The role of data analytics in formulating a business model in the South African metals manufacturing sector

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DECLARATION

I **Kelebogile Maimela,** declare that this research is my own work and has not been submitted before for any degree in this or any other university. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration in the Graduate School of Business Administration, University of the Witwatersrand, Johannesburg.

KMaimela — 30 August 2020

Signature — Date

DEDICATION

I would like to dedicate this to my grandmother (Mapule Tsagane) who has always believed that education is key. Being a black woman in this era, I am living her dream. Today I am fulfilling a dream from the fruits of her sacrifices and hard work, which she longed for her children and grandchildren.

To my mother (Maureen Maimela), this is for you. The woman that raised me single-handedly and instilled the importance of personal development. *Mme waka dithapelo tsa hao modimo o di arabilie.*

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First and foremost, I would like to thank God for giving me the courage and strength to embark on this undertaking. It was a tough one but, indeed, I managed to pull through.

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I would like to thank my family and friends who understood how unavailable I was; I missed their weddings, baby showers and bridal showers − but I never lost our friendship.

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ABSTRACT

Technological advancements are a contributing factor to the success of any business, especially with globalisation mandating flexibility within businesses. The survival of the metals manufacturing companies is dependent on many variables, but the focus will be placed on the role of data analytics in business models. A quantitative approach was used to collect the data utilising Qualtrics software and data were recorded on Excel before being coded and then loaded onto the Statistical Package for Social Sciences (SPSS) software system. All employees in the metals manufacturing companies in South Africa made up the population for this study. The results revealed a relationship between data analytics and business insight involved in developing a business model. In the absence of data, the level of success in decision making is compromised. Over 80 percent of respondents emphasised the importance of data required in making decisions. The ability to make informed decisions gives companies a competitive edge, but a dynamic capability is evidenced through people's experience in data analysis. The data collected were analysed using quantitative data analysis tools such as chi-squared tests and Cramer's phi tests, which indicated that data play a pivotal role in developing business models.

Keywords: *business model, big data, data analytics, business insights, technology*

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1. INTRODUCTION

The advancement of technology and the information gathered from connected devices has made it feasible for governments and businesses to use data analytics to better understand their stakeholders' needs, thereby enabling them to offer appropriate data-driven solutions for their needs. (Hashem, Abaker, Chan, Anuar, Nor, Adewole, Yaqoob, Gani, Abdullah, Ejaz & Haruna, 2016; Sharma, Reynolds, Scheepers, Seddon, & Shanks, 2010). It, therefore, comes as no surprise that companies that generally use data analytics smartly are those that dominate their competitive landscape (Alsghaier, Akour, Shehabat, & Aldiabat, 2017)The role of big data analytics is seen by government officials as a way to enhance the livelihood of ordinary citizens, whilst transforming every sector that contributes to a nation's economy (Hashem *et al.,* 2016). Embracing technological advancements for businesses is crucial for their survival in today's fast changing world, but this requires businesses to have certain capabilities that enable them to correctly leverage data as competitive strategy (Drnevich & Croson, 2013; Mithas, Lee, Earley, Murugesan, & Djavanshir, 2013).

Technological advancements have had a profound influence on the competitive landscape of businesses and other organisations globally. This is manifested in the complexities of running a sustainable business in today's world; hence, organisations are forced to constantly adapt to rapid changes (Bada, 2002). The future of more interconnectedness between objects will further add to the complexities of running a sustainable business (Hitt, Ireland, & Lee, 2000; Hashem, *et al*., 2016).

The impact of data has led to a paradigm shift from the traditional ways of doing things. Lahiri, Perez-Nordtvedt and Renn (2008) believe that an increase in the competitive landscape due to globalisation will either bring growth or a decline for most businesses. They further suggest that those that are able to constantly create new ideas and business models are most likely to see organisational growth. It is for this reason that having sound analytical capabilities as an organisation is key, as it may assist in gathering insights that enable better decision making.

A critical capability that a firm needs to possess is the ability to respond to threats and opportunities with speed, which Ghasemgahaei, Hassanein and Turel (2017) terms as agility. This is widely seen through the advancements made within the medical field across the globe. The speed in the advancements is driven by the industry's ability to leverage data analytics as a key organisational strategy (Mithas *et al.,* 2013). Rüßmann *et al.* (2015) extrapolates that real-time data analytics gives firms the capabilities to predict production failures, whilst increasing flexibility and manufacturing productivity.

To show the diversity in the application of data, the usage of data has also assisted in predicting the weather in real-time due to the large amounts of data that are analysed to gather beneficial insights due to trends that have been widely used (Hashem *et al.,* 2016) Technological advancements are able to create value for businesses through their ability to translate the gained knowledge into an innovative business model, which can be of assistance to organisations in being able to gain market share, this is known as the transformational approach for a business model (Gambardella & McGahan, 2010;Demil & Lecocq, 2010).

Although data analytics has played an important role in providing organisations with a competitive edge globally, this has not necessarily been the case in South Africa, as studies show that there are insufficient investments in data analytics amongst SA firms (Ridge, Johnston, & O'Donovan, 2015). The effectiveness of data analytical tools requires support through the collaboration from key players within the organisation, which is a challenge for many businesses (Motau & Kalema, 2016; Malaka & Brown, 2015).

On the other side of the spectrum Motau and Kalema (2016) claim that the public sector is more ready for big data analytics than the private sector. The authors see this as a huge opportunity lost for public and private sectors, as this could make them more competitive, provided that data analytical tools are is well used. The metals manufacturing sector has been no different to other sectors in South Africa in their inability to leverage big data analytics. The challenges of this sector are highlighted below.

1.1 METALS MANUFACTURING SECTOR CHALLENGES

In the modern era, agility has become a necessity for corporate sustainability, which has resulted in corporates searching for solutions that provide rational organisational sustainability (Tsosie, 2009). With the world looking for innovative ways to generate organisational revenue continually, the countries left behind lose the possibilities of having a stimulated economy that is fostered by innovative ideas, which contribute to a country's economic growth (Priest & John, 2006; Ahlstrom, 2010).

Amongst developing economies, the South African metals manufacturing sector has seen a decline in growth over the past few years (Brand South Africa, 2018), contrary to the growth seen from China (Edwards & Jerkins, 2014). There are multiple contributors to the decline seen within the metals manufacturing sector. One predominant contributor is lack of industrial development, which has given China the ability to penetrate the continent, negatively affecting South Africa's export percentage within the African continent (Pedersen & McCormick, 1999; Edwards & Jerkins, 2014). The contributions that technological advances have in improving organisations cannot remain ignored, one of them being the effect of data analytics during crucial operational decisions (Fahmideh & Beydoun, 2019).

According to Trianni, Cagno and Farne (2014), the lack of information about technology causes barriers in the decision-making process, which results in inefficiencies within the metals manufacturing space, more so for small- to medium enterprises (SMEs). Data analytics is a growing trend that assists in the decision-making process, which minimises the dependency on intuition (McAfee, 2010).

Chen, Chiang and Storey (2012) as well as Riggins and Wamba (2015) jointly advocate that the ability of data analytical technologies in solving business problems is an inherit capability. Data analytical tool’s ability to scrutinise the information is witnessed by organisations which gives them an internal capability (Riggins and Wamba, 2015). In the manufacturing sector, various companies have explored data analytical technologies to get intelligent ways to process information leading to smart competitive tactics and flexibility (DMC, 2015; Fahmideh & Beydoun, 2019). As demonstrated above, there appears to be a link between companies that use data analytics smartly and those that dominate their competitive landscape. This research aims to evaluate the role of data analytics in formulating smart business models within the South African metals manufacturing sector. Furthermore, the research aimed to determine whether data-driven business models makes South African manufacturing companies more competitive.

1.2 PROBLEM STATEMENT

The South African metals manufacturing sector, which consists of products such as basic iron ore and steel, basic non-ferrous metals and metals, is known to be one of the most advanced industries as it contributes R618.24 billion to the gross domestic product (GDP) (Brand South Africa, 2018). Unfortunately, the metals manufacturing sector has not been performing well for the past decade. Although a 3 percent growth was seen in 2018, it does not compare to the growth commonly known in the early 2000s (Reuters, 2018). As of the third quarter of 2017, the metals manufacturing sector accounted for 13 percent of South Africa’s GDP, compared to the 2000s (Brand South Africa, 2018). The decline in the metals manufacturing sector has potentially contributed to South Africa’s sluggish economic growth (Tregenna, 2008), resulting in a decrease of employment opportunities and increased poverty (Kreuser & Newman, 2018).

Globalisation has negatively affected the growth of manufacturers in South Africa due to increased competition and regulatory requirements, as end-users use difficult matrixes to compare local manufacturers to international manufacturers (Barnes & Kaplinsky, 2000). Consumers are price sensitive; this is a disadvantage for local manufacturers as they are not as competitive as China when it comes to pricing (Kaplinsky, 2008). The inflexibility to adjust their business models to various market conditions has resulted in dire economic conditions for South Africa.

Technology has drastically affected the sector due to the mature technological advancements that importers have. South African manufacturers are constantly being compared with manufacturers that have advanced processes, leading to many local manufacturers losing business opportunities to sustain their operational expenses (Barnes & Kaplinsky, 2000). As confirmed by the Department of Trade and Industry (2018), the high rate of inefficiencies, lack of plant improvements and high production costs has left the industry less competitive compared to its Chinese counterparts.

This confirms that the lack of technological advancements that assist in making decisions that enable flexibility are indeed a problem. This is supported by Edward and Jenkins (2014) who further elaborate that the manufacturing sectors that are commonly affected are those with low- to medium technological advancements, causing an increase in the level of pressure for exported goods within South Africa. The lack of competition within the manufacturing sector across sub-Saharan Africa gave China the opportunity to penetrate the continent and dominate it, which is made easy by the financial support they receive from their government (Jenkins & Edwards, 2015).

Therefore, it is evident that measures must be implemented to sustain the metals manufacturing sector in South Africa. Unfortunately, due to the rate of globalisation, the competitive landscape has grown, making survival within the industry much more challenging. Investment in big data analytics is one way that local manufacturers can stay competitive in a tough environment. Unfortunately, there is evidence that little progress has been made in this regard. Hence, it is important to establish empirical evidence that can demonstrate how investment in big data analytics can help improve the ailing manufacturing sector. As such, the objective of the study is to assess the reach of big data analytics in the local manufacturing sector and determine if big data can help build competitive business models for industry players.

1.3 RESEARCH OBJECTIVES

This study will assist in contributing to the body of knowledge, but also contribute in advising metals manufacturing companies about technological advancements that can enhance their competitive edge whilst global competitors exist.

1.3.1 Objective

The primary objective of this research is to assess the role of data analytics in developing business models for the South African metals manufacturing sector.

1.3.2 Sub-objectives

The sub-objectives of this research, which are in support of the primary objectives, are listed as follows:

- To evaluate the relationship between the use of data analytics and levels of business insights
- To assess the impact of business insights in developing a business model.

1.4 LIMITATIONS

- The study used a quantitative approach with close-ended questions more information justifying the findings could not be found.
- The survey was self-administrated, which meant that the level of understanding on each question could differ from person to person; to minimise this, the survey was close ended.
- The survey was circulated through social media to people within the metals manufacturing sector; inaccuracies during this process could have occurred.
- Financial constraints led to the exclusion of companies outside the Gauteng province.

1.5 ASSUMPTIONS

- The researcher assumed that the respondents would answer all the questions as honestly as possible
- It is assumed that all respondents have a good understanding of the meaning of data analytics.

1.6 DELIMITATIONS

The study focussed on the metals manufacturing sector only, without consideration for all other general manufacturing. The collected data was specifically targeted at individuals employed by South African manufacturing companies focusing on metals manufacturing.

2 LITERATURE REVIEW

As indicated in Chapter 1, the study focuses on the role of data analytics in formulating a business model for the metals manufacturing sector. This chapter presents a literature review conducted in order to establish the theoretical framework of the study. A literature review is helpful in shaping the conceptual framework of a research study from which hypotheses, that are guided by theory, may be formulated for testing (Hart, 2018).

The chapter begins with technology trends presented in Section 2.1, followed by a description of big data analytics in Section 2.2. This is then followed by a discussion on the role that big data analytics has played in shaping business insight in Section 2.3 and the role it has played in the metals manufacturing strategy (presented in Section 2.4). The chapter then ends with an account on ways in which big data analytics may anchor business models in Section 2.5 and concluding remarks are presented in Section 2.6.

