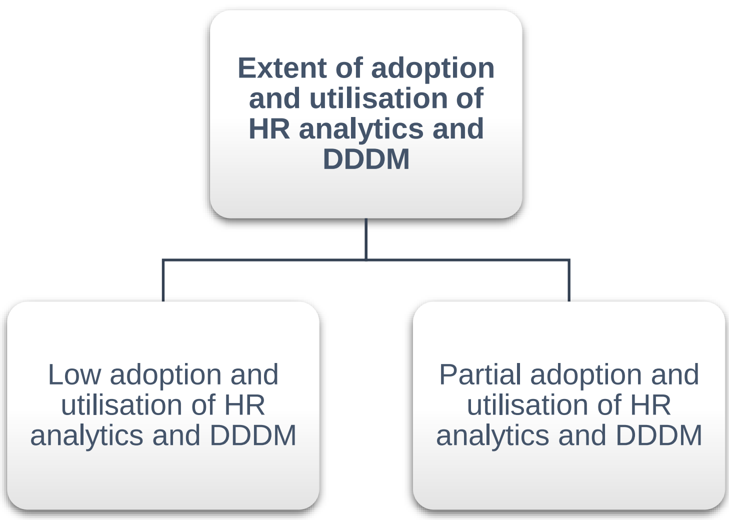
Figure 9: Conceptual framework: presentation of findings



5.5 Research Question 1: What is the extent of the adoption and utilisation of HR analytics and DDDM in your organisation?

The purpose of this question was to determine the extent and depth to which HR practitioners have adopted and are utilising HR analytics and DDDM in organisations. The question was sub-divided into three sub-questions to gain more understanding and clarity on how these organisations are implementing HR analytics with regards to the kind of data-driven decisions they make, the capabilities in hand and some of the challenges encountered in executing duties. The participants gave descriptions of how they view the extent to which organisations are adopting and utilising HR analytics and DDDM. The descriptions are presented under two themes as depicted in Figure 10.

*Figure 10**: Themes on the extent of adoption and utilisation of HR analytics and DDDM***



5.5.1 Theme 1: Low adoption and utilisation of HR analytics and DDDM

The interviews conducted revealed that only one participant believed that the extent to which their organisation adopted and utilised HR analytics and DDDM was low. The evidence of this is depicted below.

Participant	Quotation
Participant 15 (a)	*"I do not trust the data analytics that come from our system. It is unreliable. When I ask for master data from one person, and I ask for the same data from another person, I'm guaranteed to get different information."*
Participant 15 (b)	*"Most of us try as much as we can not to use the data. Only the usual dashboard reports are generated, and even those are not reliable."*

Participants 15 highlighted 2 important points in this response. The first point was regarding data quality and integrity. They indicated that although they have HR information systems that analyse data, the analysis was unreliable. An example expressed was that if the same report for the same period was requested by two different people, it would always give different information.

The second point raised was employee competence to interrogate the data and recognise that it was unreliable. The net effect was strong discomfort in sharing reports or speaking with confidence about the decisions that could be made. They would rather not use the analysis at all and only show the normal dashboard reports to business, although they also don't trust the information.

<u>Conclusion on low adoption and utilisation of HR analytics and DDDM</u>

The response from the participant indicated that data integrity is critical in the adoption and utilisation of HR analytics and DDDM. If data is unreliable, it takes away the confidence of presenting the findings and decisions to line managers. Similarly, if HR practitioners cannot use the analysis to advise line managers on decisions to implement, then DDDM is not applicable.

5.5.2 Theme 2: Partial adoption and utilisation of HR analytics and DDDM

The majority of participants indicated that although HR analytics have been adopted and are utilised in making data-driven decisions, these concepts are not applied to their full potential. Fourteen out of the fifteen participants indicated that HR analytics and DDDM were implemented but not yet fully functional and effective. There is room for improvement. This view was expressed aptly by one of the data analysts as depicted below:

Participant	Quotation
Participant 14	*"I would like an environment wherein adopting platforms in order to leverage data and analytics is fully integrated."*

Participant 14 indicated that although they have different systems where all the data is captured and can be analysed, there are certain reports that are difficult to produce and share with line managers because the systems are not well-integrated. This also hinders line managers from interacting with people's data without calling on HR practitioners to provide them with information.

Participant	Quotation
Participant 7	*"We have nice well-integrated system that can give us any analytics we want at the click of a button, but we are not using it fully."*
Participant 10	*"All our data analytics and reports are instant. Even our succession planning is no longer driven manually. It is instant. When I go to meetings, I don't have to prepare presentations, I can present from the system whatever information line managers want to see at that point in time. The only challenge is that some of our HR practitioners are not using it."*

Participants 7 and 10 indicated that they have a well-integrated state-of-the-art HRIS. However, the HR practitioners were not fully utilising the system to produce reliable analytics that would enable reliable data-driven decisions. HR practitioners are afraid to use the system and always revert to analysing data manually or asking for help from colleagues.

Participant	Quotation
Participant 11	*"We conduct heartbeat surveys that are operated by an external service provider. They provide us with reports that we can analyse, and they give us information on how our culture is looking and what we must do to improve it."*
Participant 8	*"We pay a lot of money to service providers who conduct employee engagement surveys for us."*

Participants 11 and 8 reported making use of external service providers to conduct employee engagement surveys. The analysis conducted by these service providers predicts the employees’ level of engagement and also prescribes some interventions that could be implemented to improve employee engagement.

Analysis of HR data analysts

Participant 5	*“We are building lots of reports and analytics, but I don't see the HR team using those insights and data to make decisions or to build strategy. It is more standardized reports that they would like to have and look at. But it is rare to see them using that data to make decisions. The reports are there but I haven’t seen the outputs to make decisions.”*

Participant 5, a data analyst, stated that although they did not have a state-of-the-art and well-integrated system, the analysts were able to produce a lot of reports that HR practitioners could use to inform and advise line managers on strategic issues. Unfortunately, HR practitioners are not using the reports to make data-driven decisions that impact the business. There is reluctance to advance from long established standard dashboard reports.

Participant 11	*“I don't think we are employing the proactive side to basically get to another level of data driven decision making. We are descriptive. We are far away from predictive analysis. We don’t ask a lot of questions that are related to predictive reporting and analytics.”*

Participants 11 also indicated that good systems are in place and used for HR analytics and DDDM. However, there is scope to move beyond being descriptive, to include predictive analysis. The reports that are being requested and produced through the system mostly refer to what has happened in the previous month or quarter and show the related trends and patterns. However, there is potential to predict future patterns so that HR practitioners could advise line managers on actions to take to mitigate risks.

5.5.3 Summary of research question 1

The interviews revealed two important foundational elements: a well-integrated system and HR capability need to be in place for organisations to fully adopt and utilise HR analytics and DDDM. Until such time that both are in place at the same time, it cannot be said that HR analytics and DDDM are fully adopted and effective.

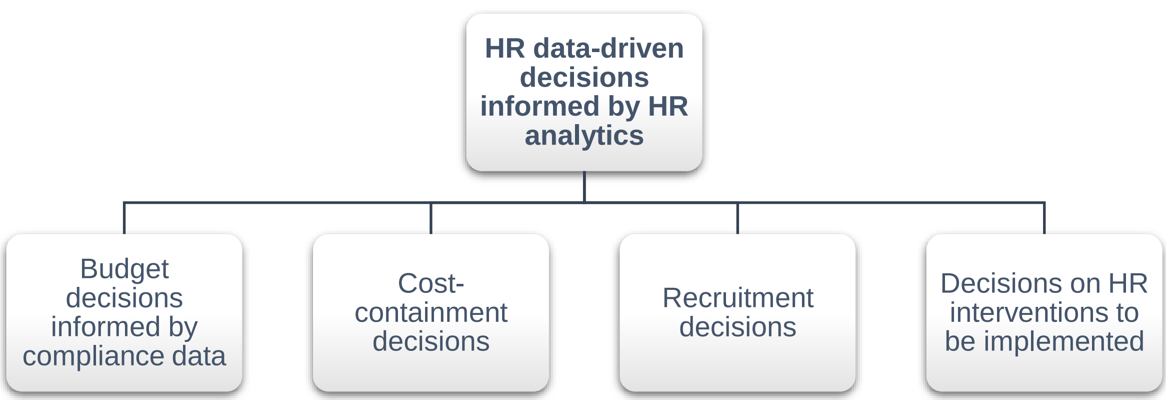
Some organisations have people with the right analytical capability, but inferior systems that are not well-integrated enough to produce reports that give depth to presentations and decisions that inspire confidence. Others have well-integrated systems, but the HR practitioners are not using these to analyse and produce the necessary reports. In addition, the systems are being used to produce analytics that referred to past performance and not information that could help managers make decisions to mitigate future risks.

The interviews further revealed that those HR practitioners that have the support of HR data analysts to analyse data and produce good reports, were also not using them optimally. Finally, data shows that the majority of the organisations conduct employee engagement surveys that are administered by external service providers. The outcomes of these surveys are analysed using the provider's IT system, and the results predict what would happen if the culture remained the same. Recommendations for HR interventions to implement and improve the organisational culture are given.

5.6 Sub question 1: What HR data-driven decisions have you made that were informed by HR analytics?

The purpose of this question was to ascertain the kind of data-driven decisions informed by HR analytics that are being made by HR practitioners. The answers to the question were grouped into four themes as depicted below. Only three themes (recruitment decisions, financial decisions on cost containment and decisions on interventions to be implemented) were analysed.

Figure 11: Themes on HR data-driven decisions



5.6.1 Theme 1 of sub-question 1 Financial decisions that enable cost containment.

Although HR does not bring revenue like other departments such as sales, it is expected to be prudent when making decisions that influence spending money. HR data is used to make cost-saving decisions that guide solutions to address requests from the organisation.

Participant	**Quotation**
Participant 2 (a)	*"The payroll system is able to give us data where we link absenteeism, versus the number of days or hours that are wasted when employees are not at work, which is also like a financial liability on our part."*
Participant 2 (b)	*It also enables us to know how much we have paid for overtime against the budget so that we can plan accordingly."*

The participants interviewed linked some of the HR key performance indicators (KPIs) that are measured on a monthly and quarterly basis to financial decisions that are made to influence business. Firms frequently embark on cost-saving exercises, and HR is expected to contribute to the kitty by ensuring that people decisions are handled in a financially prudent manner. Participant 2 indicated that tracking and reporting on KPIs such as absenteeism and overtime worked assisted HR and the business in seeing where money is spent and where it could be saved. Some of the expenditure was regarded as wasteful due to absenteeism; this is recorded as a financial liability. HR is expected to make decisions and introduce measures to help curb absenteeism.

Participant 12 indicated that by measuring turnover, HR is able to identify which areas are losing people. Exit interviews are used to determine the reasons people are leaving. The loss of people has financial implications as organisations must pay out pensions and also spend more money on recruiting replacements. These analytics help HR to intervene before more people leave the organisation. This was corroborated by Participant 5, indicated that the cost of recruitment to replace employees who have resigned is too high. In some instances, especially for critical leadership roles, replacement is done through external recruitment agencies. When people leave, a lot of money is spent on these agencies.

Participant	**Quotation**
Participant 12	*"If we look at turnover data and we see we're losing a lot of people and have to pay their pensions and benefits."*
Participant 5	*"Looking at the cost of attrition, what is the cost of replacing talent? We can look at the entire time that we are spending in terms of recruitment, what we are spending on agencies."*

Participant 3 used an example to explain the role HR analytics play in ensuring that the right decisions are made to prevent the organisation from losing money through injury claims. Data regarding injuries or safety incidents that happen in the workplace must be tracked because it affects people, performance of the business, payouts to the injured and bonuses to be received. This information also informs the learning department about the type of training needed in specific areas in order to ensure safe practices that lead to the containment of costs.

Participant	**Quotation**
Participant 3	*"For example, if you are in supply chain and struggling with injuries, where a lot of people are getting injured. You can use that information to start training the employees. You then have less injuries and the performance of the business becomes better. In essence you don't have to pay the employees that have been injured."*

<u>Conclusion of Financial decisions that enable cost containment.</u>

Although HR is regarded as a cost centre, the activities and decisions that are made by HR practitioners have an influence on the finances of organisations. Organisations frequently undertake cost-saving exercises; HR is expected to contribute by ensuring that aspects such as turnover, attrition, recruitment costs and injuries are managed with prudence. From the interviews conducted, it is evident that HR practitioners are expected to be proactive in making decisions that ensure that costs are contained.

5.6.2 Theme 2 of sub question 1 Recruitment decisions.

The interviews revealed that HR practitioners are accountable for making sure that they recruit and appoint the right talent. The participants indicated that they use data from different sources to make different recruitment decisions on whether to appoint externally or promote from within. The evidence of the interview is presented below.

