Gordon Institute of Business Science
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Big data analytics and firm performance: The role of knowledge sharing and organisational factors

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Abstract

Despite most organisations adopting big data analytics capabilities as a strategic tool to navigating the highly competitive market environment and remaining competitive through tailor-made customer solutions, operational efficiencies and effective decision-making, only a limited number of organisations have benefited from big data-analytics investment and deployment. Thus, with the recorded success of companies like Amazon, Wal-Mart, Netflix and others, it became imperative for businesses to deconvolute the requirements for successful big data analytics deployment and value creation. Due the accelerated growth in data volume, variety, velocity and veracity much attention and research in recent times has focused on technical requirements for big data analytics capabilities value creation. However, even with the vast research data readily available on technical skills, technological capabilities and applications most organisations continue to grabble with extracting value from data at their disposal. This implies that there are other dimensions that contribute to big data analytics success in firms. Until these dimensions are fully understood individually or collectively by firms, value creation will continue to remain a challenge in this context.

The research described herein therefore shifted focus from technical to non-technical capabilities and traits that an organisation should acquire to succeed with big data analytics capabilities. Consequently, the research used quantitative multivariate analysis to study the relationship between big data analytics application, knowledge or insights sharing and firm performance moderated by non-technical organisational factors such as organisational culture to decision making and entrepreneurial orientation.

The research thus found a positive correlation between knowledge sharing and business performance but organisational culture and entrepreneurial orientation even though showing primarily a positive effect on firm performance showed insignificant moderating effect on knowledge sharing. This therefore suggests that if organisations want to impact performance they must first align their knowledge sharing variables and moderating factors relevantly to be effective in big data analytics value creation.

Keywords

Big data Analytics, organisational culture, entrepreneurial orientation, knowledge sharing, firm performance

Declaration

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

Table of Contents

List of figures

List of tables

Abbreviations

BDA - Big data analytics

BDAC – Big data analytics capability

CAO - Chief analytics officer

CFO - Chief financial office

CRM - Customer relationship management

EO - Entrepreneurial orientation

DCT - The dynamic capability theory

ERP - Enterprise resource planning

Fper - Firm performance

fsQCA - Fuzzy-set Qualitative Comparative Analysis

GIBS - Gordon Institute of Business Science

KS - Knowledge sharing

MMR - Moderated multiple regression

OC - Organisational culture

PCA - Principal Component Analysis

ROI – Return on investment

SPSS - Statistical package for the social sciences

RQ – Research question

SMEs – Small and medium sizes enterprises

Chapter 1

Introduction

"Data that sit unused are no different from data that were never collected in the first place." – Doug Fisher

1.1 Research problem

The escalating competition within industries coupled with dynamic regulations and customer requirements has progressively contributed to the difficulty organisation experience lately (Tang & Chen, 2020). As a result of these pressures, businesses continue to look for alternative sources of growth through innovative solutions (Ogrean, 2018). Thus, the business question that remain is how can firms best be fit to navigate the complex, technologically changing and highly competitive environment (Weng, 2020). One approach followed by many firms is accumulating learnings from emerging industry trends and adopting them to re-energise their businesses (Weng, 2020). Lately, big data has received much attention and is characterised as a potential space for value creation and a new edge for research (Elia, Polimeno, Solazzo & Passiante, 2020). Thus, with the trend of big data usage in industry, big data is progressively viewed as a key strategic resource of the 21st century by many firms, perhaps with a similar importance attached to it as with gold and oil (Alharthi, Krotov & Bowman, 2020).

The ability for organisations to analyse large volume of various data has become critically important in gaining business insight (Gunasekaran, Papadopoulos, Dubey, Wamba, Childe, Hazen & Akter, 2017). Therefore, accessibility to this large volume of data has led to the big data revolution that has seen improved firm decision-making performance and accompanying competitive advantage (Gunasekaran, Papadopoulos, Dubey, Wamba, Childe, Hazen & Akter, 2017). Provided the data is used effectively, it has the potential to lead to more rapid and informed business decision-making, efficient operations, business being more attuned to customer's preferences and ultimately high profits (Loebbecke & Picot, 2015).

Studies have shown through the effective exploitation of big data application that some retailers can accomplish growths of up to 20% in their return on investment (Sheng, Amankwah-Amoah & Wang, 2017). This is because these retailers invested in resources such as technology and IT skilled workforce that plays a critical role in developing effective knowledge that contributes to firm performance.

Examples of these retailers include Wal-Mart which increased profits and customer satisfaction by using big data analytics to effectively manage inventories during adverse weather conditions caused by the hurricane in the US (Akhtar, Frynas, Mellahi & Ullah, 2019). Likewise, the multidisciplinary team at MegaTelCo's could retain key customers and enhance customer satisfaction through customised incentives offerings informed by big data applications (Akhtar, Frynas, Mellahi & Ullah, 2019). In the healthcare fraternity, Aridhia a leading organisation in clinical informatics has been able to offer personalised treatment through big data analytics (Roche, 2017).

Tudor (2020), state that over 90% of the world 1.8 zettabytes data was created only in the last 2 years and that businesses spend well over $180 billion per year on big data analysis. It therefore makes sense that progressive businesses and managers embrace and capitalise the vast opportunities embedded in big data for competitive advantage. This capital expenditure on big data analysis manifest in organisations like amazon through dynamic pricing where prices can change up to 2.5 million times per day and push product recommendation to customers in response to search data. This strategy has been reported to contribute 35% of the company's annual sales. With regards to Netflix the data collected through monitoring of customer's viewing habits and content rating assist the company design content grounded on data insights produced from customers (Zeng, Glaister & Keith, 2018). This strategy enables Netflix to retain user rate of up to 93% which when compared to competitors is unprecedented. Other examples of companies that effectively use big data analytics for competitive advantage include the Marriott Hotels, Uber Eats, McDonald's, Starbucks, Accuweather, Coca-Cola, HERE Technologies (for live maps for autonomous cars) and others (Tudor, 2020). Apart from healthcare, big data analytics has been applied successfully in other social settings that include law enforcement, town planning and optimisation, and sports performance (Tomar, Guicheney, Kyarisiima, & Zimani, 2016; Conde, 2020; Dmonte & Dmello, 2017). In summary, all the above highlighted examples demonstrate that big data analytics is improved only if varied skills are used to analyse the data and knowledge gained from it is acted upon.

However, Elia, Polimeno, Solazzo and Passiante (2020) maintains that while big data and big data analytics presents a great potential for improving firm performance, there remain various challenges that firms still need to overcome to realise the benefits of big data. This could be due the inability of firms to effectively improve their data-driven decision-making as only 27% of firms have reported to have obtain success in big data analytics (Gunasekaran, Papadopoulos, Dubey, Wamba, Childe, Hazen & Akter, 2017). Janssen, van der Voort and Wahyudi (2016) argues that this poor outcome is as a result of firms often neglecting to promote the necessary required conditions such as collaboration to produce insights from data analytics. Instead, firms focus mainly on data characteristics such as data volume to produce insights but fail to share these insights effectively with decision makers at each organisational level.

Therefore, big data does not guarantee automatic competitive advantage for firms since its successful deployment relies on a number of factors such as accessibility, quality, obtainability, heterogeneity, managers data analysis skills, attitude and acumen towards data (Troisi, Maione, Grimaldi & Loia, 2020). Accordingly, big data should go beyond just adoption by firms but should include total data perspective based on mind-set to extract information and meaning for competitive advantage. Therefore, adequate infrastructure for data extraction, processing and integration coupled with the data-oriented mind-set is required in organisations in order to create unified culture and set of values that encourage data gathering and organisation. Furthermore, apart from revising the business to foster the collection and use data, the internalisation of data-oriented organisational culture should be disseminated at each level of the organisation to enable managers to distil innovative features from data. This assertion therefore shows that organisational barriers still exist that require addressing if organisations want to embrace big data (Alharthi, Krotov & Bowman, 2020). Bean (2017) attributed this to the inability for firms to foster data-driven decision-making culture. Thus, organisational culture barriers as it relates to big data are still regarded as a challenging problem to overcome.

A recent study of Pakistan large firms has shown that organisational culture (OC) is significantly and positively correlated to organisational performance and the effect is mediated by innovation in (Khan, Wafa, Hassan & Kashif, 2020). A similar outcome was reported by Singgih, Suwignjo and Baihaqi (2016) in their study of 152 organisations. Thus, for firms to fully benefit from big data opportunities they need to first change their organisational culture to be supportive of data-driven decision-making and data-driven insights sharing. Therefore, the acceleration and adoption of big data within an organisation can be facilitated through the development and communication of business goals and description of how big data fits in with the organisation strategy. Moreover, by employing the generated data-driven insights to make strategy aligned decisions. Hence, organisations should focus more on primarily managing the architects that affect organisational culture instead of managing culture itself.

In addition to organisational culture, entrepreneurial orientation (EO) of an organisation has been reported to influence firm performance through the EO characteristics of responsiveness, consciousness to newness and the degree of boldness (Khan, Arshad & Kashif, 2020; Covin & Wales, 2019). Thus, entrepreneurial orientation is best defined as the organisation's ability to achieve new innovation through learning and proactiveness (Gupta & Gupta, 2015). In India, V. Gupta and A. Gupta, (2015) have studied entrepreneurial orientation and firm performance relationship in SMEs and described a entrepreneurial orientation to be significantly and positively correlation to organisational performance. Aliyu, Rogo and Mahmonod (2015) also reported a similar outcome with knowledge management dimension also added. The premise for entrepreneurial orientation is that it is intertwined with knowledge sharing and necessary for firms to survive the dynamic global business environment of today (Linton & Kask, 2017).

Knowledge remains an important resource to organisations and just like other resources it needs to be properly managed (Islam, Jasimuddin & Hasan, 2018). Thus, the essential part of managing knowledge is knowledge sharing (KS) as it empowers firms to generate and sustain a competitive advantage (Sawan & Jakarta, 2020). Accordingly, knowledge sharing is defined as the activity of distributing knowledge through the organisation thus enabling the organisation to have access to information needed for decision making and innovation (Ghasemaghaei, 2019). The knowledge obtained from analysing data integrated from both internal and external sources is generated using data analytics tools which also allow the firm to share the knowledge (Côrte-Real, Oliveira & Ruivo, 2017). Ferraris, Mazzoleni, Devalle and Couturier (2019) have found that knowledge dissemination plays a critical role in strengthening the effect of BDA capabilities, improving the quality of organisations' decisions and value creation. While Ghasemaghaei (2019) reported that knowledge sharing in the framework of big data analytics is moderated by data analytic competency.

The prospects of exploring the combined influence of the three dimensions discussed above on data-driven decision-making and organisational performance ignites academic and business curiosity while affording the opportunity to contribute to the field. This in turn presents a unique opportunity for research in big data analytics focusing on analysing the role of knowledge sharing within the elements of organisational culture, entrepreneurial orientation and firm performance.

1.2 Research objective

Thus, expanding on the research by Ghasemaghaei (2019) which studied data analytics competency as moderator of knowledge sharing and organisational performance, the current research intents to address the identified gaps in the literature by exploring the moderating effect of entrepreneurial orientation and organisational culture on knowledge sharing and company performance as results of big data analytics.

Following on from the preceding section, big data analytics in firms decision-making has gained significant attention and has been regarded as an enabler of firms competitiveness, evidence-based decision-making and performance (Maroufkhani, Wagner, Ismail, Baroto & Nourani, 2019). Furthermore, LaValle, Lesser, Shockley, Hopkins and Kruschwitz, (2011) argues that high performing firms are two times as much prone to incorporate data analytics in their business process relative to those that do not. Therefore, the necessary conditions needed by firms to harness these beneficial outcomes from investment in big data analytic deserves close investigation. From the literature reviewed it became evident that organisational culture, entrepreneurial orientation and knowledge sharing are some of the organisational dimensions that impact firm performance and competitiveness (Khan, Wafa, Hassan & Kashif, 2020; Aliyu, Rogo and Mahmonod, 2015; Sawan & Jakarta, 2020).

Organisational culture has been reported to assist in leading people's behaviours in organisational settings and helps in controlling how an organisation integrates the internal processes to enable it to respond effectively to the external environment (Khan, Usoro & Crowe, 2020). Entrepreneurial orientation consists of three elements which include proactiveness, risk propensity and innovation (Khan, Wafa, Hassan & Kashif, 2020). Furthermore, learning orientation is also closely related to entrepreneurial orientation (Wang, 1991). Finally, knowledge sharing is a mechanism of diffusing knowledge to others in the organisation in an apt presentation, assisting the organisation by whirling individual knowledge into business knowledge (Abdelwhab Ali, Panneer selvam, Paris & Gunasekaran, 2018). Thus, the literature summarised herein, clearly demonstrate that organisational dimensions such as entrepreneurial orientation, organisational culture and knowledge sharing independently or in pairs impact firm performance positively.

Therefore, the current study intents to add to the existing literature by extending the empirical evidence of the relationship between big data analytics, knowledge sharing and firm performance but also exploring the importance of organisational factors on knowledge sharing such entrepreneurial orientation and organisation culture. The findings will further provide useful insights for organisations to capitalise on big data analytics for value creation and organisational performance. The general attitudes and behaviours of knowledge sharers and receivers can become evident from the study.

Considering the afore-mentioned arguments this research intends to study the following:

- The correlation between knowledge sharing and organisational performance.
- The link between knowledge sharing and organisational performance and the effects of entrepreneurial orientation as a mederator.
- The correlation between knowledge sharing and organisational performance and the effects of organisational culture as a moderator.
- The relationship between Big data analytic application and knowledge sharing within the firms

1.3 Relevance and academic motivation for the research

Asrar-ul-haq & Anwar (2016) in their review of 64 articles composed of both qualitative and quantitative studies on knowledge sharing highlighted and summarised factors that facilitate or impede knowledge sharing in organisations. The most frequent limitation identified in the study was cooperation bias as most participants generally over-estimated participation in knowledge sharing. Furthermore, the authors identified the relationship between knowledge sharing and transfer as an area for further exploration. In a subsequent review, Zheng (2017) found that knowledge sharing is largely affected by multi-level factors that include: Organisational, team and individual level factors. The authors further add that some factors will promote knowledge sharing while some will impede knowledge sharing.

A lack of consensus among academics to which constructs measures knowledge sharing and whether knowledge sharing is multifaceted or unidimensional still persists (Asrar-ul-haq & Anwar, 2016). However, according to Vij and Farooq (2014), organisational culture and management support are a significant determinates of knowledge sharing while Li, Liu, Wang, Li and Guo (2009) maintain that entrepreneurial orientation positively moderates knowledge application. These findings are further supplemented with the outcome of Sentanu and Praharjo (2019) study that suggests that entrepreneurial orientation and knowledge sharing have an effect on firm performance.

In various market environments, the importance of entrepreneurial orientation (EO) is evident from the benefits organisations gain in sustained competitiveness and firm performance (Gupta & Gupta, 2015). This assertion is supported by numerous empirical research which confirms EO to be positively and significantly correlated to firm performance (Khan, Arshad & Kashif, 2020). However, other research has reported that entrepreneurial orientation is not significantly correlated to firm performance (Khan, Arshad & Kashif, 2020).

Furthermore, empirical research demonstrated firm culture to be positively correlated to firm performance (Khan, Usoro & Crowe, 2020). Even though there are numerous studies providing evidence supporting the positive relationship of organisational culture and firm performance (Khan, Usoro & Crowe, 2020), other studies reveal some inconstancies in the research findings (Khan, Usoro & Crowe, 2020).

In the recent study, Ghasemaghaei (2019) confirmed that knowledge sharing contributes very little to decision quality and consequently firm performance. This research outcome is largely in contradiction with published research that demonstrated knowledge sharing to be positively and significantly correlated to firm performance (Sawan & Jakarta, 2020).

Notwithstanding the contribution from several researchers on knowledge sharing and dissemination, there is still scope to further explore on the subject. Accordingly, Zheng (2017) suggests future research into exploring the antecedents and obstacles of knowledge dissemination in organisations through the lens of social media, organisational politics and communication. Additionally, Ghasemaghaei (2019) proposes future studies into other moderating factors for knowledge sharing apart from data analytics competency for decision making quality and firm performance. Grounded on the aforementioned literature review, it is therefore hypothesised that to contribute to the empirical research that attempts to resolve the inconsistencies in the literature stated, a focused study is required that investigates the collective relationship between organisational culture, entrepreneurial orientation, knowledge sharing and firm performance. It has been shown that big data and data-driven decision-making affect firm productivity, innovation and new consumers attainment positively (Bean, 2017). Therefore, the proposed study will further cement the empirical research for the necessary conditions for firm performance on the grounds of knowledge sharing and, align it to big data analytics.

1.4 Importance of the research

Big data continues to revolutionise the world of business (Lee, 2017). Thus, at the core big data is more about corporate transformation and less about technology (Lee, 2017). Therefore, businesses harness value from big data by employing the unique and actionable insights gained on customers, products and processes. In turn, these insights are used to revamp the business by optimising strategic business initiatives and identify money making opportunities (Ogrean, 2018). However, Manyika, Chui Brown, Dobbs, Roxburgh and Hung Byers (2011) have argued in their business report that organisations frequently have deficiencies in understanding the value embedded in big data and how to unlock it. In addition, the report also emphasised that the lack of structured workflows and incentivisation in firms limits the application of big data analytics for better decisions making and informed actions. By understanding factors that facilitates or impede data-driven insights sharing, organisations can develop dedicated programs to address the challenges such as motivations, incentives and management support to augment value creation through big data analytics (Farooq, 2018). This research therefore presents an opportunity that aims to generate insights that could assist business further improve value creation from big data analytics and generate business climate that support it.

The subsequent chapter will discuss recent literature available on data-driven decision-making, data-driven insights, entrepreneurial orientation, organisational culture, knowledge sharing, firm performance and their cooperative effect.

1.5 Thesis outline

The research study herein is quantitative in nature as it aims to explore the moderating effect of entrepreneurial orientation and organisational culture on knowledge sharing and firm performance within the big data analytic framework. Quantitative research focuses on hypothesis and theory testing with empirical data to determine if they are supported (Antwi & Hanza, 2015).

Firstly, literature review analysing the research constructs that include big data analytics, knowledge sharing, organisational culture, entrepreneurial orientation and data driven decision making was assembled with the objective of providing a universal understanding of the research topic and assist in constructing the study hypotheses. The constructs are initially discussed broadly and narrowed down to link with the study objectives. Secondly, the research instrument was developed based on literature data and conducted. The target respondents were individuals who were decision makers in their respective organisations and had to complete the survey regarding the mediating effect of knowledge sharing in firm performance moderated by dimensions such as entrepreneurial orientation and organisational culture linked to big data analytics. Thirdly, the survey responses were analysed through statistics and the independent and dependent variables links analysed through multiple regression.

The multiple regression outcomes were used to decide on whether the hypotheses constructed are rejected or accepted. Finally, the analysis results were discussed, and the business implication, recommendations, further research and research limitation offered. Firm performance, organisational performance, company performance and Financial and Market share performance are used interchangeably throughout the document.

Chapter 2

Theory and Literature Review

“Research means that you don’t know, but are willing to find out” - Charles F. Kettering

2.1 Introduction

Big data analytics (BDA) is characterised to be multifaceted method of analysing big data to discover information such as patterns, relationships, market trends and customer preferences which is used to assist firms to make informed decisions (Sagiroglu & Sinanc, 2013). Despite the varying impact of big data analytics on organisations, adoption and efficient use of big data analytics remain a challenge (Ghasemaghaei, 2021). There is simply no value in developing BDA capabilities without the data-orientated mindset that can visualise how to release value in BDA. Thus, it remains imperative to develop understanding of antecedents required to derive value from BDA. The literature reviewed herein focuses on providing the reader with a broad contextual background on data-driven decision-making and firm performance. The review also introduces pertinent theoretical concepts which the current research draws from for an advanced understanding of the study objectives and research question development.

Firstly, synthesis of recent literature on big data and adjacent concept will be provided. Secondly, predominant research on data-driven decision-making is discussed. Thirdly, in order to provide context, the interplay between improved decision making and knowledge sharing is deliberated. Fourthly, organisational factors as a prerequisite for improved data-driven decision-making quality is highlighted with the consequential organisational performance. Carillo (2017) made the assertion that instinctively interrogating big data without aligning it to strategy is analogous to seeking answers without understanding the questions.

Thus, considering the disorganised nature of big data, the complementary attributes of data expertise and organisational attributes are key in value creation in business (Carillo, 2017). The dominant way in which this value is derived is through incorporation of big data in the decision-making process of organisations which leverages the evolution in the information type that can be sourced from data.

2.2 Big of data

Big data is commonly defined as data sets consisting of large, varied and complex structures within it that makes it challenging to analyse and visualise for results (Ghasemaghaei, 2021). It often originate from internal systems such as CRM, ERP, servers' logs, audio, video, emails and sensor data as well as external sources such as social media platforms, market data and customer behavioural studies (Ghasemaghaei, 2021). Thus, close interrogation of big data to deconvolute hidden patterns and resultant correlations is commonly referred to as big data analytics. The information sourced from big data analytics helps firms to gain and maintain competitive advantage. It enables firms to track the impact of explorative venture and guide thinking in strategy development and decision making (Ghasemaghaei, Ebrahimi & Hassanein, 2018).

The noted characteristics of big data include velocity (making real-time data analysis near possible, is the speed in which data is created), volume (increasing amount of data), variety (sources of data and types of data) and veracity (speaks to the accuracy of data) (Ghasemaghaei, Ebrahimi & Hassanein, 2018; Pigni & Picco, 2016). Thus, big data makes for provision of more widespread and real-time data which provides business with advantageous insights into business environment and customers. Thus, it worth restating that the current study aims to study the impact of big data analytics on firm performance mediated through knowledge sharing and moderated through organisational factors.

2.3 Dynamic Capability Theory

The dynamic capability theory (DCT) is derived from the resource-based view of the firm theory which states that firms compete on the basis of uniquely defined resources that are valuable and difficult to duplicate (Teece & Pisano, 1997). These resources can be tangible and/or intangible and/or personnel-based with the ideal assembly of them being key to firms competitive advantage (Grant, 1991). Furthermore, as stipulated by the dynamic capability theory, it is the capacity to renew these resources to align with the changing business environment and objectives that offers competitive advantage. What this means is the ability for firms to proactively or in response to changing business environment adjust core operational, technical, knowledge and strategic capabilities (Tavallaei, Shokohyar, Moosavi & Sarfi, 2015).

Therefore, for firms that failing to adequately adjust to the changing market factors only serves to show the firms inability to adsorb or integrate capabilities, consequently affecting firms performance and competitive edge negatively (Barreto, 2010). Therefore, Teece and Pisano (1997) describes five elements that constitute the dynamic capability framework which include sensing, coordination, learning, integration and reconfiguring. These elements are briefly defined in Table 2.1 below.

Table 2.1: Five elements that constitute the dynamic capability framework

Elements	Brief description
Sensing	The ability to perform business environment assessment for opportunities and threats (Teece & Pisano, 1997).
Coordination	The ability to manage and harness the synchronisation of business inputs such as stakeholders, resources, objectives and tasks in relation to the business requirement (Teece & Pisano, 1997). This further applies to identifying synergies both external and internal to the organisation for beneficial collaboration.
Learning	The ability to source, assimilate, interpret and exploit knowledge to improve decision-making (Teece & Pisano, 1997).
Integrating	The process of driving firm efficiency through effectively assembling the various resources of the organisation for efficient problem resolution (Teece & Pisano, 1997).
Reconfiguring	The ability to better align firms' resources with the external business environment to execute against a strategic decision that an organisation has made (Teece & Pisano, 1997).

Dynamic capability offers a comparatively broad overarching standpoint to implementation and studies the alignment between strategic decisions of a firm and its business environment (Barreto, 2010). Thus, DCT is considered to be a suitable lens to understand the effect of data analytics application and knowledge sharing in firms. For the current study DCT is applied as a sole phrase describing a business's capacity to respond through actions to data-driven decision-making and the regulating mechanism that directs the transformation of data analytics application to firm performance.

The organisational strengths that drive high efficiencies, effectiveness and competitive use of the firm tangible and intangible assets are coined organisational capabilities (Mikalef, Krogstie, Pappas & Pavlou, 2020). These can be further defined as routines that encompass purposefully erudite behaviours that are highly patterned and repetitive and instituted in part in implicit knowledge (Winter, 2003). In addition, dynamic capability denotes process of the organisation to coordinate, learn, reconfigure, release resource to respond to market change in pursuit of competitive advantage (Eisenhardt & Martin, 2000). This assertion is strongly aligned with Henderson and Ven Katraman (1999) that empathises that dynamic capability does not happen sporadically but instead it is rooted in the process of constant adaptation and transformation.

Thus, in the context of this research, dynamic capabilities theory offers a framework for analysis whether knowledge sharing, organisational culture and entrepreneurial orientation can be leveraged to increase firm performance. Therefore, considered the most fitting lens to deconvolute the impact of data analytics on company performance.

2.4 Big data analytics and data-driven insight

Within organisations, the combination of big data analytic tools and the level of human resources skills, knowledge and data-driven insights have direct implications on strategic decisions outcomes (Mikalef, Krogstie, Pappas & Pavlou, 2020). Even though appropriate skills to critically and analytically think about data is key for data scientists, such skills are equally important for all employees throughout the organisation, particularly for those that are decision makers (Prescott, 2014). Organisational learning is thus the firm's process of producing knowledge or insights through information attainment, information diffusion, shared understanding and organisational retention (Fink, Yogev & Even, 2017).

Therefore, dissemination or sharing of data-driven insights generated from big data analytics readily throughout the organisation assist managers at all levels for strategic decisions making based on data interrogation and interpretation (Akhtar, Frynas, Mellahi & Ullah, 2019). Thus, maximised value creation using big data analytics is achieved only if various skills are employed and knowledge generated from varied sources is actioned (Akhtar, Frynas, Mellahi & Ullah, 2019).

2.5 Knowledge domain

There is overwhelming evidence in the literature that discusses the complementary effect of big data analytics and business knowledge domain in producing insights that enable organisations in making data-driven decisions, consequently improving business performance (Chen & Zhang, 2014; Akhtar, Khan, Frynas & Rao-Nicholson, 2018; Sheng, Amankwah-Amoah & Wang, 2017; Dutta & Bose, 2015).

Table 2.2: Definition of human resource knowledge dimensions in relation to big data analytics

Knowledge domain	**Definition**
Technical knowledge	Knowledge of database management, data retrieval, processing, regression, programming and neuro network analyses.
Business knowledge	The informed decision-making process significantly routed within the organisation and alignment of strategic foresight with big data deployment and extracted insights application.
Relational knowledge	Effective collaboration skills between individuals, teams and departments with varying backgrounds and agendas.
Business analytics knowledge	Data scientist knowledge that pertains to scenario development, interactive data visualisation, simulation and modelling.

Thus, the knowledge domain in relation to big data can be categorised into technical knowledge, business knowledge, relational knowledge and finally business analytical knowledge (Mikalef, Krogstie, Pappas & Pavlou, 2020). Table 2.2 below provides a brief description of these stated human resource knowledge as they pertain to big data analytics (Mikalef, Krogstie, Pappas & Pavlou, 2020).

The consolidation of the above mentioned knowledge domains in an organisation is widely referred to as big data analytics capability (BDAC) and describes the competency to produce business knowledge through data management, technology and human resource capability to improve firm competitiveness (Akter, Wamba, Gunasekaran, Dubey & Childe, 2016). Consequently, contributing significantly to increasing business and firm performance (FPER) (Akter, Wamba, Gunasekaran, Dubey & Childe, 2016). Thus, to effectively capture value from big data analytics, analytics teams should be multi-skilled such that they work together in pooling, integrating and sharing their knowledge.

2.6 Data-driven insights

The collective utilisation of the knowledge domains described above affords organisations the tools to manage, analyse and timely action data insights (Akhtar, Frynas, Mellahi & Ullah, 2019). Utilising historic and current data through the knowledge domains enables organisations to solve business problems through the process of transitioning from not knowing to solution development. This is largely achieved through identifying patterns in the data that can be used to envisage opportunities and reduce uncertainty (Awan, Shamim, Khan, Zia, Shariq & Khan, 2021). Thus, this process of solving business problems by utilising available data is defined as data-driven insights (Ghasemaghaei & Calic, 2019). Ash, Jee and Wiley (2012) defined insights as “the re-orientation of one's thinking, including breaking of the unwarranted ‘fixation’ and forming of novel, task-related associations among the old nodes of concepts or cognitive skills”. Thus, insights needed for business problem solving can be gained from deconvoluting the relationship between the components of a problem within the context, models or scenarios (Ghasemaghaei & Calic, 2019). In business therefore collecting data from various sources can greatly enhance data-driven insight from data analytics and help managers improve strategic decision making processes (Janssen, van der Voort & Wahyudi, 2017; Sivarajah, Kamal, Irani & Weerakkody, 2017).