2.1 TECHNOLOGY ON BUSINESS

Today's era of information technology is characterised by easy and fast access to information. This has impacted ways in which businesses operate across many sectors and the metals manufacturing sector is no exception to this trend. To accurately understand reasons behind technology's profound influence on the business landscape, it is important to first understand what technology is and how it can impact business activities. Technology is the body of knowledge where science is used to solve problems whilst expanding on human knowledge to realise the capabilities and needs that are inherent, which eventually assists in providing solutions (Ramey, 2013; Fettes, 2015).

Niaki and Nonino (2017) suggest that technology can contribute to a business' strategy and performance because it is able to fully provide guidance in meeting the customer requirements. When correctly leveraged, technology can facilitate a smooth engagement model between a business and its customers, enabling businesses to better understand customer needs and thereby proving solutions that meet customer needs. This ultimately leads to higher levels of customer satisfaction, which research has established may lead to greater customer loyalty and advocacy for the business (Parasuraman & Grewal, 2000). The diagram below, known as the Pyramid Model, shows how technology links a company, its employees and customers.

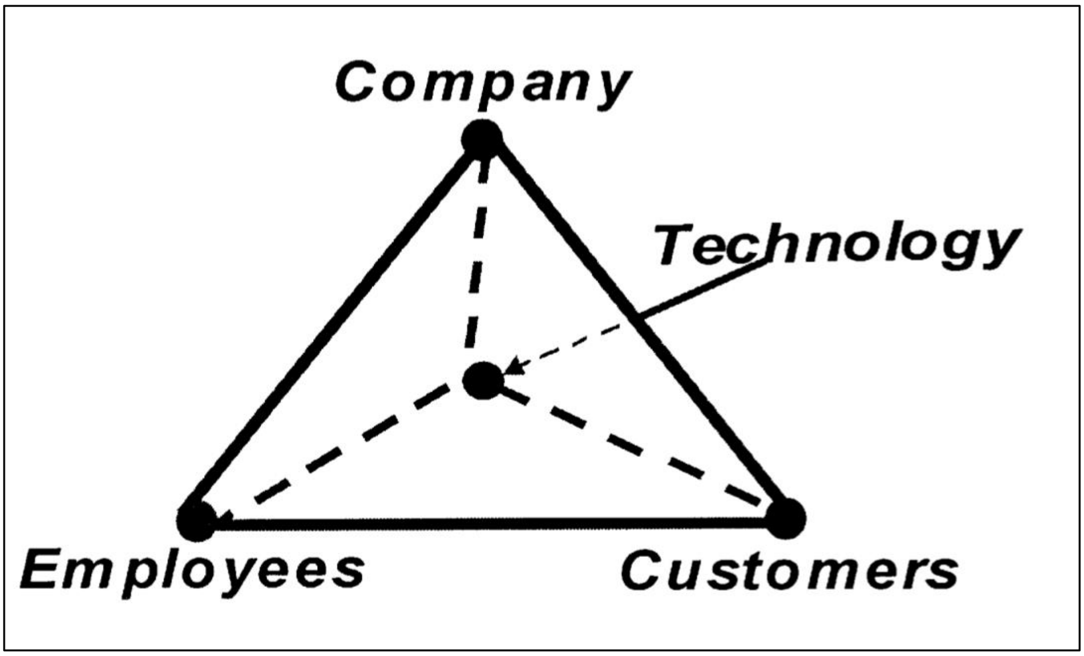


Figure 2.1: Technology Pyramid Model

Source: Parasuraman and Grewal (2000)

Technology-company linkage explains why an organisation may gain a competitive edge over its rivals through operational efficiencies while the technology-customer linkage explains how a company may leverage technology to formulate its sales process with smooth interactions between the company and the customer along the sales process. On the other hand, technology-employees linkage looks at the interactions a company's employees have with a customer and may help evaluate how the customers' perceive the level of service rendered by a company's employees (Parasuraman & Grewal, 2000).

Most businesses today are competing not only with local players in their host countries, but also with international players due to increased globalisation trends across most organisational spheres and business sectors. As stated by Lee *et al*. (2013), the use of technology must be embraced using advanced data analytical tools for businesses to survive in a highly competitive landscape. The local manufacturing sector in South Africa also faces the same challenges presented by globalisation. One way of local manufacturing players to ready themselves against increased foreign competition is to leverage technology. Park *et al.* (2009) denote that technology is key to improving inefficiencies within the manufacturing sector due to its ability to enable new insights to a business' operational tactics or business strategy. New business insights are usually learned using big data analytics and this concept will be explored in more detail below.

2.2 BIG DATA ANALYTICS

Big data analytics is known to be one of the fastest growing technological advancements and is regarded as the next innovation that will offer organisations a competitive edge when well utilised (Bhateja, Bab, Singh, & Sachdeva, 2012).

Big data refers to large amounts of data generated throughout a product's lifecycle; whereas, data are characterised by the five Vs (5Vs) known as volume, which refers to the amount of the data stored, variety, which is the different types and forms of data stored, velocity, which is the speed of the data (which basically means how quickly one wants to retrieve the data), veracity, the incompleteness and high ambiguity found in the data and value of the data collected (Tao *et al*., 2018).

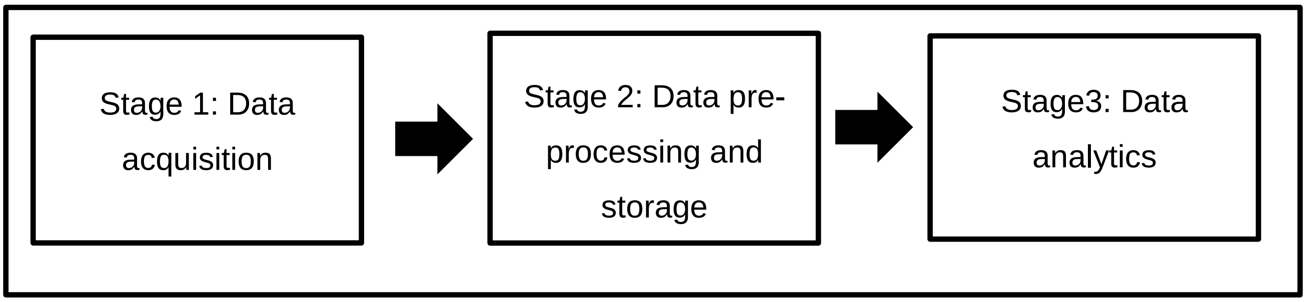


Figure 2.2: Showing the consecutive stages of data analytics

Source: Adapted from Dai, Wang, Xu, Wan, & Imran (2019)

Figure 2.2 shows the three steps that data analytics follow. These stages are an enabler for extracting valuable information, which, in return, provides problem-solving capabilities for an organisation (Dai, Wang, Xu, Wan, & Imran, 2019).Using big data, companies can utilise data-driven approaches in their decision-making processes, thus giving them a competitive advantage within their industry (Dubey, 2016). Metals manufacturing companies can leverage on the technological tools used in data gathering, provided the company has the right set of expertise to interpret the collected data (Tao *et al*., 2018). According to Dubey (2016), the capabilities of being able to predict possible production challenges will enable manufacturers to deliver proactive fixes, thus enabling flexibility within the manufacturing process.

Dubey (2016) shares that data analytics within the metals manufacturing space can assist in identifying all the bottlenecks within the production process. Through this, the planning forecast can be easily updated to accommodate this delay (Chase Jr, 2013). This confirms that data provided can indeed assist in decision making and the creation of strategic approaches.

The level of skills an organisation has to consume and understand big data sets it apart, because analysing data with no understanding limits the overall value that can be generated from data analytics (Labrinidis & Jagadish, 2012). Unfortunately, there are still many barriers, as many people within organisations cannot understand how to use the analysed data. They are unable to interpret how data may benefit their organisations (LaValle, Lesser, Shockley, Hopkins, & Kruschewitz, 2010).

Tao *et al*. (2018) further argue that eight years after the claim made by LaValle *et al*. (2010) organisations are still limited by lack of data analytics skills. To add more business value to the data collected, various analytical tools are required that offer visualisation of the entire company process through showing the current trends, historic trends as well as the ability to predict future trends (Chase Jr, 2013). This is further supported by Matthias, Fouweather, Gregory and Vernon (2017) who believe that the lack of big data analytical skills and value creation from data insights still hinder the degree of value-add that data analytics has.

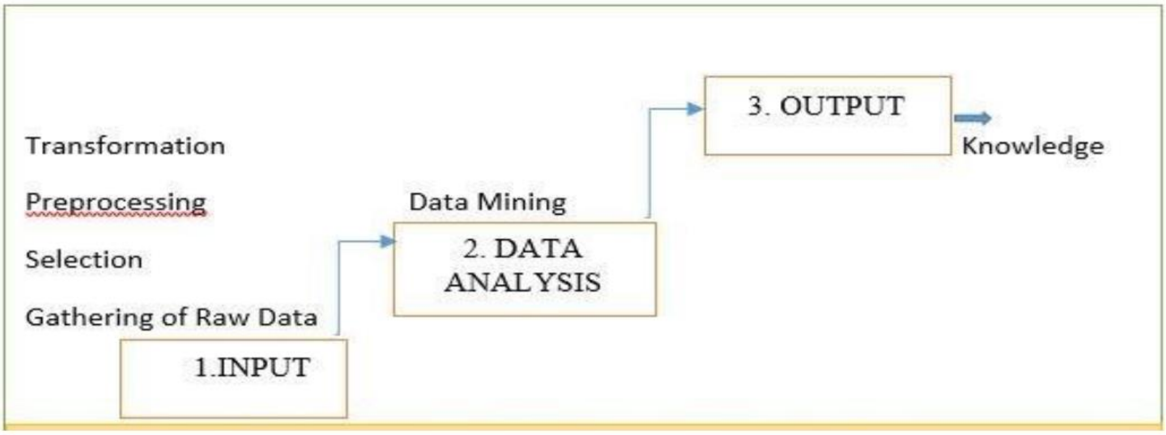
Having all the tools with limited skills to analyse the data works to the disadvantage of the organisation. Jifa and Lingling (2014) further confirm that, unfortunately, there is no value in data if it cannot be transformed to assist in making good decisions that will enhance the operational performance and bring about operational effectiveness. To generate value from analysed data, well trained personnel within the organisation to focus on continuous improvement are required

2.3 DATA ANALYTICS AND BUSINESS INSIGHT

The purpose of having data analytical tools is to assist in gathering information that will be used to nurture solutions to possible challenges faced. Having business insight as a business can be of assistance in providing solutions to identified problems (Warner, 2014). The decision-making process is also simplified; thereby, giving the business a competitive advantage. Vriens and Verhulst (2008) claim that gathered insights from data analytics enable the formulation of strategies targeted at capturing the market. Data analytical tools are able to deliver business insight to assist in making informed decisions. To do this effectively, they require specialists to run the data analytical tools and gather reports from them (Azvine, Cui, Nauck, & Majeed, 2006). The relevancy of the information gathered is based on ensuring that only the events that add value are collected (Waurznak, 2015).

LaValle *et al*.(2010) reveal that there is a relationship between the data analysed and the person interpreting the data; indicating that to get sound and relevant insight, the data analyst must fully understand the data in order to make sense of the findings.

To extract value from data analytics, a process flow needs to be embedded with the information generation process; this will add direction within the organisation.



Knowledge discovery process in Data Bases

Figure 2.3: Knowledge discovery process

Source: Tummala, Hemantha, & Kalluri (2018)

The knowledge discovery process should allow for the transformation of information, according to Tummala, Hemantha, & Kalluri (2018). Figure 2.3 shows the steps required to transform the data into knowledge, which takes all the raw data and dissects it into knowledge; the process of dissecting the information into smaller quantities is the process where the value in information is gathered, which then gets converted into knowledge. This postulates that failure to interpret the data sufficiently affects the achievement of organisational benefit and business knowledge. Hence the objective:

Objective 1: To evaluate the relationship between the use of data analytics and levels of business insights

2.4 ROLE OF DATA ANALYTICS ON METALS MANUFACTURING STRATEGY

The investment in data has grown tremendously over the years confirming the value it possesses within the world. Companies are constantly making investments in ensuring they have data, whether it be customer data or business data, as data provides them with brand value (Tao *et al*., 2018). The value of data, including its requirements, has changed over time. Knowing what happened and why it has happened is no longer sufficient for organisations, instead they want forecasts of what can possibly happen in the future, including what is happening in the interim (Tao *et al*.,2018). Therefore, the most important process after gathering data is devising measures that must be implemented to achieve optimal satisfactory results that provide manufacturing intelligence and improve flexibility (LaValle *et al*., 2010; Tao *et al*., 2018).