<u>Evidence and analysis of recruitment decisions.</u>

Participant	**Quotation**
Participant 12	*"We use the data from the plant to decide on a resourcing strategy, whether to appoint people permanently or as on contract. We need to have a proper workforce plan."*
Participant 3	*"The leadership assessments we did have helped us to identify what type of talent we should bring in when we have vacancies. We use those*

	leadership competencies to make appointment decisions to boost our leadership pipeline.”
Participant 13	*“One of our responsibilities is there to ensure that we have sufficient manpower to accelerate production and meet the targets. We use that data to decide on how many employees we need.”*
Participant 10	*“Our system allows us to see successors throughout the organisation and in different locations. We are able to make decisions on which employee is ready to be promoted or moved to another department.”*

The participants indicated that HR practitioners play a critical role in deciding who should be recruited, selected and appointed for different roles within the organisation. Participants 12 and 13 indicated that they use data from different plants to develop a workforce plan and decide on resourcing strategies in terms of the number of people to be appointed permanently and the ones who should be appointed on a contract basis.

Participant 6 revealed that they use the leadership competencies that were compiled through conducting leadership assessments to decide on what type of leadership talent to bring into the organisation in order to maintain a leadership pipeline. The leaders interviewed are assessed against those leadership competencies and those who fit the profile are appointed.

Participant 10 indicated that from an internal mobility perspective, when vacancies become available, data in the HR information system is used to identify employees that are ready to be moved and appointed to vacancies before considering external candidates.

<u>Conclusion on recruitment decisions.</u>

The interviews revealed that one of HR practitioners’ responsibilities is to recruit and bring the right people with the right skills into the organisation. This responsibility is fulfilled by using data such as the number of employees required in the operations or production line to develop workforce plans and decide on the number of employees to appoint, either permanently or on contract. HR practitioners also use data gathered through leadership assessments to decide on the type of talent to recruit so as to fill talent pipelines. Finally, the data on the readiness of employees is used to help line manager to decide on which employees to promote or move to other departments.

5.6.3 Theme 3 of sub question 1 Decisions on interventions to be implemented.

The participants indicated that HR analytics are helpful when making decisions regarding the type of HR interventions to implement in order to solve identified challenges or close a particular people-related gap. The evidence of the responses is detailed below.

Participant	Description of quote
Participant 13	*"HR analytics helped us in understanding the level of engagement because that is enabling production output. It also helped us to intervene with befitting solutions so that we uplift the level of engagement."*
Participant 11	*"If we look at the heartbeat results, our employee engagement survey, the decisions that we make when we've done heartbeat and then the interventions that come out of that where we decided that we need to shift the culture of the organization. The interventions helped us to add value in the organisation through improving the culture."*

All the participants interviewed indicated using insights gathered from surveys and discussions to decide on which HR interventions to design and implement. These HR interventions help to identify and close people-related gaps. Participants 11 and 13 referred to the results that came from employee engagement surveys. These results guided the design of interventions that served to improve engagement and productivity resulting in increased trust amongst line managers and employees.

Participant 10 indicated that the insights gathered from analysing the results of training interventions and attendance through learning and development KPI, helped to identify and decide on which training courses to implement. HR data is also able to show the courses that are in demand from employees as well as the type of channels to use in disseminating the training.

Participants 3 and 7 were of the view that without data, it would be difficult to determine the type of leadership development programs a firm needs to close the leadership gaps. Through a skills audit exercise, one HR team was able to identify, decide and implement required leadership development programs that included key needs such as coaching. This was successful as it was what the team needed.

Participant 10	*"HR analytics enabled us to make decisions regarding the type of training courses that on demand, and the learning channels we use. All this is informed by the observations and data that we collect from employees."*
Participant 3	*"HR analytics gave us a deeper understanding in terms of what the different leadership development areas we needed to focus on for our leaders."*
Participant 7	*"Currently we took our executive team through a customised leadership development program that includes coaching. We implemented this program based on the skills audit, interviews and focus groups conducted."*

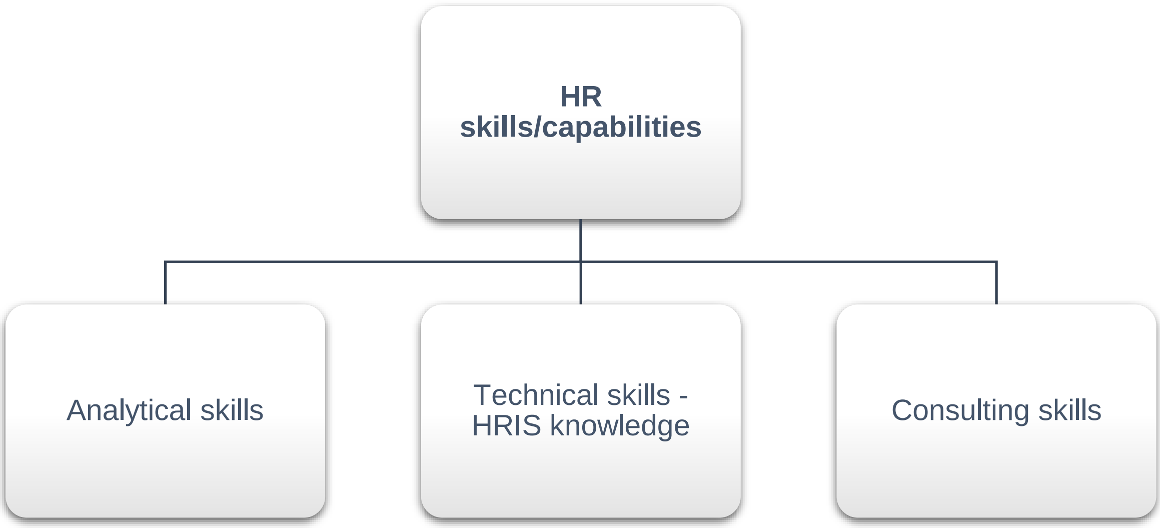
5.6.4 Summary of findings of sub-question 1

The interviews conducted clearly showed that without the right HR analytics in place, HR practitioners are not able to make the right decisions in identifying and implement people-related interventions that help improve employee engagement. Additionally, the practitioners would struggle to provide learning and development as well as leadership development programs that serve required purpose for employees and the organisation. The participants interviewed indicated that the decisions made to implement the interventions helped to add value to their organisations.

5.7 Sub-question 2 What are the skills or capabilities that HR practitioners need in order to be competent in fully utilising HR analytics to make data-driven decisions?

The purpose of this question was to find out the type of skills HR practitioners need and use in order to effectively implement HR analytics and DDDM for the organisation's benefit. The participants provided a list of competencies, which the researcher grouped into four themes as depicted below.

Figure 12: HR capabilities



5.7.1 Theme 1: Analytical skills

The participants indicated that HR practitioners should be competent in managing data and have good analytical skills. They indicated that this does not only include being able to use the system, but also using critical thinking skills, being patient and detail oriented. The evidence of the interview is presented and analysed below.

Participant	Description of quotation
Participant 4	*"In HR we get a lot of data, you still need to sit and work through it and interpret it so that you can convey it back, to your management team. You need to have attention for detail and be patient to go through the data as in some cases the data may need a bit of cleaning up."*
Participant 12	*"We need to be able to analyse the data and interpret it. Analysing data is not about presenting the graphs or numbers that you get from the system, but making sense of it and being able to tell the line managers what it means and what they must do about it."*

Participant 14	*"HR practitioners need to play in the decision page. They should be able to look at the data, analyse it and make decisions that will help the business."*

Participants 4, 12 and 14 highlighted the importance for HR practitioners to have analytical thinking capabilities. Participant 4 indicated that HR practitioners receive a lot of data when tracking the progress of HR indicators that are contracted with line managers and business. It is essential to be detail-oriented and patient when working through data, as some of it may need to be cleaned up before it can be analysed and interpreted.

Participant 12 opined that the analysis and graphs done by the system were not enough to send to line managers. They still needed to be interpreted and incorporated into detailed reports. In essence, HR practitioners should be able to explain the 'so what' to line managers. They should be able to advise on what actions line managers must take, based on the analysis. This was corroborated by Participant 14 who indicated that they must be on the same decision page. Meaning that they must be able to analyse data and formulate decisions based on objective interpretation.

Conclusion on analytical skills

The participants indicated that analytical skill is one of the critical skills that HR practitioners need to have in order to be effective in making data-driven decisions. Technology and all other tools are there to assist. However, HR practitioners are still expected to interpret and advise business. They should, therefore, be able to use strong thinking capabilities to connect dots and make sense of the information presented by the system.

5.7.2 Theme 2: Technical skills – HRIS knowledge

HR data is analysed by using different technological HR information systems. The participants interviewed highlighted the importance of technical skills or system knowledge in ensuring the successful implementation of HR analytics and DDDM. The evidence is presented below.

Participant	**Quotation**
Participant 1	*"HR officials need to be trained on how to use the system and what type of information will be required to get the reports we are looking for."*
Participant 8	*"HR practitioners need to know how to use the current HR information system we have. It gives a lot of reports but each time they will tell you that the system is not user-friendly. It is all lies; the system works*

	perfectly. Now they are convinced that a new system should be bought. I am telling you, two years down the line, they will say it doesn't produce the reports they want."

Participant 1 highlighted the need to train HR practitioners on the technical platforms that are used in different organisations. They also indicated that this would ensure that the HR practitioners know the kind of data that needs to be captured, how to capture it on the system and how to download the reports necessary to make data-driven decisions.

Participant 8 was of the opinion that getting to know the system and how to use all its functionalities was essential as some HR practitioners claim that the systems are not able to produce the reports they want. Meanwhile, HR practitioners are not using the systems to their full potential because they do not have the competence to do so.

Participants 13 and 2 highly recommended that HR practitioners attend business or data analysis courses such as PowerBI. This is set to assist in understanding how system analysis works and reports outcomes.

Participant 13	*"I would definitely recommend the use of a data analytics systems for qualification or program. Or business improvement because business improvement is what we call power BI, which enables dashboard creation."*
Participant 2	*"I would also recommend an introductory basic level of business analysts courses, maybe even if it's short courses, so that we do understand what happens in the background in terms of, analytics and how you would pull the reports and also interpret the reports."*

Participant 5 opined that HR practitioners are not using systems fully because most of them are afraid to use the required data tools, and do not want to venture outside their comfort zone. The organisation has bought a good system which integrates all the human resource's data. However, because of fear, some HR practitioners ended up relying on others to help them analyse and produce reports. This slows down responsiveness to business requests. Participant 11 indicated that for HR practitioners to be effective, they should at least know how to use Excel to analyse data. Many do not need to have advance analytical skills as most organisations have data analysts who can perform the more advance analytics for them.

Participant 5	*"HR people are very scared of data tools. They need to move out of their comfort zone. The first thing that would help them will be to understand the tool; you don't need to understand the detail. You are then able to pull the data or reports at your earliest convenience. Instead, they are always asking for help and unable to help line managers on time."*
Participant 11	*"People need to understand the basics of analytics of, let's say, maybe basic Excel, and use of pivot tables. They do not have to do everything manually. Excel is a very good tool if you know how to use it. Advanced analytics can be left out to a few people or data analysts."*

Conclusion on digital literacy

The feedback from the interviews highlights the importance for HR practitioners to move out of their comfort zone and start to engage with HR information systems and available data tools. It was indicated that HR practitioners need to understand and know how to use all the systems' functionalities to download different reports without waiting for other users to assist. However, Participant 11, an HR data analyst, opined that HR practitioners are HR experts and not statisticians, hence, they should not be expected to have advanced statistical analysis skills.

5.7.3 Theme 3: Consulting skills

The participants indicated that HR practitioners need to learn from external consultants and treat line managers as clients who are paying a lot of money for services. They must act like internal consultants. The participants listed and discussed a number of skills, which the researcher grouped under the 'consulting skills' theme. Evidence of this data is presented and analysed below.

Communication through story telling.

Participants 4 and 12 highlighted the importance of analysing, interpreting reports and telling a compelling story to line managers. They indicated that HR practitioners need to have good presentation skills that enable them to help line managers understand what actions are required from them, without bombarding them with PowerPoint presentations filled with graphs and charts. This was likened to the manner in which consultants win clients over. This can only be possible when the HR practitioners act like subject matter experts, know the data intimately and are able to answer all the questions that the line managers would ask.

Participant	Quotation
Participant 4	*“I learned in my life that, sometimes people think to take very complicated graphs and stats to the exco, will be impressive to them. It isn't because they will ask you, okay, but what do you see? What are we going to do about whatever you are presenting?”*
Participant 12	*“There could be data that looks easy for me to understand, to interpret. But we should still be able to communicate in a manner that you are telling a beautiful story for the other person that you are presenting to.”*

Change management skills.

Participants 11 and 10 indicated that in most cases HR practitioners do not ask the right questions when requested to produce reports in order to advise business on certain topics. They are not confident to challenge and explore the requests from line managers. Often, data analysts are asked to analyse and produce reports that line managers are said to request, only to find that the challenge needed a different analysis and answer. This leaves the HR practitioner ill-equipped to advise business appropriately.

