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Adoption of Advanced Workforce Analytics amongst South African HR Practitioners

A Research Report Submitted by

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ABSTRACT

The 21st century is characterised by a volatile, complex and ambiguous business environment which is primarily data driven. Those who are able to derive insight from data obtain a competitive advantage. This can be seen in the medical, engineering and even marketing industries. Due to these successes, the field of management is being challenged to move from "gut-feel" into becoming more evidence-based. It is this transition, into evidence-based management, that affords HR the opportunity to become a strategic partner in business, thus building a strong case for workforce analytics. Workforce analytics is said to offer visibility of trends, the impact of training on business outcomes and improve the quality of hire.

Workforce analytics has three levels, namely descriptive, predictive and prescriptive. It is the latter two levels which provide additional value to the business, especially surrounding effective strategy formulation and decision-making. Academic research conducted to date suggests that the adoption rate of the latter levels is slow and HR excellence is an exception in South Africa. Thus, prompting the need for this study.

Information gleaned from the literature review revealed that the field of advanced analytics is still in its infancy. It appears that the slow progress is due to lack of widely accepted management principles in the field. Other challenges include HR practitioners' lack of analytical skills, business acumen, leadership support and organisational cultures that are not supportive of evidence-based management. While there is a strong call for evidence-based management, a critique which is often levelled against it is that human behaviour is unpredictable and therefore cannot be measured accurately.

Several frameworks such as the balanced scorecard, human capital model and value-linkage model have been developed to provide instruments of calculating advanced analytics. However, none of these frameworks offer a model for prescriptive analytics. The commonality in the frameworks is that successful implementation requires that the HR practitioner should have in-depth knowledge of the business and advanced statistical competencies – skills which most HR practitioners seem to lack. As such, advanced workforce analytics has become a multi-disciplinary process.

To gain an understanding into the South African landscape, the research used a quantitative approach. A questionnaire was distributed to 5,800 HR practitioners across the country. The research found that only 11.8% of respondents reported their analytics as advanced. The implication is that 89% are indeed relying entirely on gut-feel because they are either unequipped or ill-equipped to manipulate data to derive insight. As such practitioners are unable to provide HR intelligence.

The low rate of adoption of advanced analytics should be of major concern to practitioners and business alike. Evidence-based management, achieved through analytics, provides decision-makers with timeous business information and insight required to make sound business decisions enabling businesses to gain competitive advantages. HR intelligence lies primarily in HR addressing business needs. Analytics, and thus evidence-based management, is but an enabler. Therefore, without a thorough understanding of the business needs, analytics, advanced or otherwise, will be another façade and HR practitioners risk being replaced by dashboards.

DECLARATION

I declare that the work presented in the report is my own and has not been submitted before for any degree or examination in any other university. I also declare that I have obtained consent from Wits Business School to carry out the research.

NR Malebatja February 2018

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The successful completion of this qualification is a testimony that it takes a village to raise a child. It is also the evidence of the South Africa I live in, the rainbow nation that embraces ubuntu.

Nick Baglow, my earthly angel, cheerleader, a testimony of God's love for me, I can never thank you enough.

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To my family, friends, colleagues and classmates, it was your support that got me and now **we** made it. I stand as all of you. Motho ke motho ka batho.

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INTRODUCTION

"There is a dawning awareness that data and information, as a *commodity in and of itself, has little value to an organization unless it is transformed into meaningful intelligence" pg29 (Falletta, 2014)*

1.1 Introduction

This chapter introduces the research problem as well as the rationale for the research. Subsequent chapters delve into the literature review, research methodology and findings. The research will end with a conclusion and recommendations.

1.2 Context and Purpose of the Study

Data and data management have arguably been in existence since human beings have been transacting on business activities (Carlson & Kavanagh, 2011; Simon, 2013). Through the years, the management of data has evolved from manual processes to being automated. The growth of data has also been exponential, reaching its highest peak in the second stage of internet development, Web 2.0, when web pages became interactive (Simon, 2013). This development has also led to an expansion in variety of data and an increase in the speed which data is produced, giving birth to the term big data (Russom, 2011). The four dimensions of big data are variety, velocity, volume and veracity (Wang et al., 2014).

To date data analytics has been used in many fields, most of which are customer facing. Table 1 presents some of the fields where analytics was adopted:

Table 2. BI&A Applications: From Big Data to Big Impact

	E-Commerce and Market Intelligence	E-Government and Politics 2.0	Science & Technology	Smart Health and Wellbeing	Security and Public Safety
Applications	• Recommendation systems • Social media monitoring and analysis • Crowd-sourcing systems • Social and virtual games	• Ubiquitous government services • Equal access and public services • Citizen engagement and participation • Political campaign and e-polling	• S&T innovation • Hypothesis testing • Knowledge discovery	• Human and plant genomics • Healthcare decision support • Patient community analysis	• Crime analysis • Computational criminology • Terrorism informatics • Open-source intelligence • Cyber security
Data	• Search and user logs • Customer transaction records • Customer-generated content	• Government information and services • Rules and regulations • Citizen feedback and comments	• S&T instruments and system-generated data • Sensor and network content	• Genomics and sequence data • Electronic health records (EHR) • Health and patient social media	• Criminal records • Crime maps • Criminal networks • News and web contents • Terrorism incident databases • Viruses, cyberattacks, and botnets
	Characteristics: Structured web-based, user-generated content, rich network information, unstructured informal customer opinions	Characteristics: Fragmented information sources and legacy systems, rich textual content, unstructured informal citizen conversations	Characteristics: High-throughput instrument-based data collection, fine- grained multiple- modality and large- scale records, S&T specific data formats	Characteristics: Disparate but highly linked content, person-specific content, HIPAA, IRB and ethics issues	Characteristics: Personal identity information, incomplete and deceptive content, rich group and network information, multilingual content

Analytics	• Association rule mining • Database segmentation and clustering • Anomaly detection • Graph mining • Social network analysis • Text and web analytics • Sentiment and affect analysis	• Information integration • Content and text analytics • Government information semantic services and ontologies • Social media monitoring and analysis • Social network analysis • Sentiment and affect analysis	• S&T based domain-specific mathematical and analytical models	• Genomics and sequence analysis and visualization • EHR association mining and clustering • Health social media monitoring and analysis • Health text analytics • Health ontologies • Patient network analysis • Adverse drug side-effect analysis • Privacy-preserving data mining	• Criminal association rule mining and clustering • Criminal network analysis • Spatial-temporal analysis and visualization • Multilingual text analytics • Sentiment and affect analysis • Cyber attacks analysis and attribution
Impacts	Long-tail marketing, targeted and personalized recommendation, increased sale and customer satisfaction	Transforming governments, empowering citizens, improving transparency, participation, and equality	S&T advances, scientific impact	Improved healthcare quality, improved long-term care, patient empowerment	Improved public safety and security

Table 1: Business Intelligence and Analytics Applications
Source: (Chen, Chiang, & Storey, 2012)

The last row, labelled “Impacts”, in the table above lists the potential benefits of analytics in the respective industries. Production and manufacturing companies who use data analytics report an increase in output, improved efficiency and improved risk management, especially in terms of risks which may be caused by human error (Brown, Chui, & Manyika, 2011). Also, companies who use big data and business analytics to guide decision-making are found to have a higher return on equity (Brown et al., 2011). Analytics has therefore evolved from being a reporting tool to equipping managers with information that has a meaningful impact on a business’ bottom line.

With the success of data analytics in other fields, the field of management, though being context-dependent (Delbridge & Whitfield, 2007), is being challenged to move away from ‘gut-feel’ into supporting its decisions with empirical evidence (Brown et al., 2011; Davenport, Harris, & Shapiro, 2010; Frick, 2014; Muscalu & Şerban, 2014). Evidence-based management has become very important to organisations operating in the 21st century (Davenport et al., 2010), because the

business environment has become a complex system characterised by high volatility, globalisation and disruptive technology. Carlson and Kavanagh support Davenport et al.'s viewpoint and further state that one's capacity to manage resources in an organisation, is limited by the information he/she holds (Carlson & Kavanagh, 2011).

1.3 Significance of the Study

The analysis of HR data is said to offer visibility of trends, the impact of training on business outcomes, improve quality of hire (Mondore, Spell, & Douthitt, 2016; Pemmaraju, 2007), "help debunk management myths" (Bersin, 2014) and reliability on HR intuition , improve accuracy on identification of root-causes of problems and give insight into specific departments or functions (Chahtalkhi, 2016; Huselid, 2015). Advanced workforce analytics promises to not only enable organisations to attract, engage and retain high performers, but also optimise existing workforce as well as minimise risks and costs incurred from high turnover, loss of productivity, skills and culture misfits and other human capital management risks. The supporters of workforce analytics further claim that workforce analytics will result in effective utilisation of human resources, bridge the gap between academia and practice, and provide measurable impact of HR investments (Carlson & Kavanagh, 2011; Chahtalkhi, 2016; Huselid, 2015; Rasmussen & Ulrich, 2015).

Since business intelligence is primarily about using resources to gain competitive advantage (Hannula & Pirttimaki, 2003; Kapoor, 2010; Venter & Tustin, 2009), if what is claimed above can be realised, then advanced workforce analytics is the long missing key to HR intelligence (Falletta, 2014; Fitz-Enz, 2010).

1.3.1 *Proof in the Pudding*

Companies such as IBM, Google, the Royal Bank of Canada and McDonalds to name a few (Levenson, 2014) have been using data analytics to inform their human resource management decisions. They report that the approach has

afforded them the opportunity to gain intelligent business insight, which led them to making informed decisions about their human resources across all operation levels (i.e. functional and strategic) (Dash Wu, Kapoor, & Sherif, 2012). The claims of the organisations corroborate findings of a study by LaVelle, Hopkins, Lesser, Shockley and Kruschwits (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011). LaVelle et al (2011) found that top performing organisations are three times more likely to use advanced workforce analytics and twice as likely to cite it as their competitive differentiator (Molefe, 2013). The Massachusetts Institute of Technology (MIT) and University of Pennsylvania also found that organisations who implemented advanced analytics had 5% - 6% higher financial returns (Bersin, 2014).

1.3.2 *Academic Literature – Where are we*

Despite the claimed benefits of advanced workforce analytics, there has been few academically sound studies undertaken (Marler & Boudreau, 2016). Marler and Boudreau (2016) conducted a review of journal articles dating as far back as 2004 written on the topic. Marler and Boudreau (2016) reported that although they discovered 60 articles, 32 were peer reviewed and of those only 14 were in peer reviewed journals. Of the 14 articles, only 4 were quantitative, with 2 of the articles covering some part of advanced analytics.

Within the South African landscape, there has been one academic research conducted on this particular topic to date. The study by Masenyane Molefe (2013) found that there is a shortage of analytical skills among HR practitioners resulting in continued reliance on gut-feel and therefore slow progress in adoption as well as the field remaining in its infancy. Advanced analytics is found to be prevalent in multi-nationals, whereas small and locally based companies used basic analytics for reporting purposes. The key revelation was that there is a misunderstanding amongst practitioners of what advanced workforce analytics entails. Even though Molefe's findings cannot be generalised as it was quantitative in nature with a population of 16 respondents, she has provided solid academic foundation which warrants and prompts further research in the topic.

Thus, the significance of this research was to explore the merits of advanced workforce analytics and provide a scientifically sound reference point for the various stakeholders such as HR practitioners and business.

1.4 Problem Statement

Business derives value in insights obtained from the various business units. HR also has the responsibility and obligation to produce insights into the organisation's human resources and analytics promises to be a tool that HR can adopt to develop, measure and optimise deployment of human resources (Lawler III, Levenson, & Boudreau, 2004). Workforce analytics has three levels, namely descriptive, predictive and prescriptive. Descriptive analytics refers to basic analytics that mainly entails reporting historical information. HR metrics such as employee turnover, attrition rates, recruitment turnaround time and benchmarking fall under this category. Predictive analytics is primarily about detection of trends, exploring relationships and establishing causation. The outcomes of predictive analytics inform actions to follow in the prescriptive phase. Prescriptive analytics then employs efforts to optimise resources and minimise risks. For the purpose of this research, predictive and prescriptive analytics are collectively referred to as advanced analytics.

All levels should be present for workforce analytics to provide business insight. However it is predictive and prescriptive analytics which provide added value, especially for effective strategy formulation and decision-making (Falletta, 2014; Fitz-Enz, 2010). Failure of HR practitioners to adopt advanced workforce analytics hinders HR from having the insights and intelligence required to become a strategic partner to business. As such, HR risks being replaced by dashboards (Bersin, 2014; Davenport et al., 2010; Rasmussen & Ulrich, 2015).

South Africa has labour relations regulations aimed at addressing employment equity caused by historic injustices under Apartheid. Compliance with the labour regulations is monitored through annual submissions of reports which detail the organisations' employee demographics, salary scales and skills development

initiatives. The reporting responsibility usually lies in the HR department. The information in the reports is for the most part historic data and therefore falls within the basic analytics category as. It can thus be deduced that most South African practitioners are well versed in basic analytics. To meet compliance requirements, there is opportunity for companies to use the information in these reports to inform their human capital management strategy, thus venturing into the advanced analytics category. Based on the various reports released by the Department of Labour, which indicate that the demographic profiles of senior management in South Africa is still biased towards white males, it is reasonable to assume that advanced insight and intelligence is not derived from the reports. This is not withstanding that there are other factors at play.

Furthermore, Molefe's (2013) research uncovered that the field of analytics in South Africa is still in its infancy. There is low adoption and there is misunderstanding among practitioners about the potential applications of advanced analytics (Molefe, 2013). Molefe's study was qualitative and due to the low number of respondents (16), the study cannot be generalised. There was no empirical evidence for Molefe's discoveries and little was known about the South African landscape, thus warranting a need for a quantitative study. The research therefore sought to explore the adoption of advanced workforce analytics amongst South African practitioners.

1.5 Beneficiaries of the Study

It is only when data is analysed from a descriptive, predictive and prescriptive perspective that it offers business intelligence. Fitz-Enz (2010) corroborated this through his value of analytics which indicates that the higher you go in the corporate ladder the more analytics should present business impact. Bill Robinson (2015), the training manager at Society for Human Resource Management, categorised the different levels of analytics in conjunction with their respective key stakeholders (Figure 1) (Robinson, 2015).

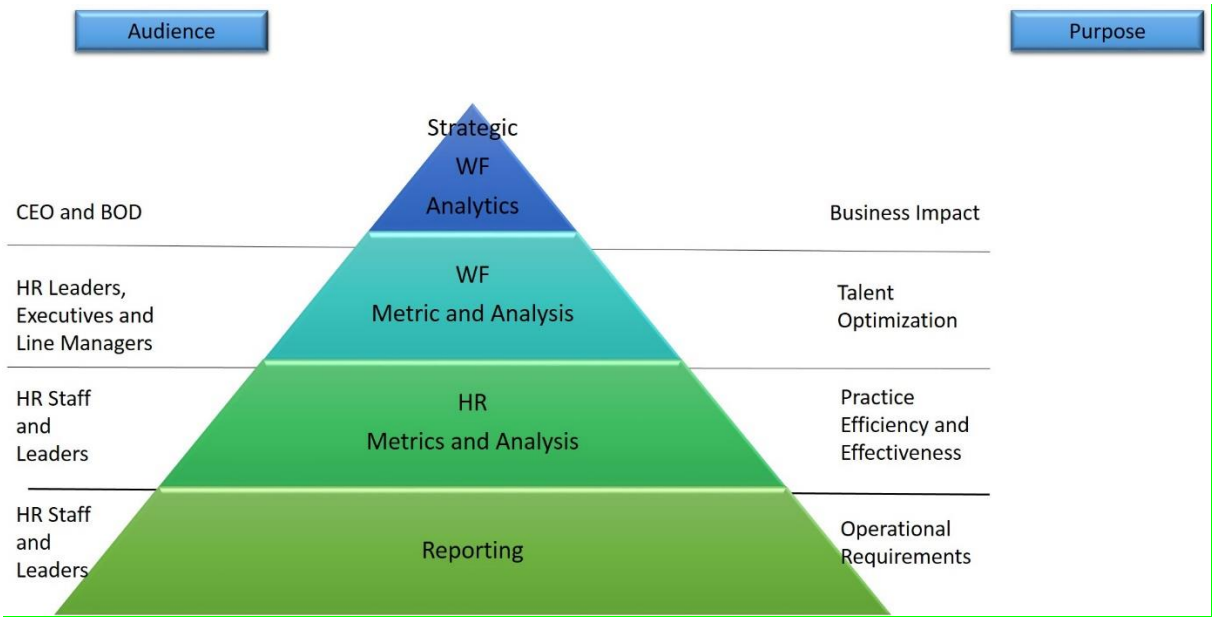


Figure 1: Human Capital Analytics Architecture
Source: (Robinson, 2015)

Thus, possible beneficiaries of the knowledge produced in the reports include executives, line managers, recruiters, talent managers, organisation development specialists, scholars and other fields in the Human Resource Management fraternity

1.6 Delimitations of the Study

The following delimitations have been identified to narrow the scope of the research project:

- **Descriptive analytics** – Bersin (2014), reported that for an organisation to experience full benefits of workforce analytics, the analytics should address the three perspectives of business decision making, which are descriptive, predictive and prescriptive analysis. However workforce analytics has, to a large extent, been used for descriptive purposes such as reporting historical information (Angrave, Charlwood, Kirkpatrick, Lawrence, & Stuart, 2016; Carlson & Kavanagh, 2011).

Descriptive analytics has been well implemented in South African companies due to compliance requirements from the Department of Labour as well as governance requirements by the King reports. Thus, this paper will focus on predictive and prescriptive analytics which will commonly be referred to as advanced analytics.

- **Technologies & techniques -** there are various types of technologies and analytical techniques highlighted in table 2, which are used in the three phases. However, the study will not discuss these further.

Table 3. BI&A Research Framework: Foundational Technologies and Emerging Research in Analytics

	(Big) Data Analytics	Text Analytics	Web Analytics	Network Analytics	Mobile Analytics
Foundational Technologies	• RDBMS • data warehousing • ETL • OLAP • BPM • data mining • clustering • regression • classification • association analysis • anomaly detection • neural networks • genetic algorithms • multivariate statistical analysis • optimization • heuristic search	• information retrieval • document representation • query processing • relevance feedback • user models • search engines • enterprise search systems	• information retrieval • computational linguistics • search engines • web crawling • web site ranking • search log analysis • recommender systems • web services • mashups	• bibliometric analysis • citation network • coauthorship network • social network theories • network metrics and topology • mathematical network models • network visualization	• web services • smartphone platforms
Emerging Research	• statistical machine learning • sequential and temporal mining • spatial mining • mining high-speed data streams and sensor data • process mining • privacy-preserving data mining • network mining • web mining • column-based DBMS • in-memory DBMS • parallel DBMS • cloud computing • Hadoop • MapReduce	• statistical NLP • information extraction • topic models • question-answering systems • opinion mining • sentiment/affect analysis • web stylometric analysis • multilingual analysis • text visualization • multimedia IR • mobile IR • Hadoop • MapReduce	• cloud services • cloud computing • social search and mining • reputation systems • social media analytics • web visualization • web-based auctions • internet monetization • social marketing • web privacy/ security	• link mining • community detection • dynamic network modeling • agent-based modeling • social influence and information diffusion models • ERGMs • virtual communities • criminal/dark networks • social/political analysis • trust and reputation	• mobile web services • mobile pervasive apps • mobile sensing apps • mobile social innovation • mobile social networking • mobile visualiza-tion/HCI • personalization and behavioral modeling • gamification • mobile advertising and marketing

Table 2: Business Intelligence and Analytics Technology and Techniques
Source: (Chen et al., 2012)

There is another interesting field of analytics emerging called sentiment analytics, which seeks to identify preferences or biases of individuals towards specific matters (Nasukawa & Yi, 2003). It is the view of the

author that sentiment analytics will significantly alter the decision-making process and indeed transition the management practice from gut-feel to evidence-based. With that said, this study will not be looking into sentiment analytics.

- **Data and data management** - the field of analytics is also inundated by various types of data, such as transactional, structured, semi-structured, unstructured, meta-data and big data, to name a few. The type of data used is not relevant to this study.
- The research will also not review the nuances of the data management processes, (from HR data points, data collection to analysis), the hardware involved or presentation of the data, that is, data visualisation.

1.7 Limitations of the Study

The study will not consider the qualifications and work experience of the respondents, the size of HR departments, industries or size of organisations respondents work in.

1.8 Assumptions

The assumption that this study makes is that HR practitioners are not perceived as strategic business partners by business leaders. Furthermore, it is assumed that HR practitioners are seeking ways to change this perception and, analytics is seen as a potential solution.

CHAPTER 2. LITERATURE REVIEW

The section outlines the literature on the topic.

2.1 Foreword on the literature review

The academic literature in the field of workforce analytics is growing, however it is currently sparse (Marler & Boudreau, 2016; Molefe, 2013). As stated in section 1.2.2, Marler and Boudreau (2016) found only fourteen articles in quality peer reviewed journals which dealt with this topic. Most of the articles were written by only a handful of academics. Annexure A presents a summary of these fourteen articles.

Their review sought to cover 5 questions. The questions together with their key findings are summarised in the table below:

Question	Key Findings
What is HR analytics – how the concept definition evolved	The articles revealed that there is no consensus on terminology or definition. Marler and Boudreau (2016) concluded that HR analytics involves using information technology to collect, manipulate and analyse data from HR as well data from other areas in the organisation in order to support people-related decisions and link these decisions to business outcomes and organisational performance.
How does HR analytics work – what are the processes	The Logic, Analytics, Measures and Process (LAMP) model is the most referenced framework. The framework is used to establish cause-effect relationship between HR processes and business outcomes.
Why does HR analytics work –	Not yet known because different scholars adopt/apply

what theories explain cause-effect relationships, antecedents and consequences	different theoretical frameworks .
What does HR analytics produce – what are the outcomes	HR analytics has the potential to make business impact (which is measured through financial performance) when it goes beyond efficiency measures. Having said that, the evidence is deemed sparse as there was only been one quantitative study in this regard.
What is required for HR analytics to succeed – what are the moderators of the analytics-outcome relationships	- Shortage of analytical skills within the profession - Shortage of HR practitioners who have business understanding - Lack of access to data from other areas in the organisation - Valid and reliable data - A Human Resources Information System (HRIS) is an added advantage but not a key determinant of success.

Table 3: Summary of Evidence-based Review of HR Analytics
Adapted from (Marler & Boudreau, 2016)

The focus of this literature review is on literature pertaining to advanced analytics which, which as evidenced by the quality documented by peer-reviewed articles above, is sparse.

2.2 Definition

The Human Resource Management field is going through an interesting time in trying to redeem itself as a strategic business partner (Rasmussen & Ulrich, 2015). Likewise, there is an explosion of new terminology which, when reviewed, still refers to the core functions of Human Resource Management as needing to attract and retain the right people, at the right cost, in a timeous manner and create a conducive environment which equips employees to operate optimally. HR analytics also referred to as workforce analytics, talent analytics or people analytics is one of the emerging terminologies (Marler & Boudreau, 2016).