In their recent paper, Ghasemaghaei and Goran Calic (2019) describes three types of data-driven insights generated by firms namely, descriptive insights, predictive insights and prescriptive insights. These insights can be shared throughout the organisation and used in decision-making and firm innovation competency enhancement. Historic data is generally used to generate descriptive insights in order to identify patterns in trends and develop an understanding of the past (Ghasemaghaei, Ebrahimi & Hassanein, 2016; Sivarajah, Kamal, Irani & Weerakkody, 2017). Therefore, the descriptive insights afford organisations a lever to better understand the current business environment from an exceptions, trends, patterns and developments point of view. This data is generally presented in dashboards and scorecards form.

Predictive insights focuses more on the understanding of possible future outcomes (Ghasemaghaei, Ebrahimi & Hassanein, 2016). The data used to gain prescriptive insights is generally sourced from organisations analysis of associations between predictive future probabilities data and trends (Ghasemaghaei, Ebrahimi & Hassanein, 2016). This type of data analysis commonly uses statistical and forecasting models to generate future possibilities insights for organisations such as sales projections based of a variety of conditions which include but not limited to price changes, events and weather. Finally, prescriptive insights deals with determining the best course of actions for optimal results attainment from exploiting a circumstance (Poornima & Pushpalatha, 2016; Appelbaum, Kogan, Vasarhelyi & Yan, 2017). These insights make use of cost optimisation models and scenario analysis with recommendation.

Thus, enabled by the significant advancement in new technologies, organisations are enhancing their data-driven insights generation through the collection of internal and external data (Abbasi, Sarker, Chiang, 2016). Accordingly, collection of these datasets by businesses aids in gaining valuable insights on customers, markets, environment and competitors (Ghasemaghaei, Ebrahimi & Hassanein, 2016). Ghasemaghaei and Goran Calic (2019) have found in their study that data veracity, data velocity and data variety enhanced data-driven insights generation while data volume did not meaningfully impact the generation of data-driven insights. In addition, the study showed that descriptive and predictive insights had a substantial impact on organisation innovation capability while prescriptive showed to have minimal impact.

2.7 Data-driven decision-making culture

Big data entails the massive amount of data presented as incentive for data analytics and data-driven decision making (Ghasemaghaei, Ebrahimi & Hassanein, 2018). Big data and big data analytics capabilities provide unprecedented innovative opportunities for companies that are willing and able to exploit it (Ghasemaghaei, Ebrahimi & Hassanein, 2018). Thus, firms and organisations are eager to assimilate big data and big data analytic for competitive advantage. In driving business goals, e-commerce businesses such Amazon, eBay, and Jami as well as information rich firms such Netflix, Facebook, LinkedIn have been successful using data as a key resource (Chen, Chiang & Storey, 2012). This is evident from the fact that globally big data and business analytics market is projected to reach $ 274 billion in 2022 (Statista, n.d.).

It is therefore vital that organisations are proficient in the application of big data in decision making and taking action to promote a data-driven decision culture (Pigni & Picco, 2016). This manifest in dissection of business events in real time, shorter decision cycle and improved customer service (Pigni & Picco, 2016). Organisational culture was demonstrated to have direct and indirect links to firm performance (Abdelwhab, Panneer selvam, Paris & Gunasekaran, 2019). Thus, akin with the generally accepted definition of firm culture (Hofstede, 1980), firm should implement data-driven decision-making culture and mind-set which can be referenced when decisions are made if firms wish to derive value from big data.

Stobierski (2019) reports highlight several enablers that data-driven decision-making can offer organisations. The author starts by stating that data-driven decision-making enables firms to make decisions more confidently. This is due to the fact that data can perform various roles in that it serves as a yardstick for what is currently obtainable and allows for better understanding of consequences of any decision made. Secondly, it allows firms to be more agile and proactive by giving a picture that a firm needs to react to. This could be market opportunities or threats that competitors are not yet aware of. Finally, data driven decision-making affords opportunities for operational efficiency improvements through decisions based on the latest available information. One example is the collaborative research between Brynjolfsson and McElheran (2019) and U.S. Census Bureau that found evidence that data-driven decision making put into action significantly improve productivity in a wide range of manufacturing settings.

2.8 Decision making quality and knowledge sharing

As result of the dynamic environment of business and knowledge sharing has become vitally important for decision-making, firm performance and success (Son, Cho & Kang, 2017). Knowledge sharing comprises of congregation and distribution of both internal and external knowledge within the firm (Nazir, Shah & Zaman, 2018). Nazir, Shah and Zaman (2018) in their studies found that firm should include knowledge sharing, collaborative decision making and transformational leadership to efficiently improve its performance and meet firm goal. Rehman, Hawryszkiewycz and Sohaib (2018) further described that knowledge sharing culture and resultant firm performance can be achieved through incentivised teams, cooperative communications and ideas exchange re-enforced with empowerment, trust and collective leadership. While a recent study by Ferraris, Mazzoleni, Devalle and Couturier (2019) demonstrated that firm with advanced BDA capabilities benefited from enhanced firm performance while knowledge sharing orientation intensified the impact of BDA capabilities on both technological and managerial level. Therefore, with big data analytic being relatively new field both in academia and business, a concerted effort by business is required to disseminate knowledge effectively in this context to improve how firms derive value from big data investment.

Knowledge sharing is considered to be a critical activity among knowledge workers and all knowledge management processes to make quality decisions. Consequently, managers are required to put more focus on the two areas highlighted to be key enablers of knowledge sharing in organisations namely, individual and organisational dimensions (Ali, Panneer selvam, Paris & Gunasekaran, 2019). The propensity for two constructs to either interfere and influence the knowledge management process contribute to the complexity embedded in managing knowledge sharing (Ali, Panneer selvam, Paris & Gunasekaran, 2019). Therefore, in order to improve organisational performance from through optimum management of knowledge sharing, these constructs need to be both understood separately and collectively Individual employees.

2.9 Individual dimensions on knowledge sharing

Embedded within the individual dimension of knowledge sharing is explicit and tacit knowledge which needs to be effectively and efficiently shared. Happ, Melzer and Steffgen (2016) states that intentions to share knowledge, relational surety, mutual relationship and individual impetus all contribute to influencing knowledge sharing behaviours in organisations. This assertion is further underpinned by the planned behaviour theory that showcased the positive relationship between individual dimensions such as attitudes, norms and perceptions and intention to knowledge sharing (Sedighi, Van Splunter, Brazier, Van Beers & Lukosch, 2016).

Work enjoyment and interpersonal trust have also been demonstrated to positively influence knowledge sharing in organisation (Ali, Panneer selvam, Paris & Gunasekaran, 2019). Thus, these two constructs enhance interest in knowledge sharing amongst employees and provides the basis for employees' interactions. Direct and generalised reciprocity, which refers to the mutual knowledge exchange between the provider and recipient of knowledge, and knowledge received from any member of the organisations represent an additional personal factor that enhance knowledge sharing. The premise is that employees will undoubtedly share information with those that readily share information with them (Sedighi, Van Splunter, Brazier, Van Beers & Lukosch, 2016). Finally, motivation is yet another dimension that is reported to drive knowledge sharing (Ali, Panneer selvam, Paris & Gunasekaran, 2019). However, some authors have reported results that are contrary to this assertion (Ali, Panneer selvam, Paris & Gunasekaran, 2019). Thus, insights as to what motivates employees to share knowledge and necessary responses by organisations to create environments that promote knowledge sharing positions organisational dimensions as a topic of interests to be reviewed.

2.10 Organisational dimensions on knowledge sharing

Management support, organisational culture, organisational structure, technology and rewards are reported to be four organisational dimensions that relates to knowledge sharing (Ali, Panneer selvam, Paris & Gunasekaran, 2019). Organisational culture and technological dimension as they relate to knowledge sharing are explored. Lee, Shiue and Chen (2016) in their study showed that organisational culture influence employees' perception of knowledge sharing which could stimulate or retard knowledge sharing activities. There are many types of organisational cultures namely, bureaucratic, creative, innovative and supportive culture (Ali, Panneer selvam, Paris & Gunasekaran, 2019). Kremer, Villamor and Aguinis (2019) have established a positive correlation between knowledge sharing, inventive and supportive culture, and a negative correlation between knowledge sharing and bureaucratic. However, herein emphasis is put on supportive organisational culture as an enabler of knowledge sharing (Ali, Panneer selvam, Paris & Gunasekaran, 2019). Organisational culture in the context of big data analytics and firm performance is an important construct explored in this research.

Technological dimension is another area that has received much attention among researchers as it relates to knowledge sharing (Ali, Panneer selvam, Paris & Gunasekaran, 2019). In this regard, technology enables organisations to develop business process that facilitates knowledge sharing and innovation (Lyu & Zhang, 2017). Thus, computer infrastructure, databases and repositories are considered critical to capture and store knowledge within organisations with data analytics key to generating insights from that data.

Matošková (2018) have in their study found that knowledge-orientated leadership had a strong positive relationship to knowledge sharing in organisations. Besides highlighting the critical resources, a firm should invest in promoting knowledge sharing to maximise the rewards of using data analytics (Aboelmaged & Mouakket, 2020). Ghasemaghaei (2019) also investigated knowledge sharing as a mediator on the influence of data analytics application on organisation decision performance. The research showed that data analytics applications enhanced knowledge sharing in firms and that knowledge sharing showed mediation on data analytics application on business decisions quality. Thus, knowledge sharing enhances the organisation decision efficiency, effectiveness and consequently firm performance (Hegazy & Ghorab, 2014). Therefore, employees need to improve knowledge sharing since it is required for high-quality decision.

Furthermore, Ghasemaghaei (2019) studied the moderating effect of data analytics capability on knowledge sharing and decision-making performance. This, therefore opens an opportunity to further add to the field by studying knowledge sharing impact on firm performance by evaluating other moderating factors apart from data analytics competency such organisational factors discussed below. This means that organisations need to have attributes that promote a knowledge sharing environment for firm performance. Therefore, investigating potential organisational factors that promote knowledge sharing derived from big data-generated insights and consequently firm performance is highly sought after.

2.11 Entrepreneurial orientation and organisational culture antecedents for effective decision-making and firm performance

Decision-making in firms is crucial to strategy implementation as it involves optimally allocating resources, understanding resource needs and sequence decisions that influence firm performance and sustainability (Brynjolfsson, Hitt & Kim, 2011). As a multi-faceted process, decision-making involves a sequence of activities that include evaluation, defining alternatives, codifying and committing to a variety of likely actions (Malakooti, 2012). Furthermore, environmental and organisational factors, timing, experience, resource availability and size of the problem all serve as inputs into problem formulation.

Thus, Ghasemaghaei, Ebrahimi and Hassanein (2016) states that in the framework of data analytics, organisations can improve data insights developments through accumulation of data from various origins for improved decision making. Thus, important organisational factors antecedents for effective decision-making and firm performance are discussed further below which will be independent variables moderating knowledge sharing and firm performance being the dependent variable.

2.12 Entrepreneurial orientation and firm performance

Entrepreneurial orientation denotes the approaches, principles and decision-making activities that facilitates new access (Lumpkin & Dess, 1996). An entrepreneurial firm is one that performs a lot of product-market innovation, not afraid to take on risky projects and regarded as a first-mover in terms of innovations, thus thrashing competitors. Therefore, such features are linked to enhance firm performance, especially now when business survival depended largely on seeking new opportunities (Hamel, 2000). The literature reviewed on corporate entrepreneurship highlights five attributes common to all entrepreneurs. These are proactiveness, ambitions above existing capability, cooperative team, capability to overcome predicaments and learning capability (Stopford & Baden-fuller, 2018). The more prominent the entrepreneurial orientation of an organisation the more proficient it is at accessing resources with the aim of guaranteeing organisational survival (Stopford & Baden-fuller, 2018). Thus, entrepreneurial orientated organisations are able to procure available knowledge and information from its surroundings for use to drive firm performance (Vafaei-Zadeh, Hanifah & Foroughi, 2019).

There is some literature precedence on EO that puts focus on the individual level (Lyon, Lumpkin & Dess, 2000), however a significant amount of impactful research has supported the organisational-level approach (Lumpkin & Dess, 1996) while other go as far as cautioning that entrepreneurial orientation associations remain fixated at the firm-level (Slevin & Terjesen, 2011). Thus, the current study will also focus on the organisational- or firm-level. Furthermore, Miller (1982) describes entrepreneurship in firms as the degree to which a firm can innovate, act proactively and its risk propensity.

2.13 Proactiveness

Proactiveness denotes the firm's capability to be progressive and foresee market prospects and risks (Lumpkin & Dess, 1996). Thus, owing to the attribute of proactiveness, organisations perform as market leaders as a result of the inclination to act on present opportunities and achieve higher profits in relation to their competitors (Lumpkin & Dess, 1996). Proactiveness is thus regarded as an advantageous strategy on its own. Therefore, proactiveness firms or alternatively referred to as first-movers are able capitalise on market opportunities to gain dominance and establish their brand ahead of competitors (Lumpkin & Dess, 1996). From a resource-based view perspective, firms that achieve the first-mover status can secure access to resources and use those resources to strategically makes it difficult for us to replicate (Barney, Wright & Ketchen Jr, 2001).

2.14 Innovativeness

This refers to the organisation willingness to venture into new and attractive states of reaching business objectives through exploration (Lumpkin & Dess, 1996). This means new opportunities, solutions, products and services might be accessed through creative ideas and trialling to fit into the conceptualisation (Lumpkin & Dess, 1996). Henceforth, in considering the hostile and volatile markets, innovation is anticipated to be necessary disruptive activity for businesses (Lumpkin & Dess, 1996).

2.15 Risk propensity

Risk propensity can be regarded as the inclination for organisation to want to secure high returns by taking on more risky decisions through venturing in to the unknown, financial commitment or leverage (Lumpkin & Dess, 1996). Miller (1982) therefore put forward a proposition that firm will not be able to proactively action any opportunity identified for product-market innovation without taking some form of risk venture or behaviour. Furthermore, these risk-taking characteristics in organisations do away with hierarchical structures that limit collaborative learning and innovation (Kuratko, Ireland, & Hornsby, 2001). Consequently, allow individuals and teams the flexibility to and freedom to be creative and voice ideas (Kuratko, Ireland, & Hornsby, 2001).

The EO-performance literature although relatively old presents overwhelming evidence that firm with focus on EO perform better (Wiklund, 1999). Some example of these include the study by Sharma and Dave (2011) that investigated a small and medium size businesses and reported entrepreneurial orientation to be positively and significantly correlated to company performance. While the finding by Ndubisi and Iftikhar (2012) with a sample of 124 SMEs agreed with Sharma and Dave (2011) findings in similar studies.

Thus, for the current study EO is employed to measure attributes of firm behaviour and it is relevant to this study as it puts weighting on the potential differences that exist in strategic postures amongst firms. It also measures the firm’s ability to achieve its business objectives (Gupta & Gupta, 2015).

2.16 Organisational culture and firm performance

“The combination of symbols, language, ideology, beliefs, rituals, and myths of an organization” constitute organisational culture (Hofstede, 1980). Organisational culture thus develops from the learning and adaptation that organisations transitions through the changing external environmental conditions and internal integration challenges and has many underlying meanings and connotations (Schein, 2017). External environmental conditions refers to marketplace dynamics which include competition, globalisation, regulatory requirements and technology advances while internal conditions refers to the required structural, strategy and innovation changes in response to the changing external conditions (Schein, 2017). Consequently, all organisations through the combination of people and artefacts have developed over time unique and relatively inimitable identity (Alvesson & Sveningsson, 2016). Therefore, organisational culture affects the knowledge sharing process by either encouraging or impeding knowledge sharing activities in an organisation (Abdelwhab, Panneer selvam, Paris & Gunasekaran, 2019). Organisational culture is seen as a vital component of decision making as it affects the process of making decisions in the present and in the future. This is because business leaders align themselves with organisational culture shifts and modify their behaviours to fit the anticipated norms (Javidan, Hanges, Dorfman, Lowry & Bet, 2002).

More specific to business big data initiatives the organisational culture in terms of attitudes and mindsets either restrict and facilitate the ability of an organisation to data-driven initiatives (Alharthi, Krotov & Bowman, 2020). This suggests that for organisations to be able to incorporate data-driven decision-making, a different mindset must implemented (Pfeffer & Sutton, 2006). Therefore, data-driven decision-making culture will be required if organisations are seeking to utilise value generated by big data effectively before executing any important decision. For an organisation to be big data enabled it is a requirement that it adopts a culture of empowerment, transparency, trust and inquiry (Applegate, 2018). Applegate (2018) further ascertain that these attributes allow for data analytics to be embedded throughout the organisation while they the effect of elevating and re-enforcing the investment and commitment to big data analytics. Thus, the follow-up section details some sub-dimensions of organisational culture in the context of big data analytics.

2.17 Empowerment

Applegate (2018) further adds that it is crucial for organisations to empower leaders to promote data-driven decisions and analytics. Stadolnik (2018) proposes that one way this can achieved is through the development of Chief Analytical Offices (CAO). The author further argues that the development of these positions commits the firm to the pursuit of data analytic and using big data to solve problems (Davenport & Bean, 2018). Additionally, the authors maintain that this move to create these positions in organisations promotes the odds of data analytics becoming the culture of an organisations. Furthermore, the presence of this individual on this important position provide an opportunity for the organisation to be persuaded to embrace and leverage data for business insights (Stadolnik, 2018).

Marshall, Mueck and Shockley (2015) contributed to the topic by emphasising that an alternative approach to developing an organisational culture that promotes empowerment towards data analytics is through employee training and development. Meaning, if all employees are trained to have some data science knowledge they will be empowered to inquiry and make data-driven decisions (Bolling & Zettelmeyer, 2014).

2.18 Trust and Transparency

Trust and openness in an organisation are largely driven by an organisational culture that promotes information to be share transparently which signifies a principal element of true leadership (Walumbwa, Avolio, Gardner, Wernsing & Peterson, 2008). In essence, the concept always provides space for members of the organisation to always present their authentic self by openly in debates and showing their true emotions within fitting limitations (Avolio, Walumbwa & Weber, 2009). The Cleveland Clinic case study demonstrates very clearly the advantages of transparency in organisations (*Cleveland Clinic: Transformation and Growth 2015*, 2016). Thus, transparency within an organisation affords the organisation the ability to be self-aware, opportunities to self-correct and affords employees to open innovate

Applegate (2018) instructs that a culture that values transparency of data promote trust and openness. Defined in another way by Avolio, Walumbwa & Weber (2009) who state that transparency is the capacity to openly deliberate thoughts and emotions within appropriate limitations. Within the context of big data, transparency regarded is to be only meaningful if big data can be readily accessible in a usable manner users (Knapp, Swinnerton, Copland & Huber, 2006). Thus, organisation culture can be promoted through accessibility provided by systems that all users can access at their fingertips. In a separate study surveying executives, Nannetti (2012) summarised that 56% of them state that the challenge organisations failing to reap the benefits of big data is that information is still segregated in department or by individual. Therefore, in order for organisations to foster culture of transparency the must be a mindset change that makes room for honest discussions and debate in order to harness creativity and innovation (Benson & Trower, 2012).

2.19 Inquiry and Innovation

Innovation and inquiry are regarded as the essential components of big data and analytics culture. Thus, key to this acceptance is employees across the whole organisation should be afforded the comfort to voice innovative ideas without being wary that their voice will not be valued or highly regarded as this will allow the organisation to excel (Marshall, Mueck & Shockley, 2015). In this way, the organisation will promote a culture of collaboration, space and time to foster creativity (Marshall, Mueck & Shockley, 2015). Inquiry and innovation can be encouraged through leaders embedding the culture of constant openness and receptive to change, new ideas and solutioning.

2.20 Big data analytics and firm performance

Big data analytics capabilities and data-generated insights are particularly vital for organisations that function in dynamic business environments that require rapid and informed decision-making (Wamba, Gunasekaran, Akter, Ren, Dubey & Childe, 2017). Furthermore, it is generally acknowledged that big data capabilities play a critical role in increasing firm performance (Wamba, Gunasekaran, Akter, Ren, Dubey & Childe, 2017). Literature highlights that organisation's commitment to big data utilisation affects big data integration through acceptance and routinisation pathways, consequently enhancing sustainable firm performance (Singh & El-Kassar, 2019; Coluccia, Dabić, Del Giudice, Fontana & Solimene, 2020).

This effect is further amplified by the data-driven decision-making culture which leads to superior performance from employees when using analytics over gut instincts (Del Giudice, Carayannis, Palacios-Marqués, Soto-Acosta & Meissner, 2018; Santoro, Thrassou, Bresciani & Del Giudice, 2021). Zeng, Glaister & Keith (2018) reported that business value creation was not only depended on data and data scientists but largely on the roles played by the organisation's data management which encompasses democratisation, contextualisation, experimentation and execution of data insights in a timely manner.

In diverse industries, big data analytics and insights have been reported to produce remarkable results in the form of operational efficiencies, product development or placement decisions derived from data-driven decision-making processes (Akter, Wamba, Gunasekaran, Dubey & Childe, 2016). Literature also provides evidence linking big data analytics and firm performance in majority of retail companies such as customer relationship management, price optimisation, profit maximisation, sales, market share and return on investment (Mikalef, Krogstie, Pappas & Pavlou, 2020). Target Corporation and Amazon.com are some of the well-known examples of organisations that capitalise big data analytics in tracking customers purchasing behaviours, predicting future buying trends, improving customer experience, reducing fraud and making timely recommendations (Maroufkhani, Wagner, Ismail, Baroto & Nourani, 2019). In the healthcare industry the benefit is observed in operational cost reduction (waste and fraud reduction) and safety enhancement resulting in quality care and treatment efficacy (Mikalef, Krogstie, Pappas & Pavlou, 2020).

Other literature examples include improvements in business-process monitoring in manufacturing, streamlined supply-chain management, development in industrial automation and enhancement of innovation in business (Mikalef, Krogstie, Pappas & Pavlou, 2020). Thus, big data analytics affords organisations the ability to be more proactive and forward-looking which in turn differentiates between low-performing and high performing firms.

Muller, Fay and Vom Brocke (2018) reported the direct relationship between ownership of big data assets and productivity with an observed average productivity increase of 4.10% over all industries. The same authors further found firm's productivity gains were more substantial in IT-intensive industries at 6.70% and competitive industries at 5.70% which highlighted the business impact and value of big data analytic, and the importance of the corresponding boundary conditions.

Nonfinancial factors, otherwise referred to as intangible benefits such as innovation, organisational learning, dynamic capability and competitive advantage derived from big data analytics are also strongly linked to firm performance (Ali, Panneer selvam, Paris & Gunasekaran, 2019).

2.21 Literature review conclusion

Due to its extensive operational and strategic capacity, big data analytics is regarded as a key enabler for businesses to enhance efficiencies and effectiveness (Fink, Yogev & Even, 2017). Brynjolfsson, Hitt and Kim (2011) and LaValle, Lesser, Shockley, Hopkins and Kruschwitz (2011) have in their respective studies demonstrated business that implement data-driven decision making achieve higher yields and productivity relative to their investment and IT capability. Ghasemaghaei (2019) further demonstrated that data analytics significantly enhances knowledge sharing fails to automatically enhance the decision quality. However, the impact of knowledge sharing was shown to be moderated by data analytics competency. The impact of data analytics competencies on the quality of decisions is now better understood. Thus, the current study does not seek to re-evaluate the findings nor nullify Ghasemaghaei (2019) research but rather is intended at exploring the impact of knowledge sharing on firm performance moderated by organisational factors.

Using the literature review, it is proposed that organisational factors in the context of big data analytics and knowledge-sharing has two dimensions namely, organisational culture and entrepreneurial orientation. Therefore, the current research intents to further support to the body of literature in big data analytics, data-driven decision making and firm performance. Figure 2.1 below shows the graphical representation of the proposed research model which maps the high-level view of the relationships between big data analytics, literature reviewed organisational constructs and firm performance.

The framework described in Figure 2.1 is intended to explain how organisations can leverage organisational factors to enhance firm performance through organisational knowledge-sharing. The literature reviewed identified data-driven insights to constitute knowledge shared for firm performance. These insights which are derived from big data analytics can either be sourced internally and/or from firm's open data networks. Firm performance that is derived from internal data is largely transaction-driven and focuses on analysis of the internal data to produce superior economic value which the firm exclusively enjoys. Open data network is relation-driven and generates superior economic rents through data collaboration which benefits both the firm and its collaborators. The combination of data-driven insights and different ideas leveraged throughout the organisation empowers firms to identify sophisticated patterns which are otherwise implausible to identify in isolation.

Therefore, it is noted that data-driven insights produced from collecting and analysing big data in an organisation that does not have an organisational culture that promote knowledge-sharing and making data-driven decisions will not benefit from the insights generated. The research herein also investigates the dimensionality of the organisation culture constructs which provides an opportunity to further provide evidence of its sub-dimensions. Therefore, organisational culture is included in the model to assess the mediation impact of big data analytics use, knowledge sharing and firm performance.

Firm performance is another construct measured in the research in relation with big data analytics and included in the model as moderated by knowledge-sharing. Knowledge sharing within the organisation can assist organisations effectively and efficiently enhance firm performance from big data analytics. In order to achieve this, organisations should understand and address any limitations introduced by the organisational factor identified in the above-mentioned literature review with the goal to enhance firm performance and competitiveness from big data analytics through knowledge sharing.

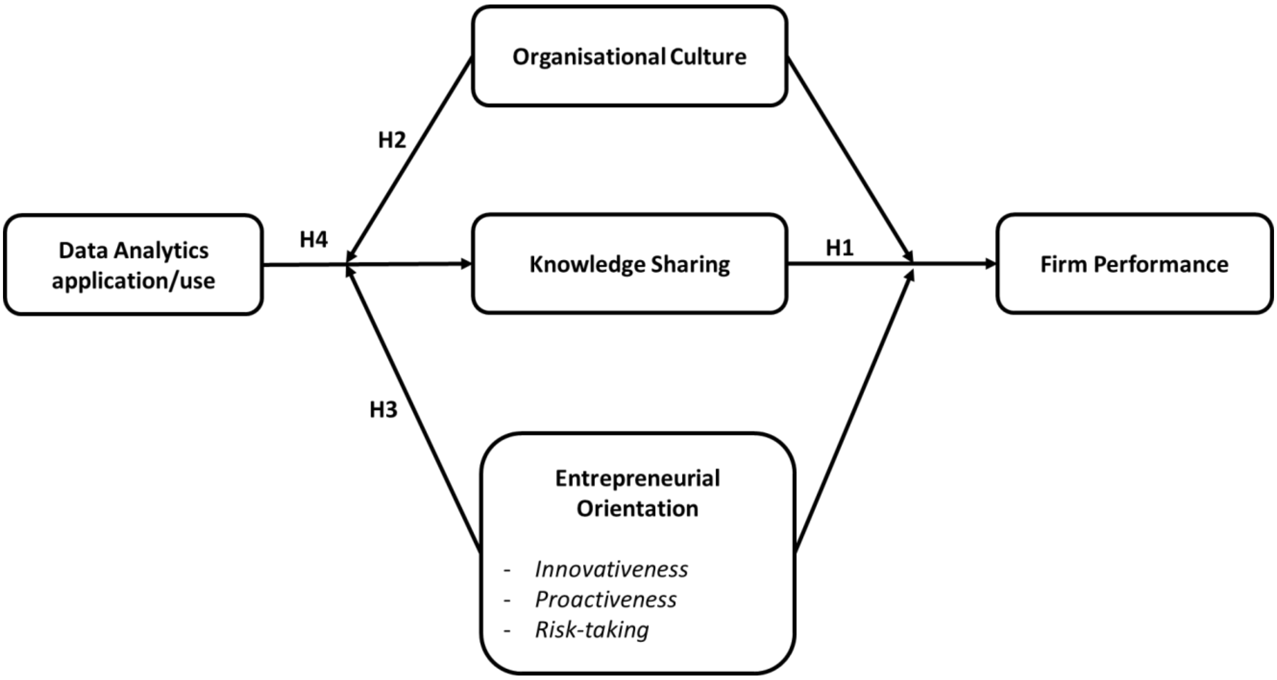

Figure 2.1: Research model

Furthermore, the current research investigates the entrepreneurial orientation of a firm to provide further empirical research to constructs necessary for firm innovativeness and resultant firm performance from data-driven insights sharing. The literature reviewed highlighted the multidimensional constructs embedded in entrepreneurial orientation and discussed its sub-dimensions. The premise is that entrepreneurial orientation in a firm further moderates' knowledge-sharing. Thus, incorporating the entrepreneurial orientations constructs in the model will further add to the literature and provide additional empirical evidence to the constructs.