Participant 11	*“Our Chief Human Resource Officer always challenges us to ask ourselves what question we are answering or what are we solving for? Unfortunately, some HR practitioners do not have the confidence to ask questions and sometimes challenge the line managers so that they can understand what the real problem they are solving for is.”*
Participant 10 (a)	*“You need to be able to ask the right questions to understand what line managers want.*
Participant 10 (b)	*“Sometimes managers resist the recommendations and decisions from the analysis. We need change management skills to be able to engage with leaders.”*

Participant 10 was of the opinion that HR practitioners need change management skills so that they are able to influence business leaders to implement the decisions that emerge from analysing data. However, because most HR practitioners are not confident enough and do not have the consulting skills to be able to ask important questions, they waste time and effort providing wrong solutions to real problems.

Business acumen

Participant 12 used finance people as an example in pointing out how to command respect when reporting data by being able to speak in commercial terms. Similarly, HR personnel must understand what the business does and where the money comes from. It is not enough just to present data and graphs; one must speak the language that the business understands.

Participant 3 expressed that HR practitioners should have an integration mindset. This means that they should be able to connect the dots with regard to how the HR data and analytics align with the business performance needs. In that way, they should be able to clearly show how HR data-driven decisions add value to business performance.

Participant 12	*“When you sit in meetings and in these excos and finance is giving their feedback to business in terms of what they see happening in the business area, you can see these people, they're talking to the commerciality of the business. And I think we lack that. We need to talk to business in commercial terms, use their language. That can only happen if we understand how the business operates.”*
Participant 3	*“We need that integration mindset, the integration understanding of the business operations is very crucial skill. Understanding the business model allows us to link the HR analytics to what it means to the business. Your reporting also makes sense to the line managers.”*

<u>*Project management*</u>

Participant 8 was of the opinion that project management is a skill that HR practitioners should possess in order to implement decisions that are arrived at through analysing data from employee data.

Participant 8	*“We need project management skills. For example, when we receive the results from our employee engagement surveys, we treat the implementation of the interventions from the results as a project. We have realized that if we don’t do that, we end up not implementing what employees have said they need to see the previous year. They then start not to trust us and are reluctant to do another survey the next year.”*

5.7.4 Summary of findings of sub question 2

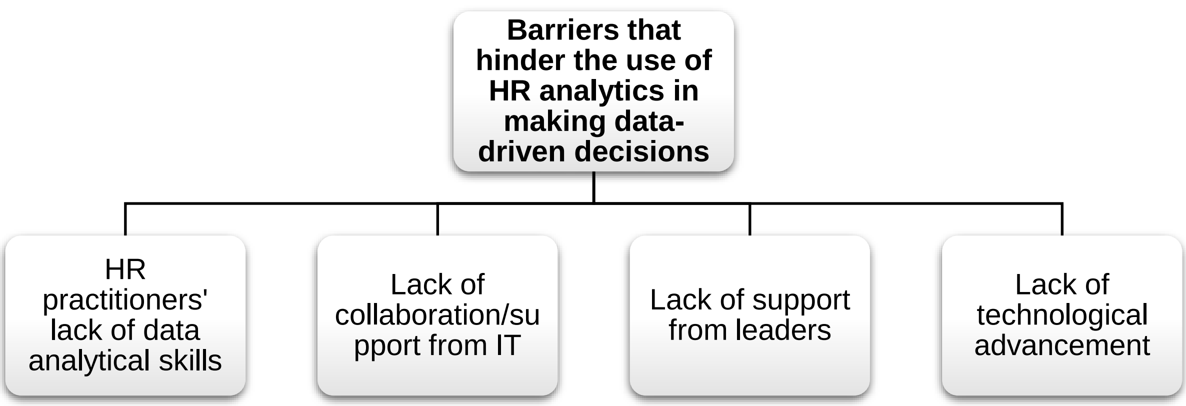
Consultants are seen as subject matter experts who have a combination of skills that enable them to influence line managers to buy into and implement advice. These skills include communication, influencing, business acumen, change management and project management. The interviews conducted revealed that there is need for HR practitioners to act as internal consultants who are subject matter experts and able to influence as well as advise line managers accordingly. When consultants speak to business leaders, the business or commercial language that the leaders understand should be used. This shows business acumen and commands respect from clients.

HR practitioners need to demonstrate understanding of how the business operates. They would then be able to advance credible solutions like other employees from sales and finance departments. Participants also expressed the need to project manage the implementation of the HR interventions identified. Hence, change and project management skills are useful.

5.8 Sub question 3 What are the barriers that hinder the effective application of HR analytics and DDDM?

The purpose of this question was to find out what challenges hindered HR practitioners from fully adopting and utilising HR analytics to make data-driven decisions. The responses from the interviews were grouped into four themes as depicted below.

Figure 13: Themes on barriers that hindered HR practitioners from using of HR analytics and DDDM



5.8.1 Theme 1: HR practitioners' lack of analytical skills.

The lack of analytical skills by HR practitioners was underscored as one of the barriers that hinder the effective application of HR analytics and DDDM.

Participant	Quotations
Participant 12	*"As behavioral scientists, it normally gives us some jitters when people talk about HR analytics. Even though it's something that's in front of*

	you that you can just look at and analyze. We still see it as an insurmountable task. Numbers are not our natural inclination."
Participant 10	*"What is missing is the human appetite to immerse ourselves in this thing called analytics. The HR practitioners in our organisation are always asking for help to analyse data and are scared to do it themselves."*
Participant 9	*"We need to move out of our comfort zone and learn more about analytics"*

Analytical competency of HR practitioners

The feedback from the participants indicated that whilst being analytical is acknowledged as important for the people management support role, most HR practitioners are afraid of analytics because it includes working with numbers. Participant 12 indicated that HR practitioners are behavior scientists and therefore more comfortable to work with peoples' behavior rather than analytics. However, given sufficient time and coaching, these professionals can be guided to understand the data, and to analyse it. However, it is still regarded a significant task.

Participant 10 indicated that what made HR practitioners scared of numbers was a lack of passion and the appetite to learn about analytics. For example, when an organisation introduced a new HRIS, most of the HR practitioners were trained but remained reticent to use the new skills. Instead, these professionals resorted to asking for help and relying on others to analyse the data, whereas the system was available for all to access. Participant 9 opined that HR practitioners should move out of comfort zones and start engaging with data to become comfortable working with it.

Additional perspective from the HR data analyst

Participant 11 expressed the need for capacity-building and training. Working closely with practitioners has made the respondent realise that the majority of HR personnel need training on how to handle and analyse data. Typically, HR practitioners do not have a math or statistical background, and therefore find it difficult to work with numbers.

Participant 11 (a)	*"HR managers need some capability building when it comes to basic analytics. So, it's not like they must all become statisticians. They just need to understand the basics in order to be more effective."*

Participant 11 (b)	*"We also need to note that analytics is not only quantitative, but also qualitative."*

Additionally, participant 11 also highlighted that data was not always in numbers but also qualitative in nature. Organisations must therefore invest money to train HR practitioners on basic analytical tools, such as in using Excel in order to be able to analyse qualitative and quantitative data.

<u>Conclusion on HR practitioners lack of data analytics skills.</u>

Analysing data includes working with numbers. The feedback from the interviews highlighted that as HR practitioners are behaviour scientists and hence may find working with numbers or data to be an insurmountable task. For them to be comfortable and confident, training on basic data analytical tools, such as Excel is essential. Individuals should also have the appetite to take initiative and engage with the data and the systems available. The HR data analyst also pointed out that data is often qualitative as well as quantitative. HR practitioners should be capacitated to be able to analyse both qualitative and quantitative methods. Taking into consideration that it is not about becoming statisticians but grasping the ability to perform basic analytics.

5.8.2 Theme 2: Lack of technological advancement in the HRIS used.

The interviews revealed that HR practitioners are aware that digital transformation and advance technology can simplify data analytics processes. However, since HR is a cost centre, most organisations are not willing to invest money in expensive HR information systems.

Participant	**Quotation**
Participant 4	*"Our technology is outdated and poorly maintained. There is lots of manual intervention in terms of cleaning the data, when you get to the actual analysis, you are exhausted and can easily make mistakes."*
Participant 5	*"We are undermining the pace that technology through digital transformation is changing at. We can't even invest in a single solution in terms of the system, how are we going to move to systems such as your machine learning and AI."*

Some organisations' system have remained basic, and have not changed with the pace of technology. Participant 4 indicated that because the company system was poorly maintained and outdated, staff often end up having to manipulate data manually, leaving it susceptible to human error. Participant 5 expressed the need for HR to quickly adapt to the pace of change. Unlike other departments, such as Finance, HR is perceived to be very slow with limited investment in HR-related technology. Continuing at this pace is set to result in HR taking a long time to start using advanced technology such as machine learning and artificial intelligence.

Participant 6	*"Currently we have challenges with data integrity because of the system that is not integrated. So, once we can get the right system to support that and then it will be much easier for the dashboard to help with the right reporting as well in."*
Participant 11	*"Currently it's a bit of a struggle because when our business is requiring certain reports, it takes quite a long time to respond because of fragmented systems. And then you lose that confidence as practitioners from the business side."*

Participants 6 and 11 indicated where different non-integrated systems are used, there are big challenges with data integrity. Participant 11 was of the opinion that more advanced HR information systems will give HR practitioners an opportunity to partner with line managers. They would be able to respond quickly to requests as the system would make HR analytics easier, faster, just-in-time and more reliable.

5.8.4 Summary of sub question 3

The interviews conducted revealed that although HR practitioners may be willing to use HR analytics to make and implement data-driven decisions, sometimes barriers are encountered that hinder success. Some of the barriers identified, such as HR practitioners lack of data analytics are internal and within the HR practitioners' control. It was highlighted that HR practitioners need to take action and start learning to be comfortable in dealing with quantitative and qualitative data. It was also highlighted that HR needs to keep up with the pace of digital transformation and technological systems. The lagging behind hinders HR practitioners from responding on time to requests from line managers. This has a negative impact on credibility and ability to be strategic partners to line managers.

5.9 Chapter conclusion

The aim of this research was to explore how HR practitioners use HR analytics to make data-driven decisions in organisations. In order to gather more information on this topic, the participants were asked to respond to one main question and three sub-questions.

The main research question was asked to ascertain the extent and depth to which HR practitioners are using HR analytics to make data-driven decisions. The interviews revealed that the majority of the HR practitioners have partially adopted the use of HR analytics to enable DDDM. However, the competency has not yet been utilized effectively to its full potential. The findings revealed that data integrity, HR practitioners analytical skills and technological systems needed to be in place for HR practitioners to fully adopt and utilise HR analytics to enable DDDM. Organisations whose adoption and utilisation of HR analytics and DDDM was low indicated that data integrity was the biggest challenge. The data used for analysis was of poor quality, and therefore the reports were unreliable, untrustworthy and unpredictable.

Organisations that indicated that partial adoption of HR analytics and DDDM had challenges with either the HR practitioners' data analytical skills or the systems used to analyse data. In cases where the HR practitioners are willing and knowledgeable, the systems used were not well-integrated. This results in some analyses being manually executed and leads to errors. On the other hand, where the system was advanced and well-integrated, the HR practitioners were not using the some of the functionalities that could assist them with reports that provide more depth than the standard descriptive dashboard reports traditionally produced. As a result, advanced functionalities are not used to produce predictive analysis that could advise line managers to take certain actions to mitigate future risks.

The **first sub question** sought to understand the type of data-driven decisions that the HR practitioners have made. The findings revealed that cost containment, recruitment and HR interventions are some of the decisions that are made based on the results of HR analysis. It was noted that decisions relating to cost-containment ensure that HR also contributeds to cost-saving exercises that organisations have been embarking on.

Although HR departments are regarded as cost centers, they were still expected to help track expenditure on human resources and advise line managers on potential for savings. In addition, HR practitioners have the responsibility of bringing the right people into the organisation. They use different data sources such as interviews, assessments, employee profiles and readiness levels to decide on the right internal or external candidate to appoint. Finally, HR practitioners used the data gathered from annual employee engagement surveys to decide on which interventions to design and implement.

The **second sub-question** explored the different skills that HR practitioners need to have in order to use HR analytics to make data-driven decisions. The responses from the participants were grouped into analytical skills, technical and consulting skills. It was noted that being detail-oriented, patient and having the ability to connect the dots through storytelling were skills that HR practitioners should possess.

This goes together with consulting skills. The participants indicated that HR practitioners should apply the skills used by consultants such as: 1) being able to ask the right questions in order to find out the real challenges line managers were facing; 2) act like subject matter experts and knowing the data intimately in order to answer all questions from line managers; 3) use change management skills in order to deal with any resistance from line managers; 4) preparing good visual presentations and presenting reports and decisions made in a professional manner; and 5) use project management skills to manage the implementation of HR interventions decided on.

The participants also indicated that since technology is key in analysing data, HR practitioners must be technically astute. They need to be able to work with the HR information systems available in organisations, as well as other data analytical tools such as Excel and PowerBI. Finally, HR practitioners need to understand how business operates. This would enable them to integrate analytics with what is happening in the business. Being able to talk in commercial terms like the other teams from finance departments would also help the HR practitioners to gain credibility with line managers.