The ability to have dynamic capabilities as an organisation assists in improving the operational business; manufacturers who have data and use it as a dynamic capability will be able to formulate an informed business model that, in turn, creates organisational and business value (Akhtar *et al.*, 2017; Wamba, *et al*., 2017).There is organisational value that can be generated from data, such as formulating strategies that in the end provide the manufacturers with a competitive advantage, which enhance the business' operations (Tao *et al*., 2018).

A manufacturing strategy is defined as the means with which a business can implement a competitive strategy within their organisation (Amoako-Gyampah & Acquaah, 2008). They further identify various strategies that can be implemented by organisations, which are able to set them apart from their competitors, but propose that data gathered from the product lifecycle can give insight about the business performance.

It can be deduced that there is value in the gathered real-time data, as the information is able to improve the organisations productivity and profit margins through various cost-cutting mechanisms, as extrapolated by Waurznak (2015).

The manufacturing company's competitive strategy is affected by its manufacturing strategy (Amoako-Gyampah *et al.*,2008) and the use of data analytical tools provides information about the overall effectiveness of the plant, machine capacity and the utilisation rate (Waurznak, 2015).

The capability for individuals to make sense of all the patterns that could assist in achieving operational improvements is required in order to create strategic approaches as an organisation (Lee *et al.,* 2013). Big data analytics can enhance the quality of the production line; this is done through the identification of defects that can easily be detected before they leave the production line. Bódi (2018) suggests that much value is generated from data analytics, which can be used to solve existing problems or identify other problems that were unknown; therefore, the organisation assumes a strategic role, which increases their competitiveness in the industry.

2.5 TECHNOLOGY IN THE SOUTH AFRICAN METALS MANUFACTURING SECTOR

South Africa's metals manufacturing sector has been negatively impacted by the international competition that exist, this is due to the increased international imports that offer customers attractive buying prices (Damm & du Preez, 2009). The decline within the South African metals manufacturing sector was predicted during 1996, despite the communicated predictions a few changes were made by businesses and the government to adapt to the upcoming change(Edwards *et al.,* 2015). This is further supported by Edwards *et al., (*2014) who proposes that the lack of the correct support structures is what lead to the demise of many businesses within the metals manufacturing sector.

To successfully grow a business great support structures are needed. The Chinese have successfully penetrated the African continent proposes Jepson (2012), specifically South Africa with ease and dominance and this was all due to the support structures that were created in China. These support structures came in the form of technological advancements and governmental funding which increased in ability for the Chinese to easily penetrate the African continent, gaining monopoly over processed rare earth metals(Edwards *et al.,* 2015;Jepson, 2012)

The inability for organisations to achieve their production targets within the South African metals manufacturing sector affected their revenue margins, making it difficult for manufactures to justify their investment in technology (Damm *et al.,* 2009). Although manufacturers struggle to justify their technological investment, value is derived from technology by South African manufactures believes Moodley (2002). In addition he suggests that the South African manufacturing companies commonly use technology to improve business processes and increase efficiencies within their existing processes.

The benefits of data has been appreciated by the South African government during their exploration of investments in greener technology. Department of Science and Technology (2014) states that the use of inadequate data affects the identification of patterns which influences an organisation's innovation. They further suggest that it is important to handle data with care. This is supported by LaValle *et al*., (2010) who proposed that to gather value from data it has to be managed correctly.

Unfortunately, Edwards *et al., (*2015) considers the growing international competition being the cause of job losses and the closure of many metal manufacturing companies in South Africa. Those who survived invested in technology were able to perform better than their competitors (Jonsson, 2000).

2.6 STRATEGIC MANUFACTURING INSIGHTS AND BUSINESS MODEL

The ways of doing business have changed and having a strategic approach to the operations of a business has become key in giving organisations a competitive edge, within the era of globalisation (Amoako-Gyampah *et al.,* 2008). A business model is not only about creating value within the products and customer offerings, it is also about making improvements on how things are done and why they are done within the business. The business model looks at both the internal and external stakeholders and finds ways to bring benefit to all of them, which is what gives a business its competitive edge (Bocken, Short, Rana, & Evans, 2014).A business model is defined as a way in which an organisation is able to create and deliver value to its consumers while generating enough revenue to keep afloat whilst making sufficient profit (Hamel, n.d.).

In business terms, value is broken down into two segments, namely tangible and intangible elements. Tangible elements can be monetary assets or stakeholder equity; whereas, intangible elements can be brand recognition and public benefit (Invensis, 2018).It can be extrapolated that a business model that is generated can constitute various forms of value, both tangible and intangible. This is all dependent on the formulated strategy. With analysed data, strategies can be implemented within the manufacturing process, providing a competitive advantage (Tao *et al.,* 2018). The use of data in making strategic decisions, assists in formulating a quick business model, which is beneficial for responding promptly to changing customer needs (Bódi, 2018; IQOMS, 2017).

In pursuing a quick response to business modelling, it is key to have a manufacturing process that allows for flexibility in the implementation of these strategic approaches; this will be the organisation's mechanism to deal with the internal and external uncertainty (Zhang, Vonderembse, & Lim, 2003). Zhang *et al.* (2003) further elaborate that the degree of flexibility increases the ability to meet the different types of customer expectations at a minimal cost, due to the elimination of a rigid manufacturing process. The manufacturing strategy is able to have an impact on the business model as organisations lately want to strategically leverage on all their capabilities, as the emphasis for most businesses is focused on not only economies of scale but also economies of scope (Gupta & Somers, 1996).

The process model (Figure *2.5*) showing the generation of insights from data analytics should be structured by starting from big data to data mining, ending with data analytics (Data Revolution, 2017).

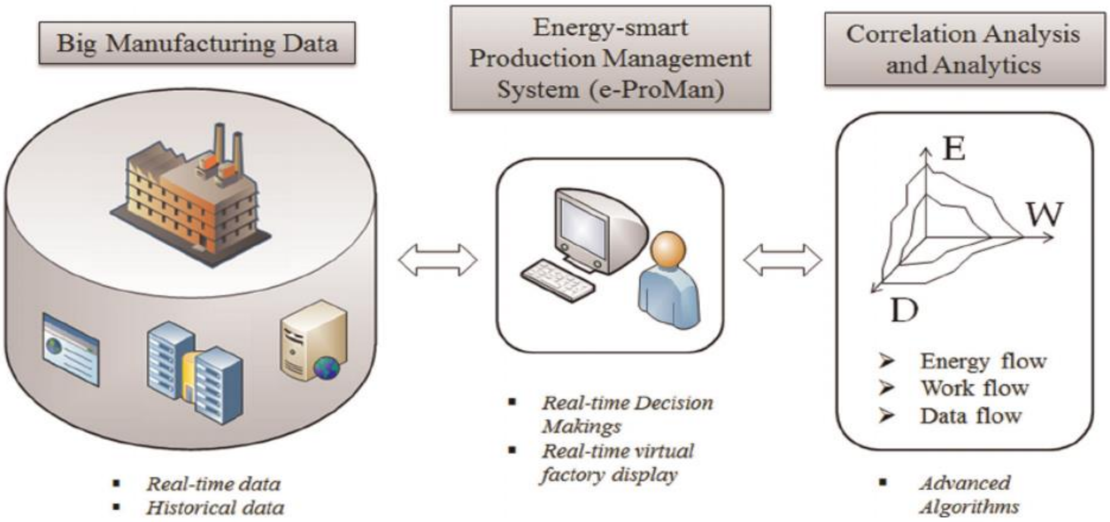


Image Source: ResearchGate

Diagram 2.5: Process model for generation of insight from data analytics

Source: Data Revolution (2017)

From these findings, the identified objective is:

Objective 2: To assess the impact of business insights in developing a business model.

2.7 CONCEPTUAL MODEL

The conceptual model is used to ensure that the correct set of tools are positioned for establishing the basis of defined hypotheses (Rekolainen, Kamari, Hiltunen, & Saloranta, 2003). The purpose of the conceptual model is to show a causal relationship between three constructs. According to Wang and Hajli (2017), the correct usage of data analytics provides business insights, leading to a successful business model. As a result, two hypotheses were established to test whether there is a causal relationship between the constructs below.

The conceptual model (diagram 2.6.1) suggests that the use of data analytical tools can assist in generating business insights for businesses (Vriens & Verhulst, 2008). As a result, in support of this statement, Hypothesis 1 was generated, which proposed that the usage of data analytics has an influential relationship with the levels of business insights.

Wamba et al. (2017) advocates that the generated business insights can assist in providing successful business models for manufacturing companies. To investigate this statement, Hypothesis 2 was established, which stated that business insights have an influence on the success of a business model.

Diagram 2.6.1: Conceptual model

Source: Adapted from Vriens and Verhulst (2008)

Hypothesis 1: Usage of data analytics has an influential relationship with the levels of business insights.

Hypothesis 2: Business insights have an influence on the success of a business model.

2.8 SYNOPSIS

The literature shows that technological advancements are key in providing businesses with a competitive advantage, especially since globalisation has taken over across the globe. Technology consists of multiple facets, but within this literature study, the focus was on data analytical tools and the benefits they possess within business. From the literature, it is evident that there are gaps in the data showing how data analytics can assist in formulating a business model within the metals manufacturing sector across South Africa. The role of data analytics within the metals manufacturing sector is evident, but the impact it has on the business is still not clear.

3 RESEARCH METHODOLOGY

Within this chapter, the methods used to conduct the research will be discussed. A detailed overview of the sampling method and how a sample was derived will be outlined. This chapter will elucidate a clear guideline of how the research was conducted.

3.1 RESEARCH DESIGN

With every hypothesis, it is key to identify a way to assess whether the hypothesis made is indeed true. A writing by Jang (1980) outlines research design as a plan used to conduct accurate assessments of something that helps in completing tasks in a well-structured approach. In summary, it is known as a way of assessing a common way of thinking (Keman, 2014). This will assist in ensuring a steady and measurable progress for the completion of this research report

A causal-comparative design was used to validate and measure the results, with the sole purpose of evaluating if patterns exist within the collected data. For the purpose of this research, the profile of the metals manufacturing sector was derived from individuals employed within the metals manufacturing sector. Vaus (2008) suggests that this type of study is called "individuals as the unit of analysis". Unfortunately, there was possibly some bias from this method as the individuals who populated the survey represented the entire sector.

The main aim of the research is to assess variables within the conducted study and investigate if relationships exist, but, most importantly, it is to investigate causality. Thus, a comparative design can provide that, as recommended by Johnson (2001), as it has the ability to evaluate a cause and effect relationship between dependent and independent variables.

3.2 RESEARCH APPROACH

The importance of a valid and reliable way of collecting data to do an analysis is critical. To conduct this research, a quantitative approach was used, which seeks to evaluate the extent of what is being investigated (Rahman, 2017). The author further proposes that the purpose of a quantitative approach is solely to quantify the social behaviour instead of looking at the meanings it brings. Grimes (2015) believes that a quantitative approach will be able to help in identifying relationships that may go unnoticed.

The insights gathered from this approach assisted in testing the hypotheses and identifying other cause and effect measures. The methodology stances associated with doing a quantitative research can give objectivity, including more accurate results during the analysis, which prevents individual bias (USC Libraries, 2019). The ability to replicate the research to gather more insights is made easier when using a quantitative research approach (USC Libraries, 2019).

3.3 RESEARCH PROCEDURE AND METHODS

3.3.1 Population

All employees in the metals manufacturing companies in South Africa will make up the population for this study. To qualify in the population, an employee should be working in a South African-incorporated and -owned metals manufacturing company.

3.3.2 Sampling method

The research methods knowledge base, sampling is regarded as the process of selecting units from a population of interest from where a study will be derived (Trochim, 2002). A non-probability sample is used when the population size is unknown (Bruwer, 2013), thus, it was used to select individuals working within the South African metals manufacturing sector.

Convenience sampling is known as a non-probability technique where participants are chosen based on availability and is an inexpensive sampling technique in comparison to other sampling techniques (Taherdoost, 2016).

3.3.3 Sample frame

A sampling frame of 150 people employed within the South African metals manufacturing sector was targeted. A convenience sample methodology was used to identify people through social media platforms, such as LinkedIn and WhatsApp, which were readily available. From the 150 targeted sample frames, only 106 people responded.

3.3.4 Sample size

Based on the data collected from 106 respondents, a total of 61 responses met the qualifying criteria and were used for data analysis. All the respondents were currently working or have worked in a metals manufacturing sector (100%), which was regarded as the qualifying question. Furthermore, the 10% guidelines for missing data was applied, as explained by Dong (2013), who suggests that if there is more than 10% of missing data in a survey, the data should not be used as it would create bias.