Levenson (2005) describes HR analytics as the use of statistics and scientific standards to identify meaningful questions and interpretation of the results into a language that is meaningful for the business.

Mondore, Douthitt and Carson (2011) loosely use the term workforce analytics. They describe it as the ability to demonstrate the impact of people data on important business outcomes (Mondore, Douthitt, & Carson, 2011).

Falletta (2014) also adopted the term HR analytics. She states that HR analytics is a pre-emptive and systematic process of using analytics to drive insightful HR outcomes that can help organisations achieve their strategic objectives (Falletta, 2014).

Deloitte refer to it as people analytics. Their definition of analytics as people-related data to improve and inform all types of management, business, and HR decisions throughout the company corroborates that of Mondore et al (2016) (GHC-Trends, 2016).

Marler and Bourdreau (2016) also attempted to offer a broad definition by defining analytics as an HR practice that uses information technology to produce descriptive, visual, and statistical analyses of data related to HR processes, human capital, organisational performance, as well as external economic benchmarks to establish business impact in order to enable decisions informed by data. Mishra, Lama and Pal (2016) sought to acknowledge the multi-disciplinarity of advanced analytics They defined HR analytics as a multidisciplinary approach that combines practice of improving the quality of people-related decisions with improvement in individual and organisational performance (Mishra, Lama, & Pal, 2016).

For the purpose of this study, the author adopted Falleta's definition, as it was the only one which acknowledged the exploratory nature of analytics, whereas the other definitions focused on the technology, research methodology and link between HR data and business impact.

The literature reveals that there is no consensus on the terminology. For the purpose of the study, the author adopted the term workforce analytics.

2.3 Evidence-based Management

Boudreau, an arguably well respected HR thought leader, raised the issue of HR lacking logical models to aid in decision making while other management fields have such (Boudreau, 2012). He claimed that instead of reinventing the wheel, HR can adopt some of the existing and well-accepted decision-aiding frameworks used in other managerial fields. Boudreau (2012) argues that adopting existing models will assist HR to frame its message to suit the audience, as well as speak the same language as decision makers and subsequently boost HR's credibility. Angrave et al (2016) on the other hand supported the development of analytical models based on social behaviour principles due to the concern that other models and algorithm-based people management practices have been harmful to the employee experiences.

Critiques of evidence-based management and thus workforce analytics state that people are not always predictable therefore cannot be measured accurately (Chahtalkhi, 2016). Due to the unpredictable nature of humans, predictive models are not universally applicable but limited to the set - up in which they are modelled (i.e. time, social conditions and economy) (GeorgetownUniversity). It is also argued that there is no straight line from analysis to action. Thus, analytics can, at best, provide input which elevates decision quality. Falleta (2014) also raises the concern that due to personal biases, analytics are used to support decisions which have already been made.

There appears to be support for evidence-based management, but the dispute is over adoption of decision-making models which meet the scientific requirements of social scientists and adhere to social behavioural principles.

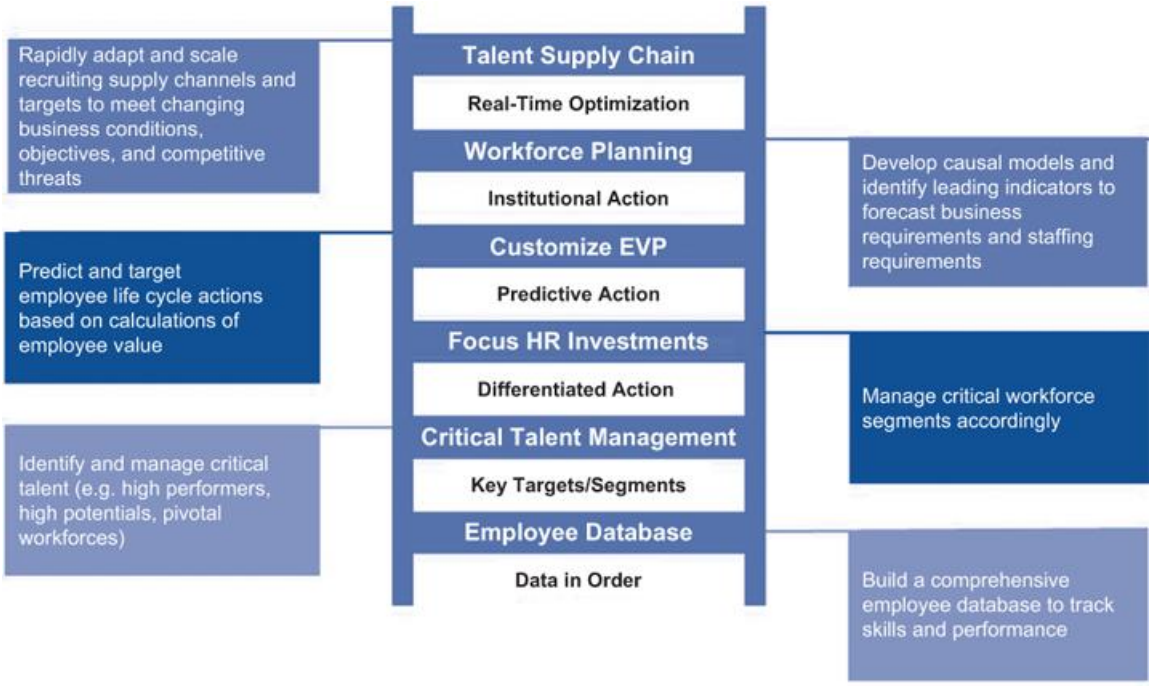
2.4 Advanced Analytics

Advanced analytics is a term adopted for the purpose of this study. It is a collective noun for predictive analytics and prescriptive analytics.

2.4.1 *Predictive Analytics*

Advanced analytics, specifically, predictive analysis, helps organisations contain HR-related costs by exposing where effort, resources and budget are not producing intended effort (Bassi, 2011) while optimising business performance as well as employee engagement and satisfaction (Mishra et al., 2016). More intriguing is Mishra, Lama and Pal's (2016) claim that predictive analytics has the potential of achieving "100% accuracy in decision making for HR" as the technology evolves.

Perhaps Mishra et al' (2016) claim is not farfetched when one considers the ladder of human capital analytics applications (the Ladder) by Davenport, Harris and Shapiro (2010) and Harris, Graig and Light (2011).



Note: The ladder shows how analytical capabilities tend to build on each other from a foundation of good data – data that is accurate, consistent, integrated, accessible and relevant

Figure 2: The Ladder of Human Capital Analytics Applications
Source: (Harris, Craig, & Light, 2011)

Mishra et al (2016) argue that the key difference between predictive and prescriptive analytics is the techniques used. Predictive analytics is said to use statistical techniques, machine learning and data mining methods while prescriptive analysis relies heavily on complex mathematics. Mondorre et al (2016) also believe that predictive analytics is about being able to establish the difference between correlation, regression and causation, as well as turning this understanding into actionable steps especially for business leaders and front-line managers (Mondore et al., 2016). This is a view that is also supported by Coco (2011). The use of statistical techniques poses a challenge to HR practitioners because there are low barriers for entering the field of HR in South Africa (Janse van Rensburg, 2009). Also, most practitioners are trained in the behavioural sciences and therefore do not have the skills required to employ statistics (Chahtalkhi, 2016; Rasmussen & Ulrich, 2015).

a) Advantages of Predictive Analytics

According to Fitz-Enz (2010), predictive analytics gives meaning to trends and patterns observed in descriptive analytics and relates what is known about present situations to the probable future (Fitz-Enz, 2010). Fitz-Enz (2010), similarly to Dash Wu et al (2012) and LaVelle et al (2011), claimed that predictive workforce analytics gives the adopter a competitive advantage. He claims that those adopting predictive analytics gain a competitive advantage over 95% of the population (Fitz-Enz, 2010). In consensus with Fitz-Enz' definition, Halo (2016) summarises predictive analytics as a tool to answer the question, "what could happen?". Several authors agree that even though predictive analytics is limited to explorative activities, the benefit is in generating data insights which drive better decisions (Boudreau, 2012; Douthitt & Mondore, 2014; Falletta, 2014; Mishra et al., 2016).

While predictive analytics appears to be useful in gaining insight into existing situations, this serves as a limited benefit especially in a volatile business

environment. Decision-makers need tools which will enable them to have insight as well as foresight.

2.4.2 *Prescriptive Analytics*

Prescriptive analytics provides managers with foresight. With the insight gained through predictive analytics, managers can implement measures to contain HR costs, manage risks associated with human capital management and optimise business performance. All these contribute to the increase return on human capital investments (Bassi, 2011; Fitz-Enz, 2010; Mishra et al., 2016). Prescriptive analytics can be pre-emptive as it includes the ability to quantify the effects of future decisions and recommending the best course of action for a given situation (Halo-BI, 2016; Rouse). The unique value of prescriptive analytics is real-time optimisation of information (Davenport et al., 2010; Molefe, 2013)

Bersin (2014) enlists some of the prescriptive analytics models as scenario planning, predictive modelling, risk analysis and mitigation and integration with strategic planning. The initiatives are undertaken using business rules and a combination of techniques such as machine learning, algorithms, computational modelling, etc. (Halo-BI, 2016; Mishra et al., 2016). Such skills are a rare commodity in HR.

Advanced analytics borrows from different fields such as behavioural sciences, IT, finance and statistics (Levenson, 2005). McCabe (2014) has termed this multidisciplinary workforce management as workforce science (McCabe, 2014). Whereas Falleta (2014) identifies it as workforce intelligence because it employs similar principles to that of business intelligence. Business intelligence relies heavily on the use of technology whereas technology is an enabler in advanced analytics therefore the association of advanced workforce analytics with business intelligence is not desirable. Workforce science is more appropriate due to the scientific approaches used in advanced workforce analytics.

2.5 Criticism of Advanced Workforce Analytics

Robinson (2015) argues that not all organisations need to conduct advanced analysis. He recommends substantial benefit may be realised from a business impact analysis. However, when one considers Robinson's and Human Capital Analytics Architecture (see Figure 1 in section 1.5) and the Ladder (see Figure 2 in section 2.4.1), it is evident that all organisations may benefit from each level of analysis. For instance, recruitment officers, regardless of the size of the organisation or type of industry, need to know the attributes of good candidate for particular positions. Impact analysis gives the benefit of hindsight and provides opportunity to determine if there is a trend whereas predictive analytics would test the relationship of the variables in the trend, that is whether it is causal or correlation. Knowing the relationship between the variables equips managers with the information required to calculate a probable future (Fitz-Enz, 2010). Thus, enable the adoption of prescriptive analytics techniques. Fitz-Enz (2010) also states that the higher you go in the corporate ladder the more analytics should present business impact. Therefore, the criticism that not all businesses require advanced analytics does not stand.

2.6 Advanced Workforce Analytics Frameworks

While it is agreed that analytics is not the same as metrics (Marler & Boudreau, 2016), the two cannot be divorced from each other as the latter is a critical input into the analytical process. Metrics include factors such as cost, time, quantity, quality and human reaction (Fitz-Enz, 1995). However, there is ongoing concern that there is a flood of metrics in the HR space (this was last measured at over 250) and little clarity on how HR is using them. Several authors have attributed this problem to HR's failure to provide meaningful business impact (Carlson & Kavanagh, 2011; Fitz-Enz, 1995; Huselid, 2015; Lawler III et al., 2004). To address the challenge of demonstrating business impact Mishra et al. (2016) identified some key aspects to consider when conducting analytics:

- **Need** – identification of a business problem

- **Approach and Application** – develop or adopt a metric/s and conduct predictive modelling.
- **Impact** – measure and evaluate activity.

Similar to Mishra et al. (2016) analytics process guidelines, is that of Rasmussen and Ulrich (2016) model, as displayed in Figure 3 below.

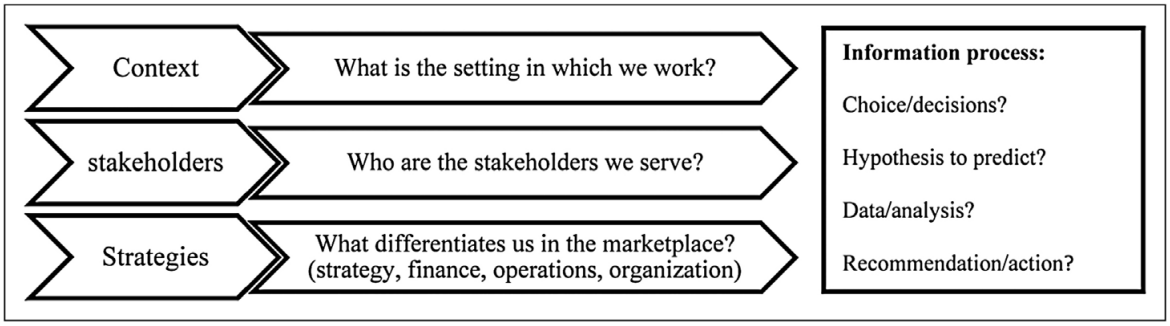


Figure 3: Information for decision making
Source: (Rasmussen & Ulrich, 2015)

Both processes provide guidelines as to how data can be used to drive business outcomes. This is the crux of advanced analytics (i.e. predictive analytics which seeks to uncover what could happen, and prescriptive analytics which provides guidance of what should be done (Halo-BI, 2016)). Frameworks are tools adopted to deliver the outcome.

Molefe (2013) lists four workforce analytics frameworks, namely Human Capital Bridge, LAMP, the Ladder and Bersin's talent analytics maturity model (Diagrams of the models are attached as **Appendix B**.

- Human Capital Bridge (HC Bridge) uses the metaphor of a bridge to create a link between investments in HR initiatives and business success. The model is based on three main elements, namely:
  - **Efficiency** in the delivery HR programmes,
  - **Effectiveness** in the implementation of HR programmes, and
  - **Impact** on the organisation (Magau & Roodt, 2010).
- Logic, Analytics, Measures and Process (LAMP) are components of the model used to drive strategic change and organization effectiveness. Logic provides the rationale for the measures, while analytics is an

enabler. Process guide actions required from the moment a need is identified to implementation and impact analysis (J. Boudreau, 2009).

- Ladder of human capital analytical applications identifies six levels in the analytics process. They are:
    - Data in order - creating a credible employee database,
    - Key targets or segments – identification of key employees,
    - Differentiated action – invest in key employees,
    - Predictive action – drive desired behaviour in key employees by aligning the organisation's employee value proposition to the employee's life cycle,
    - Institutional action – use prescriptive analytics to forecast business demands and staffing needs.
    - Real-Time Optimization – at this level the analytics provide real-time information to enable decision making on staffing needs.
- Talent analytics maturity framework identifies four evolutionary stages of analytics as operational reporting, advanced reporting, advanced analytics and predictive analytics (Bersin, 2014). Bersin (2014) regards building analytical maturity as a long-term project and evolutionary process. Furthermore, Bersin (2014) states that to build maturity, organisations need a strategic plan for analytics, a strong foundation for data governance and appropriate skills and adequate resources.

According to Molefe (2013), HC Bridge aims to link HR's initiatives to business performance, a practice which has been deemed a fatal flaw of HR practitioners as the practitioners focus on what the organisation should do about HR management instead of using human resources to address business needs.

The three other frameworks (LAMP, the Ladder and talent analytics maturity model) were designed to assist HR practitioners to ask the right business questions so that the subsequent steps of analysis, measurement, predictive modelling and eventually prescriptive analysis may result in real business impact. The LAMP framework, was referenced a lot in the articles reviewed by Marler &

Boudreau (2016) apparently due to the framework's ability to uncover cause-effect of variables and therefore evidence-based relationships.

Below are other frameworks which also aim to enable HR processes and analytics to address business question and make business impact:

2.6.1 *Human Capital Model for the 21st Century*

The human capital model for the 21st century (HCM:21) was developed by Jac Fitz-Enz in 2008. Fitz-Enz (2008) regards HCM:21 as a framework which would assist decision-making about the organisation's human capital to be logical and predictive. The framework has four stages as follows:

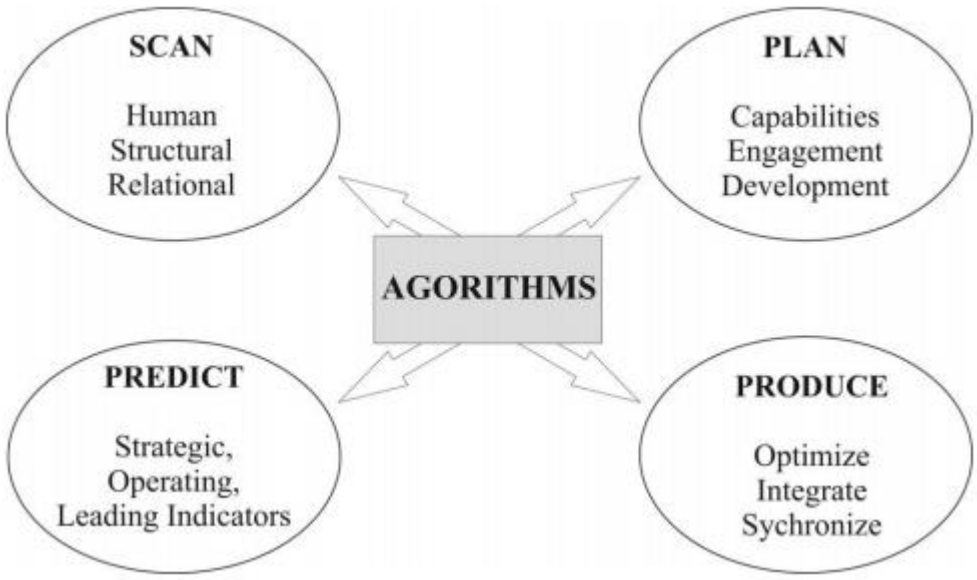


Figure 4: Human Capital Model for the 21st Century
Source: (Fitz-Enz, 2008)

Scanning – this is the first stage of analytics where an environmental scan of internal and external forces, which affect human, structural and relational capital in the organisation, is conducted. The purpose of conducting a scan is so that any relationship such as interactions or interdependencies amongst the factors may be recognised and accounted for. Fitz-Enz (2010) claims that the scanning stage is often ignored.

Planning – entails a revamp of the workforce planning process by including an assessment of the organisation's requirements, as revealed by the scan, and subsequently sourcing workforce which meets the current needs instead of the not so good-old way of just refilling positions.

Producing – during this stage analytics is employed to measure HR processes and uncover the most cost-effective factors "inputs and throughputs" which lead to the desired outcomes.

Predicting - Fitz-Enz (2010) designed a three-point measurement system which comprises of strategic, operational and leading indicators. He claims that the indicators establish causation or correlation between measured factors (Fitz-Enz, 2010).

2.6.2 *Value-linkage Model*

The value-linkage model was designed to create a scientifically sound framework which would assist organisations in employing their human capital data to drive the organisation's strategic and financial priorities. This is achieved through measuring HR data points with other non-HR data and metrics in other areas of the organisation (e.g. finance, marketing, operations). Various statistical techniques are adopted to establish causation and effect as well as quantify the relationship's strength and ability to deliver a predictive model. Mondorre et al (2016) state that structural equations modelling (SEM) is the best technique to employ when seeking to establish causation-effect. This is due to its ability to test multiple inputs and outcomes concurrently, accurately calculate ROI and correct measurement error(Mondore et al., 2016). SEM also has the ability to calculate relationships between unobserved constructs and observable constructs. Mondorre et al (2016) do note that the use of SEM does require specialist skills. Once again highlighting the multi-disciplinarity of the workforce analytics field.

SEM' ability to test multiple inputs and outcomes concurrently provides possibility of linking analysis to action and potentially alleviating some of the concerns raised by critiques of evidence-based management. The ability to link analysis to action

does not infer generalisation nor universality of the results. The unpredictability of human behaviour poses a major challenge. Coco (2011) and Douthitt and Mondore (2014) actually agree that there should not be a blanket adoption of any model as organisations requirements and environments differ. Statistical techniques should also be adopted according to the purpose and aim of the exercise (Coco, 2011; Douthitt & Mondore, 2014).

2.6.3 *Balanced Scorecard*

The balanced scorecard was initially developed by Robert Kaplan and David Norton with the aim of creating a mechanism which motivates and measures performance in line with the organisation's vision and strategy. Kaplan and Norton (1996) state that the four elements, financial, customer, internal business processes and learning and growth (illustrated in figure 5) create a balanced picture of the performance of the organisation.

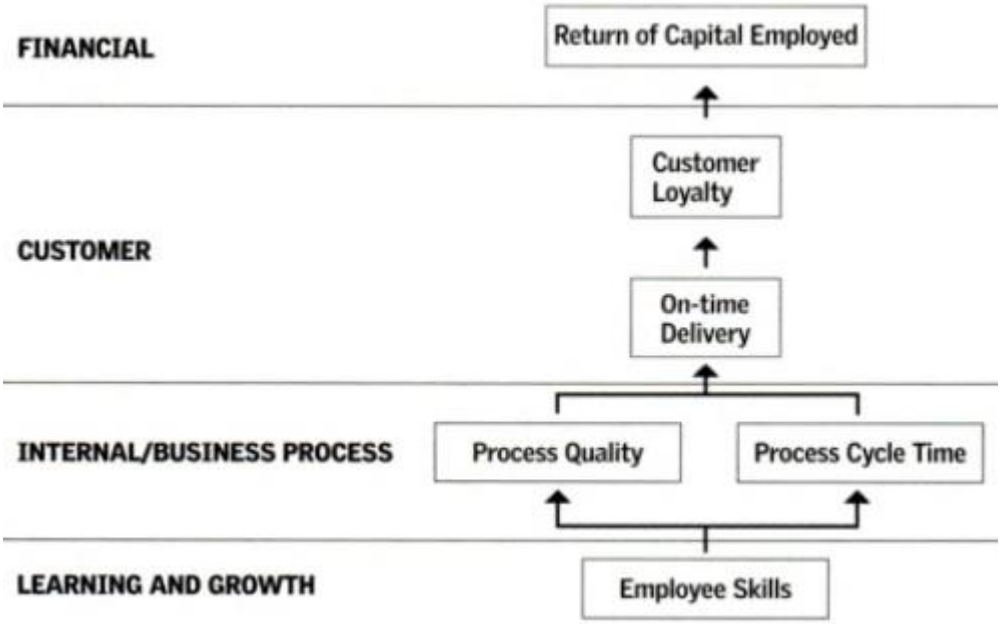


Figure 5: Balanced Scorecard
Source: (Becker, Huselid, & Ulrich, 2001)

The elements have lagging indicators which present the prevailing environment and leading indicators which are the drivers of future performance (Kaplan &

Norton, 1996). Leading indicators differ according to the organisation and environment (Coco, 2011; Mondore et al., 2016)

The financial element measures the economic value, while customer section measures market share, customer sentiment and profitability. Internal business processes measures innovation, operation and post-sales processes. Chrysler-Fox and Roodt (2014) classified the learning and growth element measures human capital drivers in to two categories as follows:

- **Core employee drivers** which were identified as job satisfaction, retention and productivity.
- **Situation specific drivers** are factors and drivers unique to an organisation. They include staff competencies, climate for action and technological infrastructure.