The aim of the **third sub question** was to explore some of the challenges that hinder HR practitioners from fully using HR analytics to make data-driven decisions. The participants indicated that HR practitioners’ lack of data analytical skills led to them being fearful and lacking the confidence to work with numbers. This stands in the way of them working with HR analytics. The lack of technological advancement put HR on the backfoot of digital transformation and progress with regards to innovative ways of analysing data. As a result, these professionals often struggles to apply HR analytics fully when making data-driven decisions.

CHAPTER 6: DISCUSSION OF FINDINGS

6.1 Introduction

The purpose of this chapter was to discuss the findings that were outlined in Chapter 5. The outcomes are discussed by comparing them with the literature presented in Chapter 2. This helps to interrogate the findings from the interviews to assess alignment with existing knowledge and identify new information that emerged. In order to ensure rigour and internal validity, a systematic, consistent process was followed throughout the discussion.

Similair to approach in Chapter 5, the findings are discussed in line with the research questions outlined in Chapter 3. The main research question, its themes, the sub questions and related themes were used as a conceptual framework depicted in **Error! Reference source not found.** that was followed to discuss the findings. The themes were analysed and compared with the literature to draw conclusions. The following steps were followed:

Step 1

Keywords from the themes in the findings were chosen and searched from three articles included in the literature review in Chapter 2. The keywords are indicated in the research paper.

Step 2

Three articles with the selected keywords were read again and the literature compared and analysed against the findings. If the keyword were not found on the chosen articles, then the researcher moved to complete step 3.

Step 3

This entailed keyword searching on Google Scholar alongside comparison with literature and the findings of this study. If there was no comparison or alignment in the literature, the findings were regarded as new contributions.

6.2 Research question 1: What is the extent of the adoption and utilisation of HR analytics and DDDM in your organisation?

6.2.1 Theme 1: Low adoption and utilisation of HR analytics and DDDM

6.2.1.1 Evidence of low adoption and utilisation of HR analytics and DDDM from findings

The findings from the interview indicated that although systems are becoming available, the data analysis competency is lagging and often unreliable. There are challenges with regard to data integrity; this is a critical barrier to the adoption and utilisation of HR analytics and DDDM. Unreliable data takes away the confidence of presenting the findings and decisions to line managers.

Insight from literature stresses the importance of having good quality data for data analytics and DDDM to be effective. According to Ghasemaghaei et al. (2017) data quality is one of the core competencies that organisations should possess in order to make data analytics effective in an organisation. Hence, it has to be arranged in a manner that it can be navigated and used to solve organisational challenges. Andersen (2017) is of the opinion that if data that is captured is garbage, therefore the outputs will also be garbage. This means that if the quality of data is questionable, the analytics, reports and decisions made will be similarly so.

Gokalp et al. (2018) developed the data analytics maturity assessment framework (DAMAF) that measures the extent to which processes have matured with regards to data analytics. The authors posit that organisations that have unreliable and unpredictable data analytics results are at the initial stage in the data analytics maturity. Accordingly, this is one of the reasons HR analytics is lagging behind as the data analytics are unreliable and unable to solve challenges faced by business (Andersen, 2017). To that end, the quality of data that is used and manipulated through technology is critical in producing reliable reports with practical and applicable recommendations to influence organisational performance (Minbaeva, 2018).

HR practitioners need to ensure that the data they use is of good quality, credible and smart (Schiemann et al., 2018; Triguero et al., 2018). Garcia-Arroyo and Osca (2021) recommend that before data can be collected; there should be a plan in place on how it will be organised, stored and interpreted.

6.2.1.3 Comparative analysis between findings and literature

The research findings indicate that the one participant was working for an organisation that in their opinion the adoption and utilisation of HR analytics and DDDM was low. This was due to the unreliability of the data. Hence, they did not feel confident in using the data analytics from the system to advise line managers on decisions and actions to take. This is consistent with literature. According to Andersen (2017) bad quality data is one of the elements that hinders organisations from maturing in their data analytics. Data has to be reliable to produce reliable reports that could give practical and applicable recommendations to line managers (Minbaeva, 2018).

DAMAF shows that organisations that are at ML1 (initial) stage of maturity with regards to the use of data analytics are not data-driven (Gokalp et al., 2021) Their data is unpredictable. The research findings also indicate that because of lack of data integrity, which means that the data and the analysis was unreliable, the HR practitioners would prefer to use their own knowledge, expertise and gut feel to make decisions.

6.2.1.4 Conclusion on low adoption and utilisation of HR analytics and DDDM

There were no differences between the research findings and the available literature. The findings confirmed that good quality data is the foundation for organisations to mature through data analytics stages. When practitioners question the integrity of the available data, they will not be confident to use the results of the analysis. Hence, they will rely on their knowledge and gut feel. Their adoption and utilisation of HR analytics and DDDM will definitely be low. According to literature, they will be at the initial stages of data analytics maturity.

6.2.2 Theme 2: Partial adoption and utilisation of HR analytics and DDDM

6.2.2.1 Evidence of partial adoption and utilisation of HR analytics and DDDM from findings

The findings revealed that the majority of organisations have partially adopted and utilising HR analytics and DDDM. They were not using it to its full potential as there are different systems used to capture and analyse data. Unfortunately, these systems are not well-integrated. This made it difficult for HR practitioners to produce certain reports that line managers may request. This also hinders line managers from interacting with people data without calling on HR practitioners to provide them with information.

The findings also revealed that there are organisations with good, well-integrated systems that can produce reliable analytics that will enable them to make reliable data-driven decisions. However, HR analytics and DDDM are not fully adopted and utilised due to the lack of necessary skills and confidence from HR practitioners. practitioners are not fully utilising the system to. They are scared of the system and always revert to analysing data manually or asking for help from their colleagues. They would rather stick to the normal dashboard reporting that does not help line managers in solving business challenges they may be facing.

The findings further revealed that some organisations have good systems in place and were using them for HR analytics and DDDM. However, they were only producing descriptive reports. They would like to move beyond being descriptive, to include predictive analysis. Unfortunately, the systems have not yet been programmed to conduct predictive analysis. In addition, they were not asking the right questions that would help them to predict what would happen in the future. This would enable them to make decisions that would assist organisations in mitigating future risks.

The findings also revealed that the majority of these organisations use the results of predictive and prescriptive analysis, which is level 2 and 3 of the HR analytics model, gathered by external service providers.

6.2.2.2 Evidence of partial adoption and utilisation of HR analytics and DDDM from literature

The insight from literature pointed out that although HR has been tagged as lagging behind with regards to the use of analytics and DDDM, Davenport (2019) found that HR analytics has become predictive. This, however, was still a debate amongst researchers and practitioners. Margherita (2022) and Mohammed (2019) agreed that organisations that are still using descriptive analysis are at the first level of HR analytics maturity. Their HR practitioners report on what has happened in the previous period under review. The reporting focuses using information gathered within and outside the organisation from different data sources to explain or describe the past (Margherita, 2022). The focus was on reporting on the HR dashboard/scorecard that shows how HR has achieved its metrices through different charts and diagrams that may be depicted by using Excel spreadsheets or PowerPoint (Mohammed, 2019).

Furthermore, the HR practitioners used simple statistical analysis that do not provide the depth needed to make value-adding, evidence-based organisational decisions as organisations are complex in nature (Minbaeva, 2018; Kryscynski et al., 2018). They were not competent nor comfortable to use more sophisticated analytical tools that will enable them to move from being descriptive to predictive analysis (Vargas et al., 2018; Álvarez-Gutiérrez et al., 2022). The data analytics maturity assessment model (DAMAF) states that organisation's data maturity levels range from ML0 to ML6 (Gokalp et al., 2021). Organisations at ML2 (managed) show that these organisations are starting to appreciate the value of data analytics. Their data is systematically managed, and frameworks and model have been developed to be followed by different departments. Those at ML3 (defined) have started to incorporate data analytics in all other processes in the different departments. A standardized approach to data analytics is followed by all the departments.

6.2.2.3 Comparative analysis between findings and literature

The research findings revealed that the majority of HR practitioners and organisations have not yet fully adopted the utilisation of HR analytics and DDDM. Some organisations have good systems that were well-integrated and able to produce reports that will enable HR practitioners to have good conversations with line managers and advise them accordingly. However, the HR practitioners were not skilled to use the systems to their full potential. This was due to HR practitioners' lack of the necessary analytical skills (Álvarez-Gutiérrez et al., 2022). Although scholars would like to see organisations mature to using predictive and prescriptive analysis, about 80% of organisations surveyed indicated that they preferred using descriptive analytics (Peeters et al., 2020). Hence the HR practitioners were comfortable with only producing standard dashboard reports that describe or track what has happened in the past month or quarter.

On the other hand, other organisations had systems that were basic, not well-integrated, and poorly maintained. As a consequence, HR practitioners had to sometimes manually manipulate the data to produce good reports that will enable them to advise line managers. The HR practitioners used their Excel knowledge to prepare PowerPoint presentations they could share with line managers.

The HR analytics model show that organisations that have partially adopted the use of HR analytics are at level 1 of the maturity level. This is called the descriptive level where the analysis conducted are focused on what has happened or what is currently happening (Mahomed, 2019 & Margherita, 2022). Unfortunately, the majority of organisations were stuck at this level. They have yet to move to level 2 where the analysis would be predictive in nature. However, the majority of the organisations also showed that they conduct employee engagement surveys that help predict what would happen if the organisation's culture does not change or improve, as well as prescribe the kind of interventions they need to implement in order to improve employee engagement and retention (Margherita, 2022). On the other hand, the DAMAF analytical model revealed that organisations would first need to achieve ML2 and ML3 where the data analytics were managed or piloted and defined or standardized (Gokalp et al., 2021).

6.2.2.4 Conclusion on partial adoption and utilisation of HR analytics and DDDM

This study found that there were similarities in the manner in which literature and findings defined organisations that have not yet fully adopted and utilised HR analytics and DDDM. The findings revealed that because of the imbalances or lack of alignment between the system and HR practitioners' capability, only descriptive analysis was used. If these organisations' maturity levels were to be rated using the HR analytics model as postulated by Mohammed (2019) and Margherita (2022), they would be at level 1 of the maturity level. However, there appears to be some nuances that could be added in the descriptions of these identified maturity levels. When closely analysing the findings, the researcher noticed that although the organisation may be operating at level 1, there are certain elements of level 2 that were evident.

On the other hand, if the DAMAF were to be used to assess the extent in which they consistently apply HR analytics and DDDM, they would be somewhere between ML2 and ML3 as the approach and system still needed to be standardized and integrated across the different departments. Finally, as indicated in literature, the majority of organisations were stuck in descriptive analytics. This was similar to the findings of this research.

6.2.3 Conclusion on research question 1

The aim of this question was to find out what the extent or depth of HR analytics and adoption and utilisation in enabling DDDM was. The findings confirmed the extant literature with regards to the descriptions provided on organisations that have yet to adopt, and those that have partially adopted the utilisation of HR analytics. They confirmed that the two most important factors (HR analytical capability and technological infrastructure) need to be in place for HR analytics and DDDM to be effective. The absence of either one of them disabled HR practitioners from fully implement HR analytics.

The findings also confirmed that good quality data was the foundation for organisations to mature through data analytics stages. When practitioners question the integrity of the available data, they will not be confident to use the results of the analysis. Hence, they will rely on their knowledge and gut feel. Their adoption and utilisation of HR analytics and DDDM will definitely be low. According to literature, they will be at the initial stages of data analytics maturity.

The findings therefore revealed that majority of organisations were at level 1 HR analytics maturity level, which is descriptive analysis. However, there appears to be some nuances that could be added in the descriptions of these identified maturity levels as organisations also use predictive and prescriptive analytics for employee engagement surveys. These nuances will be discussed in detail in chapter 7.

6.3 Sub-question 1: What HR data-driven decisions have you made that were informed by HR analytics?

6.3.1 Financial decisions that enable cost containment.

6.3.1.1 Evidence of financial decisions that enable cost containment from findings.

Although HR is regarded as a cost centre as it does not directly bring money to the business, the activities and decisions that are made by HR practitioners have an influence on the finances of their organisations. With most organisations going through cost saving exercises HR is expected to contribute by ensuring that issues such as turnover, attrition, recruitment costs and injuries are managed tightly. From the interviews conducted, it was made clear that HR practitioners were expected to be proactive by implementing measures to ensure that costs were contained.

6.3.1.2 Evidence of financial decisions that enable cost containment from literature.

In determining the HR analytics that have an impact on business performance, Harris et al. (2011) cited in Marler and Boudreau (2017) argue that although HR analytics may help organisations in identifying and saving costs, those savings were too little to have an impact on the business. They maintained that HR costs were only administrative in nature. However, Boakye and Lamptey (2020) posit that HR analytics assist organisations in saving more money than just administration costs. They argue that HR analytics, specifically predictive analysis, have the ability to help organisations in determining the chances of employees leaving the organisation (Mohammed, 2019).