3.3.5 Ethical consideration

A factor that may arise in the collection of the data is that participants may be busy and may not have the time to participate in the survey; to manage this, a follow-up message was sent to each participant. Participants could possibly feel forced to complete the survey due to constant follow ups to confirm their completion. To manage this, it was highlighted that if they were not interested in completing the survey, they could send a notification, which would eliminate the constant follow-up messages.

Since this research is targeted at people employed by companies within the South African metals manufacturing sector, to ensure that only the correct people participated within the survey, a control question was asked. The purpose of the question was to enable participants to continue with the survey provided that they are employed in the metals manufacturing sector.

3.4 RESEARCH STRENGTHS

This section will examine the methods used to gather the data, as well as the measures that were taken to ensure that the data are reliable.

3.4.1 Research instrument

The research instrument that was used within this study was a self-administrated web-based survey. An invitation was sent out to each participant requesting their time and a brief introduction of the purpose of the survey, including the set of questions that would be asked. To attain respondents, a link to the self-administrated survey was sent out to individuals who work or have worked within the metals manufacturing sector. A flexible way to collect data was required as people within the manufacturing space are production driven and, at times, do not have the luxury to sit at their desks and attend to emails, therefore, a convenient way to populate participants' responses was required. Hence, the use of a web-based survey, which will allow participants to login at anytime and anywhere; they do not have to worry about physical submissions, all will be done online. This data are easier to analyse as well (Cvent Guest, 2016).

The weakness of a web-based survey method is the concentration rate. The respondent may be distracted when completing the survey, thus affecting the response outcome. The way to tackle this is to ensure that the questions are straight to the point to eliminate confusion (Cvent Guest, 2016).Before the commencement of the survey, a disclosure was communicated to each participant who was invited to complete the survey that their information gathered would be kept strictly confidential. The purpose of the study was also communicated to each participant.

3.4.2 Pilot testing

Reeves *et al*. (2002) outline the purpose of pilot testing as the ability to establish whether correct questions were asked or make alterations to the existing questions. Pilot testing is known as an evaluation of the survey where people test the ability to answer the survey and understand the questions, which is important in finalising a questionnaire.

Within this study, a pilot test was conducted with five experts who have expertise in the manufacturing sector from both a business and academic perspective, to evaluate the structure of the questions including the terminology used. Piloting was conducted to validate the appropriateness and relevance of questions and to understand how respondents would possibly interpret the wording and meaning of sentences.

3.4.3 Validity

Research validity is known as the extent to which a survey uses the correct measurement tool to gather the correct set of data, or better known as the correct set of weightings. The definition of validity is further sustained by Golafshani (2003) who states that the aim of validity is to ensure that what was meant to be measured is indeed being measured and it is being measured correctly.

There are different types of validity tests, one of which is content validity. Content validity consists of the usage of measurement items that are universally applied by experts; hence the use five experts who were recognised in the field to review the survey.

3.4.3.1 Internal validity

Internal validity looks at whether the collected data has any *"*causal relationship between independent and dependent variables" and, if so, to what degree is the relationship (McLeod, 2013). To achieve this validity, it is key to ensure that the conditions of all the variables used are well controlled; this is supported by McLeod (2013).

According to Dunbar-Jacob (2019), there is a threat in stating that there is a relationship within certain variables where it does not exist. A Cramer phi test was done on the pilot test of the questionnaire.

3.4.4 Reliability

Reliability is defined as the extent to which the correct set of data is accurately maintained within a set period of time, whilst ensuring that it is an accurate representative of the total population (Golafshani, 2003). Reliability is a key component when conducting a quantitative study and according to Golafshani (2003), it is key to consider while designing a study and evaluating the gathered results. He furthers states that it is important to ensure all levels of stability with the instrument used, especially when dealing with a fixed measuring technique or tool.

To make sure that reliability is achieved within this report is to ensure consistency within the used analytical tools and that the process used is maintained (Noble & Smith, 2015). One way of measuring consistency of instruments is to use Cronbach's alpha to calculate reliability (Santos, 1999). The author further suggests that if reliability is 0.7 or above, it is regarded as good reliability, which is evaluated in this study.

3.4.5 Administration of survey

The survey was created on Qualtrics, which is an online application used to conduct surveys. A link to the survey was sent out as an invitation to participants. The link was distributed through LinkedIn messages, email addresses as well as WhatsApp messages.

3.4.6 Data preparation

The data were downloaded onto an Excel sheet from Qualtrics, the application that is used to conduct self-administered surveys. The data were then coded and labelled accordingly. Likert scales were coded from one to five, where one represents strongly agree and five represents strongly disagree. Nominal scales were coded from one to two.

3.4.7 Data analysis

Data were recorded on Excel and then coded before being loaded onto the IBM Statistical Package for Social Sciences (SPSS) software system. The SPSS software version 26 was used in data analysis.

The nominal scales had to be analysed individually as they cannot be generalised. With regards to Likert scales, descriptive statistics was used to analyse the data, as recommended by Boone & Boone (2012).To establish differences between the dependent variables measured at a nominal level, the chi-square statistical method was used, due to the inability to find inferential statistics (McHugh, 2013).

3.4.7.1 Chi-square test and Cramer's Phi

A chi-square measurement is known as a non-parametric statistical method, which is used to establish if two or more variables are either dependent or independent (Zibran, 2007). For the purpose of this study, the chi-square measurement test was conducted to measure the inferential relationship between business insights and business model.

This is analysed using the following equation:

$$\chi^2 = \sum_i \frac{(O_i - E_i)^2}{E_i}$$

χ^2= chi-square value; **O_i =** Observed frequency; **E_i** = expected frequency, with degrees of degrees of freedom (r - 1)(c - 1), where r and c is the number of rows and columns of the contingency table (Zibran, 2007).

However, to evaluate the statistically significant association between the variables, the Cramer's Phi (φ) measured the strength of association (Acock & Stavig, 1979), which was used in a similar way as the effect size equivalent for a chi-squared statistic. The equation for the analysis of Cramer's V is:

$$\varphi = \frac{\sqrt{\chi^2}}{N\ (k-1)}$$

Where N = total number of subjects and K = the smaller of the number of rows or columns.

3.4.7.2 GPower 3.1

A GPower test was conducted using an IBM Statistical Package for Social Sciences software system to analyse the regression and correlation that exists between variables (Faul, Erdfelder, Buchner, & Lang, 2009).The purpose of conducting the GPower tests model within this study was to investigate the high-precision statistical value for the each construct, which provides a graphical representation of variables and their relevancy (Erdfelder, Faul, & Buchner, 1996).

3.5 ETHICAL CONSIDERATION

The ethical consideration within this study that was communicated is that participation is voluntarily and confidential. A clear description of the purpose of the study was communicated to each participant, including the desired timelines to complete the survey. Participants were assured that they were not forced to complete the survey but their participation will be highly appreciated.

3.6 SYNOPSIS

The use of proactive measures to ensure the success of this study is vital, as this forms the basis of a successful study. A quantitative methodology was used to gather the data whilst a causal-comparative design method was used within this study to assess the identified objectives. The distributed survey had to be accurate and fully tested to ensure that the correct findings were gathered from this study, every level of detail had to be included. The data were gathered using a self-administered survey and a pilot study was used to assess the accuracy of the distributed survey. The use of statistical methods such as chi-squared tests and Crammer's phi were used to analyse the data and establish relationships that exist within variables.

The thorough elaboration and direction of the methodology contributed to the structure used to gather and analyse the data. This assisted in ensuring that a successful study and analysis was conducted.

4. PRESENTATION OF FINDINGS

In this chapter, the findings from the analysis are presented based on a research-question based approach using both descriptive and inferential statistics.

4.1 INTRODUCTION

The purpose of the study was to understand the influence of data analytics on the business insight and the development of a business model. The collected empirical data were analysed using the SPSS. As there was no available database to sample the study, it was not possible to determine the adequate sample size.

4.2 DATA AND DATA ANALYTIC TOOLS WITHIN THE METAL MANUFACTURING INDUSTRY

To understand the state of the data within the metals manufacturing companies the respondents were asked if they have access to the relevant data in the company and whether the business will be competitive if data is well leveraged as well as whether there is adequate investment into data analytical tools. These questions where important to obtain insights on the data and data analytical tools investment in the metals manufacturing companies. Figure 4.2.1 present the results on whether there was access to the relevant data in the company. About two in three participants (65.7%) indicated that they do have access to the relevant data, while 18.0% indicated that they did not have an access, with 16.4% not sure if they have access to the relevant data. What this means is that although the majority had access, there was still a sizable percent that did not have access.

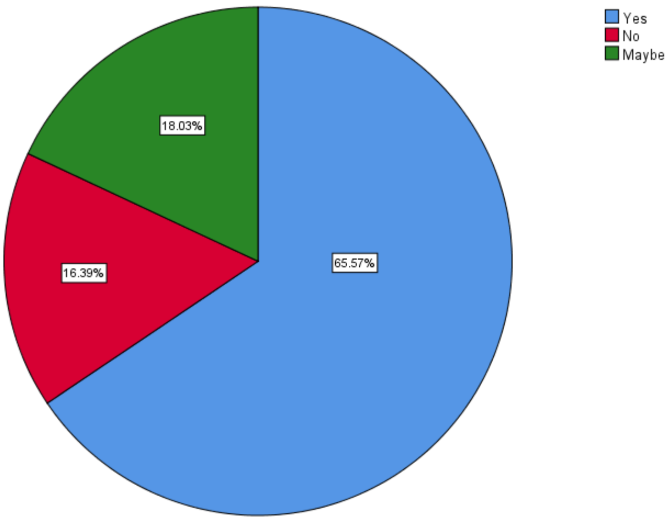


Figure 4.2.1 Access to the relevant data in the company

With regards to the leveraging of the big data, the respondents were asked if there was a risk of the company being non-competitive if they do not leverage the data. More than 90% indicated that there was the risk, which indicates that these respondents understand the importance of data and the need for the company to leverage it to continue to be competitive (Figure 4.2.2).

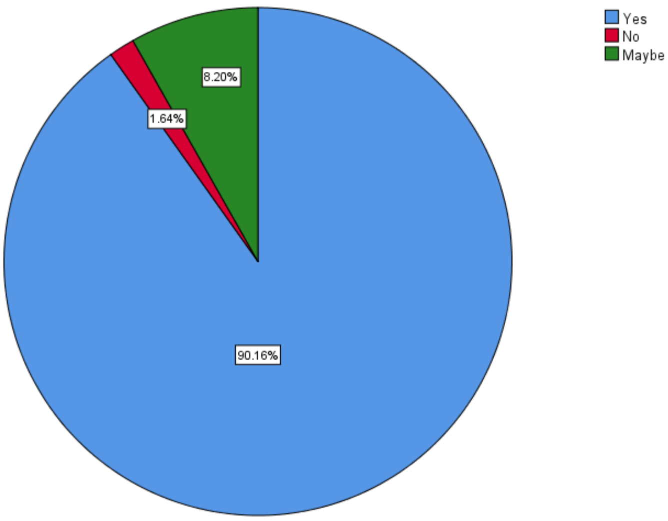


Figure 4.2.2 Risk of non-competitiveness if data are not leveraged by the company

Having understood the access to the relevant data and whether there is a need to leverage it, it was prudent to understand whether the companies have invested in adequate tools to analyse the data for the success of the company. Figure 4.2.3 presents the results, with only 16.4% of the respondents indicating that it was extremely adequate, while about a third of the respondents (32.8%) indicated that they were either extremely adequate or somewhat inadequate. The biggest group, which comprised of 42.6%, believed that they were somewhat adequate (Figure 4.2.3).