The rationale of the four elements is that they spark a chain reaction. Learning and growth are considered drivers of internal business processes, which in turn drives the customer perspective and value, and thus the financial performance of the organisation (Chrysler-Fox & Roodt, 2014; Kaplan & Norton, 1996).

Human resource practitioners however still found the balanced scorecard to be limited in terms measuring the intangible value of human capital. The concern was its lack of emphasise on employee perspectives, lack of integration into other HR functions and unintentional promotion of harmful management practices. Due to the framework's focus measuring tangible outcomes, this often came at the expense of 'soft-issues' which drove human behaviour (Chrysler-Fox & Roodt, 2014).

Other frameworks were developed to address these shortcomings. Becker et al (2001) incorporated 5 elements which are:

- Employee's competency in business insight and execution of work,
- High-performance work systems,
- Systems alignment,
- HR efficiency,

- Delivery.

However, this scorecard was still deemed to have not addressed the challenges raised in the balanced scorecard. Subsequently Huselid (2005) expanded the framework by including 4 more elements:

- **Workforce mind-set and culture** refers to communication of the strategy and cultivating a culture that will enable successful delivery of the strategy.
- **Workforce competencies**. Managers should ensure that employees in strategic positions have the appropriate skills to deliver on the organisation' strategy.
- **Leadership and workforce behaviour** that nurtures a conducive work environment and motivates high performers.
- **Workforce success** measures employees' ability to accomplish the business' strategic objectives.

According to Chrysler-Fox and Roodt (2014) the most commonly used frameworks are the Human Resource scorecard by Becker, Huselid and Ulrich (2001) and the Workforce Scorecard by Huselid (2005).

A review of the frameworks reveals the complexity of relations between employer, employee and the work environment. Of all the frameworks, the Ladder provides the most direction in terms of how analytics evolve from data to insight then foresight and eventually, the coveted business impact. The Ladder brings to reality Fitz-Enz's (2010) view that workforce analytics is a communication tool which brings together data from disparate sources to present a unified, actionable picture of current conditions and likely futures.

2.7 How is Workforce Analytics Impact Assessed?

For one to know whether the intended objective was achieved, there has to be a measuring tool. Fitz-Enz (1995) and Mishra et al (2016) identified reasons for measuring HR interventions as:

- To communicate performance expectations,
- Understand outcomes,
- Benchmarking,
- Identify performance gaps,
- Support resource allocation decisions,
- Recognise and reward performance.

Their emphasis is on connecting HR interventions to business outcomes and, thus, demonstrating tangible returns on investment (Fitz-Enz, 1995; Mishra et al., 2016). Lawler, Levenson and Boudreau (2004) also believe that metrics should be used to either measure efficiency, effectiveness or demonstrate the link between HR and organisational performance. Marler and Boudreau (2016) challenge the notion of efficiency measures making business impact as they form part of administrative costs which are usually a small percentage of business expenses.

Levenson (2005) reviewed the following commonly used measures:

Return on Investment (ROI) analysis: too time consuming and too simplistic:

What makes ROI too simplistic is that the context is excluded while all costs and benefits are presented into a single number thus disregarding information which may be critical to decision making (Levenson, 2005).

Cost-benefit analysis: more complex and meaningful:

Cost-benefit analysis takes into consideration details of individual costs and benefits which makes it meaningful but complex. It can also be just as time consuming as ROI. The shortfall is that not all activities and benefits are quantifiable even though they may be of strategic importance (Levenson, 2005).

Impact analysis: establishing causal links:

What makes impact analysis the ideal measurement is that it takes into consideration that not all costs and benefits can be expressed in monetary terms. Levenson (2005) mentions that the challenge in using this model is that HR and

line managers do not have the skills to determine which factors lead to behavioural changes needed to improve efficiency and profitability.

The key difference in the three measures is the extent to which benefits are accounted for. ROI and Cost-benefit analysis, which are finance measures, only account for variables with monetary value. The measures are inadequate for HR management. For instance, a manager might hire someone who does not have all the required qualifications but appears to have the potential to do the job. Potential cannot be measured. Another example is that of organisational culture. A culture misfit costs an organisation 50% - 60% of the employee's salary (Bouton, 2015). The calculation was done using impact analysis. However, one cannot accurately measure a cultural fit due to many uncontrollable factors which impact human behaviour. At best, as stated in section 2.5, impact analysis gives the benefit of hindsight and provides opportunity for trend analysis.

The question one asks is whether the challenges in developing suitable measures for advanced workforce analytics is due to HR practitioners lacking analytical skills.

2.8 Workforce Analytics Adoption Challenges

There are more articles and studies written by practitioners and consulting firms about the challenges faced by organisations in implementing workforce than there are academic reports. However, there is consistency on the perception of the challenges in both cases. The challenges are identified as follows:

Lack of analytical skills in HR:

HR practitioners have been trained to complete administrative tasks and respond to social behaviour. Therefore, there is a need to upskill or even retrain HR practitioners to use analytical techniques (Chahtalkhi, 2016; Rasmussen & Ulrich, 2015). While one may argue that HR practitioners do not need to be data scientists, research indicates that it is important for HR practitioners to have a basic understanding of statistical methods and techniques. This will enable HR

practitioners to develop meaningful hypotheses, understand the relationship between the variables and formulate useful metrics which allow them to communicate the performance of the organisation's workforce to the relevant stakeholders (Frick, 2014; Huselid, 2015; Levenson, 2014; Rasmussen & Ulrich, 2015). Once HR practitioners obtain this knowledge, they will be better equipped to exploit their existing data (Angrave et al., 2016) and also be able to acquire suitable analytical tools, if required.

As it currently stands, HR practitioners rate their own capabilities and readiness for the new environment low (KPMG-International, 2015). Therefore, there is awareness that things need to change.

According to Levenson (2011) and Marler and Boudreau (2016), the competencies required for having an effective workforce analytics system are:

- Data preparation,
- Root cause analysis,
- Research design,
- Survey design, and
- Quantitative data collection,
- Analysis techniques.

However, Huselid (2015) identified the competencies as:

- Critical causal thinking,
- Understanding the principles of good measurement,
- Estimating causal relationships,
- Communicating.

The two sets of competencies present different sections of social science. The usefulness of each skills set is dependent on other members of the team having complimentary skills.

As workforce analytics is an emerging field, the labour market does not offer much in the way of a solution. A study by McKinsey, conducted in 2011, on the market's

readiness for big data estimated that in the United States the demand for people with analytical skills is sixty percent more than the supply (Brown et al., 2011). With the demand for data scientists being higher than supply, it is to the organisation's benefit that all stakeholders (i.e. HR, line managers, IT, legal and executive) support initiatives to build analytical skills in-house. Furthermore, organisations seem to be understanding this as the Deloitte's HR Global Trends study for 2016 found that in comparison to the previous years, support for workforce analytics had increased and organisations were aggressively building these capabilities (GHC-Trends, 2016).

Leadership's scepticism about HR's value to business:

HR's clients i.e. the executive committee (Exco) and other business unit managers express low satisfaction overall with HR's services (Africa, 2016; Fitz-Enz, 1995; KPMG-International, 2015). The outcome of a survey conducted by KPMG in 2015 show that business leaders continue to be sceptical about HR's contribution to business (KPMG-International, 2015). The absence of convincing data which shows HR's contribution to business outcomes often results in inadequate investment in HR turnarounds.

Interestingly, Levenson, Boudreau and Lawler (2005) also conducted a study which revealed that HR's business impact was higher than Exco's perception of HR's contributing value. They claimed that the executives' perception of HR's contribution is caused by how HR communicates. Business uses financial models to measure success and as identified in section 2.7, financial models are inadequate to measure human behaviour.

Risk of data security (Brown et al., 2011):

The concern is that analytics, especially in the big data era, includes collection of sensitive personal information. While having the ability to access this information may be stringent, no security is absolute. Recent examples which show the vulnerability of data is that of the Ashley Madison hack and the Panama Papers revelations. Hence, there is concern over access control, the bridging of security or leaking of sensitive employee information, especially with regards to identity

theft. Descriptive analytics also raises concern over the violation of individual's privacy - an area which the regulation authorities seem to be lagging in. While South African law makers have implemented the Protection of Personal Information (POPI) Act, further work is still required.

Risk of theft of intellectual property (Brown et al., 2011):

Data and knowledge have become the largest and most sought-after commodities in the 21st century. Brown, Chui and Manyika (2011) warn that the integration of IT systems may expose the company's intellectual property and, as such, increase the risk of theft of intellectual property (Brown et al., 2011).

Implementation of analytical findings:

Some analytical findings may require an overhaul of existing systems or have major financial implications, making them difficult to implement (Chahtalkhi, 2016). If HR is not considered a strategic partner in the business it could be difficult to obtain the buy-in and participation of key stakeholders when addressing matters. This buy-in is crucial as it allows the process to be co-owned and thus, will have a direct impact on desired business outcomes, while at the same time minimising the risk of resistance (Rasmussen & Ulrich, 2015).

Inadequate support from academia and practice for development of workforce analytical skills:

Angrave et al (2016) query that the literature does not reveal much detail on how workforce analytics can be developed (Angrave et al., 2016). This is corroborated by Marler and Boudreau's (2016) review.

Limited value of Human Resources Information Systems:

In 2014, it was estimated that HR departments invested approximately $14 billion annually in HR software. However, several studies found that companies report a very low return on these investments (Bersin, 2014). A valuable human resources information system (HRIS) is one that enables the user to observe, measure, document and track performance accurately and transparently (Aral, Brynjolfsson,

& Wu, 2009). Angrave et al (2016) and Douchitt and Mondorre (2014) concur that most software packages do not show the cause-effect relationship as they have few programmed questions, thus limiting organisations from further strategic explorations. What is deemed to be missing from current analytics software is the ability to build longitudinal and multivariate econometric models which are needed to conduct 'end-to-end' analytics (Angrave et al., 2016; Douthitt & Mondore, 2014). Falletta's (2014) view is rather that organisations invest in technology but neglect to develop the intellectual capacity and skills required to utilise the technology development. He further warns that companies should not place too much emphasis on technology to solve the obstacles which HR departments today, as it is only one part of the equation. Without the necessary skills to process and interpret the data, it will serve little purpose to the business.

Michael Schrage in Boudreau (2012) raises an interesting point in that the technology can fail because of attempts to develop a perfect but stagnant system. Whereas, if the focus is shifted towards workforce analytics the underlying processes of using data allows the system to evolve according to the organisation's needs (Bersin, 2014; Boudreau, 2012).

Lack of business acumen by HR:

There is a theoretical argument that the internal fit between HR and the organisation will result in better financial performance (Huselid, 1995). However when Huselid (1995) conducted an empirical study, he found the relationship between the HR's fit in the organisation and the organisation's financial performance is rather modest, but established a strong correlation between high performance HR practices and the organisation's financial performance (Huselid, 1995). According to Ulrich (1997), organisations with comprehensive HR practices tend to have better financial performance regardless of the organisation's strategy.

There is consensus that HR needs a mind-set shift in terms of how it engages with business and performs its functions, if it is to prove that it is adding business value (Angrave et al., 2016; Boudreau, 2012; Fitz-Enz, 1995; Marler & Boudreau, 2016;

PwC, 2014; Rasmussen & Ulrich, 2015). The status quo is that Human Resource leaders often find it difficult to strategically align and integrate their HR functional strategies, outputs and measures to business priorities (Coco, 2011; Douthitt & Mondore, 2014). This may be due to HR practitioners lacking business acumen.

HR practitioners need a reliable and valid understanding of the business and its challenges so that they may develop solutions which directly address the business problems (Chahtalkhi, 2016; Rasmussen & Ulrich, 2015). Also, HR practitioners need to ensure that the information is presented in a manner that best suits the decision maker (Chahtalkhi, 2016). Ulrich (2011) refers to the approach as HR from the outside-in while Boudreau (2012) named it "re-tooling HR". Chahtalkhi (2016) goes further by recommending that the extension of HR to include analytics requires a restructuring of HR departments.

The continuous high levels of dissatisfaction and scepticism from managers, raises concern as to whether HR practitioners have any inclination to heed to the call (Africa, 2016; GHC-Trends, 2016; KPMG-International, 2015). The delay in response risks HR being replaced by dashboards (Bersin, 2014; Davenport et al., 2010; Rasmussen & Ulrich, 2015).

Culture - Organisations have not embraced evidence-based management:

42% of managers' report that they usually have 24 hours to make a decision, sometimes without the data to inform their options (Hannane, 2016). This might be due to a couple of reasons. However, Chahtalkhi (2016) also points out that only few companies are equipped to make data-driven decisions. Also, very few companies succeed at connecting information to decision making. This is despite the massive amounts of data that companies have at their disposal (Chahtalkhi, 2016).

The organisations' leaders are vital in driving the culture of evidence-based management. In terms of workforce analytics, there needs to be support for using a rational approach in taking decisions relating to sensitive and sometimes irrational human behaviour (Chahtalkhi, 2016). The rational approach somewhat dispels the view that management is context based, as claimed by Delbridge and

Whitfield (2007). Chahtalkhi (2016) introduces the terms unitarist and pluralist. In brief, the former occurs when employees are perceived as homogeneous and power is centralised, whereas the pluralist concept is when employees' individualism, and in essence their expertise, are appreciated and given some autonomy to complete their tasks. The reason for the debate is to demystify the impact of analytics on decision-making. A case in point is that of the Google workforce analytics department. Google had a lengthy and time-consuming promotion process. To shorten the process, the HR department, together with the analytics team, developed a model that would identify the best candidates eligible for promotion. In an environment that is data-driven one would expect rapid adoption of such an innovative solution to people management, but to the HR department's surprise, managers still rejected the model even though they found it informative (Setty, 2014). The managers still wanted to have the final say on who got promoted. What the metrics were rather useful for, was supporting the manager's decision. Setty (2014) say that the lesson learnt was that people should make people decisions.

The Google lesson highlights the caution for organisations not to treat employees as numbers, but also to consider the impact of their decisions (Bersin, 2014; Davenport et al., 2010; Rasmussen & Ulrich, 2015). It also bears true to the claim that HRIS' are inadequate to deliver the values of advanced analytics.

Researchers also found that the decision maker's preferences and experiences also have a bearing in the decision, despite the evidence presented by the analytics (Chahtalkhi, 2016; Rasmussen & Ulrich, 2015). Rasmussen and Ulrich (2015) mention that people have tendencies to reject data that threatens existing beliefs especially if it is something they have invested themselves in. Falletta (2014) corroborates Rasmussen and Ulrich (2015) views in that decision-makers are more likely to adopt evidence that is aligned to their personal biases.

Falletta (2014) raised an alarming observation that usually business uses data and analytics to validate a decision already taken or cherry pick data which supports their views. HR should not neglect the human element and power

dynamics when adopting evidence-based management (Rasmussen & Ulrich, 2015).

2.9 Key Success Factors

Key success factors reflect the direct opposite of the challenges. Organisations who successfully implemented workforce analytics had a culture of incorporating data in their decision making. Their HR departments focused on business priorities, invested in integrating and rationalising data so that it may be valid and reliable. The workforce analytics team was comprised of skills from multiple disciplines and the HR practitioners had knowledge of analytics (Angrave et al., 2016; Bersin, 2014; Rasmussen & Ulrich, 2015). The Deloitte Global Human Trends 2016 survey report indicates that supportive leadership, an emphasis on governance and decentralisation of the data analytics function also have a major impact on adoption of evidence–based decision making and successful implementation of advanced workforce analytics (GHC-Trends, 2016).

The above factors are key to any change in an organisation, but also to address success factors specifically for advanced analytics, Fitz-Enz (2010) states that there should be comprehension of past and current events, and an understanding of trends and drivers of the trends. He also states that there should be visibility of change and tools to measure the probable future outcomes (Fitz-Enz, 2010)

Advanced analytics are exploratory in nature hence there is a stern warning that workforce analytics is not a destination but a journey which is filled with trial and error (Fitz-Enz, 2010; Molefe, 2013). The analytics team should be aware of holding on to metrics which either do not work or are no longer suitable (Bersin, 2014; Boudreau, 2012; Falletta, 2014). Marler and Boudreau (2016) also found that workforce analytics causes better performance and competitive advantage when it is unique. This is congruent to Boudreau (2012) findings that analytics are about innovation, play and proto-typing.

From this perspective, it is understandable that Fitz-Enz (2010) regards analytics as a state of mind which starts with a logical progression and then supported by statistical tools.

2.10 Summary of Literature Review

In the volatile, unpredictable, complex and ambiguous (VUCA) business environment, new workplace dynamics are at play. Human Resource practitioners need to embrace the new environment if they are to prove that human resource management is still a required a business support function. Analytics, and more precisely advanced analytics, is said to provide businesses with timeous solutions and insight. This could be a true value add if managers are required to make critical staffing decisions is a short period of time.

Supporters of advanced workforce analytics claim that workforce analytics will result in cost optimisation, effective utilisation of human resources, bridge the gap between academia and practice, provide measurable impact of HR investments and minimise human capital management risks.

Academia and the business world agree on the nature of the challenges in implementing HR workforce analytics. Foremost among these are the lack of analytical skills in HR. There is consensus that workforce analytics require a multi-disciplinary team. Additionally, the difference in frames of references diminishes the impact of HR and exacerbates the lack of confidence in HR by other leaders.

Globally, organisations that have implemented advanced analytics claim to have gained a competitive advantage despite significant challenges. Keys to their success are analytics initiatives which address business needs, a culture which embraces evidence-based management, a multidisciplinary team and governance.

There are multiple frameworks which seek to ensure successful implementation of advanced workforce analytics but none appear to be more accurate than the

other. There is consensus amongst researchers that adoption of advanced workforce analytics cannot be a blanketed approach across organisations which poses an additional challenge for those wishing to adopt it as there is also inadequate support from academia and practice.

While it might appear like an uphill climb, the benefits appear to far outweigh the challenges, especially when one considers the possibility of significant increase accuracy in decision-making.

2.11 Research Hypotheses

As demonstrated above, there is still much work to be done in the field of study which surrounding workforce analytics. As a starting point, this study seeks to establish whether a relationship exists between HR practitioners' analytical skills and the adoption of advanced workforce analytics.

Based on some indications from previous studies of attachment style, this piece of research hypothesises the following:

Hypothesis 1 – Lack of analytical skills in the HR fraternity in South Africa is a major inhibitor in the adoption of advanced workforce analytics.

Hypothesis 2 – South African HR practitioners do not understand the applications of Advanced Workforce Analytics.

CHAPTER 3. RESEARCH METHODOLOGY

3.1 Introduction

A researcher should be clear on the knowledge claims and theoretical perspective, strategies of inquiry and methods of data collection and analysis (Creswell, 2013). Section 3.2 outlines the knowledge claims, theoretical perspectives and strategy of inquiry. The rest of the chapter outlines the method of data collection and analysis.

3.2 Research Paradigm

The philosophy underpinning the research study is post-positivism. Post-positivists believe that reality cannot be known with certainty as causes determine effects and outcomes. Due to this, post-positivists regard all observation as fallible and erroneous and that theories can be reversed. Hence theories need to be tested and refined. Post-positivism is also known as empirical science or quantitative research (Creswell, 2013).

Quantitative research measures concepts, seeks to generalise findings and can be replicated (Janse van Rensburg, 2009). Characteristics of quantitative research are that is has specific focus, usually large-scale case studies, uses numbers, and analysis and the researcher aims to produce objective information (Denscombe, 2014). Observations and measurement of the objective reality is the only way of demonstrating contingent relationships between concepts (Creswell, 2013; Janse van Rensburg, 2009).

The purpose of a quantitative research is to aim to develop relevant true statement, through data, evidence and rational considerations so that the statement can serve as knowledge to explain the situation that is of concern (Creswell, 2013). It is the best approach for testing a theory or claim, and hence post-positivist researchers adopt a deductive analysis approach to knowledge development.

The research adopted quantitative research as the hypothesis were drawn from the literature review which revealed claims that adoption of analytics is low in South Africa, that adoption is affected by various challenges including lack of analytical skills by practitioners and that practitioners appear to have misunderstandings on the applications of advanced analytics. None of the claims were supported by empirical evidence. As such, the research sought to collect statistical data and evidence to test the claims so that true statement regarding the state of analytics and HR practitioners in South Africa could be developed.

3.3 Research Design

Mouton (1996) states that the basis of a research design is a well-defined research problem (Mouton, 1996). The research design provides a framework for addressing the problem so as to maximise validity of results.

The author used Cresswell's (2013) checklist as the framework for designing research. The checklist together with responses is presented in table 4 below:

Is the purpose of the questionnaire design stated	Yes. Section 3.2
Are there reasons for choosing the design mentioned?	Yes. Section 3.2
Is the nature of the questionnaire (cross-sectional vs. longitudinal) identified?	Yes it was cross-sectional. Section 3.6.
Are the population and size of the population mentioned?	Yes, section 3.4. The population was HR practitioners working in South Africa. No official data on the size of the population.
Was the population be stratified?	No, due to the lack of official information on HR practitioners. Section 3.4.1.

How many people were in the sample?	5,800 practitioners across the country. 167 responded but only 76 qualified for further analysis. Sections 3.4, 4.2 and 5.1.
What was the procedure for sampling?	The sample was selected primarily through multi-stage cluster sampling. Section 3.4.2.
What instrument was used in the questionnaire? Who developed the instrument?	A structured questionnaire. Adopted from Levenson et al (2005) and Falletta (2014). Section 3.5.1
The scales?	5 point Likert Scale
What procedure was used to pilot questionnaire?	It was reviewed by Professor A Stacey, Head of Research at WBS and some colleagues who have extensive experience in the HR field.
What was the timeline for administering the questionnaire?	The questionnaire was distributed on the 1st of March 2017 to 30th April 2017
What are the variables in the study?	Hypothesis 1 variables • Independent – challenges inhibiting adoption • Dependent – adoption of analytics • Control – who conducts the analysis, role of HR in the analysis process Hypothesis 2 variables – HR practitioners, understanding of applications of workforce analytics

How do these variables cross reference with the research questions and items on the questionnaire?	Section 3.5.1 and Chapter 5
What specifics steps will be taken in data analysis to:	
a) Check for response bias?	Control variables were used. Chapter 5, sections 5.1 – 5.3.
b) Conduct descriptive analysis?	Yes. Chapter 4.
c) Collapse items into scales?	No, used 5 point Likert scale.

Table 4: Framework for Designing Research
Source: (Creswell, 2013)

3.4 Population and Sample

3.4.1 *Population*

Population is defined as the universe of units from which the sample is selected (Bryman, 2015). The profile of the target population and thus the unit of analysis of this report is HR practitioners working in South Africa.