In conclusion, the current chapter discusses pertinent literature precedence reviewed in order to provide the reader with an overview of the key constructs of big data analytics, knowledge-sharing, organisational culture, entrepreneurial orientation and firm performance as mapped out in Figure 2.1. This approach is important as it studies the application of knowledge produced by big data specialist and the value derived from intangible assets (Monino, 2021). The subsequent chapter therefore details the emanating research questions intended to deconvolute the relationship between the constructs described above in relation to firm performance in the framework of big data application.

Chapter 3

Research Questions

“The important thing is not to stop questioning. Curiosity has its own reason for existing.”
– Albert Einstein

3.1 Introduction

The literature reviewed in the chapter 2 has devoted significant attention to explore how big data analytics influences firm performance, decision-making performance and competitive advantage. Overall, the review maintains that data-driven insights have material impact on decision-making quality. Relating to firm performance, decision-making quality describes the accuracy and appropriateness of the decision taken while decision quality improves with adequate knowledge of the problem variables (Ghasemaghaei, 2019). Thus, access to knowledge required for decision making is critical for enhancing decision quality. Furthermore, Côrte-Real, Oliveira and Ruivo (2017) contend that knowledge sharing behaviour in organisations enables employees to readily share insights and expertise for enhanced opportunities and threats identification. Within the setting of big data analytics, organisations are able to integrate big data and generate data-driven insights by deconvoluting trends in historical data such as sales variations, customer preferences and predict future trends for competitive advantage (Côrte-Real, Oliveira & Ruivo, 2017; Ghasemaghaei, Ebrahimi & Hassanein, 2016).

Knowledge sharing is generally created, identified and captured through people and technology in organisations. The necessary next step is to disseminate the knowledge generated throughout the organisation. However, Oyemomi, Liu, Neaga, Chen and Nakpodia (2019) argues that even though technology is imperative in capturing and circulating knowledge, more emphasis should be directed towards the organisation having a supportive environment for knowledge sharing. Consequently, organisations that readily share and use knowledge adapted for decision making can achieve superior performance. Big data analytics is thus postulated to facilitate quality data-driven decision-making on the bases of its characteristics which include volume, veracity, velocity and variety (Alharthi, Krotov & Bowman, 2020).

Ghasemaghaei (2019) showed that knowledge sharing practices in organisation influences big data analytics, quality of decisions and firm performance. Furthermore, the literature reviewed discusses the effect of organisational culture and entrepreneurial orientation on firm performance and highlights the relationships thereof. Therefore, the current study is restricted to the assessment of two constructs namely, organisational culture and entrepreneurial orientation in addition to the model described by Ghasemaghaei (2019). Therefore, the proposed research focuses on evaluating the influence of the two distinct organisational factors within businesses on the effectiveness of knowledge sharing and firm performance measured through financial return.

Accordingly, firms that effectively generate business insights using big data analytics can enhance decision making quality and firm performance through knowledge sharing. Thus, this research provides understanding of organisational features that moderate knowledge sharing and facilitate the successful deployment of data-driven insights.

3.2 Research questions

Figure 2.1 provides an illustration of the proposed study model which intends to evaluate the impact of organisational factors on knowledge dissemination and consequently firm performance. Thus, research questions were developed from the literature reviewed and stated separately below.

3.2.1 Research question 1

Previous studies have shown that organisational learning, cross boundary management and sharing of knowledge are made efficient through big data analytics (Awan, Shamim, Khan, Zia, Shariq & Khan, 2021). Even though, effective decision-making is significantly entrenched in organisational learning, sustained business competitiveness is achieved through valuable and difficult to reproduce knowledge resources reinforced through big data analytics (Awan, Shamim, Khan, Zia, Shariq & Khan, 2021). Knowledge sharing is thus linked to firm performance through the enhancement of quality decision making capabilities, network expansion, opportunities identification and products and services optimisations (Steffen, Oliverira & Balle, 2017). In addition, firm performance is assessed through tangible indicators such as operating margin, return on investigated capital and return of equity and non-tangible indicators like innovation, dynamic capabilities and competitive advantage (Abdelwhab, Panneer selvam, Paris & Gunasekaran, 2019).

Teixeira, Oliveira and Curado (2020) further argues that knowledge sharing results in the establishment of synergies amongst employees which leads to increased creativity, elimination of redundancies and accelerates innovation. Arsawan, Koval, Rajiani, Rustiarini and Suryantini (2020) also showed that innovation, firm performance and sustainable competitive advantage are significantly influenced by the practice of knowledge sharing. Another study by Wang, Sharma and Cao (2016) established that improvement in innovation also influenced the relationship between knowledge sharing and firm performance. Thus, in line with previous research the above discussion raises the following question:

Research question 1: Is there a positive relation between knowledge sharing and firm performance?

Hence, the below hypothesis is developed to test the relationship between knowledge sharing and firm performance and further add to the body of knowledge on the subject.

H_1: There is a positive relationship between knowledge sharing and firm performance.

3.2.2 Research Question 2

Several studies have demonstrated that when there is an enabling culture for new knowledge generation and knowledge sharing, significant improvement in firm performance is realised (Lyu & Justin, 2017; Alattas & Kang, 2015). Oyemomi, Liu, Neaga, Chen and Nakpodia (2019) in their analysis using Fuzzy-set Qualitative Comparative Analysis (fsQCA) of 107 cases established that organisational culture contributes significantly knowledge sharing and firm performance. Numerous antecedents of a knowledge sharing culture explored in literature include innovation, openness, trust, rewards, organisational structure, positive attitudes, empowerment, information systems, communication and top management support (Kathiravela, Mansor, Ramayah & Idris, 2015; Kucharska & Bedford, 2019; Applegate, 2018; Marshall, Mueck & Shockley, 2015; Khan, Usoro & Crowe, 2020). Kathiravela, Mansor, Ramayah and Idris (2015) proposed the model in Figure 3.1 that supports the antecedents included in the above-mentioned literature precedence.

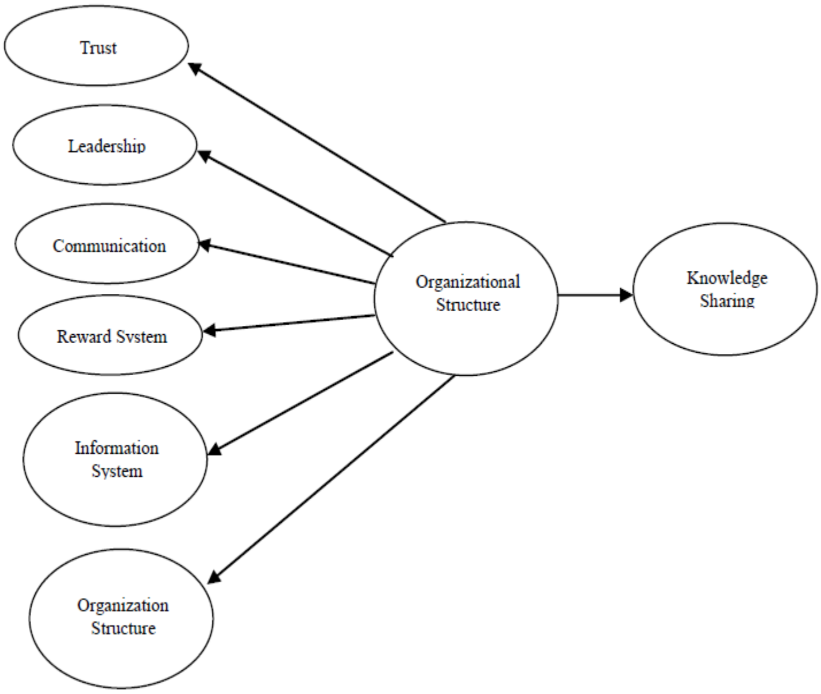

Figure 3.1: Model for organisational cultural antecedents that influence knowledge sharing. Source: (Kathiravela, Mansor, Ramayah & Idris, 2015).

Organisations employ analytical tools to assemble deep insights on historic, present and future events. Thus, if this information is shared amongst employees it assist decision makers in improving decision quality and firm performance. Thus, an organisational culture that contributes to knowledge sharing of data-driven insights is key to innovation, process optimisation, market response and firm performance. The research question below is thus drawn from the aforementioned synthesis of the literature:

Research question 2: Is organisational culture a moderator of knowledge sharing on firm performance?

Hence, the next hypothesis tests the relationship between big data analytics, knowledge-sharing and firm performance moderated by organisational culture.

H_2: Organisational culture moderates the influence of knowledge-sharing on firm performance such that the effect is more pronounced with knowledge sharing enabling culture.

3.2.3 Research Question 3

Korani & Province (2018) argues that firms can simultaneously improve their competitive advantage and identify new opportunities through strategic tools such as knowledge management and entrepreneurial orientation. The authors further emphasise that even though knowledge management and entrepreneurial orientation aid in improving firm performance independently, they are also interrelated and influence each other. In a separate study of a range of SMEs of Toos Industrial town in Iran, Matin, Nakhchian and Kashani (2013) explored the effects of entrepreneurial orientation dimensions on knowledge generation, dissemination, storage and use. The research concluded that entrepreneurial orientation positively and significantly correlates to knowledge management changes.

Knowledge sharing orientation and information technology orientation have been found to also have a significant relationship with entrepreneurial orientation (Farooq & Vij, 2020). The abovementioned literature examples provide some empirical evidence for the importance of entrepreneurial orientation and knowledge sharing in ensuring firm performance. Therefore, the current research investigates firm's entrepreneurial orientation and it impact on knowledge sharing through big data analytics. Therefore, the author posits the following question:

Research question 3: Is entrepreneurial orientation a moderator of knowledge sharing on firm performance?

Hence, the below hypothesis is developed to test the relationship between knowledge sharing and firm performance and the moderating effect of entrepreneurial orientation.

H_3: Entrepreneurial orientation moderates the influence of knowledge sharing on firm performance such that the effect is more pronounced with more entrepreneurial orientation.

3.2.4 Research Question 4

In recent times a plethora firms have invested in big data and processing this data in real time has enabled them to continually obtain new knowledge on markets, customers, products and services in order to generate new innovative ideas to produce new products and/or refine prevailing ones (Ghasemaghaei, Ebrahimi & Hassanein, 2018). Thus, exploitation and exploration of big data has been reported to improve innovation and firm success (Ghasemaghaei, 2019). Data analytics application is therefore the utilisation of technologies intended to extract value from big heterogeneous data by providing clear results for quality decision making in different business divisions (Khan & Vorley, 2017). Furthermore, this process of data processing and sensing enables firms to convert data into knowledge (Khan & Vorley, 2017).

The utilisation of big data by firms might enhance knowledge sharing. Therefore, it is of the outmost importance that employees in organisations have the necessary capabilities to distribute the insights gathered from data analytics tools. Janssen, Voort and Wahyudi (2017) asserted that if employees are unable to assimilate and decipher the insights obtained from big data analytics then knowledge sharing will degrade in the organisation. Furthermore, Ferraris, Mazzoleni, Devalle and Couturier (2019) found knowledge management orientation improves the effects of big data analytics capabilities and also increases both technical and managerial performance.

High-quality insights obtained using sophisticated tools encourages employees to readily share knowledge within the organisation. Therefore, entrenched in the knowledge-based view, big data analytics tools and big data analytics have the potential to improve organisational knowledge management (Ghasemaghaei, 2019; Ferraris, Mazzoleni, Devalle & Couturier, 2019).

Research question 4: Does big data analytic application enhance knowledge sharing within firms?

Hence, the below hypothesis is developed to test the relationship between big data analytics application and knowledge sharing.

H_4: Big data analytic application enhances knowledge sharing within firms

Chapter 4

Research Methodology and Design

"It is a capital mistake to theorize before one has data." - Arthur Conan Doyle

4.1 Introduction

The preceding chapters focused on providing the reader with empirical evidence on the mediating effect of knowledge sharing on firm performance. Furthermore, literature pivoting around the effect of organisational aspects on knowledge sharing orientation within organisations was also reviewed. Within the context of big data analytics, the current research study was directed towards empirically validating the organisation factors that impact the casual relationship that have been emphasised between big data analytics application and firm performance, mediated through knowledge sharing. Through multivariate data analysis tool, the research assessed whether the relationships are moderated by organisational factors such as entrepreneurial orientation and organisational culture (Hair, Black, Babin & Anderson, 2009). Therefore, the study describes the research methodology employed to complete this research and it was more explanatory in nature (Saunders & Lewis, 2012).

Herein, explanatory research was thus research aligned with associations in which one variable's variance and the resultant effect on the other variance was the area of curiosity (Creswell, 2012). Chapter 3 therefore outlined the research questions synthesised from the literature reviewed with the intention of addressing the research objectives. Quantitative data on data-driven decision making and firm performance was used to establish substantiating causal relationships (Ghasemaghaei, 2021).

4.2 Research methodology

The sections henceforth describe the research methodologies applied in this study starting from the broad concept of research philosophy followed by specific elements of the research agenda. A layered approach guiding this study was sought from Saunders and Lewis (2012) which maintains that the research philosophy informs the research strategy, data collection approach and analysis.

4.3 Research philosophy

The research philosophy governing this research was centred in positivism since hypothesis constructed and testing was based on existing theories (Saunders & Lewis, 2012; Wamba, Gunasekaran, Akter, Ren, Dubey & Childe, 2017). Therefore, quantitative research goals were measured and were inseparable from hypothesis and variables. Hypothesises are defined as untested propositions of casual relationship between variables while variables are constructs that have variations with numerical values (Straub, Boudreau, & Gefen, 2004).

Thus, analysis of statistical data was used to validate the applicability of the base theories of the current research and identifying opportunities to expend on the prevailing models through application of formal logic and deduction (Lee, 1991). Thus, this research was intending to further expand on existing theories in the context of big data analytics by testing hypothesis constructed and investigated the roles of the moderators on the significance and directional associations (Wamba, Gunasekaran, Akter, Ren, Dubey & Childe, 2017). This approach was further corroborated by the prerequisite for parameters of the big data analytics-firm performance relationship and various other constructs that were essentially achievable and measurable.

4.4 Methodological choices

Quantitative research is concerned with the examination of the identified problem, grounded on testing a theory through statistical analysis of numeral data and determine whether the analytical generality of a theory holds (Zikmund, Babib, Carr & Griffin, 2009). Given the proliferation of literature research on big data analytics, entrepreneurial orientation, organisational culture and knowledge sharing and more recently data-driven decision-making, this study was aimed at testing the theoretical propositions, and explaining the casual relationships between variables. Thus, deductive approach was chosen as the correct approach for this topic since it was used to test the characteristics described previously in existing theoretical models available in established literature (Saunders & Lewis, 2012).

In addition to the deductive logic followed for this research to test the hypothesised explanatory relationships, the methodology encompassed a mono-method using a quantitative technique (Saunders & Lewis, 2012). Therefore, quantitative analytical procedures were used to investigate the correlation between big data analytics use, knowledge sharing and firm performance moderated by entrepreneurial orientation and organisational culture (Khan, Wafa, Hassan & Kashif, 2020). It was maintained that the mono-method was the correct approach to achieving the research objectives.

4.5 Research strategy

For the current study, a survey questionnaire was used as the research instrument for primary quantitative data collection from a sizable population in order to obtained elements of dimensions to be statistically analysed in the form of responses to structured questions (Creswell, 2012). Therefore, from a cost effectiveness point of view, an online survey was chosen as research strategy to collect data and allowed for convenient, structured and broad reach of a large populations at low cost (Creswell, 2012). Additionally, since the current study was aimed at determining the casual relationships that have been asserted through testing, a survey questionnaire approach was found to be the most appropriate instrument as it explains phenomenon and identifies casual links within the constructs. Following this approach provided the opportunity to obtain findings that could constitute a representative sample that can be generalised to the research setting (Zikmund, Babib, Carr & Griffin, 2009).

Gefen and Straub (2005) advised that confidence in the generalisability of the findings for predictive and explanatory theory can be attained using a survey approach. While Gable (1994) further stated that survey approach provided correlation between the constructs studied and identified rich information.

4.6 Time horizon

The quantitative data was collected through questionnaire-based survey from participants sampled from the population of big data user firms (Saunders & Lewis, 2012). The time allocation for collecting data for the research was relatively short, suggesting that longitudinal study findings were not feasible. Therefore, the data collection was performed between 1 August 2021 and 30 September 2021 which qualified as snapshot data sourced in a single period, consequently representing a cross-sectional study setting (Saunders &

Lewis, 2012). Thus, the data sourced was analysed for the hypothesis testing of only that time frame.

4.7 Population

Creswell (2012) describes a population as a whole set of group members who are made up of similar characteristics. The said group is thus not only limited to persons but include organisations or regions (Saunders & Lewis, 2014) which implies that they should be clearly defined from the onset to correctly determine the applicable base from where data collection will take place (Zikmund, Babib, Carr & Griffin, 2009). The population of this study included all organisations that have accessibility to databases which could be classified as big data and professionals within those organisations employed as managers (Lee, 2017). In South Africa the sample study units of the target population were considered small since only a few organisations could be qualified as having big data platforms. Since the target population was limited, the intention was to select the entire population for the study contrary to just taking a sample (Zikmund, 2003). Contextual to this research, managers were defined as individuals in the respective organisations that make effective business decisions using data, information and intelligence or combination of the three to drive innovation and competitiveness to achieve improved firm performance (Sun & Wang, 2017). The constructs investigated in this research were believed to be present in all organisations and thus did not limit the study population severely.

Therefore, the study population was all organisations with exposure to big data with the expectation that respondents were decision-maker professionals in the respective organisations. A diversity of organisations, positions within the organisations and divisions within the organisations were targeted for the study to broaden the potential population.

4.8 Unit of analysis

In business research, individuals, groups, social interaction and organisations constitutes aggregated units of analysis (Kumar, 2019). Thus, the unit of analysis for this study was organisations that were classified as having significant data sets to enable big data analytics setting. The responses were reported from a perspective of individuals who are professionals employed as managers with positions within the organisation ranging from junior to executive management. To limit the pool of respondents to the target population, the first few questions of the questionnaire prompted the respondents to indicate their position within the organistion. Only data from qualifying respondents was thus analysed for this research. The questions were posted on an organisational level which inquired on organisational characteristics. The research objectives were to investigate generalisable characteristics thus the assessment was not specific to any organisation but more on traits that were general in organisations.

4.9 Sampling method

The procedure to synthesise conclusions from measurements of a percentage of the population is defined as sampling (Zikmund, Babin, Carr & Griffin, 2010). A sampling approach was used for the research since it was unrealistic to collect data for the entire population (Saunders & Lewis, 2012). Thus, the bigger the sample size the more accurate the analysis (Zikmund, Babin, Carr & Griffin, 2010). In the context of the current study, reaching the sample pool was challenging considering the dispersed nature of the businesses and the lack of a professional body that could be contacted for assistance. The available professional bodies found were largely platform based which were Impersonal thus limiting the ability for the researcher to follow up on responses. Therefore, to circumvent these limitations a two-pronged sampling approach was followed:

Firstly, a non-probability purposive sampling approach was used to identify prospective participants to send the survey questionnaire to. The researcher in this regard intentionally searched for qualifying professionals for the survey. Although these professionals were unbeknown to the researcher largely because the researcher is not active in the field, sampling in this manner had the potential to indirectly introduce an element of convenience sampling. This manifested through sourcing data only from the researcher's place of work or limited networks (Etikan, Musa & Alkassim, 2016). To avoid the potential bias the researcher campaigned as broad as possible across networks, platforms and industry types. The researcher reached the potential survey responders through personal networks and professional networking platforms. The criteria for participants selection was based on the position the person held in the organisation they worked in and job experience. In this way, the analysis focused more on organisational level for unit analysis.

The second sampling strategy employed was snowballing with questions in the survey identifying the participants appropriately (Saunders & Lewis, 2012). Snowballing refers to recruitment technique researchers use to get research participants to assist in identifying and reaching other potential participants. Thus, to ensure that as many as possible qualifying respondents were reached, the researcher encouraged the initially contacted networks from the purposive phase to further forward the survey to other qualifying individuals within their own networks (Saunders & Lewis, 2012). Since individual within a network might possess similar characteristics and exposure to similar views, the researcher was conscious of the possible introduction of responder bias and possible implications to the research. To mitigate against this, a diverse spectrum of participants was sourced and reached.

It was impossible to identify which responses were from purposive sampling and which were from snowballing. However, considering the small network the researcher has, it is anticipated that the bulk of the respondents came from snowballing sampling.

4.10 Measurement instrument

Primary data from the sample participants was collected through a self-managed online survey questionnaire (Saunders & Lewis, 2012). The online survey methodology was used because of the reported advantages that include; source of accurate information, provider of swift data collection, fairly cost effective and applicability to a broad population (Zikmund, Babin, Carr & Griffin, 2010). The survey was administered in English and the respondents informed of their rights at the start of the survey questionnaire through an informed consent statement. This informed consent section followed ethical principles recommended by Saunders and Lewis (2012) for managing the research process. Thus, the respondents were notified that the survey is taken voluntarily, they can pull out of participating at any point without penalty, confidentiality of all information provided was guaranteed, an indication of the approximate time required to complete the survey was indicated and guidelines to taking the survey outlined (Creswell, 2012).

The survey followed a structured questionnaire approach with the following considerations incorporated:

The survey instrument was structure in such a way that it adapts the five constructs that constitutes the main areas of this research study. These constructs included big data analytics applications and firm performance, entrepreneurial orientation, organisational culture and knowledge sharing. Thus, a model integrating these constructs constructed by adapting the research by Ghasemaghaei (2019) that investigated the relationship between big data analytics use, knowledge sharing and firm performance moderated by data analytics competency. For the current study the moderating influence of entrepreneurial orientation and organisational culture on knowledge sharing was studied (Khan, Wafa, Hassan & Kashif, 2020). These latent variables scores were calculated from the item measurements build into the questionnaire (Hair, Sarstedt, Ringle, & Mena, 2012).

The questions and responses for the survey questionnaire were derived from previous research analyses and thus considered to be well scrutinised and carefully selected to use in this study. This approach was considered important since quantitative research requires the use of validated instruments and scales for usable data (Saunders & Lewis, 2012; Agresti & Franklin, 2007).

The survey questionnaire employed to gather data for the research is included in the Appendices section under Appendix 1. The survey instrument was adopted from the research by Mourinho (2017), Ghasemaghaei (2019) and Niland (2017). Section 1 of the survey questionnaire focused on obtaining respondents demographics, job position, industry type and firm size data in order to accept or reject the responses based on relevance. Under the tab for industry type, an option to choose “Other” was included to cater for industries not listed in the drop-down menu such as consulting firms, insurance companies, content creators/providers, film production and others. Section 2 and 3 focused on questions that measured organisational culture that supported big data analytics and big data insights application in the organisation.

The questions in this section were established from Hill (2003) and Kuratko, Montagno and Hornsby (1990) and measured through a 7-point Likert scale. To measure entrepreneurial orientation, section 4 questions derived from Barringer and Bluedorn (1999) measured the degree of innovativeness, proactiveness and risk-taking in organisations which collectively provided a view of an organisation’s entrepreneurial orientation. Here too, the questions were quantified using a 7-point Likert scale. Knowledge sharing was measured using questions in section 5 of the survey instrument with a 5-point Likert scale established from Cummings (2004). Finally, the firm performance construct was measured using established questions in section 6. The questions were established from Tippins & Sohi (2003) and Wang, Liang & Zhong (2012) and measured using a 7-point Likert scale.

4.11 Sample size

Generatability of the results and the power of statistical test depends on the sample size for sound scientific contribution (Hair, Black, Babin & Anderson, 2010; Saunders & Lewis, 2012). A simple methodology to determine the sample size is offered by Tabachnick and Fidell (1996) which uses the formulas: $N \geqslant 50 + 8m$ and $N \geqslant 104 + m$ to test the multiple correlation and individual predictors where m depicts the number of independent variables, respectively. However, Field (2009) argues that the formulae proposed by Tabachnick and Fidell (1996) is a rough guide and more of a rule of thumb and propose an alternative power analysis (Cohen, 1992) which relies on the known variable which include the level of power, size effect, number of independent variable and the significant criterion. However, since the target population number was not known, the researcher avoided using the sample size spreadsheet calculator provided. Thus, Cohen (1992) approach indicated that the required sample size for the multiple regression corresponding to 7 independent variables was 102 using the generally used power analysis values of 0.80 and 0.005 for power level and significance criterion, respectively. Thus, with the sample size of 144 respondent achieved in this study the requirement for generalisability was satisfied.

4.12 Survey questionnaire pre-testing

The survey was hosted and administered on google forms. Following the construction of the survey questionnaire, the first validation was conducted by both the researcher and research supervisor to check for design, flow and appropriateness of the questions in relations to the research objectives. The researcher ensured that ethical clearance from GIBS ethics committee was granted before distributing the survey to potential respondents. In addition, a trial test of the instrument was conducted with 16 participants which included colleagues and GIBS syndicate members to assess the robustness of the instrument without using the data for the research (Saunders & Lewis, 2012; Zikmund, Babib, Carr & Griffin, 2009). This enabled the researcher to assess survey instructions for correctness, consistency, ease of understanding and whether the survey could be captured correctly (Saunders & Lewis, 2012). The targeted population was respondents at the appropriate level of profession and education to be able to easily navigate the online survey and computer systems with not challenges.

Majority of the respondents indicated that it took 15 min or less. Only 3 out of the 16 indicated that they took more than 15 min. Therefore, the time allocation for completing the survey was kept at 15 minutes. The respondents indicated that the questions were clear and easy to understand with no concerns. However, there was some feedback from the respondents highlighting several areas of concern that need correcting. The feedback highlighted the following questions to be repeating when taking the survey (questions reproduced from the survey instrument):

- "Employees receive recognition from the organisation for applying evidence-based decision making in our typical business processes."
- "How many new lines of products or services has your firm marketed in the past 5 years?"
- "In dealing with its competitors, my firm…."

The survey was therefore reviewed based on this feedback and the repeating questions deleted.

Some issues with the mobile appearance of the survey which only showed three options of the Likert scale highlighted. Some respondents contacted the researcher to enquire on how to access other options of the Likert scale. The responded suggested inserting a notification or instructions on the landing page of the survey to direct respondents on how to navigate the Likert scale if using a mobile screen. The following instruction was insert on the survey landing page: "NB: when completing the survey using a smart mobile phone you might need to slide left to see more options moving from strongly disagree to strongly agree."

4.13 Data collection process

Ones all the pre-test feedback concerns were addressed, the researcher performed a final check by completing the survey to assess if all the concerns were adequately addressed. In all cases the survey questionnaire was sent to prospective participants through direct email with a web link, WhatsApp message with a web link to the survey and posting the link on the online platform LinkedIn Groups (LinkedIn groups targeted included big data and big data analytics). As indicated before, the landing page of the survey questionnaire had a notice assuring participants confidentiality and highlighting 15 minutes time required to complete the survey. Weekly reminders were sent to all prospective participants to encourage participation and in case of snowballing the researcher continuously send reminders to the participants to keep prompting their network to complete the survey.

4.14 Statistical analysis approach

The data that gathered using the survey questionnaire for the research was quantitative, categorical and ordinal (Saunders & Lewis, 2012). Since the data collected was already in digital format, analysis was performed using SPSS with data imported from Excel data. The English language responses from the extracted google forms data in the excel sheet were firstly encoded by converting them into numeric values for analysis in SPSS (See Appendix 2). The data was analysed using two types of analysis namely, descriptive and inferential statistics. In order to define and present the sample set, descriptive statistics was applied to clearly show categories, trends and dispersions of the data (Saunders & Lewis, 2012). While inferential statistics was used to assess the nature of interdependencies of the constructs to test the hypothesises emanating from the research objectives (Hair, Black, Babin & Anderson, 2010; Saunders & Lewis, 2012).

The central question of this research investigates how independent variables influence the dependent variable. Thus, multiple regression analysis approach was performed on the data in SPPS 27 software. This analysis approach was followed because the regression analysis attempts to investigate if the dependent variables are able to predict the depended variable. Furthermore, multiple regression analysis assesses which of the variables is a stronger predictor of the dependent variable which in this regard being firm performance. Therefore, regression analysis was regarded as the most fitting analysis tool for the research herein (Pallant, 2016).