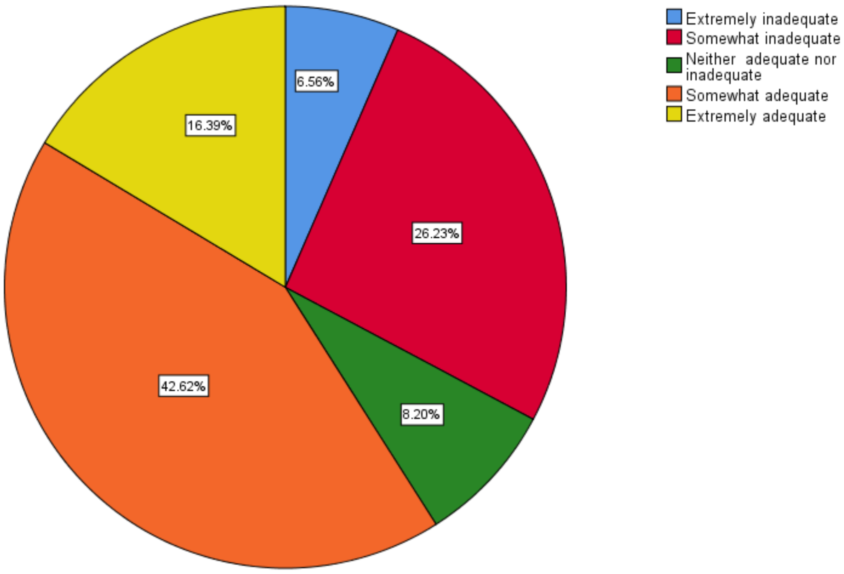


Figure 4.2.3 Adequacy of investment in data analytics tools

The respondents were asked to rate the success of a business strategy that they implemented without having business insight, which is normally obtained from the data analytics. The results were mixed with 45,9% saying it was somewhat unsuccessful or extremely unsuccessful, while only 32.7% of the respondents indicated that it was somewhat successful or extremely successful (Figure 4.2.4). This is evidence that the majority of the respondents believed that the business insight is critical for the successful implementation of a business strategy. This is confirmed by Q16 – where the respondents were asked if, given the opportunity to do things differently, would they have ensured that they have enough business insight before making a decision, to which 98,4% of them agreed.

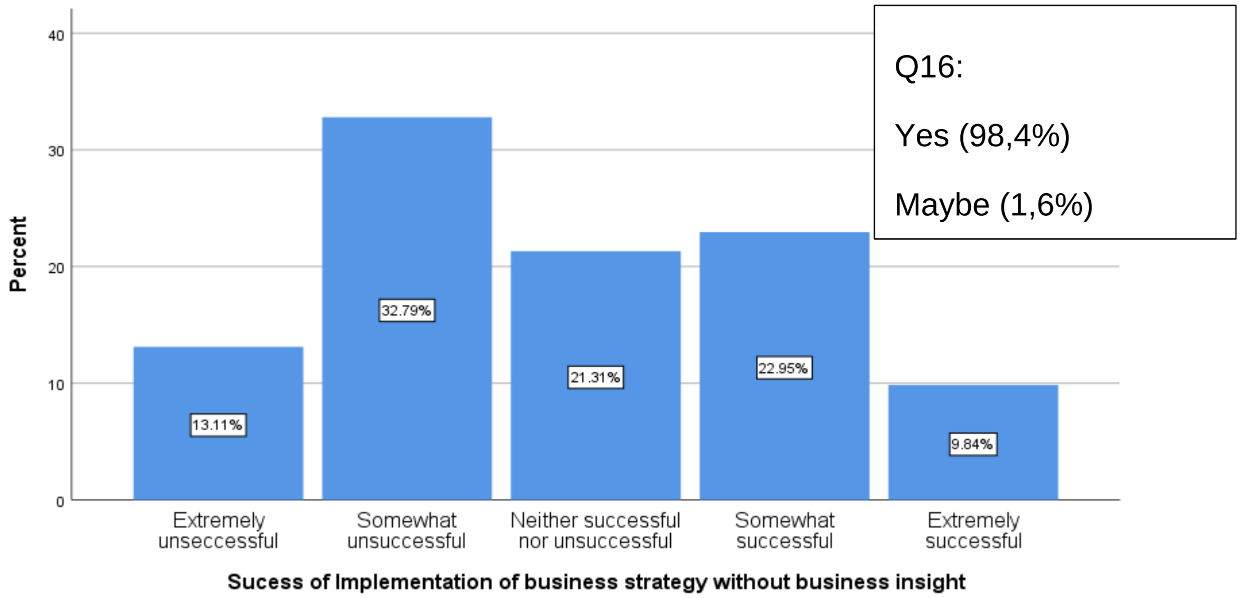


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Figure 4.2.4 Success of implementing business strategy without business insight

In summary, the majority of the respondents indicated that they had access to relevant data and this data were important for competitiveness, but the companies have not adequately invested in data analytical tools.

4.3 INFLUENCE OF BIG DATA ANALYTICS ON BUSINESS INSIGHT

The first research objective of the study was to evaluate the relationship between the use of data analytics and levels of business insight. To investigate this objective the following hypothesis was developed:

H_1: Usage of data analytics has an influential relationship with the levels of business insights

4.3.1 Frequency of variables on data analytics

There were five variables that investigated the data analytics, which were related to the value, education and experience. Table 4.3a presents the value-related variables on data analytics, while Table 4.3b presents the education and experience-related variables. The results show that 91.8% of the respondents (Q2), which was congruent with Q5 (85,2%), were of the view that there was a business value from data analytics, while 52.5% believed that the business leaders were able to use data to transform the business. What is evident was that not everyone was in agreement that their leaders were able to use the data to transform the business with 20,3% saying ‘No’ while 27,1% were not sure, saying ‘Maybe’.

Table 4.3a Frequency of variables on data analytics

	Frequency (%)		
	Yes	No	Maybe
Q2	91,8	0	8,2
Q5	85,2	4,9	9,8
Q22	52,5	20,3	27,1

Regarding education and experience, the results show that the majority of the respondents agree that a high level of education contributes to the quality of the information generated from data analytics with almost 90% either strongly agreeing or somewhat agreeing. The majority of the respondents also indicated that past data analysis experience is required to analyse data in order to provide valid information (Table 4.3b). The majority of these respondents somewhat agree or strongly agree that business insights generated from data analytics is gathered efficiently when well analyses, which indicates the importance of education and experience.

Table 4.3b Education and experience related variables on data analytics

Variables	Frequency (%)				
	Strongly Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
Q6	1,6	0	0	47,5	50,8
Q7	1,6	4,9	3,3	34,4	55,7
Q9	0	11,5	4,9	27,9	55,7

With regards to education, about two in three participants (65.6%) believed that a four-year degree or a professional degree is required to analyse data and get value from the data (Figure 4.3c).

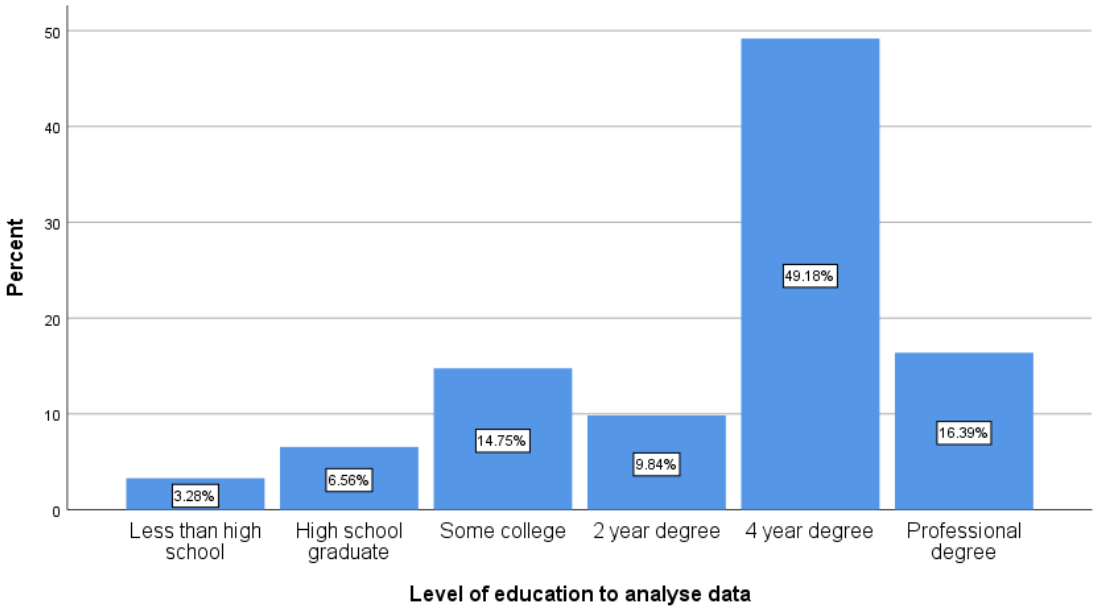

Figure 4.3c Level of education to analyse data

4.3.2 Reliability of the variables on business insight

To understand the business insight, there were four variables, namely Q10, Q11, Q23 and Q24 (Table 4.3d). The results show that 83,6% of the respondents strongly agree that data need to be used to make business decisions (Q10), with 82.0% strongly agreeing that having business insight can assist with making informed decisions (Q11). With regards to Q23, 'real-time data provides more current information' 80.3% strongly agree, while 70.5% strongly agree that the more current the data the better the business model (Q24). These results indicate that respondents believed that the business insight was critical to the business, with the four variables forming a construct, with Cronbach's alpha coefficient ($\alpha = 0.600$) indicating that this construct is reliable, based on the guidelines of Hair, Anderson, Babin and Black (2010) who suggests that a minimum sample size is a 100 when using five or fewer constructs.

Table 4.3d Frequency and reliability of the variables of business insight

	Frequency (%)					Cronbach alpha (α)
Variables	Strong Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree	
Q10	0	0	0	16,4	83,6	0,600
Q11	0	0	1,6	16,4	82,0	
Q23	0	0	1,6	14,8	80,3	
Q24	0	1,6	1,6	23,0	70,5	

4.3.3 Association between the data analytics and the business insight

The results of the chi-square using Fisher's exact test shows that there was a statistically significant association between Q9 – past data analysis experience is required to analyse data in order to provide valid information and the business insight, $\chi^2(15) = 38.45$, $p < .05$ with the association being strong, $\varphi = 0.807$ (Table 4.3e).

Table 4.3e Chi-square analysis for association between data analytics related variables and business insight

Areas	Survey Question	Value	df	Asymptotic Significance	Cramer's V (φ)	Power
Value-Related	Do you see any business value from data analytics (Q2)	8,907	5	0,113		
	Are your organisation's business leaders able to use data analytics to improve or transform the business? (Q22)	12,434	10	0,257		
Education and Experience	Business insights generated from data analytics is gathered efficiently when well analysed (Q6)	5,765	10	0,835		
	A high level of education contributes to the quality of information generated from data analysis? (Q7)	15,379	20	0,73		
	Data need to be used to make business decisions. (Q8)	21,049	25	0,69		
	Past data analysis experience is required to analyse data in order to provide valid information (Q9)	38,45	15	0,001	0,807	0,99

An analysis with the GPower 3.1 indicates that there was adequacy of the sample. The total sample size of 61 resulted in a power (1 – β err prob = 0.99), which indicated that there was a good statistical power (>0.80) and thus adequate sample size. The value-related questions Q2 and Q22 did not have a statistically significant association with business insight including the level of education with the business insight.

4.4 INFLUENCE OF BUSINESS INSIGHT ON THE BUSINESS MODEL

The second research objective was to assess the impact of business insights in developing a business model for an organisation. To investigate objective two, the following hypothesis was developed:

H_2: Business insights have an influence on the success of a business model.

4.4.1 Frequency of variables of business model

The frequency for the five variables related to the business model are presented in Table 4.4a and Table 4.4b The respondents were asked whether the business processes are driven with insights from predictive customer analytics (Q18), with 60.7% saying 'Yes' while 14.8% said 'No' and 24.6% were not sure, saying 'Maybe'.

Table 4.4a Frequency with nominal scale of business model related variables

	Frequency (%)		
Variables	Yes	No	Maybe
Q18	60,7	14,8	24,6
Q20	63,9	11,5	24,6

Additionally, Q14, Q19 and Q24 investigated the business model related variables. The results show that 68,9% of the respondents strongly agree that making decisions without business insights can have a negative impact on the level of success (Q14), while the same amount (68,9%) were of the view that data are required to form a business model (Q19) and 70,5% strongly agree that the more current the data are, the better the business model (Q24).

Table 4.4b frequency with ordinal scale business model related variables

	Frequency (%)				
Variables	**Strongly Disagree**	**Somewhat disagree**	**Neither agree nor disagree**	**Somewhat agree**	**Strongly agree**
Q14	0	0	1,6	29,5	68,9
Q19	0	0	0	31,1	68,9
Q24	0	1,6	1,6	23,0	70,5

4.4.2 Association between the business insight and business model related variables

The results of the chi-square using Fisher's exact test show that there was a statistically significant association between business insights and Q14 – Making decisions without business insights can have a negative impact on the level of success, $\chi^2(10) = 20.13$, $p < .05$ with the association being strong, $\varphi = 0.584$ (Table 4.4c). There was also a statistically significant association between business insight and Q19 - Data are required to form a business model. $\chi^2(5) = 11.36$, $p < .05$ with medium association ($\varphi = 0.439$).