There is no statutory body for HR practitioners in South Africa therefore no official database to obtain the number and profile of practitioners. The South African Board of People Practitioners was established to regulate the HR practice but membership is voluntary. The HR field has low barriers to entry, meaning that some practitioners do not have qualifications at all (Janse van Rensburg, 2009), while others have qualifications from other fields. Therefore, one could not estimate the number of practitioners based on university graduates. The population size of HR practitioners in South Africa is therefore unknown.

Due to lack of official information on HR practitioners, there was no basis to stratify the sample by social demographics or region/province and efforts to do so in order to claim representativeness would have been scientifically unsound.

3.4.2 *Sample and Sampling Method*

Samples are a subset of the population that is being studied (Bryman, 2015). They are selected to be representative, that is, microcosms of the whole population (Bryman, 2015; Janse van Rensburg, 2009). Samples may be selected either through a probability or non-probability approach. The initial plan was to use convenient sampling by approaching consulting firms who conducted annual studies among HR practitioners. However, access was not as easy as the author had presumed it would be. Also, this method would have increased the risks of sample error and response biasness. The alternative was then probability sampling.

Probability sampling minimises sampling error by offering each unit in the population an equal probability of inclusion (Bryman, 2015; Mouton, 1996). The author would have adopted simple random sampling. However, this sampling method uses a sampling fraction to ensure equal probability (Bryman, 2015). As there is no reliable database on the number of HR practitioners in South Africa, the total number of practitioners is therefore unknown. As such, the author could not adopt this selection method in its purest form but used some of the principles when applying the multi-stage cluster sampling method. Multi-stage cluster sampling is the grouping of units in the population (Creswell, 2013). The advantage of this method was that it allowed the author to have accessed to a wider sample. The sample therefore comprised of respondents who were registered with the South African Board of People Practitioners and those not registered. This mitigated the risk of sampling error.

There was also an element of snowball sampling as some of the author's classmates and colleagues were requested to forward the questionnaire. The risk with snowball sampling especially with classmates, was that their contacts most likely resided in Gauteng. However, the risk was minimal as the questionnaire

was distributed to only 6 classmates. The same risk was not applicable for the author's colleagues as they reside in other provinces.

3.4.3 *Sample Size*

The aim of sampling is to produce a representative population (Mouton, 1996), however the biggest challenge with a quantitative study is that it requires a broad sample (Huselid, 1995). The challenge for the research was that the population size and profile was unknown, therefore the only form of representativeness was through targeting a large sample, as the size of the sample can affect the outcome. (As the size increases, the chances of inaccuracy are more likely to decrease (Mouton, 1996)). The author chose what appeared as a sensible number for an academic study also considering the constraints of time and other resources. The questionnaire was distributed to 5,800 people across the country.

The questionnaire had one hundred and sixty-seven respondents, of which only seventy-six qualified for further analysis. The guideline for quantitative studies is that the study should not involve fewer than thirty cases (Denscombe, 2014). With a sample size of seventy-six respondents one could claim representativeness. Bryman (2015) also states that most quantitative studies have a response of below 50% and that low responses should not bias the outcome of the study.

3.5 The Research Instrument

Quantitative research is associated with social surveys because they can collect information from large samples of individuals (Janse van Rensburg, 2009). As such, a self-administered questionnaire was chosen as the instrument for data collection. Also because it (self-administered questionnaire) minimised bias that the researcher and respondents may have experienced through face to face contact (Bryman, 2015). Collecting data via a questionnaire was also cost effective, less time consuming and convenient. Respondents are also more likely

to be honest and reveal sensitive information when completing self-administered questionnaires (Bryman, 2015).

The disadvantage of using a structured questionnaire is that there are limited questions the researcher can ask. There was also a risk of low response rate, which the author experienced, as there were 176 responses from the 5,800 distributed.

3.5.1 *The Design of Instrument*

Bryman (2015) states that questionnaires have to be very easy to follow and easy to answer. When designing the questionnaire, the author followed Bryman's guidelines, that is:

- There were open-ended questions in the questionnaire.
- The questionnaire had an easy to follow design to minimise the risk of respondents failing to follow instructions or omitting questions.
- It was concise to minimise the risk of respondent fatigue.
- Background and keywords were explained in the cover letter. Also, there were no ambiguous terms, long questions, double-barrelled questions, leading questions. Forced choices were used in the first section to of the questionnaire to assess the eligibility of the respondents (Bryman, 2015).

The literature by Marler and Boudreau attests that there had not been a similar study conducted before. Therefore, there was no standard instrument to adopt. As such, the instrument was adopted from Levenson et al (2005) and Falletta (2014) and reconfigured to provide answers to the purpose of the research as per the hypotheses:

- Hypothesis 1 – Lack of analytical skills in the HR fraternity in South Africa is a major inhibitor in the adoption of advanced workforce analytics
- Hypothesis 2 – South African HR practitioners do not understand the applications of Advanced Workforce Analytics

The survey had thirty-six items.

The first section sought to ensure that the respondents matched the population criteria, and assess if the respondents have the necessary knowledge:

Are you an HR practitioner	Yes/No
Are you based in South Africa	Yes/No
Do you conduct any data-based analysis	Yes/No

Control variables for hypothesis 1:

If yes, who conducts the analysis	Myself/ Others in HR/ Other departments outside HR

Competencies required for data-analysis are research design, data preparation, data collection, analysis and communication (Huselid, 2015; Levenson, 2011; Marler & Boudreau, 2016). Falletta (2014) also purports that for analytics to prove insight, they should be used for decision making.

What is your role in the analysis process	Define approach/ conduct data analysis/ Interpret data/ Reporting/ use results for decision making

To answer hypothesis 1, it was important to understand the respondents' level of analytics. The author adopted Levenson et al (2005) classification to assess this. Levenson et al (2005) identified the sophistication level of analytics into three categories, namely, basic, intermediate and advanced. Adoption of Levenson et al' (2005) categories was informed and substantiated by literature which revealed that advanced analytics are explorative and that practitioners use different frameworks and techniques. The respondents were thus asked to answer the following question:

How would you rate the level of sophistication of your analytics	basic, intermediate, or advanced.

The classification was also suitable for testing the claim that analytics is still in its infancy in South Africa.

The second section listed challenges identified by Marler and Boudrea's (2016) and those in the literature review. Respondents were required to rate their respective experiences of the challenges as inhibitors in adopting advanced analytics.

To what extent do the following inhibit you from adapting advanced workforce analytics:	
Challenge	Not at all Some extent Moderate extent Considerate Very Great Extent
Lack of analytical skills in the current HR team	
Lack of advanced statistical competencies in the current HR team	
Shortage of skills in the talent market	
Lack of leadership support	
Risk of data security	
Risk of theft of intellectual property	
HRIS not providing the support required for advanced workforce analytics	
HR does not understand business needs	
Organisational culture not supportive of embracing data when making decision	

Metrics should be 100% correct before the analysis is accepted	

Section 3 sought to provide answers for hypothesis 2. The first premise in designing this section was based on Harris and Spenser's (2016) analytics maturity assessment criteria. They purported that analytics are regarded as mature when:

- HR is Forward-Looking
    - Do they assess learning requirement so that they can tailor training and development needs
    - What contribution does HR make in terms of workforce assignments
    - Does HR design processes to improve effectiveness
    - Is there a workforce risk management strategy
- HR's focus on business problem
    - Increase organisational innovation and agility
    - Increase competitive advantage
    - Optimise workforce productivity. (Harris & Spenser 2016)

Harris and Spencer' (2016) perspective is aligned and congruent to Halo-BI (2016) explanation of the purpose of advanced analytics (that is, analytics should reveal what could happen and guidelines into what should be done). Also aligned to Harris and Spencer's view is Falleta (2014) explanation of HR intelligence as well as Fitz-Enz (2010) HR analytics value chain.

Thus in identifying an instrument for this part of the survey, the author sought an instrument that would have the above elements. Levenson et al (2005) conducted a study on workforce analytics and HR transformation. Falletta (2014) together with the Organisational Intelligence Institute and Dextrel University also conducted a study on the extent to which Fortune 1000 conduct HR research and analytical practices to facilitate HR strategy, decision making and execution. Both researches had similar questions when addressing HR's role as a business problem solver and forward thoughtfulness/strategy.

Questions from both surveys were adapted for the purpose of this study:

Forward-Looking
Measure the business impact of HR programs and processes?
Measure the cost of providing HR services?
Conduct cost-benefit analyses (also called utility analyses) of HR programs?
Measure the effects of HR programs on the workforce in terms of competence, motivation, attitudes, behaviours, etc?
Evaluate and track the performance of outsourced HR activities?
Assess HR programs before they are implemented - not just after they are operational
Pinpoint HR programs that should be discontinued
Evaluate the effectiveness of HR programs and practices
Measure routine HR process execution (payroll, benefits, communication, etc.)
Support organisational change efforts
Assess and improve the HR department operations
Assess and improve the human capital strategy of the company
Employee and organisational surveys (e.g. employee opinion surveys, engagement surveys, organisational culture/climate surveys, organisational health surveys, organisational effectiveness surveys, organisational alignment surveys)
Employee/talent profiling (i.e. tracking and modelling individual data on critical talent or high-potential employees
Workforce forecasting (e.g. workforce supply/demand and segmentation analysis to forecast and plan when to staff up or cut back

Solving Business Problem
Connect human capital practices to organisational performance?
Make decisions and recommendations that reflect your company's competitive situation
Identify where talent has the greatest potential for strategic impact
Assess the feasibility of new business strategies
Contribute to decisions about business strategy and human capital management

The questions were combined in the questionnaire distributed.

A Likert scale was adopted due to its capacity to measure the intensity of a certain area in question (Bryman, 2015). It was deemed best suitable as the respondents were required to indicate their views with regards to the questions.

A five point Likert scale adopted from Levenson et al (2005) study was used in both section 2 and section 3. In section 2 and 3, the items were statements,

related to the same object and were interrelated. This was done in accordance to the requirements of construction of a Likert scale identified by Bryman (2015).

3.6 Procedure for Data Collection

The author used cross-sectional approach to data collection. The structured-questionnaire was web-based. It was distributed from 1 March 2017 to 30 April 2017. Several methods to collect data were employed. Electronic mail was sent to personal contacts and a link to the survey was posted on LinkedIn, and Facebook. A small number of respondents were contacted telephonically, while another small group were contacted physically with the survey responses captured on printed papers.

3.7 Data Analysis and Interpretation

The process for data analysis and interpretation was as follows (Creswell & Clark, 2007; Denscombe, 2014):

- Analysis of the data – the Kruskal-Wallis test was adopted to analyse the data. It is a rank-based test that can be used to determine if there are statistically significant differences between two or more groups of an independent variable on a continuous or ordinal dependent variable. The test results are presented in a table form with four columns: the independent variable, degrees of freedom, Chi-square test results and P value.

  The Kruskal-Wallis test was chosen as the variables in the study fit the assumptions required to conduct such as test. The assumptions are:
  - The dependent variable should be ordinal or continuous variable.
  - The independent variable should consist of two or more categories.
  - The observations should be independent.
  - Does not assume a normal distribution.

As the Kruskal-Wallis H test does not determine which specific groups of the independent variables are statistically significant different from each other, a post hoc test was used (LaerdStatistics, 2013).

- Data visualisation was done through graphs and tables. Details in Chapter 4.
- Validation – Denscombe (2014) identified benchmarking and triangulation as validation methods, however since no similar studies have been down before especially within South Africa, none of the validation methods can be adopted.
- Interpretation of the results is presented in Chapter 5.

3.8 Limitations of the Study

The disadvantages of quantitative research methodology is that it focuses on one aspect of the research. As such, the study did not consider the qualifications and work experience of the respondents. The HR practice has low barriers to entry and practitioners come from all walks of life. The size of HR departments, industries or size of organisations respondents work in were also not considered and these may have impact on the need for analytics.

Also, it is not always possible to consider the context when conducting a quantitative research. For instance, it was found that in the South African landscape it was multinational companies who had adopted analytics in their HR practices (Molefe, 2013), this was not verified as the unit of analysis were individuals. Could it be that multi-nationals are adopting analytics because of the lack of visibility of their employees or is there a business need.

Furthermore, because quantitative research requires a considerable sample for the findings to be generalized, the author sought the most efficient method to distribute the questionnaire, which was by electronic mail. As a result, the author missed the opportunity to find explore other inhibitors.

3.9 Validity and Reliability

Validity refers to whether an indicator truly measures the concept (Bryman, 2015). The minimum requirements of validating a measure is face validity. This was done with the assistance of the Head of Research at the business school and a few of the author's business associates who have extensive experience in the HR field. Construct validity was also conducted through deducing hypotheses from the theory.

Bryman (2015) warns that the discussion about validity and reliability is potentially misleading as not all new measures require rigorous validating or assessment of reliability as most are straight forward. The instrument used in this research was straight forward and thus qualified for exemption.

3.9.1 *External Validity and Generalization of Results*

External validity refers to the ability of the research to be generalised, and generalization depends on the representativeness of the sample (Bryman, 2015). Our population was HR practitioners in South Africa and the study sought to draw on as wide of a sample as possible hence the questionnaire was distributed to five thousand eight hundred practitioners, with a response of one hundred and sixty-seven. The sample was representative of the population criteria and the sample size exceeded the guidelines for quantitative studies. As such the findings can be generalized.

Furthermore, similar studies by Levenson et al (2005) and Falletta (2014) drew participation of forty-seven and two hundred and twenty responses respectively. With a response of seventy-six respondents this study may be deemed externally valid.

3.9.2 *Internal Validity*

Internal validity is necessary when one seeks to establish a causal relationship (William, 2006). Since this research was on the correlation effect of the variables, internal validity was not necessary.

3.9.3 *Reliability*

Reliability is the “degree to which the finding is independent of accidental circumstances of the research” (Kirk & Miller, 1986). These accidental circumstances are identified as effects associated with the researcher, research subject and context (Mouton, 1996).

To minimise these effects accidental circumstances and ensure independence of findings, the author developed a questionnaire that was adopted from surveys drafted for a similar purpose. The population sample was selected randomly and the questionnaire was distributed electronically and the responses were anonymous. Thus, the research findings are deemed reliable and the measure valid.

CHAPTER 4. RESEARCH FINDINGS

4.1 Introduction

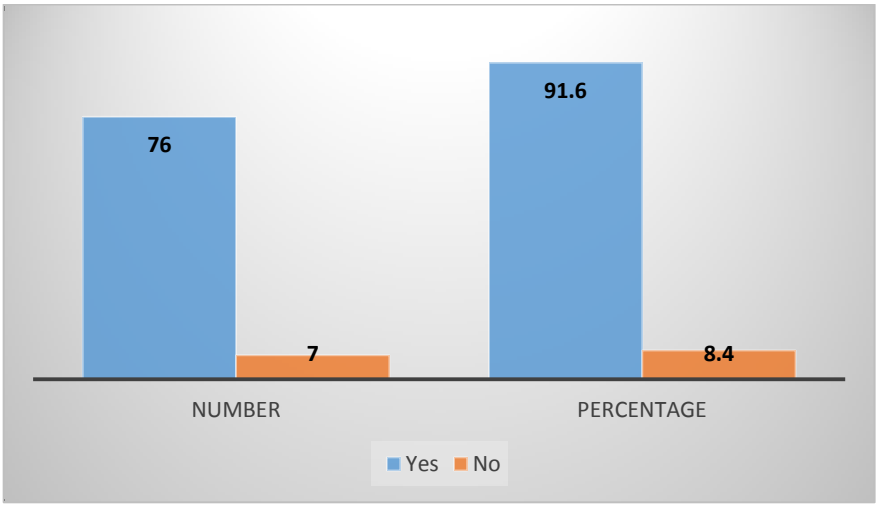
The purpose of the research was to explore the adoption of advanced workforce analytics amongst HR practitioners in South Africa. Furthermore, the author sought to explore the challenges experienced by practitioners as well as the practitioners' understanding of the applications of advanced workforce analytics. This chapter thus outlines the findings of the research.

4.2 Responses

The questionnaire was sent to approximately five thousand eight hundred HR practitioners. Of which five thousand five hundred were members of the South African Board of People Practitioners. As the target population was HR practitioners in South Africa, the first two questions in the questionnaire sought to ensure that the respondents met the criteria. The third question sought to establish whether the respondent conducted data analytics in their organisation. If the answer was no, the respondent was disqualified from further participation. The numbers are as follows:

One hundred and sixty-seven people responded to the questionnaire. Thirty-four (20.4%) respondents did not complete the questionnaire even though they had indicated that they do conduct data analysis. A further fifty (29.9%) were disqualified as they indicated that they do not conduct data analysis. 66.6% of those disqualified were HR practitioners.

Of those that completed the questionnaire, seventy-six (91.6%) were HR practitioners while seven (8.4%) were not HR practitioners.



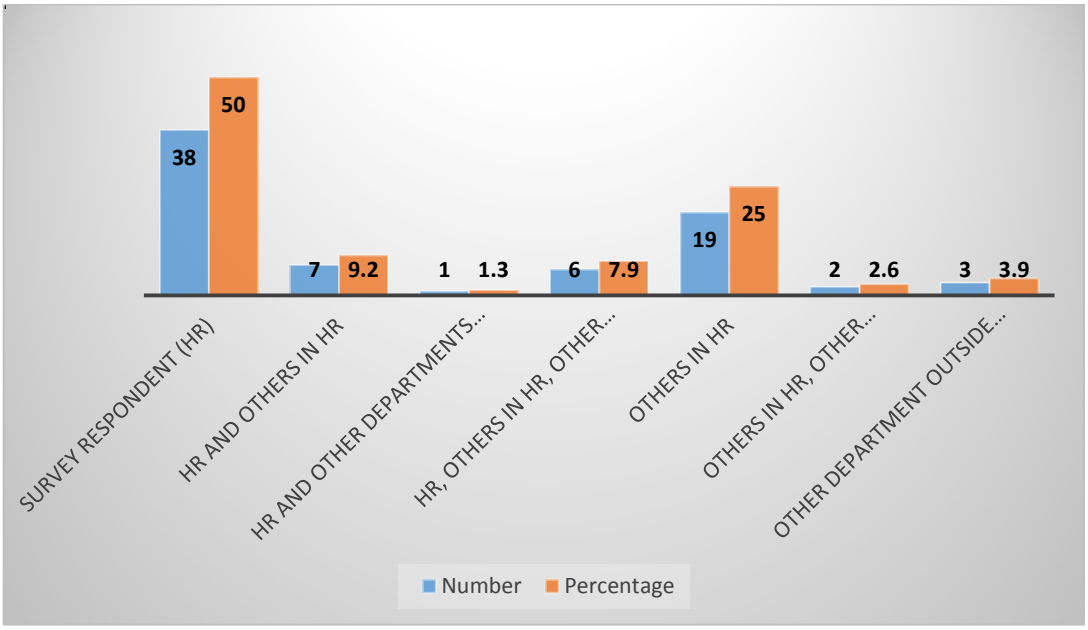
Graph 1: Questionnaire Respondents

As the study focuses on HR practitioners, the seven responses from non-HR practitioners were excluded from further analysis.

4.3 The Role of HR in the Analysis Process

Question 4 sought to determine the role of HR in the analysis process. There were three options for respondents to choose a response from, namely: myself, others in HR and other departments outside HR. The respondents chose the applicable combination. Graph 2 depicts the outcomes.

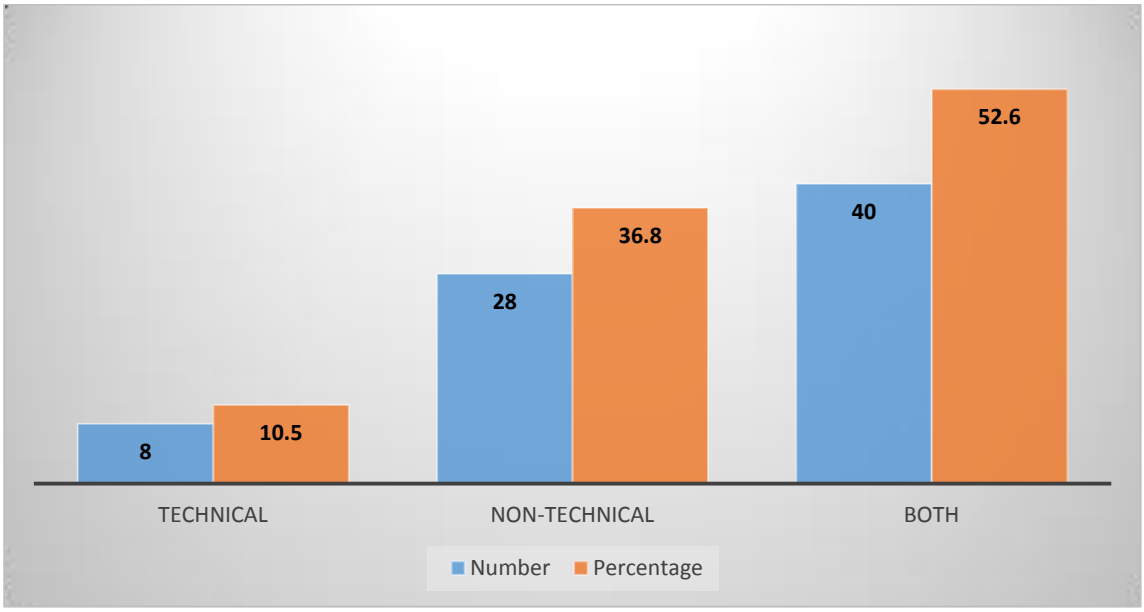
Thirty-eight respondents, representing 50% of the responses, stated that analysis is performed by the questionnaire respondent (who is a human resource practitioner). Seven, (9.2%), indicated that the analysis is performed by the questionnaire respondent (HR) together with other personnel in the HR department. One respondent, (1.3%), stated that the analysis is performed by the questionnaire respondent together with another department outside HR. Six, (7.9%), stated it is done by HR, others in HR and another department outside HR. Nineteen, (25%), indicated that the analysis is done by others in the HR department and two, (2.6%), stated that it is done by others in HR, another department outside HR. The remaining three, (3.9%), indicated that the data analysis in the organisation is performed by other departments outside HR.



Graph 2: Role of HR in the Analysis Process (a)

From these figures, one may deduce that HR is involved in the analysis process in some way in 96.1% of the responses. To gain an understanding of the exact roles HR practitioners undertake in the analysis process, five aspects of the analysis process were identified (defining approach, conducting data analysis, interpret data analysis, reporting and use results for decision-making). For the purpose of analysis, the five aspects were categorised as technical and non-technical activities. The technical category comprised of defining approach, conducting and interpreting data analysis. Non-technical included reporting and using results for decision making.

Graph 3 depicts the responses. More than half of the respondents are involved throughout the process. From the total number, eight respondents, (10.5%), perform technical duties only, twenty-eight, (36.8%), perform non-technical duties only while forty, (52.6%), perform both technical and non-technical duties.