Sousa et al. (2019) posit that HR functions are given the responsibility of saving costs by managing the spend on employee salaries, training expenditures, workforce planning, and any other people related costs they may have agreed upon. In addition, organisations save on huge amounts of money associated with recruitment costs, onboarding and training new employees, who would be replacing those that have resigned (Mohammed, 2019).

6.3.1.3 Comparative analysis between findings and literature

The research findings revealed that HR practitioners viewed themselves as contributing to the organisation's cost saving exercises. They indicated that their ability to track, analyse and report on HR KPIs such as hours worked, overtime worked and paid, productivity levels, recruitment costs, safety incidents and other HR related measures assisted their organisations to save costs. In addition, costs associated with salaries, training and workforce planning were tracked and helped organisations to make decisions that will curb unnecessary spending (Sousa et al., 2019).

The insights from literature indicated that although there was an appreciation of the benefits that HR analytics bring to organisations, the financial benefits have not been clearly articulated (Boakye & Lamptey, 2020). Hence, scholars such as Harris et al. (2011) cited in Marler and Boudreau (2017) argued that in only tracking and reporting on costs, HR was making a very small contribution to cost saving.

The findings further revealed that the majority of HR practitioners were using the results from their employee engagement surveys to implement interventions that would save the organisations money. This is similar to what was advanced by Mohammed (2019).

6.3.1.4 Conclusion

The findings confirmed were similarities in how the HR practitioners and literature viewed the manner in which data-driven decisions helped organisations to save costs. These were agreed on at an HR KPI level.

Literature also revealed that there could be some slight differences with regards to the amount of money could HR analytics help the organisation to save. Findings revealed that the practitioners believe that they were saving organisations a lot of money. On the other hand, there were scholars who held different views.

6.3.2 Theme 2: Recruitment decisions

6.3.2.1 Evidence of recruitment decisions from findings.

The insights gathered from the interviews revealed that recruitment is one of the fundamental responsibilities for HR practitioners. They are held accountable for bringing the right talent in the organisation. For that to happen, they need to remove all subjectivity from the process. Hence the use of data gathered through assessments such as leadership assessments to appoint the right caliber of leaders that fit their leadership competency profiles.

The HR practitioners also use data gathered in the organisation to develop workforce plans that inform their resource strategies. These help them to decide on the number of employees to appoint, whether permanently or on contract.

Finally, the findings also revealed that data on the readiness of employees help HR practitioners and line manager to decide on which employees to promote or move to another department or area.

6.3.2.2 Evidence of recruitment decisions from literature

HR analytics is critical in helping HR managers to use data when making decisions associated with workforce planning, recruitment, selection, training, and retention (Mohammed, 2019). Boakye and Lamptey (2020) assert that by using HR analytics to make recruitment decisions, a lot of mistakes have been removed from the process. They maintain that HR analytics enable the recruitment team to be objective and appoint the right people for the right positions at the right level. This is also made possible through the use of predictive modelling, which is level 2 on the HR analytics maturity model (Mohammed, 2019).

In addition, advanced technologies such as AI and machine learning also help improve the rate at which recruitment decisions are made. These tools extract and highlight information from a CV for the HR practitioners to zoom in, analyse and profile the candidates against the advertised position, transcribe the interview and analyse the transcription, as well as predict the right candidate to appoint (Álvarez-Gutierrez et al., 2022; Ben-gal, 2018). As a result, HR analytics show return on investment of the statistical tools and systems used (Ben-gal, 2018). Hence organisations are moving towards digitilising their recruitment processes (Minbaeva, 2018).

6.3.2.3 Comparative analysis between findings and literature.

The findings confirmed extant literature with regard to the role that HR analytics play in helping HR practitioners to make recruitment decisions (Mohammed, 2019). By using HR analytics to make recruitment decisions, both the findings and literature show that subjectivity and human errors have been removed from the process Boakye and Lamptey (2020).

They maintain that HR analytics enable the recruitment team to be objective and appoint the right people for the right positions at the right level. This is also made possible through the use of predictive modelling, which is level 2 on the HR analytics maturity model (Mohammed, 2019).

The findings also revealed some nuances in that the majority of the organisations are stuck in level 1 of the HR analytics maturity model (Margherita, 2022; Mohammed, 2019) as indicated in the main research question. This means that these organisations are lagging behind with regard to technological advancements such as AI and machine learning. Thus, they are unable to extract and highlight information from a CV for the HR practitioners to zoom in, analyse and profile the candidates against the advertised position, transcribe the interview and analyse the transcription, as well as predict the right candidate to appoint (Álvarez-Gutierrez et al., 2022; Ben-gal, 2018). As a result, HR practitioners are unable to show return on investment of the statistical tools and systems as indicated by literature (Ben-gal, 2018).

6.3.2.4 Conclusion on recruitment decisions

The findings confirmed similarities in using HR data and analytics to make recruitment decisions. HR practitioners use leadership assessments, employee readiness data from the system, and the production data to decide on who to appoint, number of people to work on the production line and employees eligible for internal mobility.

The findings also confirmed that the majority of organisations are lagging behind with regards to the use of advanced data analytical tools such as AI and machine learning in recruiting people.

6.3.3 Theme 3: Decisions that inform interventions to be implemented.

6.3.3.1 Evidence of decisions that inform interventions to be implemented from findings.

The findings from the research indicated that HR practitioners used insights from the HR analytics to design and implement HR interventions that helped to close people-related gaps identified during employee engagement surveys and discussions. The interventions implemented help in improving the organisations' cultures, employee engagement, productivity and employee retention.

The findings further revealed that HR practitioners and line managers were able to design and implement customised leadership development programmes to answer specific business challenges. These also included learning and development, or training interventions identified through skills audit surveys and interviews. Through the intelligence that was gathered through surveys, observations and interviews, HR practitioners were also able to implement learning channels that made the development of employees more effective.

6.3.3.2 Evidence of decisions that inform interventions to be implemented from literature.

The insight from literature highlights the importance of understanding the business challenge or its contribution to the organisation's strategy and performance, before developing and agreeing on a particular HR metric (McIver et al., 2018). This is because the HR analytics conducted and decisions made are derived from the data collected through tracking HR metrices (Huselid, 2018; McIver et al., 2018). This is due to HR metrices being the foundation for HR analytics. This will then influence the intervention to be implemented. Thus, elevating the role of HR practitioner from just performing transactional activities, to being a strategic partner of the business.

McIver et al. (2018) and Peeters et al. (2020) also agreed that HR analytics was a research-based field and should provide research-based solutions. As a result, apart from only analysing data, HR practitioners should be able to conduct research to find out alternative ways of solving an organisation's specific challenge that is aligned to its strategy. The findings should not only benefit the organisation, but the employees as well. They should be able to improve job satisfaction and employee engagement, contribute positively to employee wellbeing and allow opportunities for employees to grow and develop within the organisation (Gal et al., 2020). Consequently, leading to high employee retention rate (Marr, 2018).

Margherita (2022) and Mohammed (2019) agreed that when HR analytics move from being descriptive to predictive and prescriptive analysis, HR practitioners were enabled to design, develop and implement HR interventions that were informed by data. They could be used to predict the turnover rate of an organisation. Consequently, they would be able to decide on different alternatives to take that would guide the organisation to probably change or improve its decisions (Margherita, 2022). Through the use of these surveys, HR practitioners would also be able to use that information to plan and implement different.

Finally, some of the interventions that could be informed by HR analysis include compensation and reward programs, learning and development, and leadership development programmes (Hamilton & Sodeman, 2020).

6.3.3.3 Comparative analysis between findings and literature

The research findings revealed that there were similarities in how HR practitioners and literature viewed the data-driven decisions made on HR interventions to be implemented. HR practitioners use the results from employee engagement surveys conducted to decide on which HR interventions to implement (Margherita, 2022; Mohammed, 2019). These interventions contributed to employee satisfaction, improved productivity and performance as well as employee retention (Huselid, 2018; McIver et al., 2018). HR practitioners also used the insights gathered from the surveys to decide on learning and development interventions to implement, customised leadership development programmes and BBBEE targets to be met.

In essence, from the findings it could be deduced that HR practitioners used research approach and methods, albeit not formalized, to solve business challenges by first understanding what they would be solving for, collect data, analyse it through different analytical tools, interpret it and make data-driven decisions based on the findings (McIver et al., 2018; Peeters et al., 2020).

6.3.3.4 Conclusion on decisions that inform interventions to be implemented.

The findings from the study confirmed the literature regarding the data-driven decisions made regarding HR interventions to be implemented (Huselid, 2018; McIver et al., 2018). HR interventions is therefore confirmed as a data-driven decision that HR practitioners make in order to improve the organisation’s culture, job satisfaction and employee retention.

6.3.4 Conclusion on sub-question 1

The purpose of this question was to find out the type of data-driven decisions that HR practitioners made to show the use of HR analytics in enabling DDDM. The study identified four themes, however only three 1) decisions that contributed to cost containment, 2) recruitment decisions and 3) decisions relating to HR interventions to be implemented were analysed.

The findings confirmed similarities in how the HR practitioners and literature viewed the manner in which data-driven decisions helped organisations to save costs. These were agreed on at an HR KPI level. However, the study also revealed that there could be some slight differences with regards to the amount of money HR analytics help the organisation to save. These will also be discussed in detail in chapter 7.

The findings from the study further confirmed the literature regarding the data-driven decisions about the HR interventions to be implemented. (Huselid, 2018; McIver et al., 2018). HR interventions is therefore confirmed as a data-driven decision that HR practitioners make in order to improve the organisation's culture, job satisfaction and employee retention.

6.4 Sub-question 2 What are the skills that HR practitioners need in order to be competent in fully utilising HR analytics to make data-driven decisions?

6.4.1 Theme 1: Analytical skills

6.4.1.1 Recap of analytical skills from findings

The participants indicated that analytics is one of the critical skills that HR practitioners need to have in order to be effective in using HR analytics to make data-driven decisions. Technology and all other tools are there to assist, however HR practitioners are still expected to interpret and advise business accordingly. They should just be able to use their thinking capabilities to connect the dots and make sense of the information presented to them by the system. This meant that they should be detail-oriented and be patient to deal with lots of data that may need to be cleaned up first.

6.4.1.2 Recap of analytical skills from literature

Analytics is complex and requires different skills in each of its steps of collecting, sifting, manipulating and interpreting the reports (Vargas et al., 2018). This means that at each step (gathering data, developing analytical methods, analysing and interpreting data) in HR analytics, HR practitioners are required to have specific competencies. Kryscynski et al. (2018) maintained that for HR practitioners to add value in their organisations, they needed to be more comfortable in working with data and analytics. This includes working with statistics or numbers. Minbaeva (2018) argued that analytical skills were not only about the knowledge of statistics, but about the ability to tell a data story. Meaning that HR practitioners should be able to use their analytical thinking abilities to analyse and interpret the data in front of them and tell a story that made sense to line managers and the business.

Ghasemaghaei et al. (2017) concluded that people who want to work with data must be good in analytics, they need to have high cognitive and reasoning powers. This will enable them to be competent in analysing and interpreting the data and relationships between the data sets in order to gather insights to make well-informed and impactful decisions (Zaitsava et al., 2022). This challenges them to harness their thinking capabilities beyond their knowledge and experiences.

6.4.1.3 Comparative analysis between findings and literature

The findings from the research indicated that analytical skills are one of the critical skills that HR practitioners should possess in order to be able to apply HR analytics in making data-driven decisions. Besides being able to use statistical methods and tools to analyse the data, the findings revealed that the HR practitioners needed to have thinking analytical capabilities, be detail-oriented and patient when working with data.

There appears to be similarities between the findings and extant literature with regard to the requirement for HR practitioners to possess analytical skills. Ghasemaghaei et al. (2017), (Zaitsava et al., 2022), (Vargas et al., 2018), Kryscynski et al. (2018) and Minbaeva (2018) agree that the HR practitioners' thinking abilities, reasoning powers and the ability to interpret data and tell a story from it are critical skills and must be deeper than how it was articulated in the findings. also maintain the HR practitioners' analytical skills must be high.

6.4.3.4 Conclusion on analytical skills

The findings from the study confirmed the extant literature with regards to the importance of having analytical skills in order to use HR analytics to make data-driven decisions. They both concur that without the analytical skills, HR practitioners were unable to engage with line managers and were therefore not taken seriously. They therefore needed to have high cognition and reasoning powers, be able to use logic to connect the dots and present a compelling and meaningful story to line managers.

6.4.2 Theme 2: Technical skills – HRIS knowledge

6.4.2.1 Recap on technical skills from findings

HR data is analysed by using different technological HR Information systems. The findings highlighted the importance of technical skills or system knowledge and support in ensuring the successful implementation of HR analytics and DDDM. The feedback from the interviews highlighted the importance of HR practitioners to move out of their comfort zone and start to engage with their HR information systems or data tools available in their organisations. It was indicated that HR participants need to engage with their HRIS, understand and know how to use all its functionalities so that they can be able to download different reports without waiting for other users to help them. This will help in reducing the response time to business requests.

