Gordon Institute of Business Science
University of Pretoria

Big data value creation: An entanglement of capabilities view – Findings from PLS-SEM and fsQCA

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A research project submitted to the Gordon Institute of Business Science, University of Pretoria, in partial fulfilment of the requirements for the degree of Master of Business Administration.

7 November 2018

Abstract

In an era of discontinuous change, organisations are constantly seeking out 'inflection point' strategies to respond to threats and opportunities and create sustainable performance. Much research has evangelised the role of big data in organisations as an enabler for competitive performance by informing better decision making. However, very few organisations have achieved the promise of big data.

This research draws on the theories of dynamic capability, sociomaterialism and paradox dynamics to provide an entanglement of capabilities view to assess the complex interactions between Big Data Analytics Capabilities (BDAC), Distinct Dynamic Capabilities (DDC) and Firm Performance (FPer). This research therefore closes the gap between Information Systems (IS) and Strategic Management (SM) research.

A higher-order reflective structural model was developed and assessed with 155 online survey responses. The hypothesised interactions were evaluated through PLS-SEM and fsQCA statistical methods. The findings reported statistical significance between BDAC and FPer, BDAC and DDC and DDC and FPer. More importantly, a full indirect mediation of the interaction of DDC on the BDAC – FPer relationship was reported. The results of this research study provide insights for both business and academia through the entanglement of capabilities view of the mechanisms through which big data can effectuate value in dynamic environments.

Keywords

Big Data Analytics, Distinct Dynamic Capability, Sociomaterialism, 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.

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7 November 2018

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1.1 Introduction to research problem

The big data phenomenon together with the business environment has been constantly evolving over the years. Organisations which previously faced challenges of data scarcity to inform decision making are now experiencing the proliferation of the big data phenomenon which brings with it an abundance of data.

This has given rise to Big Data Analytics (BDA) which has been evangelised as one of the key business levers that organisations can adopt to create differentiated advantages in dynamic environments. Kiron, Prentice and Ferguson (2014) and Lee (2017) reported that BDA has the potential to enable organisations positively through deriving important data driven insights to enhance firm performance (FPer) in dynamic environments.

Although these studies have provided measurable understanding of BDA and its potential value, organisations are still struggling to make sense and enable the potential of big data Garmaki, Boughzala and Wamba (2016). The importance of understanding the mechanisms under which big data functions stems from the Information Technology (IT) paradox, which posits the failure to beneficiate a positive organisational outcome between investments in IT processes and strategic intent (Gupta & George, 2016).

Furthermore, big data as an organisational asset is meaningless in a vacuum. Organisations are in search of strategic inflection points to create sustainable performance under both stable and dynamic environments. As such, the application of the big data phenomenon has attracted increasing attention in academia in driving strategic decision making.

Yet, there is a poor understanding of the autonomy in which big data coexists with organisational processes and capabilities (Akter et al., 2016; Wamba et al., 2017). This is critical as IS research has previously established the relationship between IT embedded capabilities and an organisations competitive advantage (Mikalef & Pateli, 2017).

As such, this research considers big data as a co-specialising resource which alone cannot enable value, but through an organisational capability. The aim of this study is too gain a deeper understanding into the interactions between dynamic organisational capabilities and FPer in the big data environment.

1.2 The Research problem

Organisations today operate in a complex and discontinuous environment, it is generally acknowledged that under these conditions, organisations seek out new and innovative ways to compete (Gupta & George, 2016; Mathews, 2016; Mazzei & Noble, 2017; Reeves & Deimler, 2011). The evolution of technology has given rise to a wave of hyper-competition (Porter & Heppelmann, 2014), which creates its own set of complexities, uncertainties and opportunities for organisations. The rise and fall of industry giants have been witnessed over the last two decades caused by a failure to evolve the static ubiquitous 'first-order' schemata. In addition, the correlation between profitability and market share now seems non-existent in certain industries (Reeves & Daimler, 2011).

The question then arises, how can organisations compete in an era of discontinuous change, borderless economies and hyper-competition whilst mitigating risk and ensuring survival. The "inertia" inherent in organisations through a sense of dissonance in dynamic environments requires organisations to create a 'point of inflection' (Burgelman & Grove, 1996; Markides, 1999; Prange & Schlegelmilch, 2016), which changes the fundamentals of an organisation which can arguably result in value creation (Peng, 2003; Tushman & O'Reilly, 1996).