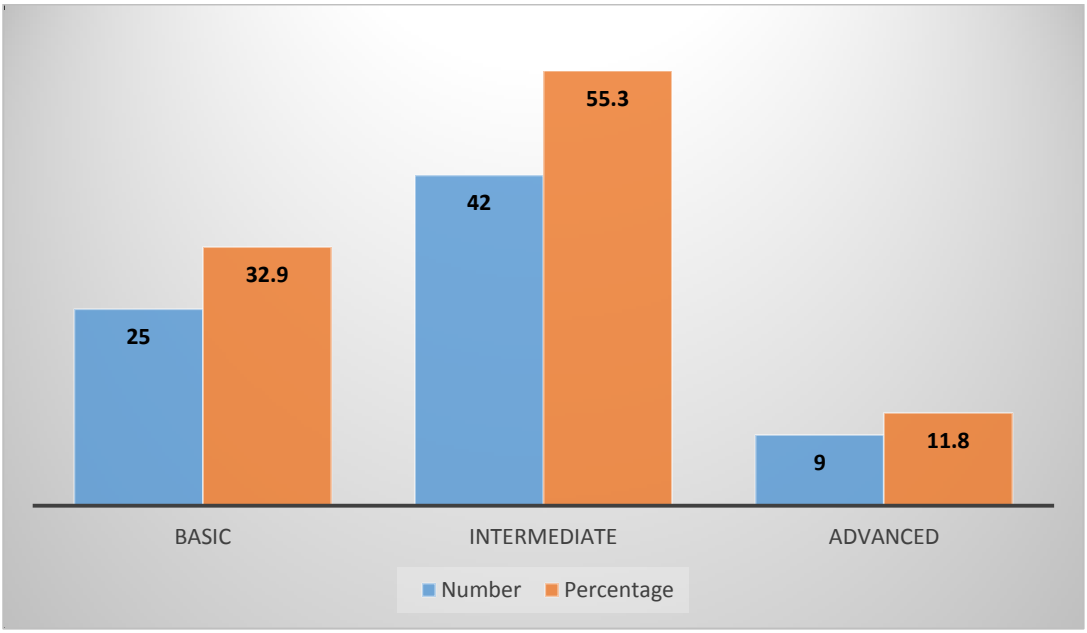


Graph 3: Role of HR in the Analysis Process (b)

The data presents a possible contradiction of what is in literature which states that the majority of HR practitioners do not have the analytical skills to conduct data analysis.

4.4 The Level of Sophistication of Analytics

Question 6 was designed to classify respondents as well as test the claim that analytics is still in its infancy in South Africa. Three analytics sophistication levels were identified as basic, intermediate and advanced. Graph 4 depicts the responses. Twenty-five respondents, (32.9%), indicated that their level of sophistication of data analytics were basic, forty-two, (53.3%), were at intermediate level while nine, (11.8%), of them had advanced level of data analytics

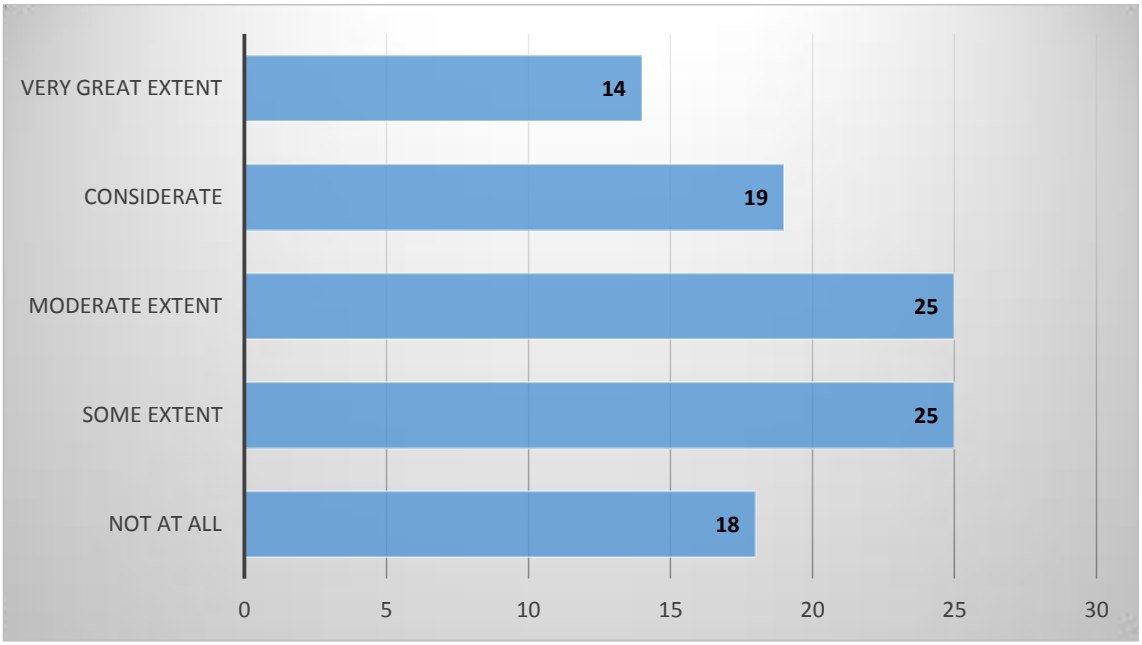


Graph 4: Sophistication Levels of the Respondents' Analytics

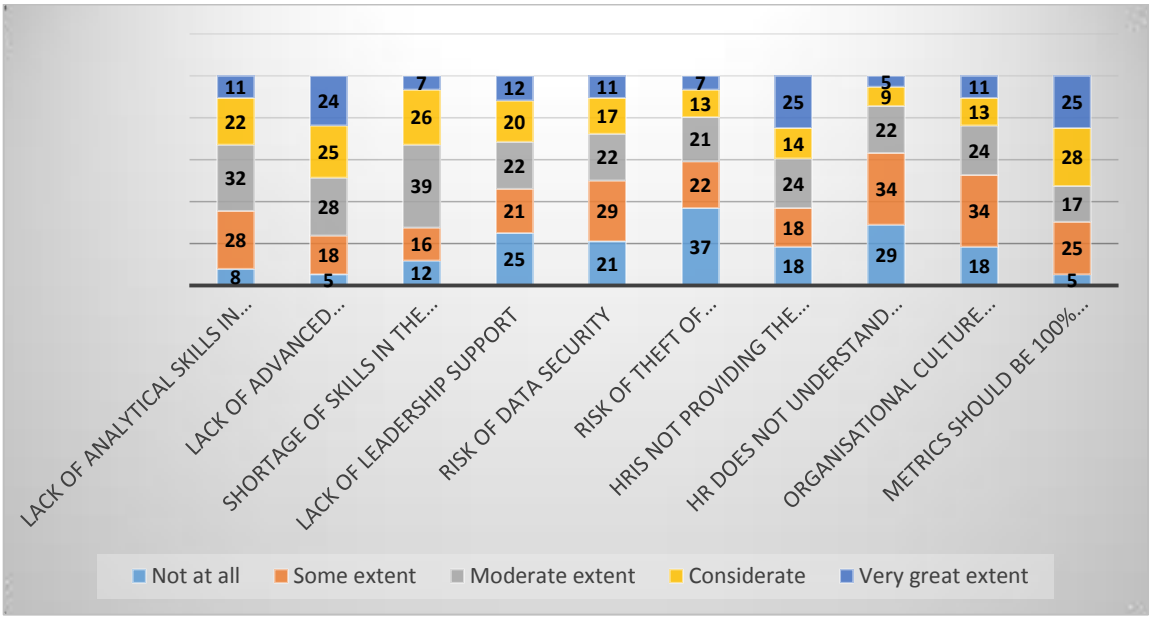
The research responses bear some testament to this. However, there is some adoption of advanced analytics even though it is at a lowly 11.8%.

4.5 Challenges which Inhibit Adoption of Advanced Workforce Analytics

The first hypothesis was that lack of analytical skills in the HR fraternity in South Africa is a major inhibitor in the adoption advanced workforce analytics. The section listed ten challenges faced by the HR practitioners in adopting advanced workforce analytics. When calculating aggregated scores for the challenges, 18% indicated that the challenges do not affect them, 25% to some extent, 25% moderate extent, 19% considerate and only 14% indicated that challenges inhibit adoption to a very great extent. Graphs 5 and 6 depict this outcome:



Graph 5: Challenges which Inhibit Adoption of Advanced Workforce Analytics (a)

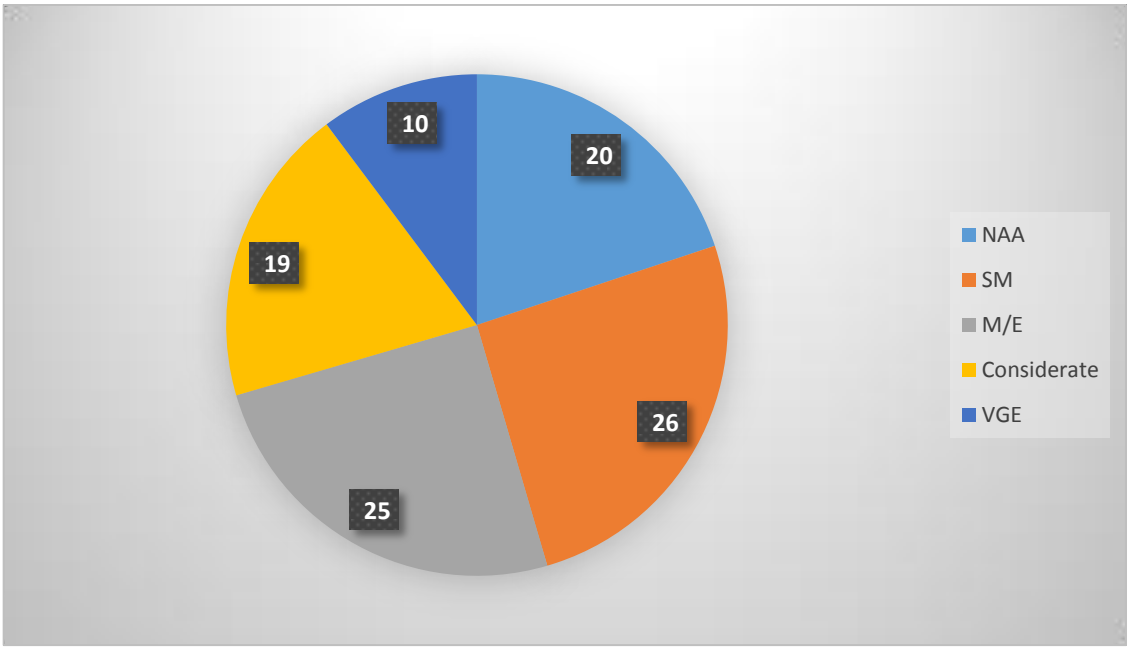


Graph 6: Challenges which Inhibit Adoption of Advanced Workforce Analytics (b)

Most challenges appear to affect the practitioners either moderately, to some extent or not at all. Could this be a potential indicator that existing literature has not yet uncovered the factors and challenges which inhibit the adoption of

advanced workforce analytics? Challenges which were regarded as inhibitors (rated as affecting practitioners considerably or to a very great extent) were: *accuracy of the metrics, shortage of skills in the talent market, HRIS not providing support, lack of advanced statistical competencies in the current HR team and lack of analytical skills in the current team*.

Another analysis was conducted excluding the basic analytics group (depicted in Graph 7). The outcomes were not much different.



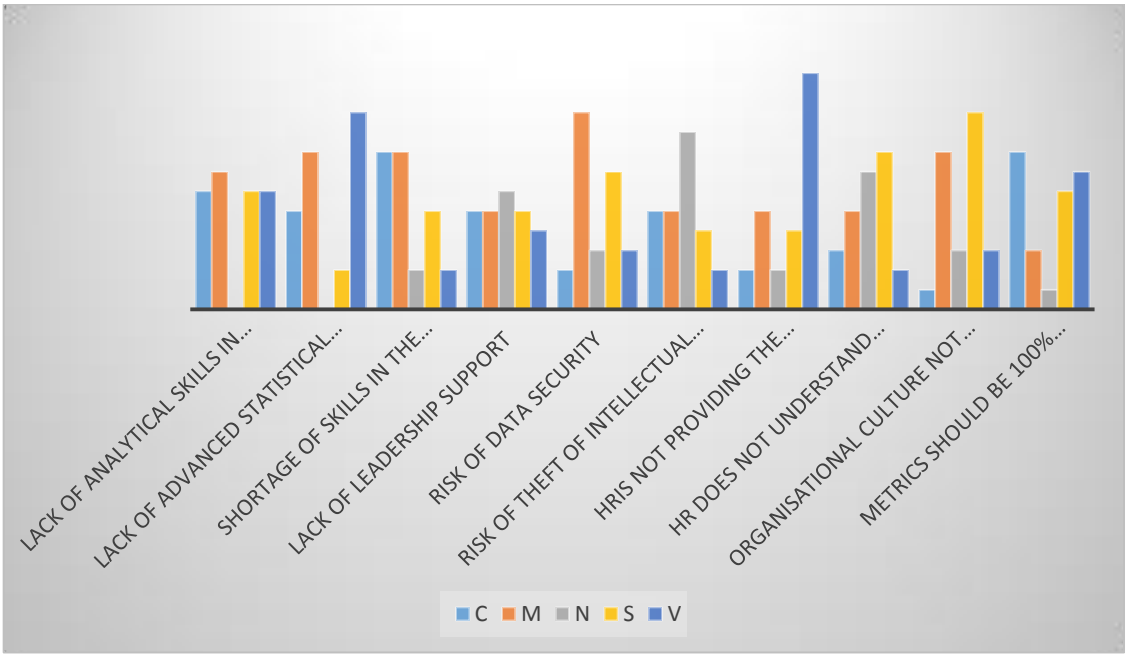
Graph 7: Challenges which Inhibit Adoption of Advanced Workforce Analytics excluding Basic Analytics

Based on the high responses for the shortage of analytical skills in the talent market, one may deduce that organisations are looking externally for the skills instead of growing their own timber. Contributing factors appear to be competencies of the existing team and organisational culture.

A Kruskal Wallis test was used to test whether HR practitioners with different analytics sophistication levels may be experiencing facing different challenges.

4.5.1 *Basic*

All of the respondents who considered their level of data analytics as basic, 33% (25), identified the lack of analytical skills and statistical competencies in their current teams as challenges of some sort.



C – Considerate, M – Moderate extent, N – Not at all, S – Some extent, V – Very great extent

Graph 8: Challenges experienced by those with Basic Analytical Skills

Challenges inhibiting adoption of Advanced Workforce Analytics	C	M	N	S	V
Lack of analytical skills in the current HR team	6	7		6	6
Lack of advanced statistical competencies in the current HR team	5	8		2	10
Shortage of skills in the talent market	8	8	2	5	2
Lack of leadership support	5	5	6	5	4
Risk of data security	2	10	3	7	3
Risk of theft of intellectual property	5	5	9	4	2

HRIS not providing the support required for advanced workforce analytics	2	5	2	4	12
HR does not understand business needs	3	5	7	8	2
Organisational culture not supportive of embracing data when making decision	1	8	3	10	3
Metrics should be 100% correct before the analysis is accepted	8	3	1	6	7

Table 5: Challenges experienced by those with Basic Analytical Skills

Six respondents, (24%,) indicated that the ***lack of analytical skills in their current team*** impedes them to a very great extent. Another six, (24%), stated it does to some extent. Seven respondents, (28%), stated that it is to a moderate extent while six, (24%), regarded it as considerate.

Regarding the ***lack of statistical competencies***, ten respondents, (40%), indicated that it does affect them to a very great extent while two, (8%), stated that it only did to some extent.

Sixteen, (64%), of the respondents indicated that ***shortage of skills in the talent market*** affect them considerate to moderate extent. While two, (8%), stated that it affects them to a very great extent, and another two, (8%), say that it does not affect them at all.

There were six, (24%), respondents who indicated that ***lack of leadership support*** does not affect their advanced analytics in any way. Four respondents, (16%), stated that it inhibits them to a very great extent, while five, (20%), stated that it does affect them.

Three respondents, (12%), stated that they are not inhibited by **risk of data security** when adapting advanced analytics. Another three, (12%), indicated that it impedes their analytics to a great extent. Seven respondents, (28%), said to some extent, two, (8%), indicated considerate, while five, (20%), stated that it does affect their analytics to a moderate extent.

Nine respondents, (36%), felt that risk of **theft of intellectual property** does not affect their adaption of workforce analytics. Two, (8%), stated that it does affect them to a very great extent. Four, (16%), indicated it affects them to some extent. Five, (20%), said it inhibits them to a moderate extent and another five, (20%), indicated considerate effect.

Two respondents, (8%), indicated that ***HRIS not providing the support required*** for advanced workforce analytics does not affect them. Twelve, (48%), indicated that it does affect them to a very great extent. Four, (16%), stated it does to some extent and two, (8%), said it was considerate.

The effect of ***HR not understanding business needs*** according to seven, (28%), of the respondents does not affect adoption of workforce analytics. Two respondents, (8%), stated that it does affect them to a very great extent. Eight, (32%), stated that it affects adoption to some extent. Five, (20%), indicated it affects them to a moderate extent and three, (12%), stated it was considerate.

There were three respondents, (12%), who indicated that ***organisational culture not supportive of embracing data when making decision*** does not affect their adoption of data analytics. Three, (12%), stated that it affects them to a very great extent. Ten, (40%), said to some extent, while eight, (32%), indicated to a moderate extent and one, (4%), regarded it as considerate.

One respondent, (4%), stated that ***metrics do not need to be 100% correct before the analysis***. Seven, (28%), stated that absolute accuracy of the metrics does affect their anaytics to a very great extent. Six respondents, (24%), indicated that it is to some extent, and eight, (32%), regarded it as considerate.

In this category, that is,. basic analytical skills, most of the challenges appear to be experienced at a moderate extent. There does appear to be an expectation that HRIS should conduct the analysis. 12% identified the lack of support from the HRIS systems as an inhibitor to adopting advanced workforce analysis.

4.5.2 *Intermediate*

Forty-two respondents, 55%, identified the level of the sophistication of their organisations' analytics as intermediate. Out of the forty-two respondents, five, (11.9%), stated that **lack of analytical skills in their current team** does not to inhibit them from adapting advanced analytics. One respondent, (2.4%), indicated that it impedes them to a very great extent Another twelve, (28.6%), stated it does to some extent. Fifteen, (35.7%), said moderate extent and nine, (21.4%), stated that it is considerate.

Two respondents, (4.8%), indicated that **lack of statistical competencies in the current HR team** does not affect their ability to adapt advanced analysis. Five, (11.9%), indicated that it does affect them to a very great extent and eleven, (26.2%), stated that it only did to some extent.

Six respondents, (14.3%), indicated that **shortage of skills in the talent market** does not affect them. Three, (7.1%), indicated that it affected them to a very great extent. Six, (14.3%), stated that it affects them to some extent. Nineteen respondents , (45.2%), indicated that it is to a moderate extent and eight, (19%), regarded it as considerate.

Twelve respondents, (28.6%), indicated that **lack of leadership suport** does not affect their advanced analytics in any way. Four, (9.5%), stated that it inhibits them to a very great extent and seven (16.7%) stated that it affects them to some extent. Nine respondents, (21.4%), said moderate extent and ten, (23.8%), indicated it was considerate.

Eleven respondents, (26.2%), stated that they are not inhibited by **risk of data security** when adapting advanced analytics. Five, (11.9%), indicated that it impedes their analytics to a great extent. Ten, (23.8%), said to some extent. Another ten respondents, (23.8%), stated it is considerate and six, (14.3%), stated that it does affect their analytics to a moderate extent.

Sixteen respondents, (38.1%), felt that **risk of theft of intellectual property** does not affect adapting workforce analytics. Two, (4.8%), stated that it does affect

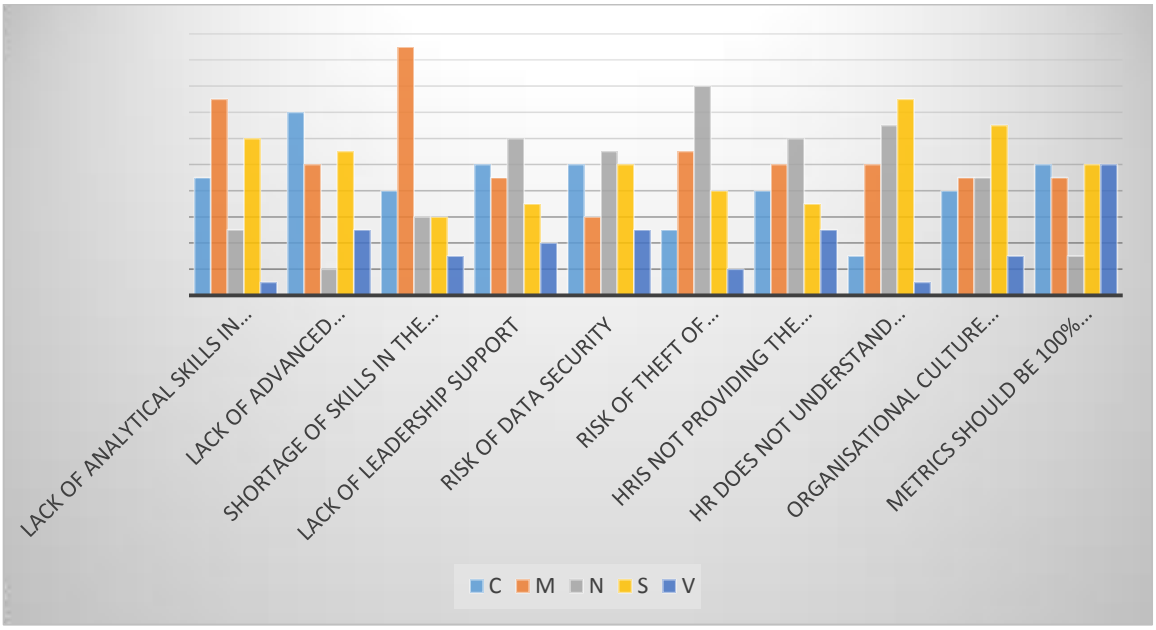
them to a very great extent. Eight, (19%), indicated it affects them to some extent. Eleven, (26.2%), said it inhibits them to a moderate extent and five respondents, (11.9%), indicated that it has considerate effect.

Twelve respondents, (28.6%), indicated that **HRIS not providing the support** required for advanced workforce analytics does not affect them. Five, (11.9%), indicated that it affects them to a very great extent and seven, (16.7%), stated it affects them to some extent. Eight respondents, (19%), regarded the challenge as considerate and ten, (23.8%), stated that it affected them moderately.

Thirteen respondents, (31%), do not regard **HR not understanding business needs** as a challenge. One respondent, (2.4%), stated that it does affect them to a very great extent. Fifteen, (35.7%), stated that it does to some extent. Ten, (23.8%), indicated affects them moderately while three, (7.1%), stated it was considerate.

There were nine respondents, (21.4%), who indicated that **organisational culture not being supportive of embracing data when making decision** affects their abilitity to adopt data analytics. Three, (7.1%), stated that it affects them to a very great extent. Thirteen, (31%), to some extent. Nine, (21.4%), to a moderate extent while eight, (19%), said it has considerable effect.