Table 4.4c The chi-square analysis for association between business insight and business model related variables

Areas	Survey question	Value	df	Asymptotic Significance	Cramer's V (φ)	Power
Business Model	Making decisions without business insights can have a negative impact on the level of success (Q14)	20,132	10	0,028	0,584	0,904
	Are your business processes driven with insights from predictive customer analytics? (Q18)	8,528	10	0,577		
	Are your organisations' sales efforts fuelled by data analytics insights? (Q20)	11,645	10	0,31		
	The more data, the easier it is to formulate a business model (Q24)	23,911	15	0,067		
	Data are required to form a business model (Q19)	11,36	5	0,045	0,439	0,802

A post-hoc analysis with the GPower 3.1 indicates that there was adequacy of the sample. The total sample size of 61 resulted in a power (1 – β err prob = 0.904) for business insight and Q14 as well as a power (1 – β err prob = 0.802) between business insight and Q19 shows good statistical power (>0.80) and thus adequate sample size.

4.5 SYNOPSIS

The 61 responses collected to analyse data were adequate in this study. The analysis indicated that there was an association between certain variables related to data analytics and business insights, as well as business insights and business model-related variables. These results are discussed in Chapter 5 with the conclusions, limitations and recommendations provided to the business, as well as suggestions for future studies to the academia.

5. DISCUSSION

The aim of this chapter is to provide a detailed discussion on the findings of the study, provide recommendations to practitioners and academics as well as suggest future research opportunities.

5.1 INTRODUCTION

Globalisation has increased the competitive landscape in business over time and the survival of many companies has been based on the adoption of innovative technologies. As a result, many businesses across the globe have realised the value of technology (Section 2.1). However, technology alone does not provide companies with a competitive advantage because it also needs enough supporting elements to function optimally. The correct technological supporting elements are particularly important in today’s globalised business landscape. The linkages between technology, customers, employees and the company are the supporting elements required to enable a company to gain a competitive advantage over others using technology (Section 2.1). These linkages are the foundations needed to successfully leverage technology to redesign business models that will optimally serve the interests of a company’s internal and external stakeholders (Section 5.4).

There are different technological devices and applications that play their individual role towards the contribution of a business’ success, one of which is data analytics. Data analytical tools assist in providing business insights derived from the data mining process, which, in turn, creates a knowledge database. The knowledge base allows for the use of transformed data to assist in problem solving (Section 2.3). The data generated from data analytical tools provides assistance in making decisions and creating various strategic approaches for businesses. Although this is the case, the key is ensuring that data analysis is done by individuals who have the correct set of skills and are well trained (Section 2.2). This is because a competitive advantage is only gained when data analytical tools are used correctly through appropriate investments in data analytical skills. This can be a differentiating factor for businesses because they would have the required skills set to sift through complex data, draw patterns and derive powerful insights that will help shape their strategies, operating and business model (Section 2.4).

The adoption of data analytical tools in shaping business insights assists in dealing with internal and external business uncertainty. This allows for business flexibility towards the formation of a business model (Section 2.5).The purpose of conducting the study was to establish the chain effect between data analytics, business insights and the formulation of business models. This will be discussed in Section 5.2.

5.2 MAIN FINDINGS OF THE STUDY

This section provides a discussion on the influence of data analytics on business insights and the influence of business insights on business models.

5.2.1 Influence of analytics on levels of business insight

Bhateja *et al*. (2012) believe that data are the next innovation that will offer organisations a competitive advantage, when well analysed. His assertions were in line with findings from the study as it was discovered that 91.8% of the respondents (Q2) felt that there is business value in data analytics. The value data has is further supported by Q17 as 90.6% of respondents suggested that a company faces the chances of being non-competitive if a business does not leverage data.

Although there is value in data analytics, the value is dependent on the skill level of the individual analysing the data (LaValle *et al*., 2010). This is because data on its own have no value, unless knowledge is created from it (Tummala *et al.,* 2018), which is enforced by the storage of valuable information and correctly categorising it. This assertion is also in line with a finding from the collected data, as 90.1% of respondents (Q7) confirmed that they strongly agree or somewhat agree that a high level of education contributes to the quality of information generated from data analysis.

Dubey (2016) posits that companies that leverage big data can get a competitive edge over others because it assists them in their decision-making processes. This is confirmed by the results from the study as 80.2% of respondents (Q10) believed that data are required to make informed decisions. Although people see value, it is unfortunate that they feel that only 52.5% (Q22) of their business leaders use the data to transform the business. This shows that the value of data analytics is not yet fully embraced by business leaders in the metals manufacturing sector.

As highlighted by Ramey (2013), technological advancements in businesses are a key trend that can be of assistance in solving problems whilst expanding on human knowledge. It can contribute to the company's strategy and provide guidance in meeting customer requirements and builds on internal capabilities (Parasuraman & Grewal, 2000). This confirms that it cannot be disputed that data is an element that contributes greatly to business insights (Vriens & Verhulst, 2008).

Data analytical skills are a combination of education and practical experience on the job. Gregory and Vernon (2017) advocates that education is not the only contributing factor to generating value from data, they argue that practical experience is of equal importance. This means that for businesses to fully leverage data in creating business insights, they must ensure that they acquire a workforce that is educated and experienced in analysing complex data.

A chi-square test was conducted between the constructs of data analytics and business insight to assess whether there was an association between the two constructs' variables, as theoretically predicted. Findings concluded that value-related data analytical variables had no association with business insights but that only the experience in data analytics was associated with business insight. The chi-square confirmed that a strong association exists between business insights and (Q9), which states "past data analysis experience is required to analyse data in order to provide valid information". This strong association is confirmed by asymptotic significance (p), which is equal to 0.001 because when $p<0.05$ then it confirms strong significations level. The magnitude of the effect is 0.807, which is also large and supports that there is indeed a large effect that past experience has on business insight. These findings confirm that business insight and past data analysis experience are indeed related, which in turn confirms LaValle *et al*. (2010) sentiments that there is a relationship between the person who analyses the data and the interpretation of the data that provides business insight. This is further supported by Tao *et al*. (2018) who advise that the correct expertise is required to interpret the data. Therefore, it can be surmised that expertise and practical experience are needed to ensure that data analytics contribute positively towards business insights.

5.2.2 Business insight and influence on business model

The literature regards business insight as a key contributor to making informed decisions, because it can assist in finding solutions to possible business challenges (Warner, 2014). This was an element that thus had to be investigated to evaluate if business insight is a contributing factor.

With business insight, strategies can be formulated as they are informed by the findings established from the analysed data. This is positioned by Vriens and Verhulst (2008) as they advocate that market targeting can be informed by insight. The relevancy of the insights gathered from data (Waurznak, 2015), is able to assist in forming a business model and influencing the business strategies due to the relevancy of the data. From the findings, 68.9% (Q19) of respondents felt that data is required to form a business model. Tao *et al*. (2018) and Tummala et al. (2018) conclude that data goes through a knowledge process when being analysed, which contributes to the growth of an organisation’s brand value. Whilst this is the case, the respondents are in support of the findings as 70.5% (Q24) of them strongly agreed that the more current the data is, the better the business model.

A chi-square using Fisher’s exact test was conducted to evaluate whether there is an association between business model variables and business insight. Although there were variables linked to the business model that were regarded as independent to business insight, two variables were deemed to have a strong association with business insight. From the analysis, one of the variables that had an association with business insight was Q14, which states "Making decisions without business insights can have a negative impact on the level of success", this confirms that there is a relation between making decisions without business insights and a business model. It can be concluded from this analysis that having business insight has an impact on the success of decisions made, which, in turn, has an impact on the business model. These findings are supported by Niaki *et al*. (2017) whose sentiments suggest that without the proper use of data, the decision-making process becomes a challenge. This affects the flexibility of the business and the business model (Bocken *et al.,* 2014).

The second variable that has an association with the business mode is Q19, which suggests "data is required to form a business model" due to its confirmed asymptotic significance value of 0.045, which is less than 0.05. This shows that a business model has a relation with data, as with no data a business model cannot be formed. This finding is advocated by Wamba *et al.* (2017) whose sentiments are that companies who have data and can use them as a dynamic capability will be able to formulate an informed business model, thus creating business value. This is supported by Sorescu (2017) who proposes that leveraging of data offers businesses the opportunity to create new business models and enhance the existing ones.

Although the value of data analytics is seen by individuals across multiple industries, locally within the metals manufacturing sector only 60.7% of respondents felt that their business processes are driven with insight from predictive customer analytics. This, unfortunately, confirms that data are not well leveraged within the metals manufacturing sector. To further support this analysis, one third of the respondents are under the perception that their businesses are not using data to predict customer's requirements.

It can thus be concluded from the propositions of the findings and the existing literature that the success of a business model is centred on the data used to provide business insights. The value of the business insights generated to form a business model is dependent on the experience of the individuals analysing the data.

5.3 RECOMMENDATION

Globalisation is an element that cannot remain ignored, it has forced companies to resort to other mechanisms to maintain their market share within a globalised economy. With a thorough analysis of the literature and the gathered findings it is important for companies within the South African metals manufacturing sector to invest in technology. To attain a competitive advantage using technology, the technological investments need to consist of linkages between employees, the company and customers. The inability to consider these linkages affects the value of technology on business; thus, causing business not be possibly witnessed the generated value within the manufacturing company.

A focus on data analytical tools and big data provides the manufacturing company with a competitive edge due to the business insights, which can be derived from data. The impact data has on business is visibly seen when individuals with the correct set of skills and experience are used to analyse the data, meaning investment in skills is crucial when investing in data analytical tools. The strong association between data and a business model confirms that without data, a business model cannot be derived. It is, therefore, key for businesses to leverage data to enhance or even change their business model. Flexibility in a business model allows for businesses to constantly adjust to changing times, providing them with the ability to retain their market share.

5.4 LIMITATIONS OF THE STUDY

The purpose of the study was to investigate the role of data analytics in formulating a business model. One of the limitations that was identified when conducting this study is that a convenience sampling method to collect the data was used, which had an impact on the spread of the respondents. Financial constraints dictated that the convenience sampling method was utilised even though it is possibly not fully suitable for this type of study.

5.5 CONTRIBUTIONS OF THE STUDY

The metals manufacturing sector of South Africa has seen a decline in revenue margins over the past years and ways to retain market share have been key for survival. Flexibility in business models to handle different market conditions has thus become crucial, resulting in evaluating the role data analytics has in formulating business models. The findings from the study established that data analytics contribute to the formulation of a business model if business insights are generated from well-analysed data. The study further established that dynamic capabilities can be established by businesses provided that their data are well leveraged and analysed by experienced personnel.

5.6 CONCLUSION

The role of data analytics in formulating a business model within the South African metals manufacturing sector has been identified. The usage of data analytics to formulate a business model can assist in providing flexibility and increase the success of the business model. The use of data within a manufacturing company provides the ability for the company to gain a competitive advantage, which can be converted into a dynamic capability. As a result, the role of data analytics in formulating a business model is indeed crucial and highly beneficial.

5.7 SUGGESTIONS FOR FUTURE RESEARCH

There have been interesting gaps and findings identified within the research, which can be further explored. These gaps were prevalent within the literature as well as the findings. As a result, it would be interesting for the following areas to be investigated:

1. The study confirmed that data do play a role in formulating a business model, but it would be interesting to know if the role played by data contributes to the financial margins within the business
2. From the findings, it was established that fewer respondents felt that their managers do not use data analytics and it is not yet fully embraced by business leaders in the manufacturing sector. A study that focuses on the extent/ size of appreciation of data analytics by business leaders in the manufacturing sector would be insightful
3. The findings highlighted that almost a third of respondents felt that their businesses are not investing enough in analytical tools; it would be interesting to further explore why this is the case.

REFERENCES

Acock, A., & Stavig, G. (1979, June 01). A measure of Association for Nonparametric Statistics. *Social Forces*, pp. 1381-1386.

African Markets. (2019, January 30). *Markets: South Africa*. Retrieved January 30, 2019, from African Markets: https://www.african-markets.com/en/stock-markets/jse/listed-companies

Ahlstrom, D. (2010, August). Innovation and growth:How business contributes to society. *Academy of management perspectives*, pp. 11-24.

Akhtar, P., Khan, Z., Tarba, S., & Jayawickrama, U. (2017). The Internet of Things, dynamic data and information processing capabilities and operational agility. *Technology Forecasting & Social Change*, 2-8.

Alsghaier, H., Akour, M., Shehabat, I., & Aldiabat, S. (2017). The importance of Big Data Analytics in business: A Case study. *American Journal of Software Engineering and Applications, 6*(4), 111-115.