4.15 Quality controls

Quality controls in the context of quantitative research is achieved using validity and reliability measurements (Saunders and Lewis, 2012). Validity implies the extent to which a notion is accurately measured against the intent while reliability is the extent to which a survey instrument can give repeatable results if applied in same situation (Hair, Black, Babin & Anderson, 2010; Saunders and Lewis, 2012). Gujarati (2021) stated that there are 10 assumptions that act as pre-requisite of running multiple linear regression. However, for the current study the following 5 were found more relevant to be diagnosed as they the most cited in quantitative research.

- Linearity
- No multicollinearity
- Homoscedasticity (variance of the residuals is constant)
- Independence of observation
- Normality

The residual scatterplot was assessed to determine the presence of outliers since they are known to distort statistical analysis. This assessment was important since multiple regression is susceptible to outliers which can be high or low scores (Hair, Black, Babin & Anderson, 2010; Pallant, 2016). Multicollinearity was also assessed on the independent variables that are correlated (Tabachnick & Fidell, 1996). This was done since large size of standard errors as a result of multicollinearity presence would lead to regression coefficient becoming insignificant (Tabachnick & Fidell, 1996). Components of Normality, Skewness (data distribution symmetry) and Kurtosis (data distribution peakedness) were evaluated to determine if the variables were normally distributed and whether homoscedastic is met Tabachnick & Fidell, 1996).

More details on the evaluation process and outcomes of the above-mentioned tests are discussion separately in section 4.15.1 below.

With regards to reliability assessment, two measures were used (Heale & Twycross, 2015). Firstly, internal consistency reliability were used to measure the extent that all items on the scale one construct using Cronbach’s alpha (Hair, Black, Babin & Anderson, 2010). Secondly, the indicator reliability measures the statistical significance of the relationship between the indicator and the constructs and whether it can put forward as a validation of the study (Zikmund, Babin, Carr & Griffin, 2012).

4.15.1 Model diagnostic tests

4.15.1.1 Linearity and Outliers

For quality control and data analysis, the preliminary analysis was required to see whether different assumptions were broken before moving on to the association and prediction tests (Flatt & Jacobs, 2019). The first test was linearity. This assumption indicates that a linear connection between the independent and dependent variables is necessary before tests of relationships can be performed. Outliers can have a drastic effect on the correlation outcomes by exceeding or underestimating the real connection (Flatt & Jacobs, 2019). Scatterplots were created and analysed between each independent variable to determine linearity and outliers.

The x-axis was used for independent variables and the y-axis for dependent variables, Figure 4.1. Conclusions derived was that scatterplots appeared to show a positive linear link across all independent variables and dependent. Moreover, the dataset did not appear to include any outliers. The analysis also validated linearity for all constructs and subdimensions utilised in the per variable. Base on scatter plot the data was declared free of outliers, Figure 4.1.

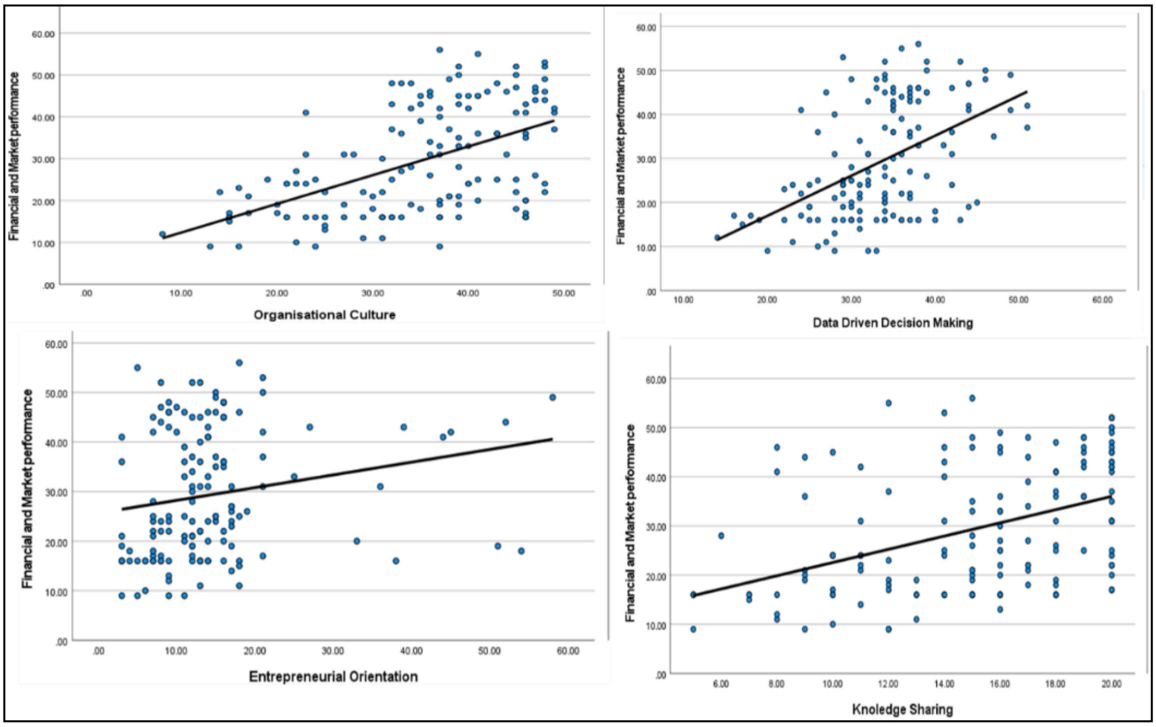

Figure 4.1: Linearity of variables

4.15.1.2 Multicollinearity

Multicollinearity must be checked since the model employs many independent variables in its analysis. Multicollinearity causes any regression model's variance to increase while also reducing its efficiency. The multicollinearity tests findings are shown in Table 4.1 which gave pairwise correlations of independent variables. The results revealed no excess correlation among regressors, implying that the study had no multicollinearity challenges. When utilising a correlation matrix to test for multicollinearity, a pairwise correlation value of 0.8 or above indicates that there is significant multicollinearity between explanatory variables (Gujarati, 2011).

Table 4.1: Multicollinearity Problem test results

	Organisational Culture	Entrepreneurial Orientation	Knowledge Sharing	Data Driven Decision Making
Organisational Culture	1	0.227**	0.524**	0.708**
Entrepreneurial Orientation	0.227**	1	0.192*	0.083
Knowledge Sharing	0.524**	0.192*	1	0.499**
Data Driven Decision Making	0.708**	0.083	0.499**	1

Thus, Table 4.1 showed that all the correlation coefficients were below 0.8. Therefore, since there is no multicollinearity the null hypothesis was not rejected. The observation was that the model was not constricted by severe Multicollinearity. It was thus, concluded that organisational culture, entrepreneurial orientation, knowledge and data driven decision making will have separate effects on the dependent variable (organisational or firm performance). Each variable had a different impact on organisational performance. However, this study did not depend only on a correlation matrix to prove the relationship between variables. This was because correlations inherently have a shortcoming in that it does not identify causality. Hence, the main analysis was derived from the regression models, which constituted the core subject of the analysis.

4.15.1.3 Heteroscedasticity test

Heteroscedasticity is defined by Gujarati and Porter (2009) as a scenario in which a model's error variances are not constant. The existence of heteroscedasticity defies the traditional linear assumptions, which hold that random variables have the same variance.

The Breusch-Pagan/Cook-Weisberg test was used on the data in this research, Table 4.2. Thus, summary of the hypothesis were as follows (Gujarati & Porter, 2009):

H_0: “There is no evidence of Heteroscedasticity”

H_1: “There is evidence of Heteroscedasticity”

Table 4.2: Table Breusch-Pagan/Cook-Weisberg test for Heteroscedasticity

Chi2(1)	3.620
Prob> chi2	0.057

For the Heteroscedasticity test the decision criteria was to reject the hypothesis (H_0) if the calculated Prob > chi2 was less than 0.05. The p-value was determined at 0.057, which was more than 0.05. Consequently, the null hypothesis (H_0) was not reject. It was thus resolved that there was no evidence of Heteroscedasticity. Accordingly, providing the justification to continue to run the regression.

4.15.1.4 Test of Normality

A diagnostic test on data normality is a well-known pre-requisite for many statistical tests and regression analysis since data's normality is the underlying assumption to perform parametric tests and Regression Analysis. Normality can be assessed using two main methods namely, graphical and numerical. Based on the magnitude of skewness and Kurtosis, some variables (i.e. financial and market performance, organisational culture, data driven decision making and knowledge sharing) were normally distributed while others were not (i.e. entrepreneurship).

Statistical tests are regarded as having an advantage of making a judgment that is objective on normality. However, often it has disadvantages of not being sensitive enough for sample size, which is unreasonably strong to large sample sizes. SPSS Statistics numerical data for the normality are presented in Table 5.19. See Appendix 3 for detailed normality test data presentation.

Table 4.3: Test for normality

		Sample	Skewness	Kurtosis
		Size	Statistic	Statistic
Overall	Knowledge_Sharing	144	-0.575	-0.638
	Innovativeness	16	0.411	-0.972
	Proactiveness	16	-0.075	-0.813
	Risk_Taking	144	-0.072	-0.724
	Financial_and_Market_performance	144	0.31	-1.235
	Organisational_Culture	144	-0.554	-0.56
	Data_Driven_Decision_Making	144	-0.084	0.406
	Entrepreneurial Orientation	144	2.403	6.818

Table 4.3 simply showed that the assumption of normality was tested using descriptive statistics of skewness and Kurtosis statistics. To be considered normal, skewness and kurtosis values must be less than 1.0 (Gujarati, 2011). These statistics are considered to be more exact relative to residual plots. According to Gujarati (2019), if any of these values for skewness or Kurtosis were less than 1.0 then the distribution's skewness or Kurtosis are not beyond the limits of normality and the data distribution can be classified as normal. If the numbers were more than 1.0 then the data distribution's skewness or Kurtosis cannot be classified as normal.

It was found that only one factor was not normally distributed in the data (i.e. overall Entrepreneurial_Orientation). The non-normality of entrepreneurship orientation was attributed to the fact that innovativeness and proactiveness had only 16 observations. This outcome justified using only risk taking to surrogate entrepreneurial orientation.

The conclusion of the tests are that assumptions of normality, linearity and homoscedasticity are met and the data free of outliers.

4.16 Limitations

As indicated the participants pool was expected to be small considering the smaller number of organisations that can be classified as big data users. This potentially introduced some sampling error (Zikmund, Babin, Carr & Griffin, 2009). Furthermore, the use of snowballing sampling to expand the pool of respondents introduced bias in the data as a result of respondents having similar characteristics, thus low variance in the samples (Biernacki & Waldorf, 1981). Finally, the time horizon for the study was cross-sectional in nature therefore had the potential to introduce bias as a result of the snapshot nature of the study outcome which cannot be extrapolated over time.

Chapter 5

Results and Analysis

"Research is formalised curiosity. It is poking and prying with a purpose"- Zora Neale Hurston

5.1 Introduction

The preceding chapter presented the research methodology, study population, descriptive data presentation and analysis techniques among others. This chapter puts emphasis on data presentation and analysis. The chapter starts by describing the characteristics of the valid respondents followed by data and analysis results presentation. Simply stated the chapter focuses on the estimation, presentation, and interpretation of study findings. Thus, it aims to answer the research questions. A statistical summary, descriptive statistics, correlation analysis, factor analysis and multiple regression analysis are all presented in this chapter. The data and interpretation of results was all done using the SPSS 27 software.

5.2 Characteristics of valid responses

5.2.1 Response rate

It is fair to describe the response rate based on what has been distributed. A total of 144 replies were collected using the online survey questionnaire over a period of 2 months (from August 2021 to September 2021) from the initial target of 120 responses based the research by Mourinho (2017), Ghasemaghaei (2019) and Niland (2017) supported by Cohen (1992) with required sample of 102. Thus, the response rate of 144 is in the upper half of Cohen (1992) guidance of 102 for acceptability in cross-sectional research. Following a thorough assessment of the responses for missing data, all responses received were found to have minimal gaps in all the questionnaire's subsections except for innovativeness and proactiveness that measures Entrepreneurial Orientation. However, these respondents still answered over 50% of the questions. Thus, no responses were left out from being applied in the analysis and the final sample size was 144 responses. This approach was thus in line with what Hair, Black, Babin and Anderson

(2010) prescribed for data selection, which states that variables or cases with over 50% missing data should be deleted. The response rate was thus considered enough based on the research questions.

5.2.2 Demographic data

Figure 5.1 categorises the respondents into male and female. The results show that females were slightly higher than males as depicted by 51% for females and 49% for males respondents.

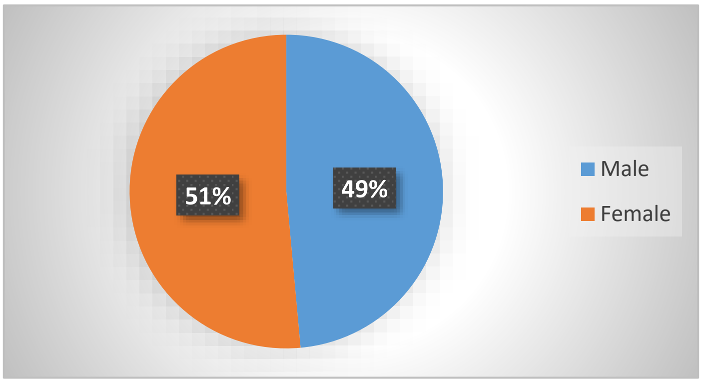

Figure 5.1: Respondents gender categorisation

Figure 5.2 shows the distribution of respondents by age group. Most respondents were in the age group 30 to 39, followed by 40 to 50, followed by 51 to 60, followed by those below 30 and the rest above 60.

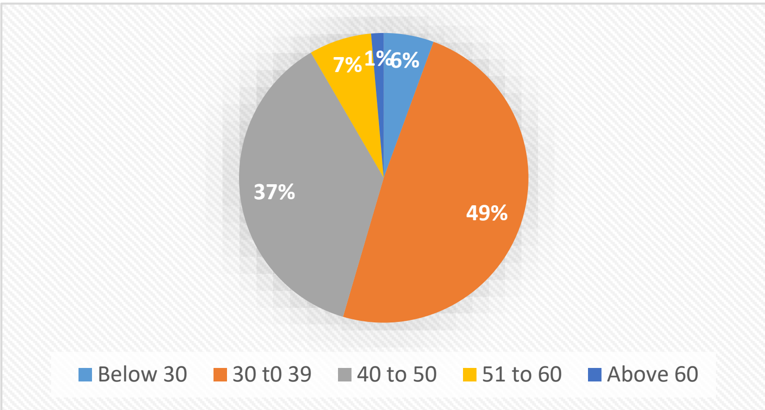

Figure 5.2: Age distribution

Table 5.1 below presents the results on the approximate number of employees in each respondent`s organisation. The results show that 56% of the organisations had more than 1000 employees, 25% had less than 99 employees, 14% had between 100 to 499 employees while 3% did not know the approximate number of employees in their organisations. Only 2% of the organisations had between 500 and 999 employees.

Table 5.1: Approximate number of employees with respondents organisation

Measure	Respondents Number	Percent of total responses
1 - 99	36	25%
100 - 499	20	14%
500 - 999	3	2%
1000 or more	81	56%
Don't know	4	3%

The study objective was to collect data from managers in organisations, irrespective of industry or type. Thus, Figure 5.3 presents the consolidation of respondents` positions in various organisations. The results show that most of the respondents were in the middle management level as shown by 37% contribution. This was followed by junior managers representing 30% of the responses and senior managers accounting for 22%. Finally, the least group were executive managers representing 11% of the overall respondents.

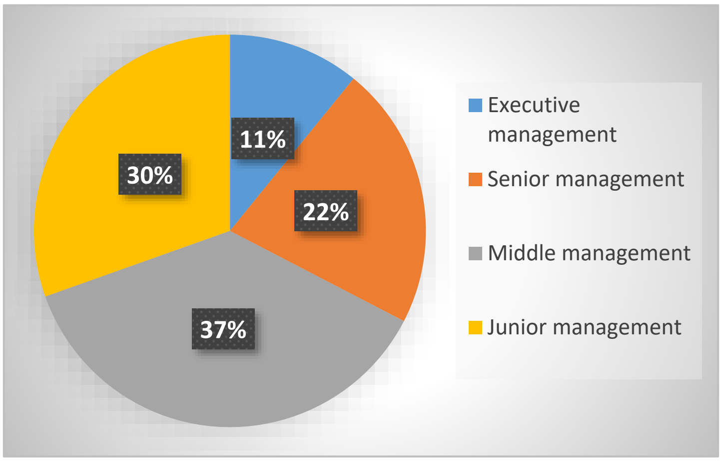

Figure 5.3: Respondent job position

Further to the job position, data on the respondents tenure within the current organisation of employment was collected, Figure 5.4. The majority (37%) of the respondents had 3 to 5 years in their current organisations, followed by 11 or more years with 33%

representation. Respondents with 6 to 8 years and 9 to 11 years tenure accounted for 15% each. Most of the junior managers had 3 to 5 years with their current organisations.

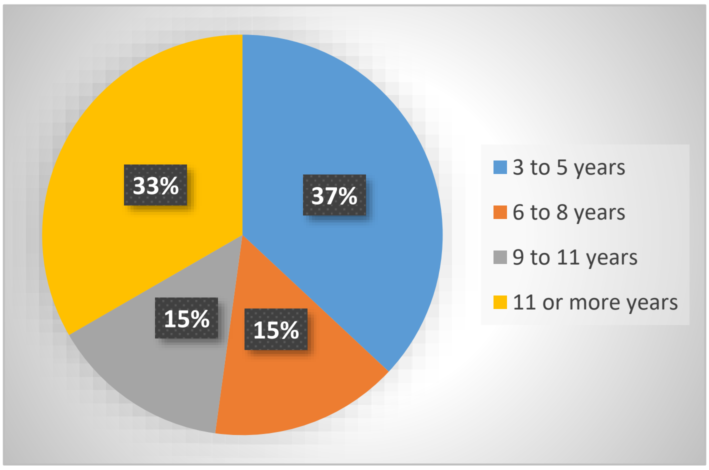

Figure 5.4: Tenure at current organisation

Respondents were also questioned to indicate the industry that their organisations operate in. Figure 5.5 below shows that most of the organisations were in the Chemical sector and Financial service industry represented by 29 and 19 companies respectively. This was followed by Energy with 12, Construction with 7 and Pharmaceuticals with 6. Mining and Manufacturing were presented by 5 companies each followed by Wholesale and Retail with 4. A total of 44 companies of the respondents indicated other while the rest of industries accounted for 13 of the companies.

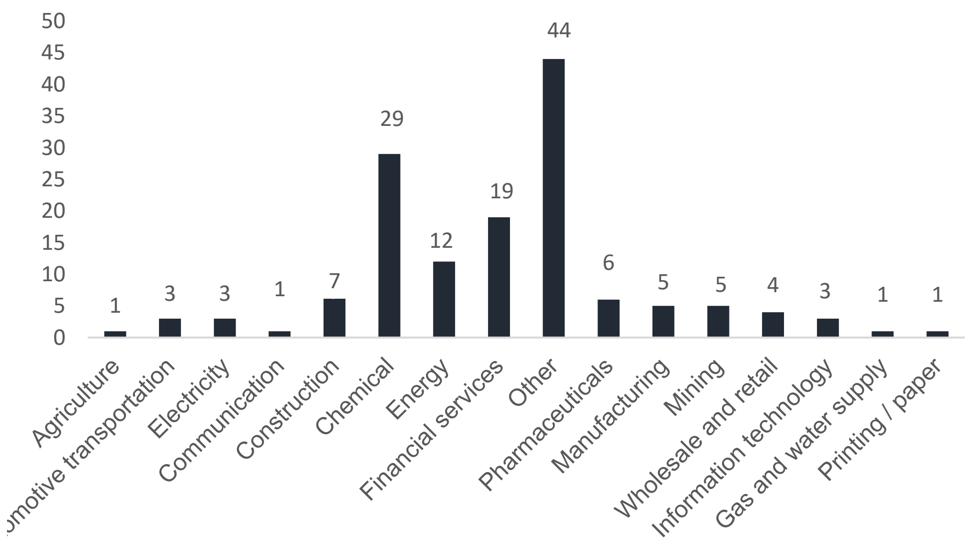

Figure 5.5: Industry in which the organisation operates

5.3 Testing for questionnaire reliability and validity

The stability and consistency of an instrument over time is determined through reliability testing (Saunders, Lewis & Thornhill, 2019). Therefore, reliability test should be carried out before analysing the data obtained using a survey instrument. Internal consistency as a measure of the instrument`s dependability was used in the research. Thus, Cronbach`s Alpha was used to measure the internal consistency of the survey questionnaire instrument (Hair, Black, Babin & Anderson, 2010).

An inter-item correlation matrix was also utilised to explain the validity. The inter-item correlation statistic allows for the detection of replies that were inconsistent with previous responses, potentially compromising the sample's validity. The below section demonstrates the reliability of components that constitutes organisational culture variable.

Table 5.2: The reliability analysis for organisational culture constructs

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.892	0.893	7

The Cronbach alpha value illustrates that the test statistics show internal consistency, as the Alpha has an approximate value that is more than 0.65, Table 5.2. Consequently, it could be further inferred that they are internal consistencies among constructs of organisational culture which would not present any reliability challenges for further analysis.

An illustration of the inter-item statistic is presented in Table 5.3, it was used as an alternative methodology to assess the questionnaire validity. The result presented shows that the study is consistent. The inter-item scale illustrates that none of the scales were redundant indicating some internal consistency within the study.

Table 5.3 shows a questionnaire measuring 7 aspects of organisational culture. The Cronbach's alpha observed was on average 0.89, specifying a high level (>0.65) of internal consistency reliability for the scale. The conclusion also emanates from the item-total Statistics which exemplifies the value that Cronbach's alpha would be if that specific item (any of 7 organisational culture items) was deleted from the questionnaire. Table 5.3

clearly shows that the removal of any question would result in a slightly lower Cronbach alpha. This indicates that organisational culture and the subscales had internal consistency therefore relevantly included in the study.

Table 5.3: Item-Total Statistics for organisation culture

Survey items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Our organisation has a widely held belief that innovation is an absolute necessity for the organisation's future	29.13	76.24	0.617	0.542	0.884
Our organisation enables learning, accumulation and application of new knowledge better than our competitors	29.96	69.16	0.813	0.677	0.861
We believe it is important to adopt new and cutting-edge practices to continuously improve product or service delivery	29.22	73.08	0.73	0.613	0.872
People in our organisation are continuously encouraged to expand their capacities to achieve more and apply new capabilities	29.77	79.23	0.646	0.444	0.882
Our organisation can be described as visionary and flexible	30.26	68.70	0.748	0.59	0.869
There is an extensive employee orientation program for new employees to ensure employees share the corporate vision and purpose	30.05	72.66	0.640	0.454	0.883
We invest in targeted training and support at all levels of our organisation to assist our organisation to understand or know how to use data that is available	30.32	72.49	0.655	0.492	0.881

Note. Survey items sourced from *Hill (2003); Kuratko and Montango (1990); Mourinho, (2017); Niland (2017)*

The above described reliability analysis approach was followed for the other constructs of the questionnaire and the results summarised below.

The overall Cronbach alpha for Decision making in the organisation construct was found to be 0.675. The reliability test is for 8 items that define what decision-making entailed. The Cronbach alpha will decrease if any of the items is deleted for all decision-making variables except for one variable (Internal politics and power struggles). However, if the same variable (Internal politics and power struggles) is deleted the Cronbach alpha will be higher at 0.715. However, Internal politics and power struggles item was not deleted since the alpha satisfied the confines of 0.65 and the deletion did not increase the alpha significant.

The overall Cronbach alpha was determined at 0.939 for entrepreneurship orientation in the organisation. The reliability test was performed on 11 items that defined what entrepreneurship orientation entails. The Cronbach alpha decreased if any item was deleted for all variables except for two variables namely, Top manager's strong emphasis on R&D and risk loving nature which increased alpha to 0.95 and 0.943, respectively. Therefore, there was no justification for deleting any construct within the entrepreneurship orientation.

For knowledge sharing construct, the overall Cronbach alpha yielded 0.893. The reliability test was for 5 items that define what knowledge sharing entails. Here, if any of the one of the variables was deleted, the Cronbach alpha decreased. Therefore, there was no justification for deleting any of the construct within the knowledge sharing.

The overall Cronbach alpha yielded 0.943 for organisational performance constructs. The reliability test was for 7 items that define what organisational performance entailed. If any of the items were deleted for all variables, the Cronbach alpha decreased except for performance6_new product success rate which yielded slightly increased 0.943 alpha. Therefore, there was no justification for deleting any construct within the knowledge sharing.

5.4 Principal Component Analysis (PCA)

This section describes a strategy for reducing huge groups of variables into smaller sets of linear combinations of the original variables (Pallant, 2016). PCA is useful for removing duplicate variables and removing multicollinearity. The objective of this study was to utilise multiple regression to better understand how independent factors like knowledge sharing and organisational culture explain variability in organisational performance. Thus, PCA was expected to decrease the number of explanatory variables required and eliminate multicollinearity.

PCA reduces the items that do not belong to other constructs by checking the multicollinearity scale. A check was performed to ensure that each variable had at least one correlation greater than 0.3 before PCA. Due to the researcher's limited depth in alternative statistical analysis, the eigenvalue rule and a scree test were employed in completing the PCA (Pallant, 2016). The PCA outcome, with component 7 having an eigenvalue of 1.003 is presented in Appendix 4. As a result, the additional component was deemed redundant since it would only explain 2.19% of the overall variance, whereas the first seven components explained 69.02% of the variation.

In examining a scree plot, a point when the curve's shape changes is the area of interest for assessment (Pallant, 2016). Component 7 appears to accentuate the most noticeable inflection point since the curve flattens throughout the duration of the curve. The eigenvalue rule and the scree test both supported the 7-component reduction.

PCA's final and most crucial stage of evaluation is component rotation and interpretation through simple visualisation of loading patterns (Pallant, 2016). There are two ways to rotate factors namely, orthogonal and parallel (uncorrelated) and oblique (correlated) which in most instances provide similar results (Pallant, 2016). For clarity an orthogonal method was adopted.

For this study factor analysis was conducted to evaluate the correlation between identified factors. Factor Analysis denotes to a statistical method describing variability amongst observed and correlated variables while considering the potentially few unobserved variables referred to as factors. Thus, PCA was carried out on all the items.

Table 5.4: Suitability of PCA- KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.887
Bartlett's Test of Sphericity	Approx. Chi-Square	3323.450
	df	561
	Sig.	0

In carrying out the factor analysis, the appropriateness of the observed data for factor analysis was determined through the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and Bartlett's Sphericity test, Table 5.4.

A KMO value greater than 0.5 was considered acceptable, while the result of Bartlett's Test of Sphericity was defined as significant if $p<0.05$. The Kaiser–Meyer–Olkin measures and verifies the sampling adequacy for the analysis was determined at KMO of 0.887, Table 5.4. Bartlett’s test of sphericity Chi-Square was calculated at (df = 561) of 3323.45, $p < 0.001$, which was an indication that the relationships amongst items were suitably large for the PCA.

Kaiser’s criterion of eigenvalue over 1 was utilised to determine the number of components extracted for the factor analysis and the result verified using a scree plot (Appendix 5).

The factor loadings were rotated using Oblimin with the Kaiser Normalisation method, and items with loadings of the absolute value of 0.4 and above were considered good loadings, Appendix 7.

Only seven (7) components had eigenvalues greater than Kaiser's criterion of one, consistent with the scree plot result (Appendix 5). These seven components account for 69.02% of the overall variance in the data collected. Component 1 accounts for 34.90% of the total variation. Component 2 for 9.08% of the total variation. Component 3 for 7.94% of the total variation. Component 4 for 5.74% of the total variation. Component 5 for 4.79% of the total variation. Component 6 for 3.56% of the total variation, and component 7 for 2.95% of the total variation (Appendix 5). The results also showed that majority of the extracted seven (7) components constituted more than half of the total variance in each object as measured by the communalities values (Appendix 7) except for DM7 and DM8.