Three respondents, (7.1%), stated that **metrics being 100% correct before the analysis is accepted** does not inhibit their data analytics. Ten, (23.8%), stated it affects their anaytics to a very great extent. Another ten, (23.8%), indicated to some extent. Nine, (21.4%), said it is moderate while ten more respondents, (23.8%), regarded it as considerate.



C – Considerate, M – Moderate extent, N – Not at all, S – Some extent, V – Very great extent

Graph 9: Challenges experienced by those with Intermediate Analytical Skills

Challenges inhibiting adoption of Advanced Workforce Analytics	C	M	N	S	V
Lack of analytical skills in the current HR team	9	15	5	12	1
Lack of advanced statistical competencies in the current HR team	14	10	2	11	5
Shortage of skills in the talent market	8	19	6	6	3
Lack of leadership support	10	9	12	7	4
Risk of data security	10	6	11	10	5
Risk of theft of intellectual property	5	11	16	8	2
HRIS not providing the support required for advanced workforce analytics	8	10	12	7	5
HR does not understand business needs	3	10	13	15	1

Organisational culture not supportive of embracing data when making decision	8	9	9	13	3
Metrics should be 100% correct before the analysis is accepted	10	9	3	10	10

Table 6: Challenges experienced by those with Intermediate Analytical Skills

In overall, the intermediate level had 21% of the respondents reporting that the challenges do not afftect them as compared to only 13% of those that identified their analytics as basic. Furthermore, those who indicated that the challenges affected them to a very great extent were almost half, (9.3%), as compared to those in the basic category, (20.4%),. Graph 9 depicts the pain points for this criteria is the lack of analytical skills in the HR team, the shortage of the skills in the market and HR not understanding business needs.

4.5.3 *Advanced*

Only nine of the seventy-six respondents identified their analytics as advanced.

Challenges inhibiting adoption of Advanced Workforce Analytics	**C**	**M**	**N**	**S**	**V**
Lack of analytical skills in the current HR team	2	2	1	3	1
Lack of advanced statistical competencies in the current HR team		3	2	1	3
Shortage of skills in the talent market	4	3	1	1	
Lack of leadership support		3	1	4	1
Risk of data security	1	1	2	5	
Risk of theft of intellectual property			3	5	1

HRIS not providing the support required for advanced workforce analytics	1	3		3	2
HR does not understand business needs	1	2	2	3	1
Organisational culture not supportive of embracing data when making decision	1	1	2	3	2
Metrics should be 100% correct before the analysis is accepted	3	1		3	2

Table 7: Challenges experienced by those with Advanced Analytical Skills

Out of the total of nine respondents who considered their level of data analytics as advanced, one, (11.1%), indicated that **lack of analytical skills** in their current team does not inhibit them from adapting advanced analytics. Another one, (11.1%), indicated that it impedes adoption to a very great extent. Three, (33.3%), stated it affects them some extent. Two, (22.2%), regarded it as moderate and another two, (22.2%), stated that it had considerable impact.

There were two of the respondents, (22.2%), who indicated that **lack of advanced statistical competencies** in their current HR team does not affect their ability to adapt advanced analysis. Three, (33.3%), indicated that it affects them to a great extent. One, (11.1%), stated that it only did to some extent and three, (33.3%), indicated moderate extent.

One respondent, (11.1%), indicated that **shortage of skills in the talent market** does not affect data analytics. Another one, (11.1%), stated that it does affect them to some extent. Three, (33.3%), said to a moderate extent and four, (44.4%), indicated it is considerate.

There is one respondent, (11.1%), who indicated that lack of **advanced statistical competencies** in their current HR team does not affect their ability to adapt advanced analysis. One, (11.1%), indicated that it does affect them to a very great extent. Four, (44.4%), stated that it only did to some extent and three, (33.3%), regard it as moderate.

From the total number, two, (22.2%), stated that they are not **inhibited by risk of data security** when adapting advanced analytics. Five, (55.6%), indicated to some extent. One respondent, (11.1%), regarded it as considerate and another one, (11.1%), stated that it does affect their analytics to a moderate extent.

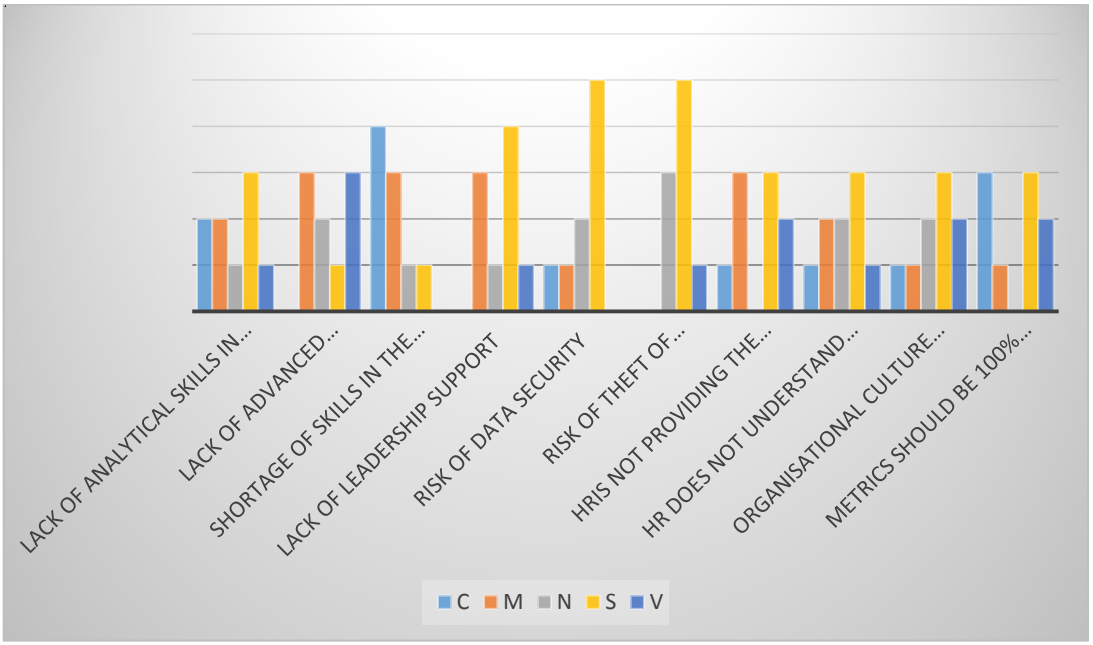
Three respondents, (33.3%), felt that **risk of theft of intellectual property** does not affect adapting workforce analytics. One, (11.1%), stated that it does affect them to a very great extent while five, (55.6%), indicated it affects them to some extent.

Two respondents, (22.2%), indicated that **HRIS not providing the support required for advanced workforce analytics** affects them to a very great extent. Three, (33.3%), stated it affects them to some extent. Another three, (33.3%), said it is moderate extent while one, (11.1%), regarded it as considerate.

The effect of **HR not understanding business needs** according to two of the respondents, (22.2%), does not affect adoption of workforce analytics. One, (11.1%), stated that it does affect to a very great extent. Three, (33.3%), stated that it does to some extent. Two, (22.2%), indicated it does to a moderate extent whie one, (11.1%), stated it was considerate.

There were two respondents, (22.2%), who indicated that **organisational culture not supportive of embracing data** when making decision does not affect their data analytics. Another two respondents, (22.2%), stated that it affects them to a very great extent. Three, (33.3%), said to some extent. One, (11.1%), regarded it as moderate while another one, (11.1%), said it was considerate.

From the data, none of the respondents stated that **metrics being 100% correct** before the analysis is accepted does not inhibit their data analytics, two, (22.2%), stated it does affect their anaytics to a very great extent, three, (33.3%), to some extent, one, (11.1%), being moderate extent while three, (33.3%), being considerate.



C – Considerate, M – Moderate extent, N – Not at all, S – Some extent, V – Very great extent

Graph 10: Challenges experienced by those with Advanced Analytical Skills

Two challenges that appear to be prominent in this section are risk of data security as well as risk of intellectual property, followed closely by shortage of skills in the market and lack of leadership support.

4.5.4 *Testing for Differences in Challenges Faced*

A Kruskal Wallis test was conducted to scientifically determine whether there were significant differences in the challenges encountered among those who considered their level of data analytics to be basic, intermediate and advanced.

The results of the Kruskal Wallis test on the challenges, presented in table 7, indicated no statistically significant variation among most of the challenges except risk of theft of intellectual property and HRIS not providing the support required for advanced workforce analytics since their p- values are less than 0.05.

	Degrees of	Chi-Square	P-value

	freedom	value	
Lack of analytical skills in the current HR team	2	1.2372	0.5387
Lack of advanced statistical competencies in the current HR team	2	4.439	0.1087
Shortage of skills in the talent market	2	1.9031	0.3862
Lack of leadership support	2	2.186	0.3352
Risk of data security	2	0.68445	0.7102
Risk of theft of intellectual property	2	7.5379	0.02308
HRIS not providing the support required for advanced workforce analytics	2	7.4712	0.02386
HR does not understand business needs	2	0.060141	0.9704
Organisational culture not supportive of embracing data when making decision	2	2.4438	0.2947
Metrics should be 100% correct before the analysis is accepted	2	0.015428	0.9923

Table 8: Comparison of Challenges Experienced by the 3 Categories

We can conclude that there is a statistically significant difference in **risk of theft of intellectual property** X^2 (2) =7.5379, p-value=0.02308. The post hoc result indicates a significant difference between the respondents whose level of data analytics is advanced compared to those that are either basic or intermediate. The post hoc results verify the findings outlined in section 4.5.1 and 4.5.3, that is, those with advanced analytics skills consider the risk of theft of intellectual property to be a serious challenge while those with basic analytics do not regard theft of intellectual property as an inhibitor.

Another area/challenge which presented statistical significance is that of **HRIS not providing the support required for advanced workforce analytics**. The post hoc result, X^2 (2) =7.4712, p-value=0.02386, indicates a significant difference between the basic and advanced respondents. The basic category displayed support of the HRIS as a major challenge, while it was not regarded as such in the advanced category.

4.6 Advanced Workforce Analytics Applications

Molefe (2013) revealed that there are misunderstandings in the application of analytics. Literature also revealed that context and environmental needs are major factors in terms of the analytics being conducted, therefore soliciting information on the analysis they conduct would have not assisted in clarifying Molefe' findings. Question 9 therefore sought to explore Molefe's findings

HR Practices	C	M	N	S	V
Measure the business impact of HR programs and processes	28	12		5	30
Measure the cost of providing HR services	23	16	1	3	33
Conduct cost-benefit analysis (also called utility analysis) of HR programs	23	13		9	29
Measure the effects of HR programs on the workforce in terms of competence, motivation, attitudes, behaviours, etc.	32	12	2	4	26
Connect human capital practices to organisational performance	29	12	1	6	28
Make decisions and recommendations that reflect your company's competitive situation	31	10	1	5	29
Identify where talent has the greatest potential for strategic impact	33	15		6	22
Assess HR programs before they are implemented - not just after they are operational	29	16	2	8	21

Pinpoint HR programs that should be discontinued	26	15	2	9	24
Assess the feasibility of new business strategies	31	16	3	8	18
Evaluate the effectiveness of HR programs and practices	30	16	1	3	26
Measure routine HR process execution (payroll, benefits, communication, etc.)	30	17		4	25
Support organisational change efforts	30	11		4	30
Assess and improve the HR department operations	29	12		3	30
Assess and improve the human capital strategy of the company	25	14		3	32
Contribute to decisions about business strategy and human capital management	29	9	1	5	31
Employee and organisational surveys (e.g. employee opinion surveys, engagement surveys, organisational culture/climate	27	11	1	9	28
Employee/talent profiling (i.e. tracking and modelling individual data on critical talent or high-potential employees	29	16		4	27
Workforce forecasting (e.g. workforce supply/demand and segmentation analysis to forecast and plan when to staff up or cut	25	9	1	7	33
Evaluate and track the performance of outsourced HR activities	25	15	5	4	27

Table 9: The Applicability of Workforce Analytics to Strategic HR Practices

All seventy-six respondents indicated that workforce analytics can applied to **measure the business impact of HR programs and processes**. Thirty (39.5%) stated that workforce analytics can be applied to a very great extent, five (6.6%) stated it can applied to some extent, twelve (15.8%) to a moderate extent while twenty-eight (38.2%) stated that it can be applied considerably.

Regarding workforce analytics being used to **measure the cost of providing HR services,** one, (1.3%), indicated that it cannot be applied, thirty-three, (43.4%), stated that workforce analytics can be applied to a very great extent, three (3.9%)

stated it is applied to some extent, sixteen, (21.1%), said to a moderate extent while twenty-three, (30.3%), stated that it can be applied considerably.

Twenty-nine, (39.2%), stated that workforce analytics can be applied to a very great extent **to conduct cost-benefit analysis** , nine, (12.2%), indicating it can be applied to some extent, thirteen, (17.6%), to a moderate extent while twenty-three, (31.1%), stated that it is applied considerably.

For **measuring the effects of HR programs on the workforce in terms of competence, motivation, attitudes, behaviours** two, (2.6%), indicated that workforce analytics cannot be applied, twenty-six, (34.2%), stated that workforce analytics can be applied to a very great extent, four, (5.3%), stated it can applied to some extent, twelve, (15.8%), to a moderate extent while thirty-two, (42.1%), stated that it can applied considerably.

In terms of applying workforce analytics to **connect human capital practices to organisational performance**, twenty-eight, (36.8%), stated that workforce analytics it can be applied to a very great extent, six, (7.9%), said to some extent, twelve, (15.8%), to a moderate extent while twenty-nine, (38.2%), stated that it is applied considerably and only one, (1.3%), indicated that it cannot be applied.

The majority agreed that analytics can be applied to **make decisions and recommendation that reflect the company's competitive situation.** Twenty-nine, (38.2%), stated that workforce analytics is applied to a very great extent, five, (6.6%), stated it is applied to some extent, ten, (13.2%), to a moderate extent while thirty-one, (40.8%), stated that it is applied considerably and one, (1.3%), regarded it as not applicable.

Regarding the application of workforce analytics to **identify where talent has the greatest potential for strategic impact**, twenty-two, (28.9%), stated that workforce analytics can be applied to a very great extent, six, (7.9%), stated can be applied to some extent, fifteen, (19.7%), to a moderate extent while thirty-three, (43.4%), stated that it can be applied considerably. It is good to see that HR practitioners are aware of the linkages between talent and strategy, especially as

the field already has standard practices supporting such intiatives such as job evaluation processes and performance management systems.

The outcomes for the **assessment of HR programs before they are implemented** were: two, (2.6%), indicated that workforce analytics cannot be applied, twenty-one, (27.6%), stated that workforce analytics can be applied to a very great extent, eight, (10.5%), stated can be applied to some extent, sixteen, (21.1%), to a moderate extent while twenty-nine, (38.2%), stated that it can be applied considerably.

Twenty-four, (31.6%), stated that workforce analytics can be applied to **pinpoint HR programs that should be discontinued** is applied to a very great extent, nine, (11.8%), stated it is applied to some extent, fifteen, (19.7%), to a moderate extent while tweny-six, (34.2%), stated that it is applied considerably and two, (2.6%), stated that it can not be applied.

Eighteen, (23.7%), respondents stated that workforce analytics is applied to **assess the feasibility of new business strategies** to a very great extent, eight, (10.5%), stated it is applied to some extent, sixteen, (21.1%), to a moderate extent while thirty-four, (40.8%), stated that it is applied considerably and state three, (3.9%), that it can not be applied.

The responses to the application of workforce analytics to **evaluate the effectiveness of HR programs and practices** were: twenty-six, (34.2%), stated that it can be applied to a very great extent, three, (3.9%), stated it is applied to some extent, sixteen, (21.1%), to a moderate extent while thirty, (39.5%), stated that it is applied considerably and one, (1.3%), said it can not be applied.

For **measuring routine HR process execution** (payroll, benefits, communication, etc.), twenty-five, (32.9%), stated that workforce analytics can be applied to a very great extent, four, (5.3%), stated it is applied to some extent, seventeen, (22.4%), to a moderate extent while thirty, (39.5%), stated that it is applied considerably.

Regarding the **support organisational change efforts**, thirty, (40%), stated that workforce analytics can be applied to a very great extent, four, (5.3%), stated it can be applied to some extent, eleven, (14.7%), to a moderate extent while thirty, (40%), stated that it can be applied considerably.

Responses to the application of workforce analytics in the **assessment and improvement of the HR department operations** were: thirty, (40.5%), stated that workforce analytics is applied to a very great extent, three, (4.1%), stated it is applied to some extent, twelve, (16.2%), to a moderate extent while twenty-nine, (39.2%), stated that it is applied considerably.

Responses to the application of workforce analytics in the **assessment and improvement the human capital strategy of the company were**: thirty-two, (43.2%), stated that it can be applied to a very great extent, three, (4.1%), stated it can be applied to some extent, fourteen, (18.9%), to a moderate extent while twenty-five, (33.8%), stated that it is applied considerably.

Thirty-one, (41.3%), respondents stated that workforce analytics can be applied to **contribute to decisions about business strategy and human capital management** to a very great extent. Five, (6.7%), stated it can be applied to some extent, nine (12%) to a moderate extent while twenty-nine, (38.7%), stated that it is applied considerably and one, (1.3%), respondent said it can not be applied.

Responses to the application of workforce analytics for **employee and organisational surveys** were: Twenty-eight, (36.8%), stated that workforce analytics is applied to a very great extent, nine, (11.8%), stated it is applied to some extent, eleven, (14.5%), to a moderate extent while twenty-seven, (35.5%), stated that it is applied considerably and one, (1.3%), said it can not be applied.

For the application of workforce analytics to **employee/talent profiling**, twenty-seven, (35.5%), stated that workforce analytics can be applied to a very great extent, fou,r (5.3%), stated it can be applied to some extent, sixteen, (21.1%), to a moderate extent while twenty-nine, (38.2%), stated that it is applied considerably.

Responses to the application of workforce analytics in the **workforce forecasting**, thirty-three, (44%), stated that workforce analytics is applied to a very great extent, seven, (9.3%), stated it is applied to some extent, nine, (12%), to a moderate extent while twenty-five, (33.3%), stated that it is applied considerably and one, (1.3%), said it can not be applied.

According to the data available, five, (6.6%), indicated that workforce analytics can not be applied to **evaluate and track the performance of outsourced HR activities.** Twenty-seven, (35.5%), indicated that can be applied to a very great extent, four, (5.3%), to some extent, fifteen, (19.7%), to a moderate extent while twenty-five, (32.9%), of the total number stated that it is applied in a considerate extent.

4.7 Testing for Differences in the Applicability of Workforce Analytics amongst the Three Analytical Levels

A Kruskal Wallis test was conducted to determine whether there were significant differences in the HR practitioners among those who considered their level of data analytics to be basic, intermediate and advanced. The results of the Kruskal Wallis test on the HR practices did not yield any statistically significant variation among the different levels of sophistication of data analytics as shown in the table above since all the p-values are more than 0.05.

HR Practices	Degrees of freedom	Chi-Square value	P-value
Measure the business impact of HR programs and processes	2	0.43226	0.8056
Measure the cost of providing HR services	2	1.6521	0.4378
Conduct cost-benefit analysis (also called utility analysis) of HR programs	2	1.6997	0.4275
Measure the effects of HR programs on the workforce in	2	1.204	0.5477

terms of competence, motivation, attitudes, behaviours, etc.			
Connect human capital practices to organisational performance	2	1.8314	0.4002
Make decisions and recommendations that reflect your company's competitive situation	2	0.99274	0.6087
Identify where talent has the greatest potential for strategic impact	2	0.73542	0.6923
Assess HR programs before they are implemented - not just after they are operational	2	0.57856	0.7488
Pinpoint HR programs that should be discontinued	2	0.84576	0.6552
Assess the feasibility of new business strategies	2	0.58681	0.7457
Evaluate the effectiveness of HR programs and practices	2	1.2693	0.5301
Measure routine HR process execution (payroll, benefits, communication, etc.)	2	3.1619	0.2058
Support organisational change efforts	2	0.18341	0.9124
Assess and improve the HR department operations	2	0.23462	0.8893
Assess and improve the human capital strategy of the company	2	0.85004	0.6538
Contribute to decisions about business strategy and human capital management	2	0.041143	0.9796
Employee and organisational surveys (e.g. employee opinion surveys, engagement surveys, organisational culture/climate	2	1.0369	0.5954
Employee/talent profiling (i.e. tracking and modelling individual data on critical talent or high-potential employees	2	1.7389	0.4192
Workforce forecasting (e.g. workforce supply/demand and segmentation analysis to forecast and plan when to staff up	2	0.16266	0.9219

or cut			
Evaluate and track the performance of outsourced HR activities	2	1.0418	0.594

Table 10: Comparison in the Applicability of Workforce Analytics amongst the 3 Categories

It is not surprising that HR practitioners understand the applications. Though the practices are said to be addressing business needs as well as forward looking, they are primarily using HR language. Ulrich appeals to HR to have an outside-in approach.

CHAPTER 5. Discussion of the Findings

‘Data knows how far you’ve come, not how far you’ll go’ (Investec, 2017)

5.1 Introduction

The research sought to explore the adoption of advanced analytics in South Africa. The questionnaire was sent to five thousand eight hundred practitioners. There were one hundred and sixty-seven responses, with seventy-six meeting the targeted population criteria and qualifying for further analysis. Analysis drawn from the research is as follows:

5.2 Hypothesis 1 – Lack of analytical skills in the HR fraternity in South Africa is a major inhibitor in the adoption of advanced workforce analytics

In the first part of the hypothesis, HR practitioners were asked to rate the level of sophistication of their analytics. Section 3 of the questionnaire, which referred to the respondents’ understanding of the applications of workforce analytics was used to check for understanding and biasness to answering question one. The outcome was that respondents indicated that they understood the applications. One may deduce that respondents understood this question and answered it truthfully.