Amoako-Gyampah, K., & Acquaah, M. (2008). Manufacturig strategy, competitive strategy and performance: An emparical study in a developing environment. *International Journal of Production Economics*, 575-592.

Azvine, B., Cui, Z., Nauck, D., & Majeed, B. (2006). Real Time Business Intelligence for the Adaptive Enterprise. *Joint Conferences*, 29-29.

Bada, A. (2002). Local adaptations to global trends: A study of an IT-based organizational change program in a Nigerian bank. *The Information Society, 18*(2), 77-86.

Barnes, J., & Kaplinsky, R. (2000). Globalistaion and death of local firms? The automobile components sector in South Africa. *Journal of Regional studies*, 797-812.

Bellhouse, D. R. (2001, January 01). The central limit theorem under simple random sampling. *The American Statistician*, 352-357.

Bhateja, A., Bab, R., Singh, S., & Sachdeva, A. (2012). Study of the Critical factor Finding's regarding evaluation of Green supply chain Performance of Indian Manufacturing Sector. *International Journal of Computational Engineering & Management*, 74-80.

Bickel, P. J., & Lehmann, E. L. (2012). Descriptive statistics for nonparametric models. In J. Rojo, *Selected Works of EL Lehmann* (pp. 465-471). Boston: Springer.

Bocken, N., Short, S., Rana, P., & Evans, S. (2014). A literature and practice review to develop sustainable business model archetypes. *Journal of Cleaner Production*, 42-65.

Bódi, K. (2018, July 2). *10 Big data use cases in manufacturing*. Retrieved January 12, 2019, from Actify: https://www.actify.com/industry-topics/10-big-data-use-cases-manufacturing/

Boone, H. N., & Boone , D. A. (2012). Analysing Likert Data. *Journal of Extension*, 1-5.

Bradford, A. (2017, July 24). *Live Science : Culture* . Retrieved from Live Science: https://www.livescience.com/21569-deduction-vs-induction.html

Brand South Africa. (2018, January 2). *Brand South Africa.* Retrieved January 14, 2019, from Brand South Africa: https://www.brandsouthafrica.com/investments-immigration/business/investing/economic-sectors-agricultural

Brand South Africa. (2018, January 2). *Brand South Africa.* Retrieved from Brand South Africa: https://www.brandsouthafrica.com/investments-immigration/business/investing/economic-sectors-agricultural

Bruwer, J.-P. (2013). *Research Methodology: Research design and methodology.* Buwer Research Solutions.

Business Dictionary. (n.d.). *Manufacturing*. Retrieved January 15, 2019, from BusinessDictionary.com: http://www.businessdictionary.com/definition/manufacturing.html

Business Dictionary. (n.d.). *Manufacturing*. Retrieved January 15, 2017, from BusinessDictionary.com: http://www.businessdictionary.com/definition/manufacturing.html

Business Dictionary. (n.d.). *Quality*. Retrieved February 02, 2019, from http://www.businessdictionary.com/definition/quality.html

Business Dictionary. (n.d.). *Quality*. Retrieved from http://www.businessdictionary.com/definition/quality.html

Chase Jr, C. W. (2013). Using big data to enhance demand-driven forecasting and planning. *The Journal of Business Forecasting*, 27-32.

Chen, H., Chiang, R. H., & Storey, V. C. (2012, December). Business intelligence and anaytics: From big data to big impact. *Business Intelligence Research*, pp. 1165-1188.

Cvent Guest. (2016, September 19). *Advantages and Disadvantages of Online Surveys*. Retrieved January 30, 2019, from Cvent: https://www.linkedin.com/pulse/face-to-face-interviews-advantages-disadvantages-charlie-marshall/

Cvent Guest. (2016, September 19). *Advantages and Disadvantages of Online Surveys*. Retrieved from Cvent: https://www.linkedin.com/pulse/face-to-face-interviews-advantages-disadvantages-charlie-marshall/

Dai, H.-N., Wang, H., Xu, G., Wan, J., & Imran, M. (2019). Big data analytics for manufacturing internet of things:opportunities,challenges and enabling technologies. *Enterprise Information Systems*, 1-25.

Damm, O., & du Preez, W. (2009, April 17). Materials Science Forum. *Process made by the South African Light Metals Development Network*, pp. 147-154.

Data Revolution. (2017, October 12). *Why is Industry 4.0 the Future of Productivity and Growth in Manufacturing*. Retrieved from Data Revolution: https://www.datarevolutionhr.com/view-article.asp?article=f1ze1id7dtbghb3

Demil, B., & Lecocq, X. (2010). Business Model Evolution: In Search of Dynamic Consistency. *Long Range Planning*, 227-246.

Denzin, N., & Lincoln, Y. (2005). *Handbook of Qualitative Research* (third ed.). California: Sage Publications.

Department of Trade and Industry. (2018, June 12). *Presentation to the Portfolio Committee on Trade and Industry.* Retrieved January 15, 2019, from The Department of Trade and Industry: https://www.thedti.gov.za/parliament/2018/SA_Steel.pdf

Department: Science and Technology. (2014). *The State of Green Technologies South Africa.* Pretoria: Academy of Science of South Africa.

DMC. (2015, November 9). *Warehouse Management*. Retrieved January 17, 2019, from dynms: https://www.dynms.com/news/warehouse-management/the-advantages-of-real-time-data-collection-in-manufacturing/

DMC. (2015, November 9). *Warehouse Management*. Retrieved from dynms: https://www.dynms.com/news/warehouse-management/the-advantages-of-real-time-data-collection-in-manufacturing/

Doody, O., & Noonan, M. (2013). Preparing and conducting interviews to collect data. *Nurse Researcher*, 28-32.

Drnevich, P. L., & Croson, D. C. (2013, June). Information Technology and business-level strategy: Towards and Integrated Throrectical Perspective. *MIS Quaterly, 37*(2), pp. 483-507.

Dubey, R. (2016). The impact of big data on world-class sustainable manufacturing. *The International Journal of Advanced Manuafacturing Technology*, 1-9.

Dudovskiy, J. (n.d.). *Validity*. Retrieved February 02, 2019, from Research Methodology: https://research-methodology.net/research-methodology/reliability-validity-and-repeatability/research-validity/

Dunbar-Jacob, J. (2019). Minimizing threats to internal validity. In B. M. Melnyk, & D. Morrison-Beedy, *Intervention Research and Evidence-Based Quality Improvements* (p. 129). New York: Springer Publishing Company.

Edward, L., & Jenkins, R. (2014). The margins of exports competition: A new approach to evaluating the impact of China on South African exports to Sub-Saharan Africa. *Journal of Policy Modeling*, S132-S150.

Edwards, L., & Jenkins, R. (2015). The Impact of Chinese Import Penetration on the South African Manufacturing Sector. *Development Studies*, 448-450.

Edwards, L., & Jerkins, R. (2014). THE COMPETITIVE EFFECTS OF CHINA ON THE SOUTH AFRICAN MANUFACTURING SECTOR. *World Bank Group* (pp. 2-12). Cape Town: University of Cape Town.

Erdfelder, E., Faul, F., & Buchner, A. (1996). GPOWER: A general power analysis program. *Behavior research methids, instruments, & computers, 28*(1), 1-11.

Fahmideh, M., & Beydoun, G. (2019). Big data analytics architecture design - An application in manufacturing systems. *Computers & Industrial Engineering*, 948-963.

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical powe analyses using G*Power 3.1: Tests for correlation and regression analysis. *Behavior research methods, 41*(4), 1149-1160.

Fettes, I. (2015, August 4). *All about Technology*. Retrieved from Timaru Technology Education Centre: https://hail.to/ttec/publication/XLmaWCn/article/ZolHOpk

Gambardella, A., & McGahan, A. M. (2010). Business-Model Innovation: General Purpose Technologies and their Implications for Industry Structure. *Long Range Planning*, pp. 262-271.

Ghasemgahaei, M., Hassanein, K., & Turel, O. (2017). Increasing firm agility through the use of data analytics: The role of fit. *Journal of Decision Support Systems*, 95-105.

Glen, S. (2016, May 05). *Population Proportion*. Retrieved November 05, 2019, from Statistics How To: https://www.statisticshowto.datasciencecentral.com/population-proportion/

Golafshani, N. (2003, December 04). The Qualitative Report. *Understanding Reliability and validity in Qualitative Research, 8*(4), pp. 597-607.

Grande, T. (2016, October 31). *Calculating the Sample Size with a Finite Population in Excel*. Retrieved November 05, 2019, from YouTube: https://www.youtube.com/watch?v=gLD4tENS82c&t=62s

Gupta, Y., & Somers, T. (1996). Business strategt, manufacturing flexibility, and organisational performance relationship: a path analysis approach. *Production and Operation Management, 5*(3), 204-233.

Hair, J. F., Anderson, R. E., Babin, B. J., & Black, W. C. (2010). *Multivariate data analysis:A global perspective* (Vol. 7). Upper Saddle River,New Jersey: Pearson.

Hamel, G. (n.d.). *The Relationship Between the Business Model and Strategy*. Retrieved January 17, 2019, from Small Business: https://smallbusiness.chron.com/relationship-between-business-model-strategy-25963.html

Hart, C. (2018). *Doing a Literature Review : Releasing the research imagination.* London: SAGE.

Hashem, I. A., Chang, V., Anuar, N. B., Adewole, K., Yaqoob, I., Gani, A., . . . Chiroma, H. (2016). The role of big data in smart city. *International Journal of Information Management*, 1-15.

Hitt, M. A., Ireland, R. D., & Lee, H.-u. (2000). Technological learning, knowledge management, firm growth and performance: an introductory essay. *Journal of Engineering and Technology Management*, 231-246.

Invensis. (2018, February 26). *The Concept of Business Value Explained*. Retrieved January 17, 2019, from Invensis: https://www.invensislearning.com/resources/pmp/the-concept-of-business-value-explained

IQOMS. (2017, August 29). *10 Ways Real Time Data Is Revolutionizing Manufacturing*. Retrieved January 12, 2019, from erpblog: https://erpblog.iqms.com/10-ways-data-revolutionizing-manufacturing/

Jang, R. (1980). General purpose of research designs. *US National Library of Medicine National Institutions of Health*, 398-403.

Jenkins, R., & Edwards, L. (2015). Is China 'Crowding Out' South African Exports of Manurfacturers? *The European Journal of Development Research*, 903-920.

Jepson, N. (2012, March). South African Institute of International Affairs. *A 21st Century Scramble: South Africa, China and the Rare Earth Metals Industry*, pp. 1-28.

Jifa, G., & Lingling, Z. (2014). Data, DIKW, Big data and Data Science. *Procedia Compter Science*, 814-821.

Joffe, A., Kaplan, D., Kaplinsky, R., & Lewis, D. (1995). *Improving Manufacturing Performance in South Africa.* Cape Town: UCT Press.

Johnson, B. (2001). Towards a New Classification of Nonexperimental Quantitative Research. *Educational Research, 30*(2), 3-13.

Jonsson, P. (2000). An empirical taxonomy of advanced manufacturing technology. *International Journal of Operations & Production Management*, 1446-1474.

Kaplinsky, R. (2008). What Does the Rise of China Do for Industrialisation in Sub-Saharan Africa? *Review of African Economy*, pp. 7-22.

Keman, H. (2014). Comparative research methods. In D. Caramani, *Comparative Politics 3* (pp. 47-59). New York: Oxford University Press.

Kreuser, C. F., & Newman, C. (2018). TOTAL FACTOR PRODUCTIVITY IN SOUTH AFRICAN MANUFACTURING FIRMS. *South African Journal of Economics*, 1-39.

Kumar, G. (2017, August 19). *How to determine the Sample Size*. Retrieved from YouTube: https://www.youtube.com/watch?v=51NS0cGjBIk&t=165s

Kwak, S. G., & Kim, J. H. (2017). Cental limit theorem: the cornerstone of mordern statistics. *Korean journal of anesthesiology*, 144.

Kwak, S. G., & Kim, J. H. (n.d.). Cental limit theorem: the cornerstone of mordern statistics.

Labrinidis, A., & Jagadish, H. V. (2012). Challenges and Opportunities with Big Data. *The 38th International Conference on Very Large Data Bases* (pp. 2032-2033). Istanbul: VLDB Endowment.

Lahiri, S., Perez-Nordtvedt, L., & Renn, R. W. (2008). Will the new competitive landscape cause your firm's decline? It depends on your mindset. *Business Horizon, 4*, pp. 311-320.

LaValle, S., Lesser, E., Shockley, R., Hopkins, M., & Kruschewitz, N. (2010, December 21). Big Data, Analytics and Path From Insights to Value. *MIT Sloan Management Review*, pp. 21-31.