Factor loadings result after rotation (using Oblimin with Kaiser Normalisation Method, Appendix 5) revealed that OC6 and OC3 had a very high positive loadings on Component 1. OC2, OC4, DM1, DM2 DM6, DM7 and MD8 had a high positive loading on Component 1. EO9, EO10 had highest loadings on Component 2. In contrast, EO11 had high positive loading on Component 2. Moreover, all performance measure (performance_1 to 6) had very high negative loading on component 3. Knowledge sharing 1 to 5 had very high negative loading on component 4. EO2, E04, E6 and E08 had a high positive loading on component 5. For component six most of the variables had a weakly positive or negative direction. However, E09, EO10 and EO11, had high positive loadings on Component 2. EO1 had high positive loadings on Component 7. DM4 and DM5 had very high loadings, which were positive and identified as component 6. DM3 had a high positive factor loading on component 6. The Appendix 6 gives the correlation of the variables with the components.

Moreover, on general PCA (Appendix 8), the result reveals that OC2 and OC5 had very high positive correlations at Component 1. OC4, OC4, OC5, 0C7, DM1 had high positive correlation with component 1. DM2, OC3 and DM2 had high positive correlations with Component 1. EO9, EO10 and EO11 had very high correlations with Component 2. In contrast, performance 4 and performance 5 had very high negative correlation with Component 3. Moreover, the result shows that Knowledge sharing variables had a very strong negative correlation with component 4. EO2, EO4 and E06 had very high positive correlation with component 5.

DM3 and DM5 had a very high positive correlation with factor six. Finally, there was a high positive correlation of DM4 at component 7.

The Component Correlation Matrix shows moderate correlations among some of the extracted components. Table 5.5 below shows the list of extracted components together with the statistics for each of the components.

Table 5.5: Component Correlation Matrix

Component	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	1	0.166	-0.381	-0.467	0.24	0.026	0.189
2	0.166	1	-0.15	-0.197	0.261	-0.194	0.024
3	-0.381	-0.15	1	0.341	-0.304	-0.032	-0.161
4	-0.467	-0.197	0.341	1	-0.201	0.067	-0.183
5	0.24	0.261	-0.304	-0.201	1	-0.045	0.114
6	0.026	-0.194	-0.032	0.067	-0.045	1	-0.005
7	0.189	0.024	-0.161	-0.183	0.114	-0.005	1
Extraction Method: Principal Component Analysis. Rotation Method: Oblimin with Kaiser Normalization.							

The reliability analysis results have shown that the Cronbach's Alpha value for all the Components attains the acceptable alpha value of 0.6 – 0.7 except Component 4 with an alpha value of 0.571, Table 5.6.

All the items under each component appear to be worthy of retention as none of the items would cause a significant increase in the alpha value if removed. The inter-item correlation matrix showed that most of the items under each component were highly correlated. Component 1 with an eigenvalue of 7.02 accounted for 35.10% of the total variation in the observed data. Cronbach's Alpha value of 0.808, Component 2 with an eigenvalue of 2.17 accounted for 10.80% of the total variation in the observed data. Cronbach's Alpha value of 0.782, Component 3 with eigenvalue of 1.81 accounted for 9.10% of the total variation in the observed data. Cronbach's Alpha value of 0.772, Component 4 with eigenvalue of 1.48 accounted for 7.40% of the total variation in the observed data.

Component 5 with eigenvalue of 1.24 with Cronbach's Alpha value of 0.571 accounted for 6.20% of the total variation in the observed data. Cronbach's Alpha value of 0.716, Component 6 with eigenvalue of 1.11 accounted for 5.50% of the total variation in the observed data. While Component 7 with eigenvalue of 1.02 with Cronbach's Alpha value of 0.688 accounted for 5.10 of the total variation in the observed data.

Table 5.6: Reliability Analysis of Components

Component	**Eigen-value**	**% variance Explained**	**Cronbach's Alpha**	**Scale Statistics**			
				Mean	Variance	Standard Deviation	No. of Items
1	7.02	35.1	0.808	16.42	9.059	3.010	5
2	2.17	10.8	0.782	3.56	5.11	2.260	2
3	1.81	9.1	0.772	16.26	7.623	2.761	5
4	1.48	7.4	0.571	5.56	0.729	0.854	2
5	1.24	6.2	0.716	9.86	3.171	1.781	3
6	1.11	5.5	0.688	13.67	8.034	2.834	4
7	1.02	5.1					1

In summary, the 34 questions used to assess respondents were PCA'd. The correlation matrix indicated that all variables had a correlation coefficient of at least 0.3 before the test. The total KMO was 0.790 with all KMOs over 0.7. Finally, Bartlett's sphericity test confirmed the data to be factorisable (p.0005).

The PCA found seven components (eigenvalues greater than 1), accounting for 35.10%, 10.80%, 9.10%, 7.40%, 6.20%, 5.50% and 5.10% of the total variance. The scree plot visual assessment also advised on keeping the seven components, which was further validation to this conclusion. Thus, this solution explained 79.20% of the variation. Finally, a Varimax orthogonal rotation was employed to help in component understanding.

5.5 Descriptive statistics

Meaningful and relevant descriptive statistics were derived from data to express the amount of knowledge sharing, decision making, entrepreneurship orientation and organisational culture in organisational performance. The research shows that defining these variables is important in setting the theme for correlation, factor analysis and regression analysis (Hair, Black, Babin & Anderson, 2010). By taking the mean of all the different items derived from every respondent, the total scale scores of all the research constructs were calculated. Calculating the mean allowed for an easier interpretation of the total scale scores as the scores were in the original scales (Pallant, 2016). Thus, the various table below summarises the implications of the different scales scores.

5.5.1 Knowledge Sharing towards big data analytics use

This section of the questionnaire was directed at gathering data on information sharing in various companies. Respondents had to respond to statements pertaining to “how often do their data analysts exchange information/knowledge within their organisations in relation to the use of data analytics tools”. Table 5.7 shows the spread of the results obtained with 5 representing (a lot), 4 (regularly), 3 (sometimes), 2 (rarely) and 1 representing never, Table 5.7.

The section responded to the hypothesis that data analysts exchange information/knowledge with the rest of their organisation.

The first statement collected data on whether data analysts exchanged information/knowledge on business goals within the rest of their organisation. It was revealed that 9.10% never shared, 24.80% rarely shared, 28.00% sometimes shared, 28.70% regularly shared and 9.80% shared a lot. A mean of 2.97 was recorded. According to (Saunders, Lewis & Thornhill, 2019), the mean score can be used to inform data interpretation on a Likert scale with neutral serving as a point reference for low and high scores on a question asked. Deductively, a score greater than the neutral point at 2.5

was considered agreeing to higher scores while those below the neutral point was considered low or disagreeing to the question asked. Since the mean was recorded at 2.97, it was determined that few people indicated that they share information like business goals and its external environment with the rest of their employees, Table 5.7.

Data on whether data analysts exchanged information/knowledge on precise conditions of a given analysis such as numerical projections and market forecasts within the rest of their organisations was gathered. The results showed that 7.70% never shared, 20.30% rarely shared, 28.00% sometimes shared, 34.30% regularly shared and 9.80% shared a lot. Since the mean was recorded at 3.09 indicating most organisations shared information on definite conditions of a given analysis like market forecasts, Table 5.7.

Data on whether analysts exchanged information/knowledge on analytical techniques such as statistical tools and testing procedures within the rest of their organisations. It was revealed that only 14.70% never shared such information. The rest of the respondents indicated that their analysts share information on analytical techniques, with 23.80% rarely sharing, 32.20% sometimes sharing, 18.20% sharing regularly and 11.20% sharing a lot. The mean score at 2.77 was considered agreeing to higher scores. Thus, most organisations shared information on Analytical techniques which included statistical tools, methods or testing measures, Table 5.7.

Table 5.7: Knowledge sharing.

Survey items	Never	Rarely	Sometimes	Regularly	A lot	MEAN
General overviews (e.g. business goals, external environment	9.10%	24.50%	28.00%	28.70%	9.80%	2.97
Specific requirements of a given analysis (e.g. numerical projections, market forecasts)	7.70%	20.30%	28.00%	34.30%	9.80%	3.09
Analytical techniques (e.g. statistical tools, detailed methods, or testing procedures)	14.70%	23.80%	32.20%	18.20%	11.20%	2.77
Progress reports (e.g. status updates, resource problems)	6.30%	18.20%	27.30%	24.50%	22.40%	3.18
Analysis results (e.g. preliminary findings, unexpected outcomes, or clear recommendations)	0.80%	18.90%	30.10%	26.60%	14.70%	3.03

Note. Survey items sourced from *Cummings (2004); Mourinho, (2017); Niland (2017)*

Responses on the sharing of information with regard to progress reports including status updates and resource constrains by data analysts showed that 6.30% never shared such information, 18.20% rarely shared, 27.30% sometimes shared, 24.50% regularly shared and 22.40% shared a lot. The mean score at 3.18 was considered agreeing to higher scores. As such, most organisations share information on progress reports, Table 5.7.

Table 5.7 above provides a description on how descriptive statistics and means were determined. For the remainder of the descriptive statistics for this section similar tables will be presented in the Appendices section to make the section decipherability.

The last statement of this section assessed how analysts exchanged knowledge on analysis results including preliminary findings, unexpected outcomes or recommendations within their organisations. The results showed that almost 100% of the companies exchanged such knowledge as only 0.80% of the respondents indicated that their organisations never shared information on analysis results. This was only one respondent out of the 143 valid responses. The rest of the organisations shared information on analysis results with 18.90% rarely sharing, 30.10% sometimes sharing, 26.60% regularly sharing and 14.70% sharing a lot. The mean score at 3.03 was considered agreeing to higher scores. As such, most organisations shared information analysis results. Overall, the mean score is 3.01 which implied that generally people agree that their organisation want to share information from big data analytics Table 5.7.

5.5.2 Organisational culture towards big data analytics use

This section sought to collect data pertaining to organisational culture towards Big Data Analysis use, Appendix 9. Several respondents indicated that innovation played an important role in their organisation’s future. This was exemplified by 44.10% who indicated to strongly agree, 23.10% who agreed and 16.10% who moderately agreed. This gave a total of 83.30% of the respondents being in support of the statement that innovation was an absolute need in their organisation`s future and 11.90% of the respondents were against the statement. This 11.90% was made up of 3.50% who strongly disagreed, 0.70% who disagreed and 7.70% who moderately disagreed. Only 4.90% of the respondents indicated neutrality. The mean score at 5.66 is greater than neutral point at here 4 such that its considered agreeing to higher scores. As such, most organisations have a culture that consider innovation as an absolute necessity.

It was sought to establish if these organisations aided learning, application and accumulation of new information better than its rivals. The results revealed that majority of the respondents supported the statement as indicated by the 26.60% moderately agreeing, 22.40% agreeing and 21.00% strongly agreeing. This gave a total of 70.00% of the respondents being in support that their organisations enable "learning, accumulation and application of new knowledge better than its competitors". 19.10% of the respondents indicated neutrality, 11.90% moderately disagreed, 4.90% disagreed and 4.20% strongly disagreed. This gave a total of 21.00% being against the statement. The mean score at 4.83 was considered agreeing to higher scores. As such, most organisations had a culture that consider application and accumulation of new information healthier than its rivals.

Respondents were also asked if it is vital to unceasingly advance product or service through adaptation of new and cutting-edge practices. The results revealed that it is crucial to incessantly advance product or service through adaptation of new and cutting edge. The table in Appendix 9 summarises the results with 39.20% indicating strongly agree, 28.00% agreeing, 14.00% moderately agreeing, 5.60% being neutral, 7.00% moderately disagreeing, 4.90% disagreeing and 1.40% strongly disagreeing. The mean score at 5.56 was considered agreeing to higher scores. As such, most organisations have a culture that improve product or service through adaptation.

Data on whether people in the organisations are increasingly advised to increase their capacities to attain more and use new capabilities was also collected. It was shown that majority of the companies encourage their people to expand their capacities. Descriptive statistics tabulated in Appendix 9 showed that 18.90% strongly agreed, 18.20% agreed, 27.30% moderately agreed, 22.40% were neutral, 8.4% moderately disagreed, 3.50% disagreed and 1.40% strongly disagreed. This gave a total of 64.4% being in support of the statement and only 13.40% who were against the statement. The mean score at 5.01 is greater than neutral point at 4 such that it considered agreeing to higher scores. As such, most organisations have a culture that continuously encourage to expansion of capacities to attain more and apply innovative capabilities.

Respondents were also asked to indicate if their organisations can be described as visionary and flexible. The results tabulated in Appendix 9 showed that 18.90% strongly agreed, 21.70% agreed, 22.40% moderately agreed, 9.80% were neutral, 8.40% moderately disagreed, 13.30% disagreed and 5.60% strongly disagreed. This showed that majority of the organisations were visionary and flexible, as supported by a total of 63.00% of the respondents. Only 27.30% of the firms were not flexible and visionary. The mean score at 4.52 was considered agreeing to the culture of being visionary and flexible.

The questionnaire further sought to evaluate the existence of a substantial employee onboarding program for new workers to certify workers segment the corporate purpose and vision. It was revealed that most companies had respondents agree to the statement that “an extensive employee orientation program for new employees to ensure employees share the corporate vision and purpose”. This is exemplified by a total of 65.10% of the respondents being in support of the statement, 7.00% being neutral and 28.00% being against the statement. The mean score at 4.74 was considered agreeing to the culture of extensive employee orientation program.

In addition, data was gathered to see if firms invest in targeted training to help their organisations to know how data that was being used. The results presented in the table in Appendix 9 showed that majority of the organisations invest in targeted training and support. 12.60% of the respondents strongly agreed, 30.80% agreed, 16.80% moderately agreed, 12.60% were neutral, 11.90% moderately disagreed, 12.60% disagreed and 2.80% strongly disagreed.

This gave a total of 58.20% of the companies investing in targeted training and support against 25.30% who did not invest in targeted training and support. The mean score of 4.47 was greater than neutral point at 4 such that it was considered agreeing to the culture of capitalising in tailor-made training and support at different stages of the organisation to help the organisation to understand how to utilise data at their disposal.

Overall, the mean score for this construct was 4.97 which implied that respondents agree that their organisations had a positive culture that supports big data analytics.

5.5.3 Decision making in the organisation

Henceforth, the focus was on establishing whether the decision-making process was being used by various firms based on the questionnaire. To gain an insight into the data used in decision making, respondents were requested to specify the extent to which they agree or disagree with the statements shown in a table in Appendix 10.

The Likert scale used ranged from strongly agree - 7, agree - 6, moderately agree - 5, neutral - 4, moderately disagree - 3, disagree - 2 and strongly disagree - 1. The responses to whether organisations methodically analyse internal data to know the kind of the challenges and how to respond before any decision making are presented in Appendix 10. Review of the responses showed that 16.80% strongly agreed, 20.30% agreed, 24.50% moderately agreed, 18.90% were neutral, 11.2% moderately disagreed, 4.20% disagreed and 4.20% strongly disagreed. This gave a total of 61.60% of those who indicated that their organisations steadily analyse internal data to deconvolute the type of challenges and what to do prior to any decision making. Only 19.60% of the respondents expressed that their organisations do not methodically analyse data before decision making. The mean score at 4.85 was considered agreeing to organisational decision taken methodically analyse internal data to better know the type of the challenge.

Data on whether workers receive credit from the firm for using evidence-based decision making in their typical business developments was also collected. The results showed 11.20% strongly agreed, 30.10% agreed, 21.70% moderately agreed, 11.90% were neutral, 11.20% moderately disagreed, 8.40% disagreed and 5.60% strongly disagreed.

Thus, many companies gave recognition to their employees for using evidence-based decision making in their distinctive business processes. This is shown by a total of 63.00% being in support of the statement compared to 25.20% who were against the statement. The mean score at 4.48 was considered agreeing to organisational decisions that apply evidence-based decision making in business activities.

Another statement in this section derived from the survey questionnaire sought to determine if managers in organisations are "inclined to believe that experience and knowledge attained on the job were the only vital source of information when deciding how to confront a challenge". The results show that managers in less than half of the organisations were inclined to believe that on the job experience and knowledge was the only important information basis when considering how to attack a problem. This was shown by a total of 40.60% supporting the statement. In deconvoluting this figure further it was found that 8.4% strongly agreed, 16.10% who agreed and 16.10% moderately agreed. The results showed that 23.10% of the respondents were neutral. A total of 35.00% of respondents were against the statement which was made up of 5.60% strongly disagreeing, 8.40% disagreeing and 21.00% moderately disagreeing. The mean score at

4.19 was considered agreeing to organisational decisions that believe in knowledge and experience obtained on the job was the only crucial basis of information.

Results on whether organisations make their decisions by examining what competitors are doing and how they are performing showed that only 35.70% supported the idea of copying, a total of 27.30% were against the statement. Most of the respondents at 37.10% were neutral. The mean score at 4.1 was considered agreeing to organisational decisions that looks at what other businesses are performing, and how it's operating for them.

On assessing the responses on the influence of internal politics and power struggles on policies and practices decision making it was found that 40.60% of the respondents were affected by internal politics and owner struggles. The results showed that 28.70% of the respondents` firms are not influenced by internal politics and power struggles in decision making. A total of 30.80% of the respondents indicated neutrality to the influence of internal politics and power struggles on decision making. The mean score at 4.36 was considered agreeing to organisational decisions that believe power struggles and internal politics affect the way organisations make decisions about policies and practices.

The research further sought to determine if organisational competitiveness depends on their analytics capability. Most of the respondents (58.10%) supported the statement that their organisational competitiveness depends on their analytics capability with only 25.20% being against the statement and 16.80% being neutral. The mean score at 4.37 was considered agreeing to organisational decisions that think that organisational competitiveness relies on data analytics ability, Appendix 10.

This part of decision-making presents data on whether all decision makers had access to a management information system. Respondents had to respond to the statement with either of the following options; never - 1, rarely - 2, very rarely - 3, occasionally - 4, frequently - 5, very frequently - 6 and always - 7, Table 5.8. The results show that majority of decision makers have access to information system as exemplified by 28.50% always accessing, 16.70% accessing very frequently, 22.90% frequently accessing, 14.60% occasionally accessing, 11.90% rarely accessing, 4.90% rarely accessing and 0.70% never accessing. The mean score at 5.8 was considered agreeing to access to a management information system.

Assessing the decision-making dimension on whether managers have the competency of critically evaluating both internal data and evidence derived from scientific research. Respondents had to respond with either; none of them (1), some of them (2) or all of them (3), Table 5.8.

Table 5.8: Managers knowledge to assess scientific research

Survey items	1	2	3
Our managers know how to critically appraise both internal data and evidence from scientific research	4.90%	84%	11.20%

Note. Survey items sourced from *CEBMa (2013); Mourinho, (2017); Niland (2017)*

Most respondents supported the statement that "managers know how to critically appraise both internal data and evidence from scientific research" with a total of 95.10% while only 4.90% were against the statement, Table 5.8.

5.5.4 Entrepreneurial orientation (EO)

This section of the questionnaire was aimed at gaining an insight on entrepreneurial orientation of the various organisations. Firstly, innovativeness which is a sub-dimension of EO was evaluated with the results tabulated in Appendix 11. In response to the statement that generally the top managers of their firms puts strong emphasis on marketing of fully developed products and services, majority (51.10%) of the respondents supported the statement while a total of 21.70% were against the statement. 27.30% of the respondents indicated neutrality to the statement. The mean score at 4.13 is greater than neutral innovativeness at 4 such that it was considered agreeing to strong emphasis on the marketing of fully developed products and services.

Furthermore, the respondents were asked whether the "firm produced and marketed new lines of products or services in the past 5 years". Responses showed that 39.20% of the respondents confirmed that their firms produced no new lines of products or services in the past 5 years. A similar proportion of 39.20% also expressed that their organisations had produced new lines of products or services in the past 5 years. 21.60% of the respondents expressed neutrality. The mean score at 2.94 was considered disagreeing to the statement that there were no new lines of products or services their firms have marketed in the past 5 years, Appendix 11.

Responses to the statement whether modifications in product or service lines had been mostly negligible nature showed that most of the respondents (44.10%) were against the statement. This figure was composed of 14.00% who strongly disagreed, 14.70% who disagreed and 15.40% who moderately disagreed. On the other side a total of 32.70% expressed that those modifications had been mostly minor in nature. While 24.50% of the expressed neutrality. The mean score at 4.38 was considered agreeing to the statement that changes in product or service lines have been mostly negligible nature

The second part of this section focused on organisational proactiveness as another dimension of EO, Appendix 11. Regarding the statement on whether “in dealing with its competitors, firms typically responds to actions initiated by competitors”, the results showed that a total of 40.60% supported the statement, 35.00% were against the statement and 24.50% expressed neutrality. The mean score at 3.88 was considered disagreeing to firm typically responding to actions initiated by competitors.

To establish if firms were occasionally the first to present new products and services. The results obtained showed that several respondents supported the statement at 38.20% while 35.70% were against the statement. A total of 25.20% expressed neutrality to the statement. The mean score at 3.99 was considered disagreeing to the statement that “in dealing with its competitors, the firm is rarely the first firm to introduce new products/services, technologies”.

The last statement of this section which evaluated “in dealing with its competitors, my firm typically seeks to avoid competitive clashes, preferring an ‘indifferent’ posture”. The results showed that 39.90% supported the statement, 30.80% were against the statement and 29.4% were neutral. The mean score at 5.18 was considered disagreeing to the statement.

Shifting focus to risk taking behaviour of the various companies, Appendix 11. The results showed that generally, the top managers of many firms do not support low risk projects with standard and guaranteed rates of return. This was confirmed by 42.70% of the respondents being against the statement compared to 35.70% who expressed support. Only 21.70% of the respondents remained indifferent. This demonstrated that generally top managers of many firms’ support high risk projects with potential for very high return.

The mean score at 4.2 was considered agreeing to firm favouring low risk projects with guaranteed rates of return.

Responses to the statement on whether generally, “the top managers favour a cautious, wait and see posture in order to reduce the probability of making costly decisions when confronted with uncertainty” showed that majority of the top management do not favour a wait and see approach. This was clearly shown by 43.40% of respondents being against the statement compared to 37.10% who were in support of the statement. Respondents who were indifferent accounted to 19.60%. This demonstrated that generally, the top managers of many firms favour a courageous posture to maximise the likelihood of exploiting new potential when confronted with ambiguity. This supports the above findings on risk taking behaviour that most managers prefer high risk high returns projects. The mean score at 3.78 was considered disagreeing to the statement.

The last aspect of this section gathered data on whether “the top managers of many firms generally believe that owing to the nature of the environment, it was best to explore gradually through cautious behaviour”, Appendix 11. The results showed that 7.70% of the respondents strongly agreed, 11.90% agreed, 21.00% moderately agreed, 23.80% were indifferent, 13.30% moderately disagreed, 11.90% disagreed and 10.50% strongly disagreed. This gave a majority of 39.60% being in support of the statement compared to a total of 35.70% who were against the statement. However, the difference was relatively small with a significant number of managers believing that due to the nature of the environment, courageous and varied actions were needed to realise firm`s goals. The mean score at 3.78 was considered disagreeing to the statement, Appendix 11.

5.5.5 Organisational performance

This section of the questionnaire gathered data on how big data analytics related to organisational performance. It was hypothesised that data analysis had a positive effect on firm financial and market performance. Respondents had to respond either with: strongly disagree - 1, disagree -2, moderately disagree - 3, indifferent - 4, moderately agree - 5, agree - 6 and strongly agree - 7, Appendix 12.

In response to the statement that “using big data analytics improved customer retention during the last 3 years relative to competitors”, 47.60% of the respondents supported the statement, 27.30% were indifferent and 25.20% were against the statement. This showed that data analytics improved customer retention for most of the organisations over the past 3 years. The mean score at 3.81 is smaller than neutral or indifferent point at 4 such that it was considered disagreeing to using big data analytics to enhanced customer retention in relation to rivals.

Data on whether using big data analytics enhanced sales growth in the last 3 years in relation to rivals was also collected. It was found that 8.40% of the respondents strongly agreed, 18.30% agreed, 19.60% moderately agreed, 25.90% were indifferent, 10.90% moderately disagreed, 9.10% disagreed and 4.90% strongly disagreed. Thus, the results revealed that data analytics improved sales growth for 46.20% of the organisations. It was also shown that data analytics did not improve sales growth for 24.90% of the companies. The mean score at 3.83 was considered disagreeing to the statement.

Data was further collected on whether "using big data analytics improved profitability during the last 3 years relative to competitors". It was shown that data analytics improved profitability as shown by 49.70% of the respondents expressing support of the statement against 27.30% who did not support the statement. Furthermore, 23.10% of the respondents were indifferent to whether the use of big data analytics had enhanced profitability over the past 3 years. The mean score at 3.92 is slightly less then the indifferent point at 4 such that it was considered respondents being indifferent to profitability enhanced from big data analytics in relation to competitors. This thus justifies further analysis through inferential statistics.

Respondents were also asked to indicate if "using big data analytics increased Return on Investment (ROI) during the last 3 years in relation to competitors". The results show that a total of 45.50% supported the statement, 25.90% were against the statement and 28.70% were indifferent. The mean score at 3.77 is less than indifferent point at 4 such that it was considered disagreeing to the statement in relation to competitors.

Data on whether employing big data analytics enhanced collective monetary performance in the last 3 years in relation to rivals was also gathered. A total of 46.20% supported the statement that the use of data analytics enhanced ROI during the last 3 years compared to rivals. A total of 27.30% expressed that the use of data analytics failed to enhance their organisations` ROI over the past 3 years in relation to their rivals. The mean score at 3.82

was considered disagreeing to the statement that in the last 3 years big data analytics improved net financial performance of the firm in contrast to rivals, Appendix 12.

In relation to the statement that the organisations` success rate of new products or services being higher than their rivals a total of 41.30% expressed support for the statement, 29.40% were indifferent and 29.40% were not in support of the statement. Thus, organisation`s proportion of success of new products or services being higher relative to their rivals for majority of the firms. The mean score at 3.63 was considered disagreeing to higher success rate relative to peer rivals on new products or services.

The last statement on the questionnaire sought to establish whether using analytics had led market share to exceed that of competitors. The results show that 4.90% strongly agreed, 11.90% agreed, 18.20% moderately agreed, 32.90% were indifferent, 11.20% moderately disagreed, 11.90% disagreed and 9.10% strongly disagreed. This gave a total of 35% being in support of the statement against a total of 32.20% who were against the statement. The mean score at 3.28 was considered disagreeing to market share has exceeding that of competitors research findings are shown in Appendix 12.

Overall organisations performance would be low in relations to big data analytics. The overall mean score at 3.72 is smaller than indifferent point at 4 such that it considered disagreeing to market share had exceeding that of competitors research findings are shown in Appendix 12.

The overall descriptive statistics for the various for the various constructs studied are summarised below in Table 5.9 with standard deviations.

Table 5.9: Overall means and Standard deviations

	Overall mean	**Standard Deviation**	**Median**
Knowledge Share	3.01	0.99	3.00
Innovativeness	3.89	1.75	4.00
Proactivess	3.93	1.85	4.00
Risk taking	3.92	1.69	4.00
Financial Performance	3.72	1.88	3.00
Organisational Culture	4.97	1.80	5.00
Data_Decision making	4.20	1.50	4.50
Entrepreneurial Orientations	3.91	1.75	4.00

5.5.6 Linkage between knowledge sharing and firm performance

The intention of the first research question was to decipher the relationship between knowledge sharing and firm performance. Various sub-dimensions of firm performance and knowledge sharing were considered before explaining the overall relationship between the two constructs. This section provides results on the correlations between the two constructs namely, knowledge sharing and organisational performance. The conclusions in this section are normally based on following thresholds or decision rule on correlation summarised in Table 5.10 (Mukaka, 2012).

Table 5.10: Correlation Benchmarks

Size of the correlation	Interpretation
+/-0.90 to +/-1.0	Ver high positive (or negative) correlation
+/-0.70 to +/-0.90	High positive (negative) correlation
+/-0.50 to +/-0.70	Moderate positive (negative) correlation
+/-0.30 to +/-0.50	Low positive(negative) correlation
+/-0.00 to +/-0.30	Negligible correlation

Note. Reprinted from "Statistics Corner : A guide to appropriate use of correlation coefficient in medical research," by M.M. Mukaka, 2012. *Malawi Medical Journal*, *24*(3), p. 71

The magnitude of the relationship between specific knowledge sharing constructs and firm performance was determined by the Pearson product moment correlation shown in Table 5.10 below. Table 5.11 presents correlation matrix for research question 1 which addresses a relationship between Knowledge sharing and organisational performance.