In response to this call of a 'point of inflection', big data in recent years have been evangelised to redefine the competitive landscape and is posited to creating business value (Akter et al., 2016; Gupta & George, 2016; Gunther, Mehrizi, Huysman, & Feldberg, 2017; Wamba et al., 2017). The term big data can be collectively described as a group of distinctive technologies and capabilities which together enable the collection, processing and targeted application of large amounts of data (Chen, Chiang, & Storey, 2012; Chen, Mao, & Liu, 2014; Hashem et al., 2015; Ozkose, Ari, & Gencer, 2015). BDA on the other hand is about technologies and analytical techniques that an organisation can employ to analyse large scale, complex data (Kwon, Lee & Shin, 2014) and report insights not attainable with past data technologies (Garmaki et al., 2016). BDA has the capability to change industries and the way an organisation operates by challenging the conventional decision-making processes (Barton & Court, 2012; Corte-Real, Oliviera, & Ruivo, 2017; Hagel, 2015).

Hughes (2018) states that in the face of complex change, organisational adaptive systems are required. Teece, Peteraf and Leih (2016) conclude that when the rules of competition are becoming increasingly ambiguous organisational exploitation and exploration strategies are required. This perspective is considered as a critical capability in discontinuous environments allowing a firm to identify and effectively respond to possible threats and opportunities (Birkinshaw, Zimmerman, & Raisch, 2016; Ghasemaghaei, Hassanein, & Turel, 2017; Paliokaite & Pacesa, 2015). In adding tothis perspective, March (1991) stated that firms need to ensure “the exploration of new possibilities and exploitation old certainties” (p. 71).

Different environmental conditions need to be linked with different organisational forms else this leads to the failure traps which can be detrimental for an organisation adopting the incorrect stature. In response to this dilemma Koryak, Lockett, Hayton, Nicolaou and Mole (2018) argue that an organisations ability to explore and exploit opportunities simultaneously, plays a key role in minimising uncertainties and risks and firms can create their own differentiated advantages. For an organisation to constantly stay adrift during turbulent conditions, Mikalef and Pateli (2017) and Wilden, Gudergan, Nielsen and Lings (2013) argue that although explorative and exploitative capabilities can result in organisational survival and create business value, a convergence is required under dynamic conditions to enhance this ability to create superior firm performance. With the extant amount of data available today, BDA has the potential to inform better decision-making strategies for organisations to create sustainable performance levels (Kiron et al., 2014). Yet previous studies have provided ambiguous results on the aforementioned value created through big data which has resulted in the big data paradox (Gupta & George, 2016; Wamba et al., 2015). Alharthi, Krotov and Bowman (2017) and Gunther et al. (2017) attribute this paradox to a poor comprehension of the big data concept, poorly implemented big data projects, lack of capabilities and traditional business models which constrain the effectiveness of big data. The autonomy of BDAC as a mechanism to leverage big data and other resources is not properly understood (Akter et al., 2016; Gupta & George, 2016; Wamba et al., 2017). Additionally, there is mixed consensus on the direct and indirect interactions in which big data enables value for organisations (Mikalef & Pateli, 2017).

There is therefore a need to assimilate the elements that constitute BDAC and its interactions with business process to effectuate value. Drawing on emerging literature from Information Systems and Strategic Management, big data has the ability to transform an organisations decision making process (Wamba et al., 2017). This research study aimed to merge the two concepts of big data and organisational exploration and exploitation to create an entanglement view of capabilities, to better understand the mechanisms under which big data can create value for organisations by enhancing firm performance.

1.3 Purpose of the research

The purpose of this research is to understand the effects of BDAC and the simultaneous strategic decision-making processes of exploitative and explorative capabilities on FPer. Gaining a deeper insight into these interactions could have valuable implications for organisations operating under dynamic environments. Furthermore, understanding the antecedents to developing and effective BDAC could allow organisations to successfully deploy and implement big data projects within their organisations.

Therefore, the objectives of this research study are to:

1. Determine the elements that constitute BDAC's,
2. Determine the most suitable way to simultaneously adopt exploitative and explorative capabilities as distinct processes and capabilities within organisations,
3. Determine the direct and indirect interactions between DDC, dynamic management of exploitative and explorative capabilities and FPer.