Lee, J., Lapira, E., Bagheri, B., & Kao, H.-a. (2013). Recent advances and trends in predictive manufacturing systems in big data envrionment. *Manufacturing Letters*, 38-41.

Lombardo, C. (n.d.). *Big Issues: 23 Advantages and Disadvantages of Qualitative Research*. Retrieved from Vittana: https://vittana.org/23-advantages-and-disadvantages-of-qualitative-research

Malaka, I., & Brown, I. (2015). Challenges to organistaional adoption of big data analytics: A case in the South African Telecommunications industry. *Annual Research Conference on South African Institute of Computer Scientists and Information Technology* (pp. 1-9). SACSIT.

Marshall, C. (2016, January 15). *Face-to-Face Interviews - Advantages and Disadvantages*. Retrieved January 31, 2019, from LinkedIn: https://www.linkedin.com/pulse/face-to-face-interviews-advantages-disadvantages-charlie-marshall/

Matthias, O., Fouweather, I., Gregory, I., & Vernon, A. (2017). Making sense of Big Data - can it transform operations management? *International Journal of Operations & Productio Management*, 37-55.

McAfee, A. (2010, January 07). *The Future of Decision Making: Less Intuition, More Evidence.* Retrieved January 30, 2019, from Harvard Business Review: https://hbr.org/2010/01/the-future-of-decision-making

McCurry, L., & Mclvor, R. (2002). Agile Manufacturing: 21st Century Strategy For Manufacturing On The Periphery? *Irish Journal of Management*, 75-93.

McHugh, M. L. (2013). *The Chi-square test of independence.* San Diego: Biochemia Medica.

McHugh, M., & Hudson-Bar, D. (2003). Descriptive statistics, part II: Most commonly used descriptive statistsics. *Journal for Specialsits in Pediatric Nursing, 8*(3), 111-116.

McLeod, S. (2013). *Research Methods: Validity*. Retrieved February 06, 2019, from SimplePsycology: https://www.simplypsychology.org/validity.html

Mithas, S., Lee, M. R., Earley, S., Murugesan, S., & Djavanshir, R. (2013, November/December). Leveraging big data and business analytics [Guest editors' introduction]. *IT professional*, pp. 18-20.

Moodley, S. (2002). *Competing in the digital economy? The dynamicsand impacts of B2B E-commerce on the South African manufacturing sector.* Helsinki: UNU World Institute for Development Economics Research.

Morris, M., & Einhorn, G. (2008, December). Globalisation, welfare and competitiveness: the impacts of Chinese imports on the South African clothing and textile industry. *Competition & Change*, pp. 355-376.

Motau, M., & Kalema, B. M. (2016). Big data analytics readiness: a South African public sector perspective. *Internation Conference on Emerging Technologies and Innovative Business Practices for the Transformation of Societies* (pp. 265-271). IEEE.

Mukhopadhyay, T., Kekre, S., & Kalathur, S. (1995). Business Value of Information Technology: A Study of Electronic Data Interchange. *Management Information Systems*, 137-140.

Niaki, M. K., & Nonino, F. (2017). Impact of additive manufacturing on business competitiveness: a multiple case study. *Journal of Manufacturing and Technology Management*, 56-74.

Noble, H., & Smith, J. (2015, February 04). Issues of validity and reliability in qualitative research. *Evidence-Based Nursing*, pp. 34-35.

Olson, A. (2017, October 02). *The importance of good middle management in manufacturing growth*. Retrieved November 04, 2019, from Global Manufacturing: https://www.manufacturingglobal.com/leadership/importance-good-middle-management-manufacturing-growth

Oxford Dictonary. (n.d.). *Value*. Retrieved January 17, 2019, from Oxford Dictionaries: https://en.oxforddictionaries.com/definition/value

Parasuraman, A., & Grewal, D. (2000). The Impact of Technology on the Quality-Value-Loyalty Chain: A Research Agenda. *Journal of the Academy of Marketing Sciences*, 168-174.

Park, C.-W., Kwon, K.-S., Kim, W.-B., Min, B., Park, S.-J., Sang, I.-H., . . . Seok, J. (2009). Energy consumption reduction technology in manufacturing - A selective review of policies, standardsand research. *International journal of precision engineering*, 151-173.

Pedersen, P. O., & McCormick, D. (1999). African business systems in a globalising world. *Jornal of mordern African Studies*, 109-135.

Plug Things In. (2012, April 30). *Internet Speed*. Retrieved January 17, 2019, from Plug Things In: http://www.plugthingsin.com/internet/speed/latency/

Plug Things In. (2012, April 30). *Internet Speed*. Retrieved from Plug Things In: http://www.plugthingsin.com/internet/speed/latency/

Priest, D. M., & John, E. P. (2006). Alternative Revenue Sources. In *Privatization and Public Universities* (pp. 88-93). Bloomington: Indiana University Press.

Rahman, S. (2017). The advantages and Disadvantages of Using Qualitative and Quantitative Approaches and Methods in Language "Testing and Assessment" Research: Literature Review. *Journal of Education and Learning*, 102-112.

Ramey, K. (2013, December 12). *Home: Techuaction*. Retrieved from Use of Technology Web Site: https://www.useoftechnology.com/what-is-technology/

Reeves, R., Coulter, A., Jenkinson, C., Cartwright, J., Bruster, S., & Richards, N. (2002). *Development and pilot testing of questionnaires for use in the acute NHS trust inpatient survey programme.* Europe: Picker Institute. Retrieved from https://www.researchgate.net/profile/Angela_Coulter/publication/253253738_Development_and_pilot_testing_of_questionnaires_for_use_in_the_acute_NHS_trust_inpatient_survey_programme/links/00b7d5295949bec9ab000000.pdf

Rekolainen, S., Kamari, J., Hiltunen, M., & Saloranta, T. M. (2003). A conceptual framework for identifying the need and role of models in the implementation of the Water Framework Directive. *International Journal of River Basin Management*, 347-352.

Reuters. (2018, December 11). *Creamer media Engineering News.* Retrieved January 15, 2019, from Engineering news: http://www.engineeringnews.co.za/article/south-africas-manufacturing-output-jumps-boosting-rand-2018-12-11

Reuters. (2018, December 11). *Creamer media Engineering News.* Retrieved from Engineering news: http://www.engineeringnews.co.za/article/south-africas-manufacturing-output-jumps-boosting-rand-2018-12-11

Ridge, M., Johnston, K. A., & O'Donovan, B. (2015). The use of big data analytics in the retail industries South Africa. *African Journal of Business Management*, 688-703.

Riggins, F. J., & Wamba, F. (2015). Research Direcrion on the Adoption, Usage and Impact of the Internet of Things through the Use of Big Data Analytics. *48th Hawaii International Conference on Systems Sciences* (pp. 1531-1540). Hawaii: 48th Hawaii International Conference on Systems Sciences.

Ritchie, J., & Lewis, J. (2003). *Qualitative Research Practice : A guide for Social Science Students and Researchers.* London: SAGE.

Rosenblatt, M. (1956, November 10). A central limit theorem and a strong mixing condition. *Proceedings of the National Academy of Sciences of the United States of Africa*, pp. 43-47.

Rüßmann, M., Lorenz, M., Gerbert, P., Waldner, M., Justus, J., Engel, P., & Harnisch, M. (2015, April 09). *Industry 4.0: The future of productivity and growth in manufacturing industries.* Boston Group Consulting.

Sahay, B., & Ranjan, J. (2008). Real time business intelligence in supply chain analytics. *Information Management & Computer Security*, 28-48.

Santos, J. R. (1999). Cronbach's alpha: A tool for assessing the reliablity of scales. *Journal of Extension, 37*(2), 1-5.

Sharma, G. (2017). Pros and cons of different sampling techniques. *International Journal of Applied Research*, 749-752.

Sharma, R., Reynolds, P., Scheepers, R., Seddon, P. B., & Shanks, G. (2010). *Business Analytics and Competitive Advantage: A Review and a Research Agenda.*

Taherdoost, H. (2016). Sampling methods in Research Methodology: How to choose a Sampling Technique for Research. *International Journal of Academic Research Management*, 18-27.

Tao, F., Qi, Q., Liu, A., & Kusiak, A. (2018). Data-driven smart manufacturing. *Journal of Manufacturing systems*, 1-9.

Tracey, M., Vonderembse, M., & Lim, J.-S. (1998). Manufacturing technology and strategy formulation: Keys to enhancing competitiveness and improving performance. *Journal of Operations Management*, 411-428.

Tregenna, F. (2008). The contributions of manufacturing and services to employment creation and growth in South Africa. *South african Jornal of Economics*, 175-204.

Trianni, A., Cagno, E., & Farne, S. (2014). An empirical investigation of barriers, drivers and practices for energy efficiency in primary metals manufacturing SMEs. *Energy Procedia* (pp. 1252-1255). Milan: The 6th International Conference on Applied Energy.

Trochim, W. (2002, July 21). *What is the Research Methods Knowledge Base?* Retrieved from Anatomy facts: http://www.anatomyfacts.com/research/researchmethodsknowledgebase.pdf

Tsosie, R. (2009). Cliamte Change, Substainability and Globalization: Charting the future of indegienous environemental self-determination. *Environement & Energy Law & Policy Journal*, 189-254.

Tummala , Y., Hemantha, K., & Kalluri, H. k. (2018). A review on Data Mining & Big Data Analytics. *Internation Journal of Engineering & Technology*, 92-94.

United States Department of Labor. (2019, January 11). *Industries at a Glance*. Retrieved from Bureau of Labor Statistics: https://www.bls.gov/iag/tgs/iag31-33.htm

USC Libraries. (2019, November 04). *Research Guides*. Retrieved November 04, 2019, from University of Southern California: https://libguides.usc.edu/writingguide/quantitative

Vaus, D. D. (2008). Comparative and cross-national designs. In P. Alasuutari, L. Bickman, & J. Brannen, *The SAGE handbook of social research methods* (pp. 249-264). London: SAGE Publications.

Vriens, M., & Verhulst, R. (2008, Winter). Unleashing Hidden Insights. *Business insights need to be extracted and prepared to have impact*, pp. 12-13.

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J.-f., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Jornal of Business Research*, 356-365.

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

Warner, D. (2014, August 1). *Creativity and Innovation:What is Business Insight?* Retrieved January 18, 2019, from Ready to Manage: http://blog.readytomanage.com/what-is-business-insight/

Waurznak, P. (2015, October 1). *Why Manufacturng Needs Real-Time Data Collection*. Retrieved January 12, 2019, from Advanced Manufacturing: https://advancedmanufacturing.org/manufacturing-needs-real-time-data-collection/

Yilmaz, K. (2013). Comparison of Quantitative and Qualitative Research Traditions; epistemological, theoretical, and methodological differences. *European Journal of Education, 48*(2), 312-324.

Zhang, Q., Vonderembse, M., & Lim, J.-S. (2003). Manufacturing flexibility : defining and analyzing relationships among competence, capablity and customer satisfaction. *Journal of Operations Management*, 173-191.

Zibran, M. F. (2007). CHI-Squared Test of Independence. *Department of Computer Sciences*, 1-7.

APPENDIX I CODE BOOK

Variables	
Q3	Have you worked in or are you working in the metal manufacturing sector? (Final product is produced using metal e.g metal sheets, coils, metal press shop, metal fabrication)
Q2	Do you see any business value from data analytics?
Q4	My company investments into data analytical tools is adequate
Q5	Is there any business value gathered from data analytics?
Q6	Business insights generated from data analytics is gathered efficiently when well analysed?
Q7	A high level of education contributes to the quality of information generated from data analysis?
Q10	Data needs to be used to make business decisions
Q8	What level of education do you think is suitable to analyse data?
Q9	Past data analysis experience is required to analyse data in order to provide valid information.
Q11	Having business insights can assist with making informed decisions?
Q13	Do you have access to relevant data in your company today?
Q14	Making decisions without business insights can have a negative impact on the level of success.
Q27	How would you rate the success of a business strategy you implemented without having business insights?
Q16	Given an opportunity to do things differently would you have ensured that you had enough business insight before making a decision?
Q17	Do you think there is a risk of becoming uncompetitive when a business does not leverage data?
Q18	Are your business processes driven with insights from predictive customer analytics?
Q19	Data is required to form a business model.
Q20	Are your organisation's sales efforts fuelled by data analytics insights?
Q21	The more data, the easier it is to formulate a business model.
Q22	Are your organisation's business leaders able to use data analytics to improve or transform the business?
Q23	Real-time data provides more current information.
Q24	The more current the data is, the better the business model.