Table 5.11: Relationship between knowledge sharing and firm performance

	Knowledgeshare1_General overviews	Knowledgeshare2_Specific requirements	Knowledgeshare3_Analytical techniques	Knowledgeshare4_Progress reports	Knowledgeshare5_Analysis results	Performance1_customer retention	Performance2_Sales Growth	Performance3_Profitability	Performance4_ROI	**Performance5_OVERALL**	Performance6_newproductsuccessrate	Performance7_marketshareincrease	Knowledge_Sharing
Knowledgeshare1_General overviews	1												
Knowledgeshare2_Specific requirements	0.635**	1											
Knowledgeshare3_Analytical techniques	0.526**	0.651**	1										
Knowledgeshare4_Progress reports	0.630**	0.636**	0.529**	1									
Knowledgeshare5_Analysis results	0.617**	0.693**	0.589**	0.757**	1								
Performance1_customer retention	0.332**	0.285**	0.337**	0.289**	0.346**	1							
Performance2_Sales Growth	0.316**	0.328**	0.349**	0.336**	0.330**	0.877**	1						
Performance3_Profitability	0.348**	0.333**	0.288**	0.296**	0.325**	0.741**	0.835**	1					
Performance4_ROI	0.409**	0.404**	0.375**	0.339**	0.380**	0.742**	0.799**	0.841**	1				
Performance5_OVERALL	0.410**	0.354**	0.335**	0.280**	0.306**	0.713**	0.748**	0.821**	0.896**	1			
Performance6_newproductsuccessrate	0.239**	0.352**	0.247**	0.323**	0.325**	0.556**	0.573**	0.512**	0.594**	0.551**	1		
Performance7_marketshareincrease	0.282**	0.242**	0.202*	0.259**	0.268**	0.664**	0.705**	0.574**	0.671**	0.616**	0.684**	1	
Knowledge_Sharing	0.814**	0.863**	0.792**	0.844**	0.873**	0.380**	0.396**	0.380**	0.456**	0.404**	0.354**	0.299**	1

Overall, there was a positive relationship between all constructs of knowledge sharing and organisational performance. However, the relationship was found to be either negligible (0.00 to +0.30) or low positive (+0.30 to +0.50).

Table 5.11 shows negligible positive relationship between organisational performance measured by market share and knowledge sharing. This implied that the relation was positive and significant but very negligible to increase market share.

For knowledge sharing 1 (i.e. which is general sharing of business goals, eternal environment and mission statement) it had a very negligible positive relationship with new product success rate such that it also had negligible positive relationship with increase in market share compared to its competitors. The knowledge sharing 1 had a low positive relationship with most of the performance measures (i.e. customer retention, sales growth, profitability, return on investment and overall performance). On knowledge sharing (i.e. sharing of specific numerical projections and market forecasts) showed a positive but a negligible relationship with customer retention, market share increase.

A low positive relationship is however realised between knowledge sharing 2 with sales growth, profitability, return on investment, new product success rate and the overall performance. For knowledge sharing 3 (i.e. sharing of progress report) there is negligible relationship with customer retention and company profits. However, a low positive relationship was found with sales growth, return on investment and product success rate. There was an overall negligible relation of knowledge sharing with progress report and overall performance. Finally, knowledge sharing through analysis of results showed a low negative relationship with customer retention, sales growth, profits, return on investment, new product success rate, and overall performance. Moreover, the market share performance measure had a negligible positive relationship with knowledge sharing through analysis results. Overall, the relationship between knowledge sharing and overall performance was low (r=0.404), Table 5.11.

5.6 Analysis Based on the Regression Model

5.6.1 Running and interpreting the regression for research question 1

Since the requirement of the above-mentioned regression assumptions in Chapter 4 were met, the SPSS program was used to run the regression. After running SPSS, the model estimated was expressed as follows:

Financial and Market share performance= -5.36 + 0.271 (Organisational Culture) + 0.204 (Data_Driven_Decision_Making) + 0.085 (Entrepreneurial Orientation) + 0.172 (Knowledge_Sharing)

The model estimated showed that organisational culture, entrepreneurial orientation, knowledge sharing, and data driven decision making had a positive impact on financial and markets performance (organisational performance). However, entrepreneurial orientation had an insignificant impact as exemplified by p-values >0.05. The model had the following outputs to demonstrate how the above summary of estimated regression (Interpretations are made after presenting output) was arrived at.

Table 5.12: Model Summary[c] for research question 1

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.578a	0.334	0.315	10.669
a. Predictors: (Constant), Knowledge Sharing, Entrepreneurial Orientation, Data_Driven_Decision_Making, Organisational Culture				

Table 5.12 is the first table that showed the model summary and showed that the model allowed specification of multiple models in a single regression command. The SPSS output provided different forms of **R**'s. It provided R^2, R, Adjusted R^2 and the estimated standard error. All the Rs squared studied the effectiveness of independent variables in explaining the dependent variable.

The following specific interpretation were made (Gujarati, 2021; Lawrence, 2019):

The R defined the square root of R-Squared. The R-Square as indicated by Gujarati (2021) as the quantity of variance in the dependent variable (i.e. financial and market performance) which can be forecasted from the independent variables (i.e. knowledge sharing, entrepreneurial orientation, data driven decision making and organisational culture). This value indicated that 33.40% of the variation in Financial_and_Market_performance could be predicted from knowledge sharing, entrepreneurial orientation, data driven decision making and organisational culture. The Adjusted R-square analysis was aimed at producing a reliable value to approximate the R-squared for the population after considering the degree of freedom (Gujarati, 2021). The value of R-square and Adjusted R-square were 0.334 and 0.315, respectively.

Table 5.13: ANOVA output data

ANOVA[a]						
Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
1	Regression	7923.375	4	1980.844	17.403	.000b
	Residual	15821.264	139	113.822		
	Total	23744.639	143			
a. Dependent Variable: Financial_and_Market_performance						
b. Predictors: (Constant), Knowledge_Sharing, Entrepreneurial_Orientation, Data_Driven_Decision_Making, Organisational_Culture						

Following the above discussion, the Model specified multiple models in a single regression command.

Regression, Residual and Total showed that the total variation was subdivided into regression (explained by Knowledge Sharing, Entrepreneurial Orientation, Data Driven_Decision_Making, Organisational_Culture and Residual variance (errors or other variables), Table 5.13. The Sum of Squares exemplified the Sum of Squares linked with knowledge sharing, entrepreneurial orientation, data driven decision making and organisational culture as four sources of variance. The df values indicated the degrees of freedom linked with the origin of the variance. The intercept was automatically included in the model. There were five expressions including the intercept, thus the model possessed 4 degrees of freedom with the Residual degrees of freedom being 139.

The Mean Square denoting the quotient of the Sum of Squares and the respective df are the Mean Squares. For the Regression, 7923.375/4 = 1980.844. For the Residual 15821.264/139 = 113.822. The F-value is the Mean Square Regression (1980.844) divided by the Mean Square Residual (113.822), giving F of 17.403. The p-value correlated with this F value was determined at 0.000. Thus, these values assisted in answering the question, "Do the independent variables namely, knowledge sharing, entrepreneurial orientation, data driven decision making and organisational culture reliably predict the financial market performance as a dependent variable?" Since the p-value at 0.000 was smaller than 0.05, The conclusion was thus “Yes” that knowledge sharing, entrepreneurial orientation, data driven decision making and organisational culture reliably predict the dependent Variable (i.e. financial and market performance) Table 5.13.

Table 5.14: Regression coefficient equation for research question 1

Coefficients[a]						
Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
		B	Std. Error	Beta		
1	(Constant)	-5.356	4.663		-1.149	0.253
	Organisational_Culture	0.353	0.136	0.271	2.6	0.01
	Data_Driven_Decision_Making	0.380	0.188	0.204	2.017	0.046
	Entrepreneurial_Orientation	0.111	0.094	0.085	1.185	0.238
	Knowledge_Sharing	0.535	0.261	0.172	2.054	0.042
a. Dependent Variable: Financial_and_Market_performance						

The Unstandardised B refers to unstandardised coefficients owing to the fact that they are measured in ordinary units (Lawrence, 2019). The coefficients are incomparable in determining which one was predominant in the model due to the fact that they could be measured on different scales. The Std. Error refers standard errors related to the coefficients (The knowledge sharing, entrepreneurial orientation, data driven decision making and organisational culture). The knowledge sharing, entrepreneurial orientation, data driven decision making and organisational culture had 0.261, 0.094, 0.188, 0.136 standard errors, respectively (Table 5.14).

The Standardised Beta values exemplifies the standardised coefficients. These are the coefficients attained by standardising all the variables in the regression plus all the independent variables and dependent then running the regression. This enables comparison of the magnitude of the coefficients to evaluate which has more profound impact. More significant betas are equated to larger t-values (Lawrence, 2019). Here the null hypothesis coefficient/parameter was tested see if it satisfied the 0 (ibid) by using the t-value and 2 tailed p-values at an alpha level of 0.05. The coefficient for organisational culture at 0.271 was found to be significantly different from 0 with p-value of 0.010 lower than 0.05. The coefficient for data driven decision making at 0.204 was significant with a p-value of 0.046 lower than 0.05. The coefficient for knowledge sharing at 0.172 was significant at the 0.05 level because the p-value of 0.042 was less than 0.05. The coefficient for entrepreneurial orientation at 0.085 was not statistically significant with a p-value at 0.238 lower than 0.05. These results thus showed data driven decision making, knowledge sharing and organisational culture had significant impact on financial and market performance. However, entrepreneurial orientation, had no effect on the financial and market performance, Table 5.14.

5.6.1.1 Moderating effect analysis of OC on KM on Performance for research question 2

The relationship between two variables and how its influenced by a third variable's value is assessed through the moderator analysis (Hair, Black, Babin & Anderson, 2009). With this in mind, this subsection examines the link between a continuous dependent and continuous independent variable that includes the moderator (Hair, Black, Babin & Anderson, 2009). To test the moderating impact the (linear) interaction term to a multiple regression model was added to the above expression. Stated differently a moderated multiple regression (MMR) was employed for the analysis (Wang, Zhang & Goh, 2018).

The continuous dependent variable was "Financial and market performance", the continuous independent variable was "Knowledge Sharing" and the moderator variable was "organisational culture". The test was whether organisation culture (i.e. the moderator variable) moderated the connection between knowledge sharing and organisational performance.

Table 5.15*:* Model Summary[c] for research question 2

					Change Statistics				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**R Square Change**	**F Change**	**df1**	**df2**	**Sig. F Change**
1	.557a	0.31	0.300	10.77857	0.31	31.691	2	141	0
2	.557b	0.31	0.298	10.81422	0.0002	0.477	1	140	0.491

a. Predictors: (Constant), Organisational Culture , Knowledge Sharing
b. Predictors: (Constant), Organisational Culture , Knowledge Sharing, culture_knowledgesharing
c. Dependent variable:Financial and market performance

By transferring the culture*knowledge sharing interaction term, an assessment to test if the inclusion of this interaction term to the current regression model improved the estimation of organisational performance was done. In addition, this action allowed for the determination of whether the interaction term was statistically significant. Thus, Model 2 denotes this regression model with knowledge sharing, organisational culture and culture*knowledge sharing variables included in the results produced by this moderating test procedure,

Table ***5.15***. Thus, the impact of the adding the interaction term was determined by the difference between Model 1 and Model 2.

The R squared variation option was employed to determine the impact of adding the interaction term to the model (i.e. assessing the presence of the moderation effect). The output produces multiple tables convoy the moderator analysis such that for the objective of the current study only one of the presentation table was used to assess if organisational culture modified the association between knowledge sharing and organisational performance. Since the data already meets the multicollinear, homogeneity and normality assumptions, there was no need to interpret the Model Summary table.

An increase in variance explained by the interaction term is shown under, "R Square Change" (i.e., the change in R^2), Table 5.15. The change in R^2 was recorded at 0.002, which was a proportion. The change in R^2 was 0.20% (i.e. 0.002 x 100 = 0.20%), which represented the percentage change in the variance attributed to the introduction of the interaction term. This outcome however did not signify statistical significance for the increase ($p>0005$), as observed in the "Sig. F Change" column, Table 5.15. The relationship between knowledge sharing and organisational performance was thus not moderated by organisational culture. Stated differently, the two independent variables had main effect on the dependent variables but they do not interact.

The coefficient values for the moderated multiple regression equation were found in column "B" of the Coefficients table, presented in Table 5.16, below. Using the values obtained in Table 5.16, the regression equation can be reported as follows:

Financial and Market share performance = 0.997 + 0.659 (knowledge sharing) + 0.505 (organisational culture) + 0.080 (organisational culture*knowledge sharing)

Table 5.16: Regression coefficient equation for research question 2

Coefficients[a]										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	0.537	3.799		0.14	0.888	-6.974	8.049		
	Organisational Culture	0.537	0.107	0.412	5.01	0	0.325	0.748	0.725	1.38
	Knowledge Sharing	0.674	0.255	0.217	2.64	0.009	0.169	1.179	0.725	1.38
2	(Constant)	0.997	9.756		0.26	0.797	-16.344	22.23		
	Organisational Culture	0.505	0.308	0.388	1.49	0	-0.149	1.068	0.088	11.3
	Knowledge Sharing	0.659	0.732	0.212	0.67	0.011	-0.958	1.938	0.089	11.3
	culture_knowledgesharing	0.002	0.021	0.055	0.27	0.491	-0.036	0.047	0.032	31.2
a. Dependent Variable: Financial and Market performance										

5.6.1.2 Moderating effect analysis of EO on KM on Performance for research question 3

To test the moderating impact the (linear) interaction term to a multiple regression model was added to above expression was done. Simply stated, a moderated multiple regression (MMR) was employed (Wang, Zhang & Goh, 2018).

The continuous dependent variable was "Financial and market performance", the continuous independent variable was "Knowledge Sharing" and the moderator variable was "entrepreneurial orientation". The test was whether entrepreneurial orientation (the moderator variable) moderated the connection between knowledge sharing and organisational performance.

Table 5.17: Model Summary[c] for research question 3

Model Summary[c]									
					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.448a	0.201	0.189	11.60246	0.201	17.693	2	141	0
2	.454b	0.206	0.189	11.60577	0.005	0.92	1	140	0.339

a. Predictors: (Constant), Entrepreneurial Orientation, Knowledge Sharing
b. Predictors: (Constant), Entrepreneurial Orientation, Knowledge Sharing, entrepreneurship orientation_knowledgeshare
c. Dependent Variable: Financial and Market performance

By transferring the entrepreneurial orientation*knowledge sharing interaction term, an assessment to test if adding the interaction term (moderating effect) to the current regression model or whether this improved the prediction of organisational performance was performed, Table 5.17. Since the data already meets the multicollinear, homogeneity and normality assumptions, there was no need to interpret the Model Summary table.

An increase in variance explained by the interaction term is shown in the first column, "R Square Change" (i.e., the change in R^2). The change in R^2 was recorded at 0.005. The change in R^2 was 0.50% (i.e. 0.005 x 100 = 0.50%), attributed to the percentage change in the variance explained by the introduction of the interaction term. This outcome however did not signify statistically significance from the increase (p>0005), as observed in the "Sig. F Change" column. The relationship between knowledge sharing and organisational performance was therefore not moderated by entrepreneurial orientation. The coefficient values for the moderated multiple regression equation can be found in the "B" column of the Coefficients table, presented in Table 5.18:

The values attained above were used to generate the regression equation which can be expressed as follows:

Organisational Performance = 0.848 + 1.721 (knowledge sharing) + 0.743 (entrepreneurial orientation) + 0.038 (entrepreneurial orientation*knowledge sharing)

5.6.1.3 Results and analysis for research question 4

The data for research question 4 was analysed through descriptive statistics and correlations, and the results and analysis discussed in chapter 6.

Table 5.18: Regression coefficient equation for research question 3

Coefficients[a]										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	7.962	3.728		2.136	0.034	0.593	15.331		
	Knowledge Sharing	1.275	0.239	0.41	5.343	0	0.803	1.746	0.963	1.038
	Entrepreneurial Orientation	0.154	0.1	0.118	1.538	0.126	-0.044	0.352	0.963	1.038
2	(Constant)	0.848	8.303		0.102	0.919	-15.567	17.263		
	Knowledge Sharing	1.721	0.523	0.553	3.291	0.001	0.687	2.755	0.201	4.987
	Entrepreneurial Orientation	0.743	0.622	0.569	1.194	0.234	-0.487	1.972	0.025	40.049
	entreprenuershiporientation_knowledgeshare	-0.036	0.038	-0.504	-0.959	0.339	-0.11	0.038	0.021	48.735
a. Dependent Variable: Financial and Market performance										

Chapter 6

Research Finding and Discussion

"Research is creating new knowledge."- Neil Armstrong

6.1 Introduction

With a specific focus on big data analytics, the research goal was to better understand the relationship of knowledge sharing of data analytics items after considering seemingly moderating organisational factors such as organisational culture and entrepreneurship orientation. The preceding chapter gave descriptive analysis and statistical tests to address the study questions and accompanying hypothesis. With research questions in mind this chapter discusses the findings from Chapter 5. Questions 1 intents to prove the relationship between knowledge sharing of data analytics and firm performance. Question 2 and 3 respectively sought to assess if an organisation's evidence-based decision-making culture and entrepreneurial orientation influenced the impact of knowledge sharing on organisational performance. Question 4 intent to determine whether big data analytics application enhances knowledge sharing within firms. In simple terms the study assessed the role of information sharing and other organisational factors on the performance of the firm contextual to big data analytics.

The following hypothesis were made:

Hypothesis 1: there is a positive relationship between knowledge Sharing and firm performance.

Hypothesis 2: there is a positive moderating effect of organisational culture towards big data analytics use on the impact of knowledge sharing on firm performance.

Hypothesis 3: there is a positive moderating effect of entrepreneurial orientation towards big data analytics use on the impact of knowledge sharing on firm performance.

Hypothesis 4: Big data analytic application enhances knowledge sharing within firms.

6.2 Assessment of the relationship of variables to firm performance

6.2.1 Discussion of Hypothesis 1

Hypothesis 1: There is a positive relationship between knowledge Sharing and firm performance.

Owing to the changing corporate environment, knowledge sharing has become critical for decision-making, company performance and success (Son, Cho & Kang, 2017). Organisational learning is essentially the process through which a company generates knowledge or insights through the acquisition, transmission and interpretation of information as well as the use of organisational memory (Fink, Yogev & Even, 2017). Hypothesis 1 sought to determine respondents' perceptions on the relationship between knowledge sharing and firm performance. The idea was that the relationship between knowledge sharing as a central organisational capability being evaluated could be directly linked to the envisioned result which would be improved firm performance. This was important to the research since it proved a causal relationship between knowledge sharing as a core capability that improves firm performance.

As shown in Table 5.7 mean scores of all the variables under knowledge sharing were greater than 2.50. The coefficient on the regression also showed a positive and significant relationship of knowledge sharing and firm performance. Therefore, in line with Zehir & Özşahin (2008), who discovered that a firm's performance may be improved by incorporating knowledge sharing, participatory decision making, and transformational leadership this research also found a positive relationship between knowledge sharing and firm performance. Furthermore, it demonstrated that knowledge sharing resulted in the attainment of value by the organisation, indicating an area worth investigating as well as to be considered by business in order to promote an organisation's capability.

The study found that more than half of the organisations share information of the organisations like business goals and its external environment with the rest of their employees. In order of knowledge sharing most organisations share information on specific requirements of a given analysis like market forecasts, followed by sharing information on progress reports, followed by sharing information analysis results and finally share information on analytical techniques. An overall mean score of 3.0 was found which implied that respondents agree that their organisation want to share information for big data analytics.

These findings are also supported Ali, Panneer Selvam, Paris and Gunasekaran (2019) who noted that to make excellent decisions, information sharing is a crucial activity among knowledge workers and all knowledge management activities. In addition, the results are further supported by Stobierski (2019) who confirmed that data-driven decision-making empowers businesses to make more confident decisions. This is because data may serve several functions, including serving as a baseline for what is currently accessible and allowing for a better understanding of the ramifications of any decisions made. As such, data-driven decision-making allows for operational efficiency gains by making decisions based on the most recent information. The research findings are also supported by those of Ferraris, Mazzoleni, Devalle, and Couturier (2019) who found in their studies that companies with advanced information sharing orientation had a vital role in amplifying the impact of BDA capabilities, both technological and managerial.

In their research, Matoková (2018) discovered that information-oriented leadership has a substantial positive link with knowledge sharing in organisations. A correlation coefficient of 0.172 was found between information sharing and firm performance. This indicated a low influence of knowledge sharing on firm performance. To maximise the benefits of adopting data analytics, a company should spend time on increasing knowledge exchange in addition to emphasising essential resources (Aboelmaged & Mouakket, 2020). According to the study, data analytics increases knowledge sharing in organisations and knowledge sharing plays a mediating role in the impact of data analytics on the quality of company decisions. As a result, knowledge sharing improves the efficiency and effectiveness of firm decision-making and consequently firm performance.

The easy dissemination of data-driven insights derived from big data analytics helps managers at all levels make strategic decisions based on data analysis and interpretation (Akhtar, Frynas, Mellahi & Ullah, 2019). Knowledge sharing was shown to have a positive impact on firm performance similar to Akter, Wamba, Gunasekaran, Dubey and Childe, (2016) and Wamba, Gunasekaran, Akter, Ren, Dubey and Childe (2017). As a result, the hypothesis of a positive correlation between information sharing and business performance is supported both by literature and the current empirical findings.

6.2.2 Discussion of hypothesis 2

Hypothesis 2: Organisational culture towards Big Data Analysis moderates the influence of knowledge sharing on firm performance.

Organisational culture emerges as a result of organisations' learning and adaptation as they navigate changing external environmental conditions and it has a wide range of underlying meanings and connotations (Schein, 2017). Organisational culture has been linked to company success in both direct and indirect ways (Abdelwhab, Panneer, Selvam, Paris & Gunasekaran, 2019; Rohim & Budhiasa, 2019; Attar, Ehtemam-Haghighi, Kent & Dargusch, 2018; Farooq, 2018). The second hypothesis seeked to establish the association between organisational culture and big data analytics application and firm performance anchored on the moderating effect on knowledge sharing.

The research findings showed that majority of the respondents had a culture that consider innovation as an absolute necessity, a culture that consider accrual and use of new knowledge better than its rivals, a culture that adopt novel and high-tech process to consistently enhance product or service quality, a culture that continuously encourage to the development of capacities to achieve more and apply new capabilities, a culture of being visionary and flexible, a culture of extensive employee orientation program and a culture of investing in targeted training and support is needed. The findings of this study are supported by Applegate (2018) who posited that a culture of empowerment, transparency, trust, and inquiry is required for an organisation to be big data enabled. These characteristics, according to Applegate (2018) enable data analytics to be integrated throughout organisations while elevating and reinforcing the investment and dedication to big data analytics.

Organisational culture is viewed as a critical component of decision-making because it influences how decisions are made now and in the future (Rohim & Budhiasa, 2019). More specifically, organisation's culture, in terms of attitudes and mindsets can either limit or facilitate an organisation's ability to implement data-driven initiatives (Alharthi, Krotov & Bowman, 2020). As a result, organisational culture impact firm performance by either supporting or hindering knowledge sharing activities in any company (Abdelwhab, Panneer, Selvam, Paris & Gunasekaran, 2019).

The research findings had an overall mean score of 4.97 for this hypothesis and this showed that a positive relationship exists between organisational culture towards big data analytics and firm performance as indicated by many respondents that indicated that their organisation had a positive culture that supports big data analytics.

This means that organisations have adopted a good organisational culture attitude that incorporates data-driven decision-making. As a result, if companies want to properly use the value provided by big data before making any major decisions, they will need to assume a data-driven decision-making culture.

In addition to what has already been deliberated on in this chapter, several previous studies have reported extensively on research on various moderator variable. Particularly the research focused on the moderating effect of variables with regard to organisational culture (Rohim & Budhiasa, 2019; Nguyen & Prentice, 2020). The research on culture included various focus areas, including evidence-based decision-making culture.

More importantly, linear regression on the relationship between knowledge sharing and firm performance initially showed an R-squared of 0.187. After adding organisational culture towards big data analytics an adjusted R-square improved to 0.31, signifying a small adjustment. The inclusion of the organisational culture as a moderator variable did not significantly increase the goodness of fit. This is besides the fact that the adjusted R-square in this model produced a value that was relative high compared to the model without the moderator variables.

To clarify on the moderation effect, a moderator analysis was done through a moderated multiple regression (Wang, Zhang & Goh, 2018). The continuous dependent variable was "Financial and market performance", the continuous independent variable was "Knowledge Sharing", and the moderator variable was "organisational culture". The test was whether organisation culture (the moderator variable) moderated the connection between knowledge sharing and organisational performance.

By including the interaction term ‘culture*knowledge sharing’, an assessment test if the introduction of this interaction term to the regression model improved the prediction of organisational performance was done. This also allowed the determination of whether the interaction term was statistically significant.

The research employed the R squared alteration option to evaluate the effect of the introducing the interaction term to the model. The change in R^2 was recorded as 0.002, which denoted the change in R^2 to be 0.20% as a percentage change in the variance explained by the introduction of the interaction term. The observed increase was however statistically insignificant ($p>0.05$). Therefore, relationship between knowledge sharing and organisational performance is not moderated by organisational culture. In other words, the two independent variables (knowledge sharing and organisational culture) have only the main effect and not the interaction effect on organisation performance. Therefore, no evidence of moderation was found. The result is therefore contrary to Rohim and Budhiasa (2019), who found that the relationship between organisational rewards and knowledge sharing for the success of the organisation was moderated by organisational culture.

The results are also not in line with a several of researchers who studied the interaction effect between knowledge sharing and organisational culture which found that the moderation effect existing (Trivellas, Arkrivouli & Tsoutsa, 2015; Nguyen, 2019; Attar, Ehtemam-Haghighi, Kent & Dargusch, 2018; Farooq, 2018). Specifically, Trivellas, Akrivouli, Tsifora and Tsoutsa (2015) found that organisations with knowledge sharing culture strengthened general competencies thus increasing the prospect on achieving higher job satisfaction and effectiveness. The findings are however supported by other researchers who report that it is not reasonable for organisational culture to moderate on the effect of knowledge sharing on organisation performance (Nguyen & Prentice, 2020; Kobarg, Stumpf-Wollersheim & Welpe, 2018; Liu, Lin, Joe & Chen, 2019).

Therefore, the hypothesis that organisational culture towards big data analytics application moderates the influence of knowledge sharing on firm performance is rejected in this study. This is because organisational culture had only main effect on organisational performance and not moderating effect as declared by the theoretical and empirical literature.

6.2.3 Discussion of hypothesis 3

Hypothesis 3: Entrepreneurial orientation moderates knowledge sharing on firm performance.

The Entrepreneurial orientation method is used to measure characteristics of business behaviour, and it works well in this study because it gives weight to possible disparities in strategic postures among firms. It also assesses the company's capacity to meet its objectives (Gupta & Gupta, 2015). The research hypothesis proposed that there is a positive and moderating effect between entrepreneurial orientation and knowledge sharing on firm performance. An entrepreneurial company is one that engages in a lot of product-market innovation, is not hesitant to embark on risky ventures, and is known for being a first-mover in terms of innovation, allowing it to outperform competitors (Stopford, 2018). As a result, such characteristics are connected to improved firm success, especially since that corporate survival is heavily reliant on finding new opportunities.

Before being specific on the moderating effect of EO, respondents were asked about what they think was the status of EO toward big data analytics. The questions asked questions searching respondents` points of views to first determine the characteristics of the relationship between these two variables. The data was gathered, and the findings showed that entrepreneurial orientation had some positive impact on a firm as shown by an overall mean of 3.70. However, a coefficient of 0.085 was obtained from the regression analysis. This signified the presence of a low positive correlation and impact between entrepreneurial orientation and firm performance. Consequently, the results confirm what Vafaei-Zadeh, Hanifah & Foroughi, (2019) found that not all entrepreneurially oriented businesses can gather available knowledge and information from their surrounds and use it to improve their performance.

The findings of this research are similar to those reported by Ndubisi and Iftikhar (2012) who found the presence of a low positive association between entrepreneurial orientation and firm performance. Nevertheless, these findings are different from those of Sharma and Dave (2011) who found entrepreneurial orientation and firm performance to have significant relationship in a study of SMEs.

Closer examination of the descriptive statistics revealed that generally the various organisation respondents believed that their organisations were less innovative, less proactive and less risk-talking. This is exemplified by the 7-point Likert scale with means scores of 3.88, 3.93 and 3.92, respectively. These findings were well aligned with the findings of Linton and Kask (2017) which also used the 9-item scale (Covin & Jevin, 1989), measured on a 7-point Likert scale to observe mean values of 3.30, 3.70 and 3.10 for innovativeness, proactiveness and risk- taking, respectively. In addition, Lechner and Gudmundsson (2014) described a similar outcome to both the current study and the study by Linton and Kask (2017) for the same dimensions of EO at mean scores of 2.30, 2.70 and 3.00 using a 5-point Likert scale, respectively.