The findings also highlighted by one of the HR data analysts that HR practitioners did not need to have advance statistical analytical skills because there are data analysts who would perform the statistical analysis for them. They just needed to have a basic understanding of statistics and the ability to use simple analytical tools such as Excel. The participants also expressed the importance of continuous learning and challenge HR practitioners to study courses on data or business analytics.

6.4.2.2 Recap on technical skills from literature

Technical or systems knowledge has been identified as an important skill that HR practitioners should possess in order to apply HR analytics and DDDM (Green, 2017; Álvarez-Gutiérrez et al., 2022; Huselid, 2018). Kryscynski et al. (2018) maintain that part of being able to analyse data is the ability to use the available HRIS and different statistical tools in the organisations. Currently, most HR practitioners use simple statistical analysis that do not provide the depth needed to make value-adding, evidence-based organisational decisions as organisations are complex in nature (Minbaeva, 2018; Kryscynski et al., 2018). They are not competent nor comfortable to use more sophisticated analytical tools that will enable them to move from being descriptive to predictive analysis (Vargas et al., 2018). Thus, some leaders undermine the strategic role played by HR.

Kryscynski et al. (2018) maintain that appointing a team that is responsible for HR analytics would mitigate the challenge of not being taken seriously by business. This team should comprise of members with deeper knowledge and understanding of the HRIS, and advanced statistical analytical skills to assist the HR practitioners in performing predictive and prescriptive analysis (Mohammed, 2019; McCartney et al., 2021). This include using professional visuals such as graphs and charts that are appealing to the end use (Peeters et al., 2020).

6.4.2.3 Comparative analysis between findings and literature

The findings from the research confirmed that HR practitioners needed to have knowledge of the HRIS in order to apply HR analytics as indicated in extant literature. The ability to use all the system's functionalities would help them in being able to make use of the system to its fullest potential by analysing and downloading reports that would provide depth and value-add to the business (Kryscynski et al., 2018). They would also be able to respond timeously to business requests without waiting for other users to help them.

Similarly, findings revealed that HR practitioners needed to be trained on how to use the systems as stated in literature (McCartney et al. 2021). There are also similarities with regards to the extent or depth of knowledge that HR data analysts should have (Vargas et al., 2018; Kryscynski et al., 2018). Both findings and literature indicate that HR analysts, and not HR practitioners should have more advanced statistical analytical skills.

6.4.2.4 Conclusion on technical skills – HRIS knowledge

The findings confirm the extant literature with regards to the technical skills or systems knowledge that HR practitioners and HR data analysts should have. HR practitioners are expected to understand how the HRIS works and all its functionalities so that they can be able to use it to its full potential. HR data analysts need to have advance statistical skills so that they can support the HR practitioners with more advanced analysis.

6.4.3 Theme 3: Consulting skills

6.4.3.1 Recap on consulting skills from findings

Consultants are seen as subject matter experts who have a combination of skills that enable them to influence line managers to buy into and implement their advice. These skills include communication, influencing, business acumen, change management and project management. The interviews conducted revealed that there was a need for HR practitioners to act as internal consultants who are subject matter experts and are able to influence as well as advise line managers accordingly. When consultants speak to business leaders, they use the business or commercial language that the leaders understand. They show business acumen. Hence, they gain respect from their clients.

HR practitioners also need to show that they understand how the business operates. They would then be able to gain respect and credibility from business leaders like other employees from sales and finance departments. The participants interviewed expressed the need to manage the implementation of some of the HR interventions decided on like a project. Hence, their change and project management skills would be useful.

6.4.3.2 Recap on consulting skills from literature

According to Peeters et al. (2020), HR practitioners need to understand who their critical stakeholders are. They maintain that senior managers, line managers, HR managers, other analytics teams and employees have been identified as stakeholders. Before trying to implement any HR solution or intervention, it is important to clarify and understand what the stakeholders need (McCartney et al. 2021).

HR practitioners need to be curious to ask questions until they understand which analytics and report to use, and what they will be solving for (Huselid, 2018). To that point, they need to be confident in who they are and act like subject matter experts who are able to advise line managers accordingly. This also includes the ability to coach line managers and provide them with solutions that are well-informed and based on data analytics. Furthermore, without good story-telling skills, the team will never be able to communicate the insights and actions to be taken to the line managers (Peeters et al., 2020). As a result, HR practitioners will be able to avoid using a linear, narrow and inward focused analysis of HR data as cautioned by Levenson (2018). This will also enable them to add value to the business and influence organisational performance.

6.4.3.3 Comparative analysis between findings and literature

The findings from the research study revealed similarities with extant literature on the need for HR practitioners to act as internal consultants for their organisations. They must use the skills used by external consultants to influence line managers. These skills range from being able to ask the right questions, listening closely so as to develop the right solution, design and develop professional visuals, present the intelligence in a compelling manner, and finally use change and project management skills to manage resistance and implement the decisions agreed on.

Levenson (2018) pointed out that HR practitioners needed to stop being internally focused by only looking at their HR processes and practices. However, they should understand what is happening in the business, what challenges was the business facing in order to develop data-driven solutions that have an impact on business. This can only be possible when they are able to ask the right questions (Huselid, 2018), present solutions in a compelling manner (Fu et al., 2022; Peeters et al., 2020).

6.4.3.4 Conclusion on consulting skills

The findings confirm literature on the different skills listed under the theme “consulting skills”. There are similarities between findings and extant literature with regards to the need for communication skills, being able to tell a good story, having business acumen.

However, it should be noted that the word “consulting skills” and “project management” were not part of the literature review. A word search was conducted on the first three chosen articles, and they were not found. The researcher then did a word search on Google scholar and found one article from a low-ranking journal article (AJG – 2).

6.4.4 Conclusion on sub-question 2

HR capability has been flagged as one of the foundational elements that need to be in place for HR practitioners to apply HR analytics and DDDM in their organisations. The findings revealed three themes (analytical skills, technical or system knowledge and consulting skills) that covers the skills needed by HR practitioners to be effective in their roles.

The study confirmed the extant literature with regards to the importance of having analytical skills in order to use HR analytics to make data-driven decisions. They both concur that without analytical skills, HR practitioners would be unable to engage with line managers and would therefore not be taken seriously. Hence, they needed to have high cognition and reasoning powers, be able to use logic to connect the dots and present a compelling and meaningful story to line managers.

The findings also confirmed the extant literature with regards to the technical skills or systems knowledge that HR practitioners and HR data analysts should have. HR analysts are expected to understand how the HRIS and all its functionalities works so that they can be able to use it to its full potential. HR data analysts need to have advance statistical skills so that they can support the HR practitioners with more advanced analysis.

The findings confirm literature on some of the different skills listed under the theme “consulting skills”. There are similarities between findings and extant literature with regards to the need for communication skills, being able to tell a good story, and business acumen.

However, it should be noted that the words “consulting skills” and “project management” were not part of the literature review. A word search was conducted on the first three chosen articles, and they were not found. The researcher then did a word search on Google scholar and found one article from a low-ranking journal article (AJG – 2).

6.5 Sub-question 3 What are the barriers that hinders HR practitioners from using HR analytics to make data-driven decisions?

6.5.1 Theme 1: HR practitioners’ lack of analytical skills.

6.5.1.1 Recap on HR practitioners lack of analytical skills from findings.

The feedback from the interviews highlighted that as HR practitioners are behavior scientists, they found working with numbers or data to be an insurmountable task. For them to be comfortable and confident they needed to be trained and they should also have the appetite to move out of their comfort zone and engage with the data and the system available. The HR data analyst also brought in the point that data was not only quantitative, but also qualitative. HR practitioner should be capacitated to be able to analyse both qualitative and quantitative methods. Taking into consideration that they did not need to be statisticians but should be able to perform basic analytics.

6.5.1.2 Recap on HR practitioners lack of analytical skills from literature.

HR practitioners that do not have these analytical skills end up being excluded from strategic discussions and decisions (Álvarez-Gutiérrez et al., 2022). Unfortunately, HR practitioners have been known to be afraid of dealing with numbers (Boakye and Lamptey, 2020). They have been flagged as people who are unable to make data-driven decisions because they lack basic analytical skills such as being able to engage with line managers to find out their challenges, as well as using basic statistical tools to analyse data (Minbeava, 2018). This prevents the adoption and utilisation of HR analytics in organisations (Angrave et al. 2016). In certain areas, the HR analytics role has been taken over by IT and statisticians because the HR practitioners are not playing a strategic role (Boakye & Lamptey, 2020; Marler & Boudreau, 2017).

6.5.1.3 Comparative analysis between findings and literature

The findings revealed similarities with extant literature with regards to the manner in which HR practitioners’ relationship with data or numbers was viewed. The participants indicated that as behavioural specialist, they found it easier to deal with human behaviour rather than numbers. They stated that they found working with data challenging and would prefer not to do so. This similar to the extant literature. Unfortunately, this mindset gave the HR practitioners a bad reputation in business (Minbeava, 2018). Because they are not able to speak the business language, they are flagged as not being strategic enough, some of their responsibilities are being taken over by other people from IT and finance (Boakye & Lamptey, 2020).

6.5.1.4 Conclusion on HR analytics scared of analytics.

The findings confirmed extant literature on the fact that the majority of HR practitioners were experts in human behaviour and were thus comfortable in dealing with words rather than numbers. This has become a huge barrier for them not to be able to apply HR analytics in making data-driven decisions.

6.5.2 Theme 2: Lack of technological advancement

6.5.2.1 Recap on lack of technological advancement from findings.

Digital transformation is influencing all business processes, HR included. The interviews conducted showed that HR practitioners were aware of the technological advancements that are needed in order to make HR analytics and DDDM more effective in their organisations. The fact that HR is slow in adopting the latest technology, it took long for them to respond to business queries. In addition, they have challenges with data integrity. All these could be solved if organisations were willing to invest money in buying more technologically advanced systems.

6.5.2.2 Recap on lack of technological advancement from literature

HR analytics need to be enabled by digital technology in order to add value to people and organisational decisions (Margherita, 2022). Knowing that it is impossible for data analytics to be free of error (Mohammed, 2019), technology becomes a critical enabler and accelerator in making HR successful. It helps in manipulating and reporting on the data to make sense of what has happened and possible predict and prescribe accurately what needs to happen (Vargas, et al., 2018). Organisations must therefore provide the right infrastructure and HR practitioners need to be competent in the use of such technology.

Unfortunately, due to high costs associated with technological advancement, and the fact that HR is usually one of the functions that receives low budget, most organisations are reluctant to spend money on the technology required (Belizón & Kieran, 2021; Boakye & Lamptey, 2020; Fernandez & Gallardo-Gallardo, 2020). Hence most organisations are stuck on level 1 of the HR data analytics maturity level (Mohammed, 2019). The current technology and HRIS do not have the functionalities to perform more advanced statistics and reporting. Furthermore, although it is known that technology plays a critical role in enabling HR analytics, there is still some doubt on whether it was necessary for organisations to spend money on upgrading the systems. Hence, Margherita (2022) suggested that more research be conducted to determine whether more advanced technology positively contributes to the successful application of HR analytics within organisations.

6.5.2.3 Comparative analysis between findings and literature

The findings revealed similarities with extant literature on organisations' reluctance to invest in technological advancements. Although it is known that HRIS technological tools are one of the important foundational elements of ensuring that HR practitioners apply HR analytics to make data-driven decisions, organisations still see it as a grudge purchase. Scholars also want more research to be conducted to determine whether it would improve application or effectiveness of HR analytics and DDDM (Margherita, 2022).

Similarly, although HR capability has been given as one of the reasons HR practitioners were unable to apply HR analytics, the lack of investment on IT infrastructure for HR analytics has been given as one of the reasons that the majority of organisations are stuck in descriptive analysis (Mohammed, 2019).

6.5.2.4 Conclusion on lack of technological advancement

The findings confirm literature with regards to lack of technological advancement being one of the barriers that hinder HR practitioners from using HR analytics in making data-driven decisions. Although the organisations could still use the basic system available, it unfortunately causes them to remain at level 1 maturity level.

6.5.3 Conclusion on barriers to effective application of HR analytics and DDDM

The findings confirmed extant literature on the barriers to effective application of HR analytics and DDDM. There are similarities in the findings and literature with regards to how HR practitioners viewed lack of analytical skills and the lack of technological advancement as barriers to effective application of HR analytics and DDDM.

6.6 Chapter conclusion

The findings from this study revealed 15 themes. Only 10 themes were discussed by comparing them to extant literature. Their similarities and slight nuances of differences were indicated in the discussions and depicted as a summary below.

Research question	Themes	Comparative analysis	Outcome/ insights
Extent of HR analytics and DDDM adoption and utilisation	Low adoption and utilisation of HR analytics and DDDM	Similarities to literature	Data quality and integrity are critical for an organisation to adopt HR analytics and DDDM.
	Partial adoption and utilisation of HR analytics and DDDM	Nuances of differences identified	When comparing the descriptions from the findings and literature, there are certain elements such as the use of external providers that could be added to literature on HR analytic models.
The data-driven decisions made	Recruitment decisions	Slight nuances were identified	Due to the majority of organisations being stuck in the descriptive stage (level 1) of the HR analytics maturity level, they cannot take advantage of advanced data analytics models that would help them to predict the right employees to appoint.
	Decisions relating to cost-saving	Slight nuances were identified	There is a need to clearly articulate how and to what extent do HR data-driven decisions contribute to organisations' cost saving exercises in literature.
	Decisions relations to HR interventions to be implemented	Similarities to literature	Employee engagement surveys inform the organisations on which interventions to implement to improve organisational culture, employee productivity and retention.