Robinson’s human capital analytics architecture was used to illustrate the outcome of responses about analytics sophistication levels:

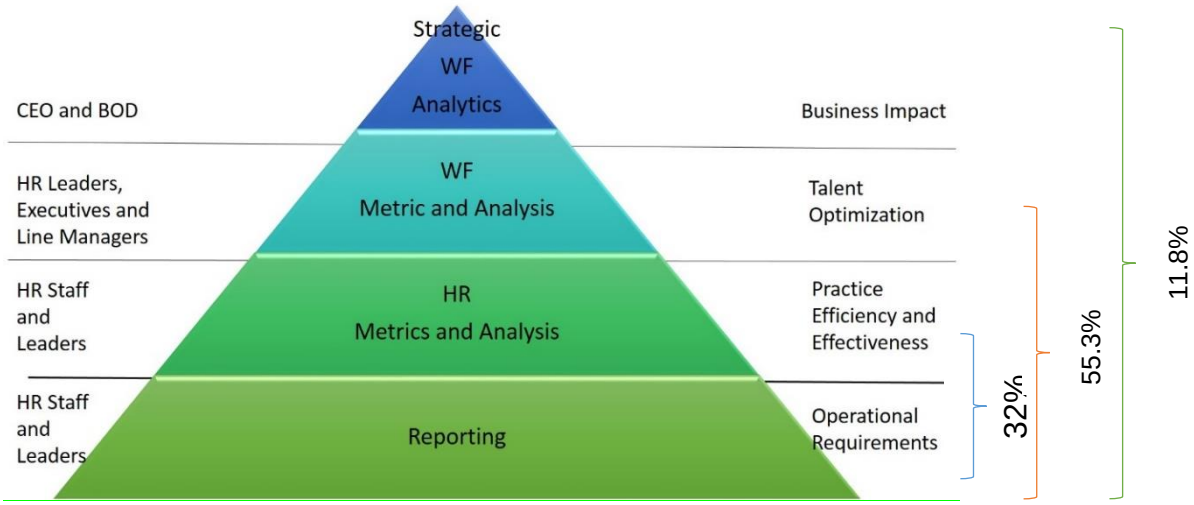
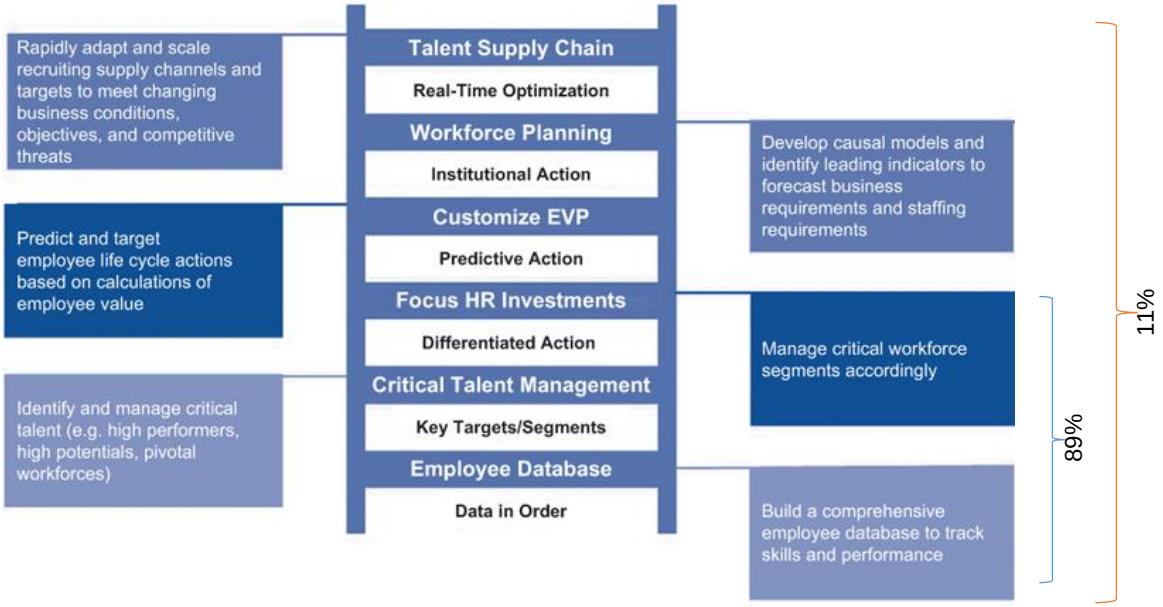


Figure 1: Human Capital Analytics Architecture
Source: (Robinson, 2015)

32% indicated that their analytics are basic while most, (53%), regarded their analytics as intermediate. Shortage of skills in the current market and lack of advanced statistical competencies in current HR teams were noted as major challenges for this group therefore it is not likely that they will progress quickly to advanced analytics. Demand for data scientists is 60% higher than supply. The figures are for developed markets. Official figures for South Africa are not available however one may safely deduce that the demand in emerging and third world economies is higher. This renders data analytics a scarce skill and thereby creating talent war.

Only 11% reported their analytics as advanced. Molefe's (2013) claim that workforce analytics in South Africa is still at its infancy was found to be true.

Davenport et al' (2010) ladder of human capital analytics applications is used to illustrate these findings (figure 2) :



Note: The ladder shows how analytical capabilities tend to build on each other from a foundation of good data – data that is accurate, consistent, integrated, accessible and relevant

Figure 2: The Ladder of Human Capital Analytics Applications
Source: (Harris et al., 2011)

89% of practitioners provide value until the third step, that is, Focus HR Investments to manage critical workforce segments accordingly. Even if one was to adopt Robinson's (2015) argument that not all organisations require predictive analytics but rather HR practitioners should analyse the impact of their initiatives, it would still limit the value of HR offerings to the third step. Focused HR investments produce efficiency, which Marler and Boudreau (2016) argue that efficiency does not make business impact as it part of the administrative costs, and administrative costs form a small percentage of business costs. Also, while it is agreed that impact analysis is the best assessment measure, Levenson (2005) points out that line managers and HR practitioners do not have the skills required to determine factors which lead to behavioural change, therefore they are unable to conduct a meaningful impact assessment.

The value of advanced analytics is to enable HR to offer HR intelligence by solving business problems and providing insight related to people management (Falletta, 2014; Fitz-Enz, 2010; Harris & Spenser 2016). Frameworks such as

LAMP, the analytics maturity model, human capital model for the 21st century, value-linkage model and balanced scorecard were designed to enable HR practitioners to deliver this business value. The frameworks' primary premise is that people management and people decisions have a direct impact on the operations and performance of the organisation. For instance, the balanced scorecard, which metamorphosed into the workforce scorecard, emphasises the chain reaction between various HR practices (such as learning and development, management practices, culture, etc.), business growth and the organisation's financial performance. All the frameworks have elements of statistical calculation used to calculate or measure the relationship between people activities and organisational performance. In essence, they seek to establish cause-effect relationship. Advanced statistical competencies are required to undertake such an assignment, competencies which as the questionnaire revealed, only 11% of practitioners in South Africa have.

Benefits of advanced workforce analytics include minimisation of risks caused by human error, optimisation of resources, improved efficiency and risk management, gaining competitive advantage and effective strategy formulation (Carlson & Kavanagh, 2011; Chahtalkhi, 2016; Dash Wu et al., 2012; Huselid, 2015; Lawler III et al., 2004). Top performing organisations are twice as likely to cite advanced workforce analytics as their competitive differentiator (Molefe, 2013). With adoption being so low in South Africa, it means that HR practitioners are relying on gut-feel and committing avoidable and costly errors.

The implication of the findings (i.e. 11% adoption of advanced analytics) is that 89% of HR practitioners rely on gut-feel because they are either unequipped or ill-equipped to optimise data as a resource at their disposal. Thus 89% of HR practitioners in a VUCA environment are unable to provide HR intelligence. As such, South African organisations loose opportunity to have higher return on their equities (Brown et al., 2011) due HR failing to solve business problems and adopt a forward-looking perspective (Harris & Spenser 2016).

Advanced workforce analytics also promises to bridge the gap between academia and practice. Therefore, the low adoption also affects the development of the

support system required which is somewhat of a predicament as it creates a chicken and egg challenge due to the dependency between practice and academia.

5.2.1 *HR practitioners lack analytical skills and advanced statistical competencies*

HR needs to have at least basic understanding of statistics and principles of good measurement to have sufficient knowledge and be able to ask the right questions of data, understand how to formulate metrics and hypotheses, know the difference between correlation and cause-effect as well as be able to communicate HR strategic performance results to all stakeholders including senior line managers (Frick, 2014; Huselid, 2015; Levenson, 2014; Rasmussen & Ulrich, 2015). Having these skills enable HR practitioners to exploit their existing data (Angrave et al., 2016). Most HR practitioners have been trained on administration and social behaviour and therefore need to upskill or even retrain on analytical skills (Chahtalkhi, 2016; Rasmussen & Ulrich, 2015). Needless to mention that in South Africa the profession does not have barriers to entry and some practitioners do not have any formal qualifications (Janse van Rensburg, 2009).

Majority of the research respondents did not regard the lack of analytical skills and/or advanced statistical competencies in the current teams as inhibitors to adopting analytics. This might be because 53% of practitioners reported that they are involved throughout the analysis process (that is, technical and non-technical aspects), while 11% are involved in technical process only. The seniority of the respondent, organization and the practitioners' background (not all practitioners have from a social science background) and the size and skills set of the HR department might have contributed to the responses.

37% reported that they are not involved in the technical process. This is a substantial number of practitioners who are not involved in the design or analysis processes. Angrave (2016) warned that the exclusion or withdrawal of HR practitioners from the technical process puts the HR practice at a risk of adopting methodologies that are not necessarily suitable to address people-related issues.

His concern is that algorithm-based management practices may harm employees' experiences. A possible anecdote to such a risk is the impact analysis assessment model as it provides defence against algorithm-based management practices as it links individual and group factors to process improvements as well as non-monetary costs and benefits.

The majority, (89%), of the respondents rated their analytical skills as either basic or intermediate, it is therefore understandable why they indicated a strong inclination to source the skills from the talent market. Therefore, the hypothesis that the lack of analytical skills posed a major challenge in adopting advanced workforce analytics was true to those with basic and intermediate skills.

The South African picture of looking externally is going against global trends. A report written by Deloitte stated that organisations are aggressively building their own HR analytical skills. The high demand will force organisations into become price-takers if they intend to attract and retain these skills. If HR practitioners continue to look externally, will South African organisations be able to offer competitive salaries to attract and retain these skills?

On the other hand, there is the reality that most of the challenges were not experienced very strongly as inhibitors, raising the possibility that the actual challenges might be unknown. The questionnaire had a section for additional comments, however none of the respondents completed it. Therefore, this study was unable to reveal other potential challenges.

5.2.2 *Metrics Accuracy and Human Resources Information Systems*

Falletta (2014) warned that too much faith is placed on technology at the cost of development of skills and competencies required to utilise it. 94% of practitioners regarded the accuracy of metrics as a challenge, while 82% said that human resources information systems do not provide the support required. The questionnaire results on HRIS are not surprising: metrics' accuracy is limited to context as most software packages do not show a cause-effect relationship (Angrave et al., 2016; Douthitt & Mondore, 2014).

Technology will continue to prove insufficient due to the explorative nature of analytics. At best, the software is required to build longitudinal and multivariate econometric models needed to conduct end-to-end analytics (Angrave et al., 2016; Douthitt & Mondore, 2014).

HRIS is an added advantage but not a key determinant of success (Marler & Boudreau, 2016). Without the analytical skills and competencies required, HR practitioners are not able to assess the software offerings accordingly, as a result costing their companies $14 billion (annually) in bad investments.

5.2.3 *Data Security and Theft of Intellectual Property*

Analytics includes collection of sensitive personal information and integration of IT systems may expose the company's intellectual property and increase risk of theft (Brown et al., 2011).

Data security and theft of intellectual property were however rated as the least of the challenges by those in the basic and intermediate levels. Their perception is likely to change as the level of their analytics mature. The expected change in perception is evidenced by the ratings of those with advanced analytics, whom the majority regarded data challenge as a considerable concern.

5.2.4 *HR does not understand business needs*

"Most Chief Human Resource Officers can not relate HR to real-world business needs. They do not know how key decisions are made, and they have great difficulty analysing why people—or whole parts of the organization—are not meeting the business's performance goals." Ram Charan (Watson, 2017)

HR is admitting to not understanding business needs, however the respondents do not regard it as an inhibitor to adopting analytics. 29% reported that it does not affect them at all, 34% to some extent, 22% moderately, 9% considerably and 5% rated it as a challenge to a great extent.

Advanced analytics, more specifically prescriptive, includes quantifying effects of future decisions and recommending the best course of action for a given situation (Halo-BI, 2016; Rouse). HR practitioners cannot recommend best courses if they do not understand business needs.

Huselid (1995) found that there is a modest relationship between the internal fit of HR practitioners and the organisation's financial performance, however found a strong correlation between high performance HR practices and the organisation's financial performance. It is interesting that he divorced HR practices from the practitioners, whereas Rasmussen and Ulrich (2015) and Chahtalkhi (2016) believe that HR practitioners' understanding of the business which enables the practitioner to develop solutions which directly address the business problems. It is these solutions which lead to better financial performance (Dash Wu et al., 2012). Also, all analytics approaches and frameworks enlisted in the literature review (section 2.7) as well as Harris and Spenser (2016) workforce analytics maturity assessment criteria regard solving business problems as the core of analytics. Therefore, one may deduce that the HR practices Huselid referred to qualify as high performance because they meet business requirements. And since HR practitioners are usually the primary custodians of HR practices, it therefore means that the high-performance practices were driven by HR practitioners who understood business needs and developed HR solutions to address them.

Several longitudinal studies about views of businesses on HR services show that managers continuously express low satisfaction and are sceptical about HR's contribution to business (Africa, 2016; Fitz-Enz, 1995; KPMG-International, 2015). The outcomes of the studies may also be influenced by biasness of firms who have been participating over time. The possibility of the biasness may be an explanation for the findings by Levenson et al (2005), that HR business impact was higher than the perception of HR value by the organisation's leaders. Another factor contributing to the low satisfaction might be that HR practitioners are said to find it difficult to strategically align HR outputs to business priorities (Coco, 2011; Douthitt & Mondore, 2014). This perhaps also contributes to the

lack of leadership support experienced by HR practitioners. Levenson et al (2005) alluded to the fact that decision makers regarded metrics drawing from finance models as valuable. One may assume that the 'miscommunication' negatively impacts the relationship with leadership and hence leadership's support was regarded as a challenge by 75% of the research respondents.

There is consensus from respectable thought leaders in the field is that HR needs a change of mind-set in terms of how it engages with business and performs its functions if it is to prove that it is adding business value (Angrave et al., 2016; Boudreau, 2012; Fitz-Enz, 1995; Marler & Boudreau, 2016; PwC, 2014; Rasmussen & Ulrich, 2015). It is HR practitioners' responsibility to ensure that the information is presented in a manner that best suits the decision maker (Chahtalkhi, 2016). Ulrich refers to the approach as HR from the outside-in while Boudreau named it "re-tooling HR". Chahtalkhi (2016) goes further by recommending that the extension of HR to include analytics requires a restructuring of HR departments (Chahtalkhi, 2016). The author is inclined to agree with Chahtalkhi due to the multi-disciplinary approach requirement of analytics.

Even though practitioners do not deem lack of business needs as a challenge, it appears that the South African Board of People Practitioners (SABPP) has been attentive to business complaints. SABPP developed a competency model (figure 6) which incorporates elements promoting the new approach (that is HR from Outside-In).

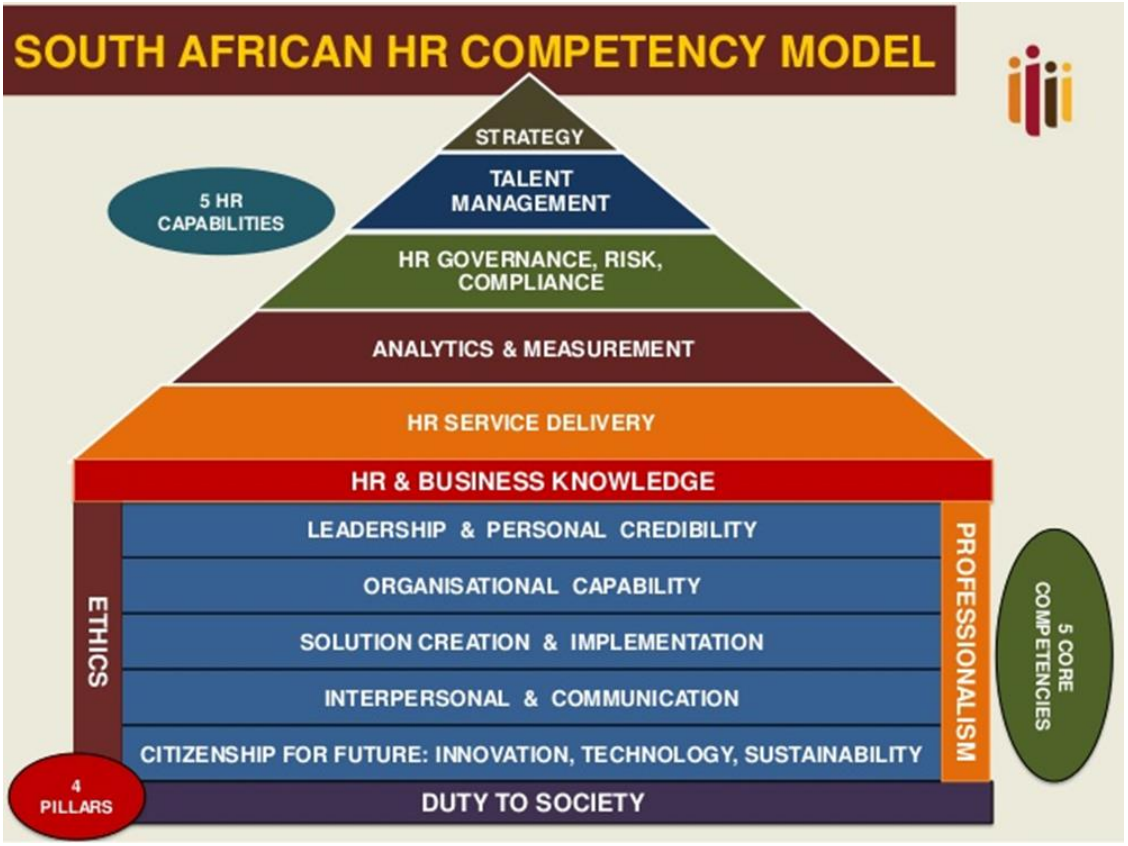


Figure 6: South African Board of People Practitioners Competency Model
Source: (SABPP, 2014)

SABPP is creating the much needed support structure for all stakeholders to ensure that HR is a strategic partner to business.

5.3 Hypothesis 2 – South African HR practitioners do not understand the applications of Advanced Workforce Analytics

Molefe (2013) purported that there is misunderstanding among the practitioners about the potential applications of workforce analytics. From the questionnaire responses, there appears to be a theoretical understanding of how analytics can be applied to strategic HR issues. A small number of practitioners (less than 3%), stated that analytics did not apply while an average of 8% reported that analytics apply to some extent. Therefore, the majority regarded analytics as applicable.

While theoretically there is hope, it appears that it is in the actual application that practitioners experience challenges. All three categories rated the challenge of the metrics not being 100% as affecting them to some extent, with only 5% reporting that it is not an inhibitor. This expectation may be due to a lack of key competencies (basic statistics, principles of good measurement, formulating metrics and hypotheses, and knowing the difference between correlation and cause-effect) coupled with the challenge of advanced analytics being a multi-disciplinary function.

Other contributing factor may be the lack of support from academia and practice. The literature does not reveal much on how analytics can be developed (Angrave et al., 2016; Marler & Boudreau, 2016). Having attended a few practical courses taught by subject matter experts, the courses were more about building metrics than the essence of analytics, and, as Marler and Boudreau (2016) noted, metrics are not analytics but rather building blocks. Learning metrics is very misleading and a futile exercise for someone with minimal statistical knowledge as there are over 250 metrics, most of which were developed for specific environments. Also, as the field is emerging and evolving there is not even consensus on the terminology or definition, making it difficult for a novice to acquire knowledge.

According to Fitz-Enz (2010), due to the exploratory nature of analytics, acquiring the skills and support is insufficient as advanced analytics is a mental framework that is supported by statistical tools. The literature is also unanimous that it is the business needs and context which drive methodologies, therefore practitioners need to be comfortable to embark on a journey that is uncertain and might be filled by trial and error. The question to bag therefore is whether HR practitioners have the willingness to adopt the required mental framework.

CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

“Analytics should drive business outcomes by uncovering competitive advantages and root-causes” Mondore, Spell and Douchit (2016).

The purpose of venturing into the research was to explore the credibility of workforce analytics and if found, provide a practical guide to adopting it.

The author focused on advanced analytics as it is a legislative requirement for South African companies to report on their human capital to various government entities, thus she could confidently deduce that South African organisations are already conducting basic and some intermediate analytics.

One of the discoveries was that advanced workforce analytics is an emerging field thus the theory is still developing. It was an uphill battle to collate academically credible information as a similar paper has been written before. Even the sources available cite the same few thought leaders. This poses a challenge for those intending to study the topic further in future.

The literature reveals that there is support and appetite for evidence-based management from thought leaders in the field and business leaders. The South African Board of People Practitioners even has analytics as one of the key competencies of HR practitioners. The HR profession needs to get the basics right. The first challenge for the field however, is agreeing on the terminology for the field itself. The naming varies from human resources to workforce, people, talent or human capital and all other related HR activities follow this trend. This causes confusion for the various stakeholders including practitioners. Secondly, a retooling of HR so that practitioners can adopt the outside-in approach and be equipped to communicate with business accordingly, and subsequently HR’s value will be more visible. This is what will position HR to be a strategic partner, not analytics.

There should be clarification on what the purpose of workforce analytics is and the expected outcomes. Falletta (2014) stated this purpose as delivering HR insight.

However, insight is drawn by people. Aral et al (2009) stated that value is derived when one can observe, measure, document and tract performance accurately and transparently. Hence the author's view is that workforce analytics is a tool that can be used to provide information regarding workforce related decisions in real-time and be used to measure the impact of those decisions in relation to employee productivity, business outcomes and organisational performance.

With the outcomes addressed, then it may be easier to resolve the how. Advanced analytics at its simplest explanation, is about understanding and differentiating between variables that correlate and those that have a cause-effect relationship. While there are frameworks developed to measure this, the LAMP is the most preferred. However, none of the frameworks can be adopted blindly. The challenge to date has been developing predictive and prescriptive HR frameworks which reasonably incorporate the complexity of human behaviour and uniqueness of various business environments. It is because of this challenge that there are no universally acceptable methods or approaches that novices can adopt. The role of information technology is that of an enabler to automate the process of data collection and analysis, hence emphasis is in the development of skills and intellectual property.

Organisations who ventured into analytics and won, claim to have acquired business insights which lead to them gaining competitive advantage in the market. Fitz-Enz (2011) further claims that predictive workforce analytics gives the adopter competitive advantage over 95% of the population. A claim corroborated by LaVelle et al (2010) study which found that top performing organisations are three times more likely to use advanced workforce analytics. There appears to have been slow progress since Fitz-Enz and LaVelle's studies, as the research findings were that 11% of South African HR practitioners have adopted advanced workforce analytics.

The key outcome from the literature is that the process of workforce analytics is explorative, hence testing for usage of specific metrics and frameworks would have not best served the purpose of the research. Fitz-Enz (2010) summarised the evolution of the field beautifully. He states that analytics is a mental

framework which starts with logical progression and ends with statistical tools. This ties in with Ulrich's analogy of analytics being a journey.