Overall, the outcome of this assessment supported the view that most organisations studied were not necessarily entrepreneurial orientated thus less innovative, less proactive or less risk-taking).

The hypothesis was clearly answered through moderator analysis that examines whether a relationship between two variables is impacted by a third variable's value (Hair, Sarstedt, Ringle, & Mena, 2012). With this in mind, a study of the link between a continuous dependent and continuous independent variable (that includes the moderator) was done. To test the moderating impact, the a (linear) interaction term was introduced to the multiple regression model. The moderated multiple regression (MMR) was done (Wang, Zhang & Goh, 2018).

The continuous dependent variable was "Financial and market performance", the continuous independent variable was "Knowledge Sharing" and the moderator variable was "entrepreneurial orientation". The test was whether entrepreneurial orientation (the moderator variable) moderated the connection between knowledge sharing and organisational performance.

By incorporating the entrepreneurial orientation*knowledge sharing interaction term, the assessment tested if the introduction of this moderating effect to the existing regression model or whether this improved the prediction of organisational performance. Since the data already meets the multicollinear, homogeneity and normality assumptions.

An increase in variance explained by the interaction term is shown in the first column, "R Square Change" (i.e. the change in R^2). The change in R2 was recorded at 0.005. The change in R2 was 0.50%, which was the percentage change in the variance explained by the introduction of the interaction term with the increase not being statistically significant. The relationship between knowledge sharing and organisational performance was therefore not moderated by entrepreneurial orientation.

These findings could be attributed to various factors ranging from rapid technological change, market volatility and prompt response to heightened competition through accelerated creativity and innovation in firms (Purnama & Subroto, 2016; Prajogo, 2016). Thus, these developments, perceived rapid change and external environment pressures could thus negatively impact the respondents perception of their own organisational entrepreneurial orientation.

An analysis of the mean scores of 3.30, 3.70 and 3.10 all three sub-dimensions innovativeness, proactiveness and risk-taking, respectively suggested that the entrepreneurial orientation was low. Therefore, supporting the view that EO was a unidimensional construct that presents no significant effect moderating effect. This research outcome is aligned with majority of current EO research (Saeed, Yousafzai & Engelen, 2014).

Stemming from the above discussion and analysis, it can be concluded that organisations that have ambitions to be more innovative and accomplish competitive advantage in the market must proactively pursue new opportunities and maintain a posture of risk-taking. Thus, the hypothesis that there is a moderating effect of entrepreneurship orientation on knowledge sharing is rejected and conclude that neither entrepreneurship orientation has a main effect, nor it has a moderating effect on the impact of knowledge sharing on the organisational performance.

6.2.4 Discussion of hypothesis 4

Hypothesis 4: Big data analytic application enhances knowledge sharing within firms

Malakooti (2012), posited that big data analytic application decision-making is a multi-faceted process that encompasses a series of activities such as evaluating, defining alternatives, rating, and committing to a variety of possible actions. However, the issue of Big data analytic decision-making process and its capacity to promote knowledge sharing has drawn considerable attention among businesses. The fourth hypothesis of the study determined whether big data analytics decision making will enhance knowledge sharing. The nature of the relationship between the two was determined by the respondents' perspectives on a number knowledge sharing constructs. On this hypothesis descriptive statistics on constructs that simultaneously speak about big data analytics decision and knowledge sharing have clarified on this hypothesis.

This research examines big data analytics and conclude that it is a knowledge sharing enabler. Descriptive statistics on knowledge sharing shows that big data analytics help organisations better manage knowledge by visualising and analysing unstructured material. As such, descriptive statistics shows that Big data analytics (BDA) ensures adequate scrutiny and arranged of data into usable insights for enterprises, resulting in improved in knowledge sharing and subsequently improve performance. To be specific, Big data text analytics can play an important role in knowledge management. The kind and quality of knowledge created through effective knowledge management in building a competitive edge. The study has major implications for big data text analytics in knowledge management, particularly the type and quality of knowledge created by text analytics. Data on whether data analysts information/knowledge sharing on precise conditions needed for analysis of numerical projections and market forecasts gave the mean of 3.09 which indicated that most organisations share information on exact requirements of a given data analytics like market forecasts. Descriptive statistics shows that most organisations share information on data analytical techniques such as statistical tools, methods, or testing processes.

Responses on the sharing of information on progress reports including status updates, resource problems by data analysts gave a mean score of 3.18 which was greater than neutral point at 2.50 indicating most respondents agree to higher scores. Consequently, majority of organisations share information readily on progress reports.

The last statement of this section evaluated at how analysts exchange knowledge on analysis results such as primary findings, unpredicted outcomes or directive recommendations. The evaluating for the statement gave a mean score of 3.03 which was greater than the neutral point at 2.50 such that it considered agreeing to higher scores. As such, big data analytics has an effect on knowledge sharing. Overall, the mean score was 3.00 which indicated that the respondents would agree that in their organisation big data analysis has led to a positive culture of information sharing. The findings of this research that big data analytics have a positive effect on firm knowledge sharing agrees with the findings of Mwangi (2012), who concludes that knowledge sharing is a deliverable outcome of big data analytics. The results also conform with Akhtar, Frynas, Mellahi and

Ullah, (2019), that big data analytics enable data-driven insights which then assisted managers at all levels of the organisation to make strategic decisions based on data analysis and interpretation.

The results are also supported by Ghasemaghaei (2019) who showed that competency in data processing and analysis assisted in disseminating information and insights obtained through data analytics. Thus, the elements reported to advance data analytics competency might possibly influence the sharing of knowledge. Thus, large data processing by companies contributes to insights generation about their business, markets, and consumers (Zheng, 2017). Consequently, big data utilisation could promote knowledge sharing within corporations. Accordingly, employees must also be able to communicate the information gained through data analytics tools (Ghasemaghaei, 2019).

The descriptive analysis discussed above is further supported by Janssen, van der Voort and Wahyudi (2017), who concluded that knowledge sharing may be significantly compromised if workers do not have the required competency to analyse and comprehend their IT-based discoveries. The implications of the outcomes suggests that employees who scrutinizes specific and relevant data generate better results which makes it easier to share knowledge with others. Therefore, the descriptive analysis substantially supports the hypothesis that big data analytics enhances knowledge sharing. Deductively, the hypothesis of a big data analytic application enhances knowledge sharing within firms is supported both by literature and the current empirical findings.

Chapter 7

Research Conclusions and Recommendations

"Research is seeing what everybody else has seen and thinking what nobody else has thought."- Albert Szent-Györgyi

7.1 Introduction

According to the research architecture used in this study, the role of big data analytics application on knowledge sharing and firm performance was examined. Thus, this chapter intents to provide the implications of study by distilling the most important contributions that can be drawn from the research and suggestions pertinent for theory and practice in business settings. In addition, recommendations for future studies are provided in relations to the research completed in this study. The main objectives of this research was to analyse how companies can utilise knowledge sharing in big data analytics context with the intention of improving decision making and firm performance.

A non-probability purposive sampling was utilised to obtain a sample of 144 participants for a cross-sectional descriptive survey, which was conducted using the results of the survey. This chapter starts by going through the research questions individually in order to review how they have been answered. The section then provides the contribution of the study. The final sections will deliver the conclusion of the research, recommendations for successful knowledge sharing or management activities as well as directions for further research.

7.2 Consolidation of research outcomes that answer research questions

The conclusions from data analysis and literature review were simultaneously used to answer the following four research questions.

RQ1: Is there a positive relation between knowledge sharing and firm performance.

The research question is partly answered by literature, whereby the literature unearthed the impact of knowledge sharing on organisational performance. Son, Cho and Kang (2017) posited that adapting to a changing business environment requires knowledge exchange to make decisions and operate effectively. This is also supported by Fink, Yogev & Even (2017) who pointed out that a firm creates knowledge or insights through the acquisition, transfer and interpretation of information as well as the application of organisational memory.

The questions are answered by descriptive statistics that shows that all factors under knowledge sharing had mean scores greater than 2.50. A mean score of 3.00 indicates that people agree their organisation wants to exchange data for big data analytics. Also, the regression presented a positive link between knowledge sharing and business performance. As a result, both the literature and empirical data herein gave a supporting answer that information sharing has a positive effect on organisational performance.

Research Q2: Is organisational culture a moderator of knowledge sharing on firm performance?

The research question is partly answered by literature, whereby the literature unearthed why organisational culture a moderator of knowledge sharing often impacts on firm performance. For instance, researchers pointed out that company's organisational culture is connected to both direct and indirect corporate success (Abdelwhab, Panneer, Selvam, Paris & Gunasekaran, 2019; Rohim, & Budhiasa, 2019; Attar, Ehtemam-Haghighi, Kent & Dargusch, 2018; Farooq, 2018). Empirically, the literature was proven right by descriptive statistics which showed that organisation culture has a positive effect on performance as the overall mean was found to be 4.97, indicating a positive effect of culture related variables. However, close examinations to precisely answer the current research question showed that the moderate multiple linear regression was supposed to be modelled. The moderation effect results showed a slight and an insignificant improvement in R^2 (0.20% as a result of the interaction effect) as a result of moderation effect or organisational culture.

Thus, organisational culture has little influence on the connection between Knowledge sharing and performance. Differently stated, neither of the independent variables (knowledge sharing nor organisational culture) had a major influence on organisational performance. So, there was no indication of moderating. Thus, the research question on whether big data analytics culture moderates the impact of information sharing on business performance is rejected. As such theoretical and empirical research findings was only relevant to prove that organisational culture has a primary effect on performance but not a moderating effect.

Research Question 3: Is entrepreneurial orientation a moderator of knowledge sharing on firm performance?

The question was partly answered by the literature review where most of researchers reported that entrepreneurial attitude and information sharing had a positive and moderating influence on business success (Stopford & Baden-fuller, 2018). The descriptive research showed an overall mean of 3.7 for entrepreneurial orientation showing that it has some beneficial influence on a business performance. Regression and correlations also show a positive coefficient of 0.085 suggesting a positive connection and influence between entrepreneurship orientation and company performance. However, as supported by Vafaei-Zadeh, Hanifah and Foroughi (2019) who discovered that not all entrepreneurial firms can acquire and use information from their surroundings to improve performance as low positive correlation between entrepreneurial orientation and business performance was discovered. This is because the mean values entrepreneurial orientation dimensions were found to be low in the study.

Peculiarly, respondents tended to hold an opinion that their organisations were not always creative, aggressive or risk-taking. Modified multiple regression (MMR) was used in this study with "Entrepreneurial Orientation" acting as moderator variable. The moderation, through the interaction term insignificantly increases R^2 by 0.50%. Thus, entrepreneurial orientation had no moderating influence on the connection between Knowledge sharing and organisational performance. However, the entrepreneurial orientation has a main effect on the performance of the organisations as established by the regression equations.

RQ4 Hypothesis 4: Big data analytic application enhances knowledge sharing within firms

This question was mainly answered based on literature review. The literature made it clear that data-driven decision-making speed has received considerable attention from corporations in recent times. The findings from this research study can thus be summarised as follows; the observed mean value of 2.97 was interpreted as respondents indicating that they communicated information about their organisation's goals and external environment with other employees. The mean of 3.09 indicated that most organisations provided information on actual requirements of a certain analysis like market forecasts. Data on whether analysts communicate information/knowledge gave a mean score of 2.77 which was larger than neutral point at 2.50. Furthermore, most companies share statistical tools, comprehensive methodology, and testing protocols were summarised with a mean of 3.03.

Thus, big data analytics impacts knowledge exchange. Overall, a 3.00 mean score indicates that respondents think that big data analysis has contributed to a constructive culture of information sharing. The outcomes of this study demonstrate a strong positive link between big data analytics application and corporate knowledge exchange. Thus, both the literature and current study support the premise that big data analytics use improves knowledge exchange inside businesses.

7.3 Theoretical contribution by the research study

The current researched is grounded on the foundation research focused on investigating big data analytics capabilities within organisations which particular emphasis on its influence on knowledge sharing and data-drive insights (Wamba, Gunasekaran, Akter, Ren, Dubey & Childe, 2017; Ghasemaghaei, 2019). With reference to the current study the objectives were to deconvolute the posture which organisations should portray in order for big data analytics to impart organisational success. Hence, the study focused on providing authentic empirical findings to corroborate this question by broadening the knowledge base in assessing additional constructs of knowledge sharing capabilities such as organisational culture, entrepreneurial orientation and consequential impact on big data analytics deployment and use.

This study thus presented a model which demonstrated the interactions of the various variables constructs in order to develop a narrative for the observed variations in organisation’s performance due organisational attributes and big data analytics. Herein, broader constructs influence were assessed from a perspective of the organisation contrary to what has been studied before.

While the significance of these three big data analytics capabilities are relatively well researched (Wamba, Gunasekaran, Akter, Ren, Dubey & Childe, 2017; Wamba, Gunasekaran, Akter, Ren, Dubey & Childe, 2017), this study is posed as contributing the evaluation of the knowledge sharing effect on big data analytics and its collective moderation from organisational culture and entrepreneurial orientation towards organisation performance in the context of South Africa. Thus, this emphasised the role of culture, entrepreneurship and knowledge sharing in the process of big data analytics application. The complexity of the relationship between culture, entrepreneurship orientation, knowledge sharing was exemplified through direct correlations of big data analytics and firm performance mediated by knowledge sharing as well as moderation of the of culture and entrepreneurship orientation.

Furthermore, this study contributes to the foundation theories on big data analytics strategy and provides insight on how to leverage big data analytics as a capability within organisations to support organisational performance and maintaining competitive edge. This is achieved through the notion that the important traits namely, knowledge sharing, organisational culture are central components that should characterise big data analytic ability to impart value to organisations through organisational performance. Notably, these constructs characterised features of the interaction starting with reception of an innovation followed by deployment and finally use or application.

7.4 Practical implications to business

An investigation on the big data analytics environment within organisations and in particular the effect on performance was carried out (Akter, Wamba, Gunasekaran, Dubey & Childe, 2016; Wamba, Gunasekaran, Akter, Ren, Dubey & Childe, 2017). With these studies, the emphasis shifted from technical to non-technical capabilities and traits that an organisation should acquire to succeed with big data analytics capabilities. Consequently, the study contributed to the body of knowledge by addressing additional elements of organisational skills and their influence on big data analytics implementation and application.

The study offered a model that demonstrated the interactions between components to elucidate the variation observed in organisational performance as a function of organisational characteristics, big data analytics interactions and features of big data analytics implementation in an organisation. Therefore, the concept was used primarily in the South African setting, as opposed to the USA, China or other developed countries. Importantly, different viewpoints from the business persons were obtained allowing for a balanced assessment of the capacity.

In addition, it is proposed that the effect of big data analytics on knowledge sharing within organisations primarily in south Africa by checking for moderating effect of envisaged organisational factors positions study among the first research the topic locally. Also studied was the relative effect of organisation factor that impact organisational performance. This suggests that if organisations want to impact performance they must first align their knowledge sharing variables and moderating factors relevantly to be effective in big data analytics.

7.5 Suggestions for future research

The complexity of the organisational environmental characteristics being measured in this study cannot be underrated. Hence, there is considerable potential for further research which studies the impact of other dimensions of the organisational environment and not only limited culture, knowledge sharing and entrepreneurial orientations on the big data analytics use with the intention of improving organisational performance. Here are some recommendations collated:

- Despite a few overseas answers, the sample frame was predominantly south African. These opinions of big data analytics and its impact on performance may be influenced by cultural norms inside businesses in South Africa. The various organisational cultures and customs may provide important understanding in how to optimally implement tailored skills in organisations throughout the world. This applies to huge enterprises that compartmentalise talents and perspectives. These may have been successful in certain areas, but not in others, like in international businesses or developed countries with significant utilisation of big data analytics technologies.
- More detailed analysis of the organisational dimensions such as empowerment, trust and innovation can studied instead of the overarching organisational culture in the context of data analytics.

- To mitigate non-response bias, survey respondents' profiles may be verified for size, industry exposure to big data analytics and degree of maturity of big data analytics installations in South Africa. Non-response bias can be examined using chi-square testing.
- Address concerns regarding the model's broad ongoing applicability, assessing its predictive ability across more situations would further verify its appropriateness and allow for re-evaluation of its components and potential for it to be more flexible, possibly with fewer questions asked. A case study that is focused on a single industry type in a South Africa contrasted with a same industry in developed country might reveal impactful learnings to directly influence business leaders in shaping and harnessing big data applications in their firms.

7.6 Limitations of research

The cautions and potential flaws found for this study are described below.

In terms of the effect of the connection between big data analytics use and performance, the constructs examined in this research are not all encompassing. Other literature-based constructs with potential implications include but are not limited to talent acquisition, non-data scientist development, tech-savvy leadership and appreciation of scientific method by business executives. Executing these opinions of big data analytics and its impact on firm performance may be influenced by cultural norms inside business in South Africa. In the lack of adequate sample data, these issues cannot be addressed sufficiently. South Africa has a small market from a big data analytics viewpoint, thus there are few organisations on whom data might have been obtained. Because the unit of analysis was organisation-level, the relative sample of organisations examined was small.

As a result of this, there is a market perception that big data analytics is conceptually out of reach for most individuals, whereas in fact, unless one is a data scientist or data analyst, this complexity does not need to be transmitted to data analytics users. Regrettably, these are the same perceptions that appear to be impeding big data platform adoption by not aggressively pushing suitable business model innovation. This may also have reduced response rates. This observation is likely owing to poor understanding of the big data environment by the majority of individuals resulting from an overly complicated perception about data analytics. Consequently, leading participating avoidance which is the contrary to what is necessary for the success of this study. Thus, big data analytics must be actively promoted as a tool with the complexity of the analysis separated from the outcome. Therefore:

- Due to the complexity of the environment, the reality of a company's big data analytics environment may not be accurately described.
- In addition to being busy, potential respondents might have been motivated to complete the survey due to the massive volume of them being received or the depth and breadth of the questionnaire. This would mostly lead to inaccuracies or dishonesty in responses to questions may have caused bias as a result of guessing or answering questions albeit not understanding them fully. Consequently, leading to non-representative dataset (Saunders & Lewis, 2012).
- It's possible that respondents did not completely examine the aspects being assessed since they are complex, under-researched, and their interrelationships with the topic matter are not well-known in corporate contexts.
- Most organisations with adequate data to create big data analytics capabilities appear to be in the early stages of implementing big data analytics as a business capability. Thus, respondents' opinions of big data analytics' impact and implications on firm performance may differ from known mature big data analytics arrangements in business. Therefore, respondents might not be very familiar with the intended outcomes of big data analytics on company performance.
- Non-probability and snowball sampling approaches may have resulted in sample biases, since not all relevant workers in the company were surveyed because they were outside the researcher's sphere of influence (Zikmund, Babin, Carr & Griffin, 2012).
- The author of this study acknowledges not having prior experience in this field, having previously focused on absolute positivism in analytical scientific research which could have hampered the research execution in terms of establishing constructs, questions and their combinations in the questionnaire.
- The options provided as replies may not have accurately represented respondents' thoughts or sentiments.
- The questionnaire gave a set list of responses from which a respondent may choose from. Though the questionnaire's components and questions were drawn

from literature, they may not have been thorough examinations of the constructs due to time constraints.

- The sample size, both overall and per stratum (descriptive divisions or qualities of respondents), was small, limiting the capacity to analyse or extrapolate data correlations. Though the influence of this was intentionally attempted to be minimised by obtaining a large sample, it remains a factor in this study. Thus, extrapolation of findings should be done with care.
- The research survey instrument was circulated broadly to potential respondents, however the lack of heterogeneity in the group of replies might have been due to non-responses thus resulting in the non-representative sample (Zikmund, Babin, Carr & Griffin, 2012).

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Appendices

Appendix 1: Survey research questionnaire

Section 1: Demographic information		Response options
1	Age	Open response
2	Gender	Open response
3	Job title	Open response
4	What is the approximate total number of employees within your organisation?	• 1-99 • 100 – 499 • 500 – 999 • 1000 or more • Don't know
5	Position in organisation?	• Junior management • Middle management • Senior management • Executive management
6	Tenure at current organisation?	• Less than 2 years • 3 – 5 years • 6 – 8 years • 9 – 11 years • 11 or more years
7	Industry in which your organisation operates?	Aerospace Agriculture Automotive transportation Chemical Communication Construction Electrical equipment Electricity Energy Financial services Food products Gas and water supply Information technology

		Machinery Manufacturing Mechanical Media Mining Pharmaceuticals Printing / paper Steel and non-ferrousmetals Textile Wholesale and retail Other	
Section 2: Organisational Culture			
	Organisational Culture to Big Data Analytics Capability	**Questions type**	**Reference**
8	Our organisation has a widely held belief that innovation is an absolute necessity for the organisation's future	Likert Scale(1 – 7)	Hill (2003); Kuratko and Montango (1990)
9	Our organisation enables learning, accumulation and application of new knowledge better than our competitors	Likert Scale(1 – 7)	Hill (2003); Kuratko and Montango (1990)
10	We believe it is important to adopt new and cutting-edge practices to continuously improve product or service delivery	Likert Scale(1 – 7)	Hill (2003); Kuratko and Montango (1990)
11	People in our organisation are continuously encouraged to expand their capacities to achieve more and apply new capabilities	Likert Scale(1 – 7)	Hill (2003); Kuratko and Montango (1990)
12	Our organisation can be described as visionary and flexible	Likert Scale(1 – 7)	Hill (2003); Kuratko and Montango (1990)
13	There is an extensive employee orientation program for new employees to ensure employees share the corporate vision and purpose	Likert Scale(1 – 7)	Hill (2003); Kuratko and Montango (1990)
14	We invest in targeted training and support at all levels of our organisation to assist our organisation to understand or know how to use data that is available	Likert Scale(1 – 7)	Hill (2003); Kuratko and Montango (1990)
15	Our executive level actively and visibly support our big data analytics capability	Likert Scale(1 – 7)	Hill (2003); Kuratko and Montango (1990)
Section 3: Big Data			
	Data Driven Decision Making in the Organisation	**Questions type**	**Reference**
16	Before any decision is taken we	Likert Scale(1 – 7)	CEBMa (2013)

	systematically evaluate internal data to better understand the nature of the problem and what to do about it		
17	Employees receive recognition from the organisation for applying evidence-based decision making in our typical business processes	Likert Scale(1 – 7)	CEBMa (2013)
18	Managers in our organisation tend to believe that experience and knowledge gained on the job is the only important source of information when considering how to tackle a problem	Likert Scale(1 – 7)	CEBMa (2013)
19	We make decisions by looking at what other organisations are doing, and how it's working for them	Likert Scale(1 – 7)	CEBMa (2013)
20	Internal politics and power struggles influence the way we make decisions about policies and practices	Likert Scale(1 – 7)	CEBMa (2013)
21	We believe that our competitiveness depends on our analytics capability	Likert Scale(1 – 7)	CEBMa (2013)
22	Our decision makers all have access to a management information system	Likert Scale(1 – 7)	CEBMa (2013)
23	Our managers know how to critically appraise both internal data and evidence from scientific research	Likert Scale(1 – 7)	CEBMa (2013)
Section 4: Entrepreneurial Orientation (EO)			
	EO: Innovativeness	**Question type**	**Reference**
24	Generally, the top managers of my firm favour... **Statement A**: A strong emphasis on the marketing of tried and true products and services. **Statement B**: A strong emphasis on R&D, technological leadership and innovation.	Likert Scale(1 – 7)	Barringer and Bluedorn (1999).
25	How many new lines of products or services has your firm marketed in the past 5 years? **Statement A**: No new lines of products or services. **Statement B**: Many new lines of products or services.	Likert Scale(1 – 7)	Barringer and Bluedorn (1999).

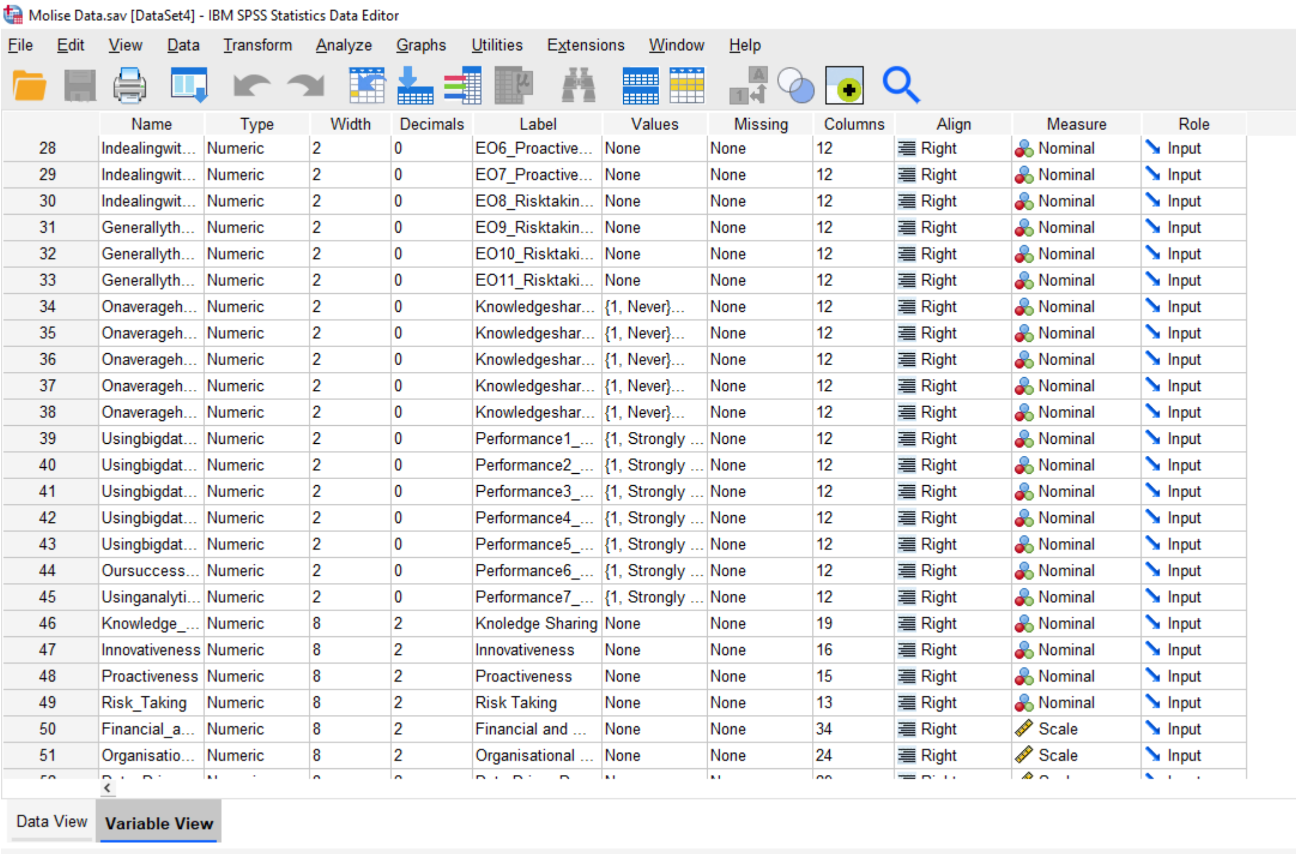
26	How many new lines of products or services has your firm marketed in the past 5 years? **Statement A**: Changes in product or service lines have been mostly of a minor nature **Statement B**: Changes in product or service lines have usually been quite dramatic	Likert Scale(1 – 7)	Barringer and Bluedorn (1999).
	EO: Proactiveness	**Question type**	**Reference**
27	In dealing with its competitors, my firm... **Statement A**: Typically responds to actions which competitorsinitiate. **Statement B**: Typically initiates actions to which competitors then respond.	Likert Scale(1 – 7)	Barringer and Bluedorn (1999).
28	In dealing with its competitors, my firm... **Statement A**: Is very seldom the first firm to introduce new products/services, operating technologies, etc. **Statement B**: Is very often the first firm to introduce new products/services, operating technologies, etc.	Likert Scale(1 – 7)	Barringer and Bluedorn (1999).
29	In dealing with its competitors, my firm... **Statement A**: Typically seeks to avoid competitive clashes, preferring a “live- and- let-live” posture. **Statement B**: Typically adopts a very competitive, “undo-the-competitor” posture.	Likert Scale(1 – 7)	Barringer and Bluedorn (1999).
	EO: Risk-taking	**Question type**	**Reference**
30	Generally, the top managers of my firmfavour... **Statement A**: Low-risk projects with normal and certain rates of return **Statement B**: High-risk projects with changes of very high returns.	Likert Scale(1 – 7)	Barringer and Bluedorn (1999).
31	Generally, the top managers of my firm favour... **Statement A**:	Likert Scale(1 – 7)	Barringer and Bluedorn (1999).