Research question	Themes	Comparative analysis	Outcome/ insights
Skills needed by HR practitioners to be effective in making data-driven decisions	Analytical skills	Similarities to literature	HR practitioners need to have critical analytical skills, detail-oriented, patient and be able to connect the dots.
	Technical skills	There are some nuances to literature	In relation to technical skills, literature refers more to HR analysts and not HR practitioners in general.
	Consulting skills	Nuances found	The consulting and project management needed in relation to HR analytics appear to be in low-ranking journals.
Barriers to application of HR analytics and DDDM	Lack of analytical skills	Similarities with literature	HR practitioners would prefer to work with words and human behavior rather than numbers
	Lack of technological advancement	Similarities with literature	Without technological advancement, HR analytics will remain at level 1 of the HR analytics maturity model.

1. CHAPTER 7

7.1 Introduction

The main aim of this study was to ascertain how HR practitioners use HR analytics to make data-driven decisions in their organisations. In order to answer this question, semi-structured interviews were held with 15 HR practitioners from different South African organisations. These participants were asked one main question (what the extent of adoption and utilisation of HR analytics and DDDM is). In order to seek more clarity of the main aim of the study, 3 sub-questions which are 1) what kind of data-driven decisions that were informed by HR analytics have they made; 2) what are the skills that are required for HR practitioners to effectively use HR analytics in making data-driven decisions; 3) what are the barriers that hinder HR practitioners from effectively using HR analytics to make data-driven decisions?

The aim of this chapter is therefore to outline the conclusions and recommendations from the study conducted in answering the above-mentioned research questions. This will be done by outlining a summary of the principal conclusions per research question, contributions of the study, limitations, and recommendations for future research.

7.2 Principal conclusions per research question

In order to answer the main research question, the principal conclusions of each research question are presented below.

7.2.1 Conclusion of research question 1

What is the extent of adoption and utilisation of HR analytics and DDDM in your organisation?

The aim of this question was to find out the extent or depth at which organisations have adopted and are utilising HR analytics to enable DDDM. In answering this question, two themes were identified; 1) low adoption and utilisation of HR analytics and DDDM; and 2) partial adoption of HR analytics and DDDM.

7.2.1.1 Low adoption of HR analytics and DDDM

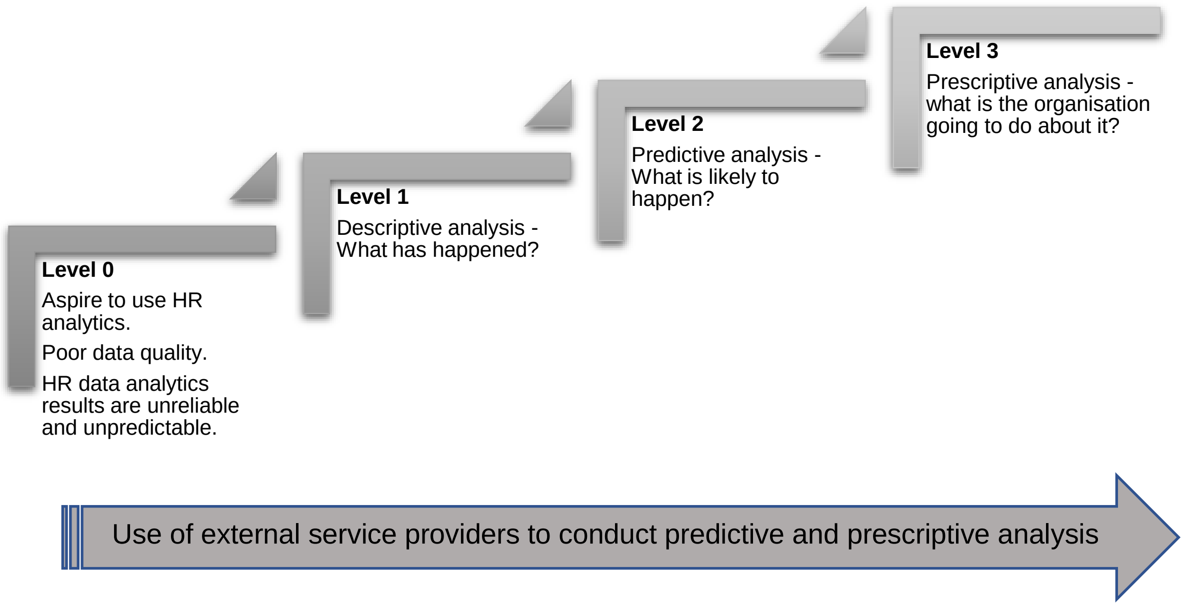
Data quality and integrity are one of the most important competencies an organisation that wishes to adopt and utilise HR analytics and DDDM should have (Ghasemaghaei et al., 2017). An organisation with poor quality and unreliable data will produce unreliable and unpredictable HR analytics and decisions (Anderson, 2017). As a result, HR practitioners will not have the confidence to use those analytics for DDDM. As a result, the extent of adoption and utilisation of HR analytics and DDDM is low, and these organisations are said to be at maturity level 1(ML1), which is the initial stage of the data analytics maturity assessment framework (DAMAF) (Gokalp et al., 2018).

7.2.1.2 Partial adoption and utilisation of HR analytics and DDDM

In addition to good quality data, organisations need HR practitioners with the right analytical capabilities and the right IT infrastructure - well-integrated system - that can be used to analyse the data in order to fully adopt and utilise HR analytics and DDDM (Ghasemaghaei et al., 2017; Kryscynski et al., 2018). Unfortunately, the majority of organisations are stuck and are operating at the descriptive analytics stage, which is level 1 of the HR analytics maturity model (Margherita, 2022; Mahommed, 2019). These organisations are said to be at maturity level 2 (ML2), which is the managed stage of the data analytics maturity assessment model (Gokalp et al., 2018).

The research findings revealed some nuances of differences with literature that could be used to refine literature on the HR analytics model. Firstly, the HR analytics model as presented by Margherita (2022) and Mahommed (2019) does not have a level similar to ML1 (initial) stage of the DAMAF model. Secondly, there could be a provision that shows that organisations operating at any level could use external service providers to conduct predictive and prescriptive analytics for organisations at ML1 (initial) stage of the DAMAF and level 1 of the HR analytics model. The modified model below shows the level 0 as well as an indication that organisations operating at any maturity level can appoint service providers to produce predictive and prescriptive analysis.

Figure 14: Modified HR analytics model



Source: Researcher's own modified HR analytics model

7.2.2 Conclusion on sub-question 1

What HR data-driven decisions have you made that were informed by HR analytics?

The aim of this question was to find out what kind of data-driven decisions that were informed by HR analytics have the HR practitioners made. Four themes were identified and three were analysed and discussed.

7.2.2.1 Cost containment decisions

HR practitioners are expected and do make decisions that relate cost-savings. They use their HRIS to track costs associated with recruitment, onboarding, salaries, training, workforce planning other HR related costs (Sousa et al., 2019). Hence, they are able to help organisations to make decisions that will curb unnecessary spending and contribute to cost saving. However, these cost-saving decisions appear not to be clearly articulated in literature (Boakye & Lamptey, 2020). Hence, scholars such as Harris et al. (2011) cited in Marler and Boudreau (2017) argued that in only tracking and reporting on costs, HR was making a very small contribution to cost saving. This presents an opportunity to do further research.

7.2.2.2 Recruitment decisions

HR practitioners have the responsibility of recruiting and bringing people with the right skills and will contribute to their team's achievement of the set goals and targets. Using objective data such as assessments results, employee readiness data from the system, and the production data to decide on who to appoint, number of people to work on the production line and employees eligible for internal mobility helps to remove subjectivity from the process (Boakye & Lamptey, 2020). In addition, advanced technologies such as AI and machine learning used to analyse candidate data from different sources and match it with the job requirements will also help improve the rate at which recruitment decisions are made (Álvarez-Gutierrez et al., 2022; Ben-gal, 2018). Hence organisations are moving towards digitilising their recruitment processes (Minbaeva, 2018).

7.2.2.3 HR interventions decisions

HR practitioners use insights from data gathered from different sources such as employee engagement surveys, interview questionnaires, focus groups and observations to make decisions regarding the type of interventions to implement (Margherita, 2022; Mohammed, 2019). These interventions include learning and development courses for compliance and general training, as well as customised leadership development programmes. They are used to contribute to meeting certain compliance targets, employee satisfaction, improved productivity and performance as well as employee retention (Huselid, 2018; McIver et al., 2018).

7.2.3 Conclusion on sub-question 2

What are the skills that HR practitioners need in order to be competent in fully utilising HR analytics to make data-driven decisions?

The aim of this question was to determine the different types of skills HR practitioners need in order to use HR analytics in making data-driven decisions. These skills were grouped into three themes.

7.2.3.1 Analytical skills

The study confirmed that in order to use HR analytics to make data-driven decisions, HR practitioners needed to have analytical skills. These skills include critical thinking, patience, and attention to detail (Vargas et al., 2018). They also need to be comfortable with working with numbers or quantitative data (Kryscynski et al. (2018). It is important to note that although the use of data analytics statistical tools is important, what is critical for HR practitioners is being able to read and analyse the analysis reports, connect the dots and tell a compelling data story in a manner that makes sense to line managers and propels them to act (Minbaeva, 2018).

7.2.3.2 Technical skills

HR practitioners are expected to have technical skills to be able to use their HRIS and all its analytics functionalities. This will enable them to download different reports from the system that provide the depth needed to make value-adding, evidence-based organisational decisions (Kryscynski et al., 2018). Currently, most HR practitioners use simple statistical analysis that do not as organisations are complex in nature (Minbaeva, 2018; Kryscynski et al., 2018). They are not competent nor comfortable to use more sophisticated analytical tools that will enable them to move from being descriptive to predictive analysis (Vargas et al., 2018). Thus, some leaders undermine the strategic role played by HR.

7.2.3.3 Consulting skills

HR practitioners have been challenged to stop focusing on only tracking how business is performing against the HR KPIs without understanding the challenges that business was facing (Levenson, 2018). For them to add value to the business, HR practitioners needed to take on the role of being internal consultants who have a number of skills including communication, presenting, storytelling, business acumen, change management and project management (Peeters et al., 2020).

7.2.4 Conclusion on sub-question 3

What are the barriers that hinders HR practitioners from using HR analytics to make data-driven decisions?

The aim of this question was to find what were some of the barriers that were hindering HR practitioners from using HR analytics to make data-driven decisions. Four themes were identified during the study, only two have been analysed and discussed.

7.2.4.1 HR practitioners' lack of analytical skills.

In order to deal with HR analytics, HR practitioners must be able to work with numbers or statistics (Minbaeva, 2018). However, the majority of HR practitioners are scared of working with numbers and would prefer to work with human behaviour or words. This fear unfortunately stands in their way of being strategic partners to business in that business leaders understand and prefer information that is backed by data (Álvarez-Gutiérrez et al., 2022). Unfortunately, they get sidelined from strategic discussions and some other departments such as IT and finance start taking over HR's responsibilities (Boakye & Lamptey, 2020).

7.2.4.2 Lack of technological advancement

Advance technology such as AI and machine learning have been identified as critical to ensuring that organisations move from descriptive analysis (level 1 maturity level) to predictive as well as prescriptive analysis (levels 2 and 3) (Akther et al. (2019). Unfortunately, due to high costs associated with technological advancement, and the fact that HR is usually one of the functions that receives low budget, most organisations are reluctant to spend money on the technology required (Belizón & Kieran, 2021; Boakye & Lamptey, 2020; Fernandez & Gallardo-Gallardo, 2020). This mindset and attitude put HR at the backfoot and will always be lagging with regards to innovations and the use of HR analytics and DDDM.

7.2 Theoretical contribution

This study aimed to add on to the body of knowledge with regard to understanding how HR practitioners use HR analytics to make data-driven decisions, specifically in South African organisations. Extant literature indicate that the use of HR analytics has a positive impact on organisational performance (McIver et al., 2018; Minbaeva, 2018). However, organisations seem to be slow in adopting and utilising HR analytics in order to make data-driven decisions (Davenport, 2019; Vargas et al., 2018). The study gives more clarity and understanding with regards to:

- The reasons the majority of organisations are stuck at descriptive analytics or level 1 of the HR analytics maturity model (Margherita, 2022; Mohammed, 2019). Existing literature describes the characteristics or focus of organisations at that level. This study also looked at what could be missing for them to move to the next stage.

- The slight nuances on the HR analytics model also suggest that there could be a need to modify the model to include Level 0, where there is infrastructure, however the analysis is not used. This could also include an explanation of the stage where organisations use external service providers for the analysis.