Key success factors emerged to be direct opposites of the challenges. It therefore seemed sensible to seek clarification on the challenges practitioners experience in adopting advanced workforce analytics. Indeed, there appeared to be a consensus on the challenges that practitioners face, which also proved to be applicable within the South African space. However, interestingly it was not necessarily the lack of analytical skills that emerged as a major inhibitor, but rather shortage of skills in the talent market. A practical question from this insight is whether South African practitioners are developing strategies to win in this apparent war for talent of analytics specialists and if they do win, how they plan to retain and protect the intellectual property.

6.1 The Complexity of Re-Tooling HR Practitioners

Even though South African practitioners are looking to the external market for analytical skills, there is a risk that due to HR having the inside-out approach and excluded from the technical process, analytics may become a façade (Falletta, 2014) or result in harmful management practices. This raises the need for HR practitioners to re-tool themselves.

From insight gleaned during the research, the author purports that there are five factors which contribute to the complexity of upskilling current practitioners and developing the required support systems for analytics to mature. The factors are multi-disciplinary approach, decision-making models, complexity of human behaviour, business context and statistical techniques. These are discussed further below:

- Multi-disciplinary approach - despite acceptance that HR practitioners do not possess adequate skills to conduct analytics let alone advanced analytics, more than 74% of practitioners in this study reported that they are undertaking the process on their own, with only 16% HR practitioners collaborating with other departments. Thus, efforts are wasted and

opportunities missed to partner with departments which have the required skills. Hence sourcing skills from external market is a risk.

Advanced analytics borrows from different fields such as behavioural sciences, IT, finance and statistics (Levenson, 2005). Organisations who were found to be successful collaborated with other departments especially as data is collected from multiple points. Falletta (2014) and McCabe (2014) refer to this emerging field as workforce intelligence and workforce science respectively.

- Decision-making models – according to Chahtalkhi (2016) few companies know how to make decisions using analytics and fewer succeed at connecting information with decision-making. HR also lacks logical models to aid decision making while other management fields have (Boudreau, 2012), and people have personal biases which influence their decisions (Falletta, 2014). Whilst HR decision making models are needed, Boudreau (2012) warned against HR reinventing the wheel as there are already accepted decision-making frameworks from other disciplines. He supports the adoption of existing models so that HR can use the same language as decision-makers. However even with adoption of decision-making models, the human element should not be neglected as people can manipulate information and data to support their preferences (Falletta, 2014; Rasmussen & Ulrich, 2015).
- Complexity of human behaviour – people are not always predictable and can be irrational at times. Behaviour is limited to time, social conditions and economy. Therefore predictive models are not universally applicable (Chahtalkhi, 2016; GeorgetownUniversity).
- Business context – business environments also have unique attributes influenced by various factors such as management practices and group dynamics. It is the business needs which determine the analytics required. Chahtalkhi (2016) identified that business adopts either a unitarist or pluralist management approach which drives how employees are viewed and therefore the type of workforce analytics conducted. Huselid (2005) found that there is a strong correlation between HR practices and an

organisation's financial performance. This was supported by frameworks such as the balanced scorecard (and subsequent models) and the value-linkage model.

- Statistical techniques - the process of predictive and prescriptive analytics involves complex maths and algorithms (Halo-BI, 2016; Mishra et al., 2016). Mondorre et al (2016) noted that advanced analytics require advanced statistical techniques which can distinguish between causation, regression and correlation. These skills and competencies are not commonly found in HR practitioners.

6.2 Recommendations

The prospects and potential benefits of predictive and prescriptive analytics to the HR practice are incredible and do indeed warrant further research.

6.2.1 *Recommendations for Organisations and HR Practitioners*

The customer is always right. Organisations employ HR practitioners with the expectation that the practitioner will provide value but the reality is that most organisations are not seeing that value. The onus is on HR practitioners to prove that they do provide value. The first step is for HR practitioners to gain solid knowledge of the business operations. This will enable practitioners to understand business needs and provide an opportunity to be proactive in identifying solutions.

The second step which should be undertaken concurrently with the third step is for HR practitioners to enrol in business statistics and research methodology courses so they can gain the analytical skills required. This is not to turn HR practitioners into data scientists, but to ensure that they have sound knowledge of research principles and can interpret and critically analyse statistical findings.

The third step is collaboration. It cannot be overemphasised that advanced analytics is a multi-disciplinary approach. Therefore, HR practitioners should

collaborate with other departments that are already using advanced analytics in their operations.

There also needs to be a mindset shift. HR practitioners should embrace agility and learn to fail fast and fail cheaply. Furthermore, business leaders' support cannot be demanded. Credibility and trust are built with small wins over time. It is therefore recommended that HR practitioners start with smaller ventures to build both skills and case studies for bigger projects.

6.2.2 *Recommendations for Other Stakeholders*

Academia is one of the key stakeholders in equipping HR practitioners to adopt advanced analytics. A review of the HR qualifications offered by South African higher education institutions, in particular, the bachelor of commerce in human resources management degree, reveals that statistics is offered as a mandatory subject either in year one or year two, while research methodology is only offered for honours degree programmes. Academic institutions should therefore revise their curriculum to incorporate statistics and research methodology as part of the core subjects throughout the qualification.

Another stakeholder who has a critical role to fulfil is the South African Board of People Practitioners. SABPP has made great strides in developing a competency framework for HR practitioners. They are also partnering with learning institutions to advocate for the HR curriculum to adopt the framework. Their next step should be to provide governance for the HR practice and ensure HR has the same credibility as other disciplines such as finance and engineering. This would also address the issues of low barriers of entry that HR has. Once there is a governance framework, it would be easier for business to assess whether the practitioner has suitable skills.

6.2.3 *Recommendations for Future Research*

Molefe (2013) made good recommendations for future research; however, the author would warn against conducting case studies at this stage as they often

unintentionally promote the one size fits all approach. With that said, to expand on Molefe's list, the author recommends an in-depth study into competencies required for workforce analytics practitioners. Such a study would assist learning institutions to develop academically sound curriculums which addresses the current needs and challenges of the profession. A desktop study reveals that there is a shortage of support for those wishing to venture into analytics; instead what is offered are short courses which tend to promote metrics rather than analytics. The factors listed above provide a foundation for the study.

Currently most of the literature around factors influencing the adoption was conducted through qualitative studies, therefore there is need for qualitative studies.

Furthermore, most of the challenges were not experienced very strongly as inhibitors, raising the possibility that the actual challenges might be unknown

6.3 Concluding Remarks

The author concurs with Mondore et al (2016) that analytics should drive business outcomes. For analytics to drive business outcomes, HR needs a thorough understanding of their business needs, or all other efforts to move HR to become a strategic partner risk are wasted. Dave Ulrich alluded to this when he canvassed for HR to start operating from the outside-in. Understanding one's business and its environment is crucial in providing the support and solutions the business requires and HR is not exempted. In an age of automation, the timing is most suitable for HR to understand this and start acting accordingly or as Davenport and colleagues warned that failure to do so risks HR being replaced by dashboards. The urgent conversation for the profession should be how HR should be supported to make this turnaround.

It is known and accepted that people have a high degree of unpredictability, therefore seeking measures that are absolute and universal is a futile exercise. Analytics, even advanced ones, serve as an enabler for informed decision making and not as evidence for the decision. There are two factors that one should

consider when seeking to introduce quantifiable measures into decision making, firstly there must be trust that the process was fair and not manipulated to suit certain parties. Secondly, regardless of the evidence, people are bound to trust their intuition. These are valuable lessons from the Google HR team.

Most importantly, the journey into advanced analytics is both explorative and contextual, therefore while methods may be borrowed from other fields and lessons learned from other organisations, which is highly encouraged in order to expedite progress in the field, it is highly unlikely that a universal approach or framework will be found thus HR practitioners who wish to be perceived as valuable business partners should start getting comfortable with experimenting, or as academics would put it, researching and innovating.

For those wishing to delve in to analytics, the journey appears long and tumultuous. It would benefit them to seek support from their leaders and collaboration with other departments such as finance, marketing and IT.

Lastly, while the study was focused on the South African market, most of the findings were similar to most of the claims made in literature and practitioner reports except in two cases: research respondents reported that they were looking for the talent externally instead of grooming their own people and the challenges identified were not regarded as major inhibitors.

APPENDIX A – SUMMARY OF EVIDENCE-BASED REVIEW HRA ARTICLES

Table 2. Categorization of Peer-reviewed Journal Publications.

Study Authors	What is HR Analytics?	How does it work?	Why does it work? Theoretical logic and frameworks	What are the outcomes?	What are moderators to outcomes?	Level of Analysis	Empirical or Not	Research Method
Lawler et al. (2004) *Academics*	Process using statistical techniques linking HR practices to organizational performance	Logic, Analytics, Measures and Process (LAMP Model)	Strategic HRM based on Resource-based view perspective	Efficiency measures are widespread; only 34% of survey companies have HR measures assessing impact		Company	Empirical	Descriptive Statistics of Survey of 37 Fortune 500 companies
Harris et al. (2011) *Consultants*	6 types of analytical processes for analyzing HR data	Various analytical techniques		Effectiveness and Impact		Company	Non-quantitative Empirical	Illustrative Case Studies
Bassi (2011) *Consultant*	An evidence-based approach for making better decision on the people side of business and consists of an array of tools and technologies, ranging from simple reporting of HR metrics all the way up to predictive modeling		Premise is strategic HRM; HRA predicts improved individual and organizational performance		HR professionals' analytical capability	Involves individuals, groups and company levels	Non-empirical	
Mondare et al. (2011) *Consultants*	Demonstrates the direct impact of people data on important business outcomes	6-step process beginning with identifying key business outcomes, collecting data, and structural equation modeling	None discussed-HR Scorecard implied	General Reference to Business Impact	Need statistical capabilities	Individuals and groups within a company	Non-quantitative Empirical	Illustrative company case study
Coco et al. (2011) *Consultant and Business Professional*		Using a value linkage decision model that identifies causal linkages between people measures and key business metrics	None discussed-HR Scorecard implied	General Reference to Business Impact	Management buy-in	Individuals and groups within a company	Non-quantitative Empirical	Illustrative case study of Lowe's introduction of HR Analytics
Levenson (2011) *Academic and Consultant*		AMO Strategic HRM model; Contingency theory of Organizational design; Competitive labor markets	Strategic HRM based on Resource-based View perspective	General Reference to Business Impact	HR professionals' analytical skills; TMT political support	Individual, group within a company	Non-quantitative Empirical	Illustrative case studies and descriptive statistics of Fortune 500 Company survey
DiBernardino (2011) *Consultant*		Using 3 new Human Capital Metrics that link measures of human capital costs to financial measures to calculate HR ROI		General Reference to Business Impact		Company	Non-quantitative Empirical	Illustrative case study
Aral et al. (2012) *Academics*	A way to measure and monitor individual performance	Combining incentive pay practices with HR Analytics with HCM software	Agency theory	16.5% higher sales	Use of incentive pay and HCM software; industry – more applicable to manufacturing	Company	Empirical	Conducted fixed and random effect regression analyses on 5-year (1995--2006) panel data of 189 firms
Giuffrida (2014) *Consultant*		HR teams can build ideal hiring profiles and predict hiring quality		Efficiency and Effectiveness	Executive buy-in; necessary resources	Company	Non-empirical	Reports third-party descriptive survey results
Falletta (2014) *Academic and Consultant*	Defines HR Analytics in terms of 18 HR practices and surveys companies to see which are used. Employee surveys clearly predominant. Next talent profiling and HR metrics			15% companies with HR Analytics play central role in HR strategy;; 75% have a group or employee dedicated to HR Analytics; primarily firms conduct employee surveys		Company	Empirical	Descriptive results of Survey of Fortune 1000 companies; 220 respondents

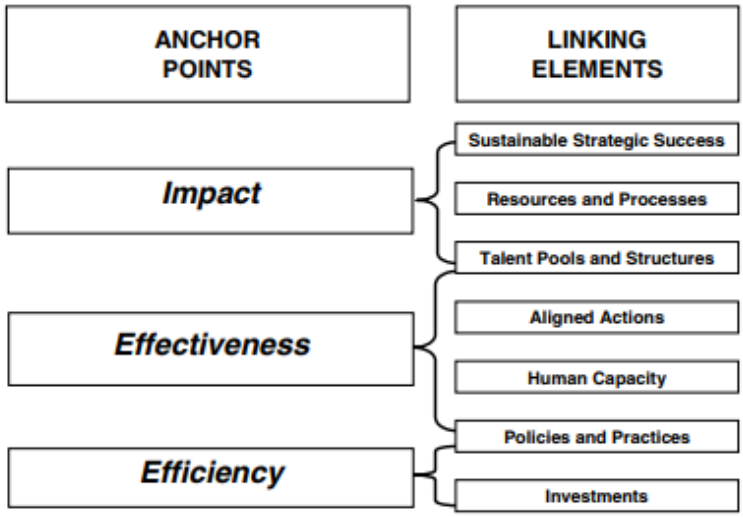
(continued)

Study Authors	What is HR Analytics?	How does it work?	Why does it work? Theoretical logic and frameworks	What are the outcomes?	What are moderators to outcomes?	Level of Analysis	Empirical or Not	Research Method
Douthitt and Mondore (2014) *Consultants*		Multi-step method described-see Mondare et al. (2011)	HR Scorecard by Becker et al. (2001)		Unintegrated data from Legacy HCM systems	Individuals and groups within company	Non-quantitative Empirical	Illustrative case study of unnamed retail company
Rasmussen and Ulrich (2015) *Academic and Business Professional*	HR Analytics is a fad	Multi-step process beginning with business problem-follow LAMP Model	Strategic HRM and psychological theory of cognitive dissonance	No outcome predicted except that HRA will not be a part of the HRM function in organizations	HR professionals lack analytical mindset; existing beliefs and cognitive dissonance	Individuals and groups within company	Non-quantitative Empirical	Illustrative case studies from Maersk Drilling
Pape (2016) *Academic*	Decisions based on analyses of relevant HR data	HRA depends on collecting key data necessary to conduct a particular analyses	Operational research methods	Most cost effective data elements to collect and store in a HCM software to support HRA; Efficiency and Effectiveness		HR processes; Individuals and companies	Empirical	Operational research methods
Angrave et al. (2016) *Academic & Business Professionals*		Multi-step process beginning with business problem-follow LAMP Model; Why it does not work	Resource-based View and Institutional isomorphism theories	HRIS delivers only efficiency metrics; Suppliers of HR Analytics do not deliver business impact; Low HR Analytics adoption rate; Risk HR Analytics coopted by Finance	Lack of skills in HRM function		Non-empirical	Based on interview with HR professionals and literature reviews

Figure 7: Categorisation of Peer-reviewed Journals
Source: (Marler & Boudreau, 2016)

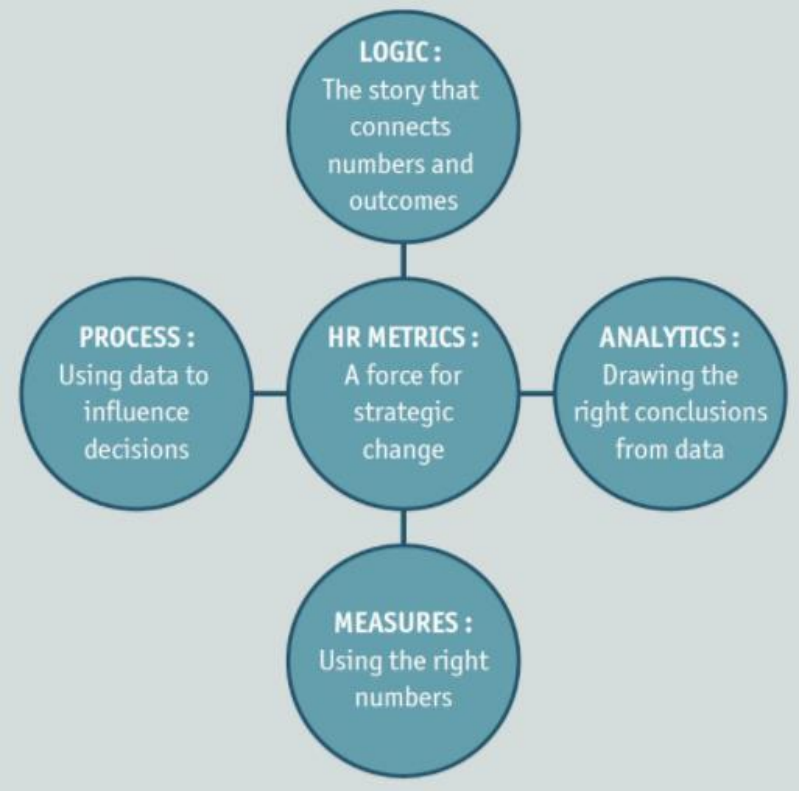
APPENDIX B – ADVANCED WORKFORCE ANALYTICS FRAMEWORKS

HC Bridge



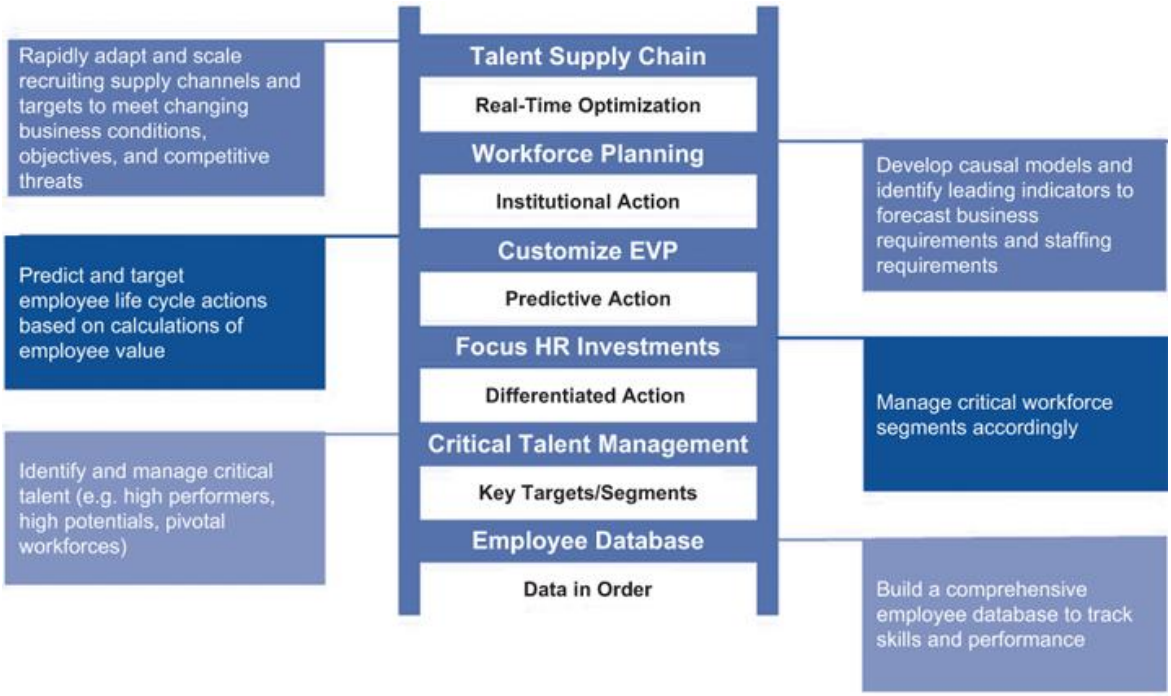
Source: (J. W. Boudreau, 2003)

LAMP



Source: (Cascio & Boudreau, 2010)

Ladder of Analytics Applications



Note: The ladder shows how analytical capabilities tend to build on each other from a foundation of good data – data that is accurate, consistent, integrated, accessible and relevant

Source: (Harris et al., 2011)

Talent Analytics Maturity Model

Adapted: (Bersin, 2014)

APPENDIX C – RESEARCH INSTRUMENT C

Dear Sir/Madam

Request for Participation in an Academic Research Study

Ntswaki Rosina Malebatja, an MBA scholar at the Wits Business School, seeks to undertake a study of the South African market with the emphasis on advanced workforce analytics. Advanced workforce analytics entails HR going beyond basic metrics and descriptive statistics that report historical data to adopting predictive and prescriptive analytics to ensure that they (HR) are solving business problems as well as preparing the workforce for the future.

Ntswaki therefore requests your participation in the study through the completion of an online questionnaire. The questionnaire seeks to review the extent advanced workforce analytics is applied in South Africa. It takes approximately 7 minutes to complete. The results will be used solely for the purposes of the study and responses will be confidential.

Please follow the link https://wits.eu.qualtrics.com/SE/?SID=SV_cGFr5ANcl1DYzGt to complete the questionnaire.

Should you know of other HR practitioners, please feel free to distribute further."

Yours Sincerely

Ntswaki Malebatja

Supervisor contact details:

Dr Thanti Mthanti
Thanti.mthanti@wits.ac.za

Questionnaire

Are you an HR practitioner: Yes , No

Do you work for a South African Company: Yes , No

Do you conduct any data-based analysis: Yes , No

If YES, who conducts the analysis: Myself , Other people in H , Other departments outsid

What is your role in the analysis process: Define Approa , Conduct Data Ar , Interpret Dat Reporting , Use Re r Decision Making

How would you rate the level of sophistication of your analytics: B , Inte e , Advanced

Challenge	Not at all Some extent Moderate extent Considerate Very Great Extent
Lack of analytical skills in the current HR team	
Lack of advanced statistical competencies in the current HR team	
Shortage of skills in the talent market	
Lack of leadership support	
Risk of data security	
Risk of theft of intellectual property	
HRIS not providing the support required for advanced workforce analytics	
HR does not understand business needs	
Organisational culture not supportive of embracing data when making decision	
Metrics should be 100% correct before the analysis is accepted	

Please indicate the extent workforce analytics can be applied in the following HR practices:

HR Practice	Not at all Some extent Moderate extent Considerate Very Great Extent
Measure the business impact of HR programs and processes?	
Measure the cost of providing HR services?	
Conduct cost-benefit analyses (also called utility analyses) of HR programs?	
Measure the effects of HR programs on the workforce in terms of competence, motivation, attitudes, behavious, etc?	
Evaluate and track the performance of outsourced HR activities?	
Connect human capital practices to organisational performance?	
Make decisions and recommendations that reflect your company's competitive situation	
Identify where talent has the greatest potential for strategic impact	
Assess HR programs before they are implemented - not just after they are operational	
Pinpoint HR programs that should be discountinued	
Assess the feasibility of new business strategies	
Evaluate the effectiveness of HR programs and practices	
Measure routine HR process execution (payroll, benefits, communication, etc.)	
Support organisational change efforts	
Assess and improve the HR department operations	
Assess and improve the human capital strategy of the company	
Contribute to decisions about business strategy and human capital management	
Employee and organisational surveys (e.g. employee opinion surveys, engagement surveys, organisational culture/climate surveys, organisational health surveys, organisational effectiveness surveys, organisational alignment surveys)	
Employee/talent profiling (i.e. tracking and modelling individual data on critical talent or high-potential employees	
Workforce forecasting (e.g. workforce supply/demand and segmentation analysis to forecast and plan when to staff up or cut back	

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