	A cautious, “wait and see” posture in order to minimize the probability of making costly decisions when faced with uncertainty. **Statement B**: A bold, aggressive posture in order to maximize the probability of exploiting potential when faced with uncertainty.		
32	Generally, the top managers of my firm believe that... **Statement A**: Owing to the nature of the environment, it is best to explore gradually via cautious behaviour. **Statement B**: Owing to the nature of the environment, bold, wide-ranging acts are necessary to achieve the firm’s objectives.	Likert Scale(1 – 7)	Barringer and Bluedorn (1999).
Section 5: Knowledge Sharing			
	On average, how often do your data analysts exchange information/knowledge with the rest of your organisation in the following areas in relation to the use of data analytics tools?	**Questions Type**	**Reference**
33	General overviews (e.g., business goals, external environment, etc.)	Likert Scale (1 – 5)	Cummings (2004)
34	Specific requirements of a given analysis (e.g., numerical projections, market forecasts)	Likert Scale (1 – 5)	Cummings (2004)
35	Analytical techniques (e.g., statistical tools, detailed methods, or testing procedures)	Likert Scale (1 – 5)	Cummings (2004)
36	Progress reports (e.g., status updates, resource problems)	Likert Scale (1 – 5)	Cummings (2004)
37	Analysis results (e.g., preliminary findings, unexpected outcomes, or clear recommendations)	Likert Scale (1 – 5)	Cummings (2004)
Section 6: Firm Performance			
	Firm Financial and Market Performance	**Questions Type**	**Reference**
38	Using big data analytics improved customer retention during the last 3 years relative to competitors	Likert Scale(1 – 7)	Tippns and Sohi (2003); Wang, Liang, Zhong, Xue and Xiao (2012)
39	Using big data analytics improved Sales Growth during the last 3 years relative to competitors	Likert Scale(1 – 7)	Tippns and Sohi (2003); Wang, Liang, Zhong,

			Xue and Xiao (2012)
40	Using big data analytics improved Profitability during the last 3 years relative to competitors	Likert Scale(1 – 7)	Tippns and Sohi (2003); Wang, Liang, Zhong, Xue and Xiao (2012)
41	Using big data analytics improved Return on Investment (ROI) during the last 3 years relative to competitors	Likert Scale(1 – 7)	Tippns and Sohi (2003); Wang, Liang, Zhong, Xue and Xiao (2012)
42	Using big data analytics improved overall financial performance during the last 3 years relative to competitors	Likert Scale(1 – 7)	Tippns and Sohi (2003); Wang, Liang, Zhong, Xue and Xiao (2012)
43	Our success rate of new products or services has been higher than our competitors	Likert Scale(1 – 7)	Tippns and Sohi (2003); Wang, Liang, Zhong, Xue and Xiao (2012)
44	Using analytics our market share has exceeded that of our competitors	Likert Scale(1 – 7)	Tippns and Sohi (2003); Wang, Liang, Zhong, Xue and Xiao (2012)

Note. Survey instrument adopted from *(2013); Mourinho, (2017); Niland (2017); Ghasemaghaei (2019)*

Appendix 2: Sample of SPSS data preparation and encoding



	Name	Type	Width	Decimals	Label	Values	Missing	Columns	Align	Measure	Role
28	Indealingwit...	Numeric	2	0	EO6_Proactive...	None	None	12	Right	Nominal	Input
29	Indealingwit...	Numeric	2	0	EO7_Proactive...	None	None	12	Right	Nominal	Input
30	Indealingwit...	Numeric	2	0	EO8_Risktakin...	None	None	12	Right	Nominal	Input
31	Generallyth...	Numeric	2	0	EO9_Risktakin...	None	None	12	Right	Nominal	Input
32	Generallyth...	Numeric	2	0	EO10_Risktaki...	None	None	12	Right	Nominal	Input
33	Generallyth...	Numeric	2	0	EO11_Risktaki...	None	None	12	Right	Nominal	Input
34	Onaverageh...	Numeric	2	0	Knowledgeshar...	{1, Never}...	None	12	Right	Nominal	Input
35	Onaverageh...	Numeric	2	0	Knowledgeshar...	{1, Never}...	None	12	Right	Nominal	Input
36	Onaverageh...	Numeric	2	0	Knowledgeshar...	{1, Never}...	None	12	Right	Nominal	Input
37	Onaverageh...	Numeric	2	0	Knowledgeshar...	{1, Never}...	None	12	Right	Nominal	Input
38	Onaverageh...	Numeric	2	0	Knowledgeshar...	{1, Never}...	None	12	Right	Nominal	Input
39	Usingbigdat...	Numeric	2	0	Performance1_...	{1, Strongly ...	None	12	Right	Nominal	Input
40	Usingbigdat...	Numeric	2	0	Performance2_...	{1, Strongly ...	None	12	Right	Nominal	Input
41	Usingbigdat...	Numeric	2	0	Performance3_...	{1, Strongly ...	None	12	Right	Nominal	Input
42	Usingbigdat...	Numeric	2	0	Performance4_...	{1, Strongly ...	None	12	Right	Nominal	Input
43	Usingbigdat...	Numeric	2	0	Performance5_...	{1, Strongly ...	None	12	Right	Nominal	Input
44	Oursuccess...	Numeric	2	0	Performance6_...	{1, Strongly ...	None	12	Right	Nominal	Input
45	Usinganalyti...	Numeric	2	0	Performance7_...	{1, Strongly ...	None	12	Right	Nominal	Input
46	Knowledge_...	Numeric	8	2	Knoledge Sharing	None	None	19	Right	Nominal	Input
47	Innovativeness	Numeric	8	2	Innovativeness	None	None	16	Right	Nominal	Input
48	Proactiveness	Numeric	8	2	Proactiveness	None	None	15	Right	Nominal	Input
49	Risk_Taking	Numeric	8	2	Risk Taking	None	None	13	Right	Nominal	Input
50	Financial_a...	Numeric	8	2	Financial and ...	None	None	34	Right	Scale	Input
51	Organisatio...	Numeric	8	2	Organisational ...	None	None	24	Right	Scale	Input

Appendix 3: Test for normality

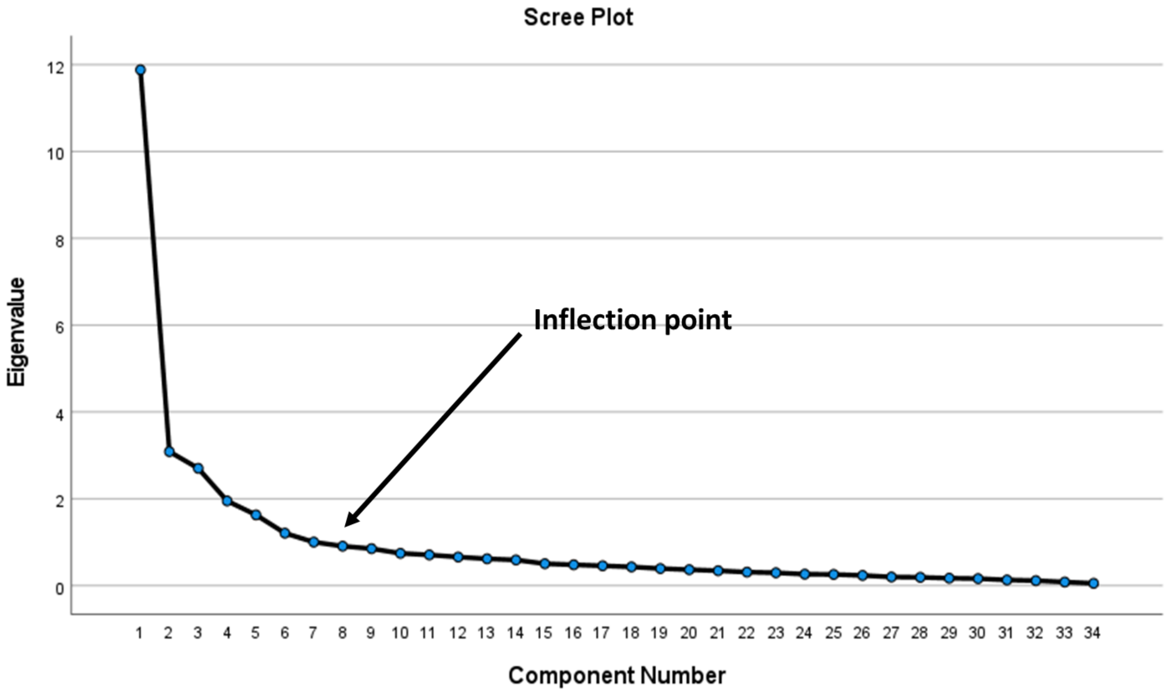
		Sample	Skewness	Kurtosis
		Size	Statistic	Statistic
Demographics	Age	138	0.857	2.008
	Gender	138	0	-2.03
	number_of_employee	144	-0.464	-1.514
	Position	144	0.47	-0.815
	Tenure	144	0.054	-1.717
Organisation Performance	OC1_Innovation_culture	144	-1.336	0.744
	OC2_Learning_Culture	144	-0.587	-0.923
	OC3_newcutting-edge_practices	144	-1.182	0.139
	OC4_Expansion_culture	144	-0.389	-0.25
	OC5_visionary_flexible	144	-0.349	-1.379
	OC6_Employee_orientation_program	144	-0.458	-1.235
	OC7_Targeted_training	144	-0.296	-1.493
Decision Making	DM1_Systematic_evaluation	144	-0.524	-0.294
	DM2_employee_recognition	144	-0.422	-1.297
	DM3_ on_job_experience and knowledge	144	-0.034	-0.697
	DM4_Decision_others	144	-0.287	0.078
	DM5_Internal politics	144	-0.026	-0.734
	DM6_Competiveness_on_analytics_capability	144	-0.178	-1.566
	DM7_access_management_Inforsytems	144	-0.459	-0.76
	DM8_Appraise internal data	144	0.549	2.951
Entreprenereurial_Orientation	EO1_Innovation_RnD	144	-0.266	-0.514
	EO2_innovation_Newlinesproducts	144	0.083	-1.083
	EO3_innovation_Newlineproducts_dramatic	16	0.417	-1.004
	EO4_innovvation_newlinesproducts_2	144	0.159	-0.942
	EO5_proactiveness_competitors	16	-0.174	-0.995
	EO6_Proactivesness_prdt_technology	144	-0.089	-0.733
	EO7_Proactiveness_undocompetitors	144	-0.079	-0.894
	EO8_Risktaking_riskloving_a	144	-0.142	-0.519
	EO9_Risktaking_riskloving_b	144	0.029	-0.843
	EO10_Risktaking_aggressive_posture	144	0.038	-0.876
	EO11_Risktaking_nature	144	-0.125	-0.773
Knowledge Sharing	Knowledgeshare1_General overviews	144	-0.484	-0.955
	Knowledgeshare2_Specific requirements	144	-0.689	-0.681
	Knowledgeshare3_Analytical techniques	144	-0.33	-1.057
	Knowledgeshare4_Progress reports	144	-0.826	-0.436
	Knowledgeshare5_Analysis results	144	-0.667	-0.703
Organisation Performance	Performance1_customer retention	144	0.169	-1.467
	Performance2_Sales Growth	144	0.217	-1.487
	Performance3_Profitability	144	0.058	-1.479
	Performance4_ROI	144	0.167	-1.546
	Performance5_OVERALL	144	0.226	-1.53
	Performance6_newproductsuccessrate	144	0.417	-1.375
	Performance7_marketshareincrease	144	0.635	-10.059

Overall	Knowledge_Sharing	144	-0.575	-0.638
	Innovativeness	16	0.411	-0.972
	Proactiveness	16	-0.075	-0.813
	Risk_Taking	144	-0.072	-0.724
	Financial_and_Market_performance	144	0.31	-1.235
	Organisational_Culture	144	-0.554	-0.56
	Data_Driven_Decision_Making	144	-0.084	0.406
	Entrepreneurial Orientation	144	2.403	6.818

Appendix 4: Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	11.882	34.948	34.948	11.882	34.948	34.948	5.474	16.100	16.100
2	3.088	9.081	44.030	3.088	9.081	44.030	5.449	16.028	32.128
3	2.702	7.948	51.978	2.702	7.948	51.978	3.847	11.314	43.442
4	1.952	5.741	57.719	1.952	5.741	57.719	3.106	9.135	52.577
5	1.629	4.793	62.511	1.629	4.793	62.511	2.657	7.814	60.391
6	1.209	3.556	66.068	1.209	3.556	66.068	1.618	4.759	65.150
7	1.003	2.950	69.018	1.003	2.950	69.018	1.315	3.868	69.018
8	.909	2.675	71.692						
9	.852	2.507	74.199						
10	.744	2.189	76.388						
11	.708	2.082	78.470						
12	.659	1.938	80.409						
13	.619	1.819	82.228						
14	.592	1.741	83.969						
15	.505	1.486	85.455						
16	.481	1.414	86.869						
17	.457	1.345	88.213						
18	.432	1.271	89.484						
19	.394	1.158	90.641						
20	.368	1.082	91.723						
21	.344	1.011	92.734						
22	.311	.916	93.650						
23	.296	.872	94.522						
24	.264	.777	95.299						
25	.258	.758	96.057						
26	.235	.691	96.749						
27	.199	.586	97.335						
28	.191	.562	97.897						
29	.171	.504	98.401						
30	.162	.475	98.877						
31	.131	.384	99.261						
32	.115	.339	99.600						
33	.083	.244	99.844						
34	.053	.156	100.000						

Appendix 5: Scree plot



Appendix 6: Principal Component Analysis after rotation

Pattern Matrix[a]

	Component						
	1	2	3	4	5	6	7
OC2_Learning_Culture	.737	-.115	-.109	-.013	.236	-.063	-.029
OC3_newcutting-edge_practices	.562	-.152	-.185	-.120	.217	.076	-.115
OC4_Expansion_culture	.717	.356	-.011	.005	-.081	.076	.017
OC5_visionary_flexible	.750	.016	-.055	.058	.143	-.105	.146
OC6_Employee_orientation_program	.831	-.087	.058	.002	-.116	.028	.100
OC7_Targeted_training	.668	.014	-.220	-.055	-.125	-.068	.020
DM1_Systematic_evaluation	.727	.030	-.102	-.086	-.076	.076	.002
DM2_employee_recognition	.512	.034	-.245	-.183	-.182	-.142	.236
DM3_ on_job_experience and knowledge	.216	-.152	.077	-.097	.148	.735	-.025
DM4_Decision_others	-.018	.037	-.059	-.130	-.071	.380	.731
DM5_Internal politics	-.077	.028	-.012	.139	-.072	.823	.125
DM6_Competiveness_on_analytics_capability	.440	-.062	-.084	-.223	.061	.034	.234
DM7_access_management_Inforsytems	.529	.094	-.031	-.034	.081	.157	-.130
DM8_Appraise internal data	.288	.170	.198	-.286	.111	-.138	-.078
EO1_Innovation_RnD	.192	-.014	.145	-.012	.312	-.224	.606
EO2_innovation_Newlinesproducts	.020	.171	-.104	-.059	.690	.005	.189
EO4_innovvation_newlinesproducts_2	-.057	.138	-.171	-.009	.706	-.024	.204
EO6_Proactivesness_prdt_technology	-.033	.015	-.225	-.166	.666	-.025	.056
EO8_Risktaking_riskloving_a	.036	.174	.015	-.005	.647	.056	-.157
EO9_Risktaking_riskloving_b	-.026	.858	-.016	-.050	.078	.034	-.078
EO10_Risktaking_aggressive_posture	.023	.873	.002	-.059	.051	-.031	.046
EO11_Risktaking_nature	.006	.734	-.132	.085	.210	-.173	.092
Knowledgeshare1_General overviews	.094	.095	-.064	-.724	-.071	.000	.034
Knowledgeshare2_Specific requirements	.002	.102	-.017	-.835	.045	.035	-.051
Knowledgeshare3_Analytical techniques	.018	.084	-.077	-.694	-.110	-.116	.148

Knowledgeshare4_Progress reports	-.044	-.188	.009	-.894	.108	.042	.026
Knowledgeshare5_Analysis results	-.071	-.021	-.044	-.909	.004	.000	-.032
Performance1_customer retention	.117	.004	-.808	.007	.050	-.003	.020
Performance2_Sales Growth	.089	-.116	-.858	-.030	.118	-.039	-.032
Performance3_Profitability	.037	.065	-.880	-.056	-.051	.026	-.091
Performance4_ROI	.038	.104	-.882	-.099	-.066	-.017	-.005
Performance5_OVERALL	-.023	.085	-.905	-.068	-.087	-.052	.017
Performance6_newproductsuccessrate	.108	.055	-.502	-.023	.294	.138	.081
Performance7_marketshareincrease	.029	-.083	-.693	.039	.305	-.018	.031

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 10 iterations.

Appendix 7: Communalities values

	Initial	Extraction
OC2_Learning_Culture	1.000	.739
OC3_newcutting-edge_practices	1.000	.607
OC4_Expansion_culture	1.000	.696
OC5_visionary_flexible	1.000	.711
OC6_Employee_orientation_program	1.000	.657
OC7_Targeted_training	1.000	.620
DM1_Systematic_evaluation	1.000	.657
DM2_employee_recognition	1.000	.670
DM3_ on_job_experience and knowledge	1.000	.665
DM4_Decision_others	1.000	.725
DM5_Internal politics	1.000	.731
DM6_Competiveness_on_analytics_capability	1.000	.517
DM7_access_management_Inforsytems	1.000	.380
DM8_Appraise internal data	1.000	.315
EO1_Innovation_RnD	1.000	.620
EO2_innovation_Newlinesproducts	1.000	.745
EO4_innovvation_newlinesproducts_2	1.000	.742
EO6_Proactivesness_prdt_technology	1.000	.691
EO8_Risktaking_riskloving_a	1.000	.512
EO9_Risktaking_riskloving_b	1.000	.783
EO10_Risktaking_aggressive_posture	1.000	.838
EO11_Risktaking_nature	1.000	.793
Knowledgeshare1_General overviews	1.000	.663
Knowledgeshare2_Specific requirements	1.000	.756
Knowledgeshare3_Analytical techniques	1.000	.628

Knowledgeshare4_Progress reports	1.000	.777
Knowledgeshare5_Analysis results	1.000	.784
Performance1_customer retention	1.000	.771
Performance2_Sales Growth	1.000	.865
Performance3_Profitability	1.000	.817
Performance4_ROI	1.000	.881
Performance5_OVERALL	1.000	.842
Performance6_newproducts uccessrate	1.000	.579
Performance7_marketsharei ncrease	1.000	.686

Extraction Method: Principal Component Analysis.

Appendix 8: Principal Component Analysis

Structure Matrix

	Component						
	1	2	3	4	5	6	7
OC2_Learning_Culture	.815	.099	-.442	-.418	.418	-.029	.155
OC3_newcutting-edge_practices	.696	.032	-.468	-.433	.376	.109	.064
OC4_Expansion_culture	.764	.440	-.317	-.386	.185	.030	.152
OC5_visionary_flexible	.805	.198	-.387	-.376	.354	-.090	.303
OC6_Employee_orientation_program	.785	.008	-.227	-.342	.053	.070	.231
OC7_Targeted_training	.752	.150	-.458	-.428	.122	-.044	.178
DM1_Systematic_evaluation	.795	.148	-.393	-.446	.151	.090	.163
DM2_employee_recognition	.694	.177	-.485	-.529	.094	-.133	.386
DM3_ on_job_experience and knowledge	.257	-.213	-.080	-.118	.120	.755	.031
DM4_Decision_others	.202	-.007	-.210	-.243	.044	.365	.752
DM5_Internal politics	-.105	-.186	.037	.212	-.130	.827	.075
DM6_Competiveness_on_analytics_capability	.626	.083	-.376	-.498	.246	.041	.377
DM7_access_management_Inforsytems	.571	.181	-.267	-.292	.227	.148	-.009
DM8_Appraise internal data	.382	.298	-.051	-.403	.219	-.193	.014
EO1_Innovation_RnD	.323	.138	-.115	-.237	.392	-.239	.657
EO2_innovation_Newlinesproducts	.317	.386	-.398	-.310	.805	-.061	.303
EO4_innovvation_newlinesproducts_2	.243	.350	-.420	-.248	.806	-.080	.306
EO6_Proactivesness_prdt_technology	.303	.257	-.482	-.376	.772	-.063	.192
EO8_Risktaking_riskloving_a	.188	.334	-.199	-.148	.677	-.007	-.074
EO9_Risktaking_riskloving_b	.150	.877	-.163	-.211	.300	-.139	-.042
EO10_Risktaking_aggressive_posture	.214	.908	-.180	-.262	.303	-.206	.088
EO11_Risktaking_nature	.201	.829	-.288	-.178	.445	-.315	.141
Knowledgeshare1_General overviews	.461	.245	-.345	-.800	.145	-.059	.188
Knowledgeshare2_Specific requirements	.418	.274	-.325	-.860	.238	-.042	.113
Knowledgeshare3_Analytical techniques	.384	.232	-.320	-.758	.101	-.172	.281

Knowledgeshare4_Progress reports	.371	.001	-.290	-.857	.226	.012	.187
Knowledgeshare5_Analysis results	.362	.153	-.320	-.882	.173	-.057	.128
Performance1_customer retention	.438	.157	-.869	-.338	.326	.024	.176
Performance2_Sales Growth	.432	.071	-.914	-.362	.374	.006	.139
Performance3_Profitability	.381	.194	-.894	-.358	.242	.042	.063
Performance4_ROI	.421	.248	-.924	-.425	.258	-.012	.157
Performance5_OVERALL	.349	.218	-.907	-.372	.222	-.041	.162
Performance6_newproductsuccessrate	.409	.205	-.666	-.320	.495	.131	.221
Performance7_marketshareincrease	.340	.102	-.776	-.263	.497	.010	.173

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

Appendix 9: Descriptive data for Organisation culture to big data analytics application

Survey items	1	2	3	4	5	6	7	mean
Innovation is an absolute necessity in the organisation`s future,	3.50%	0.70%	7.70%	4.90%	16.10%	23.10%	44.10%	5.66
Organisation enables learning, accumulation and application of new knowledge better than its competitors,	4.20%	4.90%	11.90%	19.10%	26.60%	22.40%	21.00%	4.83
It is important to adopt new and cutting-edge practices to continuously improve product or service,	1.40%	4.90%	7.00%	5.60%	14.00%	28.00%	39.20%	5.56
People in the organisation are continuously encouraged to expand their capacities to achieve more and apply new capabilities,	1.40%	3.50%	8.40%	22.40%	27.30%	18.20%	18.90%	5.01
Our organisation can be described as visionary and flexible	5.60%	13.30%	8.40%	9.80%	22.40%	21.70%	18.90%	4.52
Existence of an extensive employee orientation program for new employees to ensure employees share the corporate vision and purpose	4.20%	9.80%	14.00%	7.00%	18.90%	24.50%	21.70%	4.74
Firm invest in targeted training and support at all levels of our organisation to assist our organisation to understand or know how to use data that is available	2.80%	12.60%	11.90%	12.60%	16.80%	30.80%	12.60%	4.47

Note. Survey items sourced from *Hill (2003); Kuratko; Montango (1990)*

Appendix 10: Descriptive data for Decision making in the organisation

Survey items	1	2	3	4	5	6	7	mean
Before any decision is taken, we systematically evaluate internal data to better understand the nature of the problem and what to do about it,	4.20%	4.20%	11.20%	18.90%	24.50%	20.30%	16.80%	4.85
Employees receive recognition from the organisation for applying evidence-based decision making in our typical business processes	5.60%	8.40%	11.20%	11.90%	21.70%	30.10%	11.20%	4.48
Managers in our organisation tend to believe that experience and knowledge gained on the job is the only important source of information when considering how to tackle a problem,	5.60%	8.40%	21.70%	23.08%	16.10%	16.10%	8.04%	4.19
We make decisions by looking at what other organisations are doing, and how it's working for them	6.30%	5.60%	15.40%	37.10%	20.30%	11.90%	3.50%	4.10
Internal politics and power struggles influence the way we make decisions about policies and practices,	4.20%	9.10%	15.40%	30.80%	11.20%	16.80%	12.60%	4.36
We believe that our competitiveness depends on our analytics capability	1.40%	11.90%	11.90%	16.80%	18.90%	27.30%	11.90%	4.37
DM7_access_management_Inforsytems	0.70%	4.90%	11.90%	14.60%	22.90%	16.70%	28.50%	5.18

Note. Survey items sourced from *CEBMa (2013); Mourinho, (2017); Niland (2017)*

Appendix 11: Descriptive data for EO (Innovativeness, Proactiveness and Risk-tasking)

EO: Innovativeness	1	2	3	4	5	6	7	mean
Generally, the top managers of my firm favour a strong emphasis on the marketing of tried-and-true products and services	4.20%	6.30%	11.20%	27.30%	19.60%	16.80%	14.70%	4.13
There were no new lines of products or services firms have marketed in the past 5 years	8.40%	14.00%	16.80%	21.80%	11.20%	10.50%	17.50%	2.94
Changes in product or service lines have been mostly of minor nature,	14.00%	14.70%	15.40%	24.50%	11.20%	10.50%	11.90%	3.86
EO: Proactiveness	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**mean**
In dealing with its competitors, my firm typically responds to actions initiated by competitors	10.50%	11.90%	12.60%	24.50%	22.40%	9.10%	9.10%	3.88
In dealing with its competitors, my firm is very seldom the first firm to introduce new products/services, operating technologies etc,	10.50%	15.00%	9.80%	25.20%	19.60%	11.90%	7.70%	3.99
In dealing with its competitors, my firm typically seeks to avoid competitive clashes, preferring “liv e-and-let-live” posture	6.00%	10.50%	14.70%	29.40%	20.30%	14.00%	5.60%	3.92
EO: Risk taking	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**mean**
Generally, the top managers of my firm favour low risk projects with normal and certain rates of return,	12.60%	14.00%	16.10%	21.70%	19.60%	9.10%	7.00%	4.11
Generally, the top managers of my firm favour a cautious, “wait and see” posture in order to minimise probability of making costly decisions when faced with uncertainty,	13.30%	13.30%	16.80%	19.60%	20.30%	9.10%	7.70%	3.78
Generally, the top managers of my firm believe that owing the nature of the environment, it is best to explore gradually via cautious behaviour,	10.50%	11.90%	13.30%	23.80%	21.00%	11.90%	7.70%	3.78

Note. Survey questions sourced from *Barringer and Bluedorn (1999)*.

Appendix 12: Descriptive data for Firm Performance

Survey Items	1	2	3	4	5	6	7	mean
Using big data analytics improved customer retention during the last 3 years relative to competitors	7.00%	6.30%	11.90%	27.30%	23.10%	16.10%	8.40%	3.81
Using big data analytics improved Sales Growth during the last 3 years relative to competitors	4.90%	9.10%	10.90%	25.90%	19.60%	18.20%	8.40%	3.83
Using big data analytics improved Profitability during the last 3 years relative to competitors	6.30%	6.30%	14.70%	23.10%	23.10%	19.60%	7.00%	3.92
Using big data analytics improved Return on Investment (ROI) during the last 3 years relative to competitors	7.00%	4.90%	14.00%	28.70%	17.50%	23.10%	4.90%	3.77
Using big data analytics improved overall financial performance during the last 3 years relative to competitors	4.20%	9.10%	14.00%	26.60%	18.20%	21.00%	7.00%	3.82
Our success rate of new products or services has been higher than our competitors	4.20%	11.20%	14.00%	29.40%	18.20%	16.80%	6.30%	3.63
Using analytics our market share has exceeded that of our competitors	9.10%	11.90%	11.20%	32.90%	18.20%	11.90%	4.90%	3.28

Note. Survey questions sourced from *Barringer and Bluedorn (1999)*.

Appendix 13: Approval letter for Ethical Clearance

Gordon Institute
of Business Science
University of Pretoria

Ethical Clearance Approved

Dear Molise Mokhadinyana,

Please be advised that your application for Ethical Clearance has been approved.
You are therefore allowed to continue collecting your data.
We wish you everything of the best for the rest of the project.

Ethical Clearance Form

Kind Regards

This email has been sent from an unmonitored email account. If you have any comments or concerns, please contact the GIBS Research Admin team.