- Findings also revealed that there are organisations going through austerity measures, where departments have been asked to contribute to cost saving (Sousa et al., 2019). The study revealed that there could also be a need to conduct further research on how HR analytics contribute to cost saving.
- The study further focused on the skills that HR practitioners need in order to use HR analytics to make data-driven decisions. Literature showed that there appears to be a need to separate the skills needed from HR practitioners and HR data analysts.

7.3 Practical contribution

It is important for leaders and HR practitioners to understand the importance of using data to make decisions. With the advent of digital transformation and the data era, the ability to use HR analytics effectively is regarded as a competitive advantage (Davernport, 2019). The study focused on HR practitioners and how they see view their usage of HR analytics in making data-driven decisions. Literature indicates that organisations have been slow in adopting and using HR analytics to make data-driven decisions. The study can be used by leaders and HR practitioners to:

- Motivate for increased investment in HR systems or technological advancement (Mohammed, 2019). This will enable them to use advance technological statistical methods to analyse data in order to produce predictive and prescriptive analysis and progress to higher levels in the HR analytics maturity model.
- The study revealed that there could be a difference of opinion between the roles and skills required for HR practitioners and HR data analysts. The clarity of roles and responsibilities will also ensure that there is clarity with regard to the level of analytical skills required from HR practitioners (Vargas et al., 2018).

7.4 Limitations of the study

This study followed a qualitative research methodology, and therefor contains all the limitations as indicated in Chapter 4. The limitations of the study are indicated below:

- The study was conducted from the perspective of HR practitioners at senior and middle management. It did not include HR leadership at top management.
- The study was also done from an HR perspective and did not include the perspective of line managers from the business.

- Only 2 HR data analysts were involved in the study, more analysts' voices needed to be heard.
- The study focused on two barriers to the use of HR analytics in making data-driven decisions and did not include the other barriers identified in literature.

7.5 Recommendations for future research

This study focused on HR's perspective of how they could use HR analytics in making data-driven decisions. Given the fact that the adoption and utilisation of HR analytics seems to be stuck on level 1, further research need to be conducted to include topics such as:

- The study focused on the views and perceptions of HR practitioners. It is recommended that future study be conducted to explore the views of line managers outside of HR on how HR through the use HR analytics and DDDM contributes to the achievement of organisational strategy.
- The study revealed that there were organisations who although they were still operating at level 1 (descriptive analysis) of the HR analytics maturity level, they had the potential to progress to level 2 (predictive analysis) and 3 (prescriptive analysis). It is recommended that a case study be conducted on those specific organisations to explore what needs to be in place for them to progress to the next levels of analytics maturity.
- It is also recommended that case study research be conducted on organisations that are operating at level 3 of the HR analytics maturity model with the intention of finding out how they managed to progress from where other organisations are stuck.
- The study revealed that there seems to be limited research on how HR analytics can help organisations save costs. It is therefore recommended that further research be conducted on the role of HR analytics in cost-containment interventions within organisations.
- Further research could be conducted to clarify the roles and responsibilities of the HR practitioners and HR data analysts in the value chain of HR analytics and DDDM.

7.4 Conclusion of the study

The aim of this study was the explore how HR practitioners use HR analytics to make data-driven decisions. This was a response to an invitation to close the research gap in order to guide practitioners on the implementation of HR analytics in their organisations. An exploratory qualitative study was conducted to answer the research question. 15 semi-structured interviews with HR practitioners from different organisations and industries were held were held through Ms. Teams and Zoom platforms. The study confirmed extant literature that the majority of organisations are stuck at level 1 (descriptive analysis) of the HR analytics maturity level. It also outlined some of the data-driven decisions that HR practitioners made that add value to business. Data quality, HR capability and availability of IT infrastructure were found to be some of the enablers that need to be in place for HR practitioners to effectively apply HR analytics and DDDM in their organisations.

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APPENDIX 1: INTERVIEW PROTOCOL

The application of HR analytics and DDDM in HR Management

Research Question	Interview Question
• **What is the extent of adoption and utilisation of HR analytics and DDDM**	• What is your understanding of data-driven decision making in HR? • What do you think is the relationship between DDDM and HR analytics? • What are the HR data metrices/analytics that your organisation uses to make decisions? • What is the extent of adoption and utilisation of HR analytics and DDDM in your organisation?
• **What are the data-driven decisions that HR practitioners have made**	• What do you think are the benefits of using data analytics in making HR decisions in an organisation? • What kind of HR decisions do you or have you made that were/are informed by HR analytics?
• **What are the skills needed by HR practitioners to effectively apply HR analytics and DDDM?**	• Who is responsible for HR data analytics in your organisation? • What do you think are the skills that HR practitioners need in order to be competent in fully utilising HR data analytics in making decisions that benefit the whole organisation, and not only HR?

• **What are some barriers that are hindering you from applying HR analytics and DDDM?**	• What are the barriers that are hindering HR practitioners from fully applying HR analytics and DDDM? • How technologically advanced is the HR information system that you use in analysing your HR data? • Would you say that your organisation has these skills and competencies to be effective in HR analytics? • How does your organisation's culture support the use of HR data analytics in making decisions?

APPENDIX 2: CODES

Codes

Codes	**Code Groups**	**Themes**
Financial constraints	Budgets/ expenditure	Cost saving
KPI Seta Funding	Training budgets/expenditure	Cost saving
Skills - digital	HR capability	Technical skills
Skills - business skills	HR capability	Business acumen
Skills - business owner	HR capability	Business acumen
Skills - use of data tools	HR capability	Technical skills
Skills - understanding how the report is linked to the business strategy	HR capability	Storytelling
Listening skills	HR capability	Communication
influencing skills	HR capability	Consulting
able to tell a story.	HR capability	Story-telling
consulting skills	HR capability	Consulting
change management skills	HR capability	change managemen
Skills - how to conduct analytics	HR capability	Analytical skills
Skills - How to use the system	HR capability	Technical skills
Skills - business acumen	HR capability	Business acumen
R2 - HR analytics - understanding and interpreting data	HR capability	Analytical skills

Playing a strategic partnering role - trusted advisor to line managers	HR capability	Consulting
Skill/ Attributes - passion	HR capability	Analytical skills
HR practitioners - scared of analytics	HR capability	Analytical skills
HR practitioners' attitude	HR capability	Analytical skills
HR capabilities - reporting skills	HR capability	Analytical skills
Skills - agility - basics of business analysis	HR capability	Business acumen
HR skills - basic analytics	HR capability	Analytical skills
HR skills - familiarise self with the system	HR capability	Technical skills
HR skills - HR practioners dont need to know advanced analytics	HR capability	Technical skills
HR skills - interpreting reports from the system	HR capability	Analytical skills
HR skills - understand the question being asked	HR capability	Consulting
Skills - analytical thinking	HR capability	Analytical skills
Skills - problem-solving skills	HR capability	Analytical skills
Skills - BI	HR capability	Technical skills
Business skills. We need commercial skills	HR capability	Business acumen
Story-telling	HR capability	Story-telling
Skills - project management	HR capability	Projectmanagem ent
Skills - ability to influence people	HR capability	Consulting
KPI - skills gap analysis	HR capability	Analytical skills
Skills - interpretation of data	HR capability	Analytical skills

Skills - communication and analytical skills	HR capability	Communication
Presentation skills	HR capability	Communication
Skills - system knowledge	HR capability	Technical skills
Skills - coaching	HR capability	Consulting
Skills - attention to detail	HR capability	Analytical skills
Skills - simplify the story	HR capability	Story-telling
Skills - honesty	HR capability	Analytical skills
to manipulate data because sometimes you have your own, uh, you know, um, your own view, your own opinio	HR capability	Technical skills
Skills - work accurately under pressure	HR capability	Analytical skills
Skills - sense of urgency	HR capability	Analytical skills
Utilisation in between	Extent of adoption and utilisation	Partial adoption
HR analytics - predictive	Extent of adoption and utilisation	Partial adoption
HR analytics seen as focusing only in the past - descriptive	Descriptive analytics - extent of utilisation	Partial adoption
HR analytics - things that happened in the past	Descriptive analytics - extent of utilisation	Partial adoption
Utilisation at operational level low	Extent of adoption and utilisation	Low adoption
Level of utilisation is zero	Extent of adoption and utilisation	Low adoption
Utilisation is above average	Extent of adoption and utilisation	Partial adoption

Utilisation is at above average	Extent of adoption and utilisation	Low adoption
Utilisation inbetween	Extent of adoption and utilisation	Partial adoption
Utilisation is inbewteen	Extent of adoption and utilisation	Partial adoption
Level of utilisation - high	Extent of adoption and utilisation	Partial adoption
Utilisation is between above average - environment is operational	Extent of adoption and utilisation	Partial adoption
Utilisation - inbetween	Extent of adoption and utilisation	Partial adoption
Utilisation level -high	Extent of adoption and utilisation	Partial adoption
Utilisation at inbetween- documentation and processes in place - implementation is a challenge	Extent of adoption and utilisation	Atensaeeo -and processes in place - f o-
Utilisation - inbetween	Extent of adoption and utilisation	Partial adoption
Utilisation - above average	Extent of adoption and utilisation	Partial adoption
Level of utilisation - inbewteen	Extent of adoption and utilisation	Partial adoption
Utilisation in between	Extent of adoption and utilisation	Partial adoption
Integration	HRIS- technological tools	Partial adoption

Techology - advanced	Technological advancement	
Barriers - investment - increase budget	Barriers to application	Lack of technological advancement
Technology - development stage, level 2	Barriers to application	Technological advancement
R1 - IT	Barriers to application	Technological advancement
R2 - digitilisation	Barriers to application	Technological advancement
Decisions - reporting	Barriers to application	Technological advance - 1 - manual
Data source - big data	Barriers to application	Technological advancement - 4
Skills - basics of IT - cybersecurity	Barriers to application	Technological advancement not necessary
Technology advancement - 2 - no integration	Barriers to application	Technological advancement
Technological advancement -	Barriers to application	Technological advancement
Technological advance - 1 - outdated and not well-maintained	Barriers to application	Technological advancement
DDDM - investing in the right technology	Barriers to application	Technological advancement

Automation - don't have to struggle	Barriers to application	Technological advancement
System not intergrated	Barriers to application	Technological advancement
Technological advancement - moved away from Excel	Barriers to application	Technological advancement
Technological advancement not necessary	Barriers to application	Technological advancement
I think this would be at 1 or 2. And the reason I say that is because they are they are offering a plug on a system that was bought for either finance well, let's say finance	Barriers to application	Technological advancement
Technological advancement - 1 - use Excel	Barriers to application	Technological advancement
Technology - advanced - at 4	Barriers to application	Technological advancement
Skills - analysing reports	Barriers to application	Technology advancement - 2 - no integration
Decisions - offered career growth opportunities for Engineers	Decision-making	Interventions
Decision - improved Employee Value Proposition	Decision-making	Interventions
Reporting - able to report to Exco	Decision-making	Cost saving
Decisions made - Coaching programme	Decision-making	Interventions
Decisions - Leadership development	Decision-making	Interventions

Decision - Recruitment	Decision-making	Recruitment decisions
Decisions - training on safety	Decision-making	Cost saving
Decision made - leaders undergoing a leadership development programme	Decision-making	Interventions
Decisions - number of hours people must work	Decision-making	Cost saving
Decisions - compliance	Decision-making	Cost saving
Decisions based on employee engagement survey	Decision-making	Interventions
Decisions - permanent resourcing	Decision-making	Recruitment decisions
Decisions - interventions	Decision-making	Interventions
Decisions associated with availability of manpower	Decision-making	Recruitment decisions
Decisions - training interventions	Decision-making	Interventions
Decision - employee engagement	Decision-making	Interventions
Decisions - compliance to legislation	Decision-making	Cost saving
Decision - the cost of attrition	Decision-making	Cost saving
Barriers - undermining the pace of technology	Barriers to application	Technological advancement
Barriers - understanding the system	Barriers to application	Technical skills
Barriers - integrated system	Barriers to application	Technological advancement
Barriers - change management	Barriers to application	Lack of analytical skills

Barriers - we don't need systems	Barriers to application	Analytical skills
Barriers - the way the strategy is cascaded and communicated	Barriers to application	Communication
Barriers - project management and prioritisation	Barriers to application	Lack of analytical skills
Barriers - technology	Barriers to application	Technological advancement
Barriers - technology - IT - AI	Barriers to application	Technological advancement
Barriers - system	Barriers to application	Technological advancement
Barriers - ownership of the system	Barriers to application	Technological advancement
Barriers - being comfortable with numbers	Barriers to application	Lack of analytical skills
Decisions - what training to provide	Decision-making	Interventions
HR practitioners and technology	Barriers to application	Technological advancement
Gap between HR and business	HR capability	Business acumen
Technology - system integration	Barriers to application	Technological advancement
Barriers - leaders acting on the results	Barriers to application	Partial adoption
HR skills - courage	HR capability	Anasyt cas hr skills

technology. We are still very manual in our processes.	Barriers to application	Technological advancement
Investment	Technological advancement	Technological advancement