As such, the scope of this research is limited to the aspects of the sociomaterialism concept of BDAC and the organisational capabilities of exploitation and exploration relationship between FPer.

1.3.1 Academic rationale

Given the relative infancy in academia for big data literature, there is a need to understand the underlying interactions under which big data enables organisational fitness (Akter et al., 2016; Wamba et al., 2017). Big data research has viewed BDAC in technical terms which cover aspects of IT infrastructure systems, data analytic tools and techniques, database sizes and structured data decoding mechanisms (Lee, 2017). However, IT capabilities have been closely linked to BDAC (Akter et al., 2016; Kiron et al., 2014; Wamba et al., 2017), and have been studied using dynamic capability and resource-based theories (Corte-Real et al., 2017). These theories have been extensively studied and have identified empirical links between an organisation's capabilities and FPer (Birkinshaw et al., 2016). By analysing big data using the dynamic capability view, the researcher can contribute to the lacking empirical evidence of the dynamic interplay between big data and FPer (Davenport, Barth, & Bean, 2012; Garmaki et al., 2016) and posits that the big data phenomenon is fundamentally positioned as an embedded organisational artefact to enable superior value.

Furthermore, by building on the emerging concept of sociomaterialism within Information Systems literature, this research study addresses the need to effectively understand the anatomy of BDAC within an organisation (Garmaki et al., 2016; Gupta & George, 2016). Linton and Kask (2017) argued that more research is required within the big data environment and on the ability of an organisation to leverage big data for informed decision making. This perspective is further enhanced by the need for more research to examine the role interactions of organisational factors (Akter et al., 2016; Ghasemaghaei et al., 2017). Wamba, Akter, Edwards, Chopin and Gnanzou (2015), following their longitudinal study on the impact of big data reported that organisations need to align organisational capabilities with big data to enable value and future research is required on leveraging the “information ecosystem” (p. 244). In addition, Gunther et al. (2017) calls for empirical research into the dynamic interplay between organisational models and big data. Adding to this theoretical complexity is the need to understand how organisations can operate in dynamic environments (Birkinshaw et al., 2016). The researcher proposed a merging of the big data parody with exploitative and explorative strategies drawing from the seminal work of Levinthal and March (1993). This complex entanglement has not been tested in the big data environment as the literature on big data was identified to be in its infancy. Furthermore, the relationship between exploitative and explorative capabilities has been shown to represent a paradoxical relationship (Smith, 2015). Research on the role of IT capabilities and explorative and exploitative capabilities has mostly focussed on either one component (Lin & Wu, 2014). Whereas, research utilising both capabilities portrayed more of the competitive nature of the constructs instead of the organisational orientation (Ghasemaghaei et al., 2017; Wamba et al., 2017). These perspectives present an opportunity for further research to bridge the gap between Information Systems and Strategic Management fields and more specifically to gain a deeper insight between the interactions that create value for organisations in the big data environment.

1.3.2 Business rationale

The practical implications of big data for businesses has gained increased attention over the last decade (Gunther et al., 2017; Wamba et al., 2015). Emerging literature refers to the phenomenon of big data as the new “management revolution” (McAfee & Brynjolfsson, 2012, p. 3) and having the ability to challenge traditional business models by “unlocking business value by unleashing new organisational capabilities and value” (Wamba et al., 2015, p. 234). Organisations can improve their ROI by up to 20% (Wamba et al., 2015) by transforming their decision-making processes through the capability of big data (McAfee & Brynjolfsson, 2012). However, many big data projects have not been correctly implemented for organisations to achieve these benefits (Alharthi et al., 2017; Gunther et al., 2017). For big data not be fully engulfed in the IT paradox, organisations need to understand the effective factors that improve big data implementations and beneficiations. Furthermore, businesses need to understand the dynamism under which big data can be leveraged to enable the potential value.

This study assesses the anatomy of the BDAC within an organisational setting to gain insights on the influence of the entanglement of capabilities and FPer. More specifically, this study evaluates the core elements of BDAC and their appropriability in an organisational ecosystem. This can provide insight to organisations on specific areas to focus on to realise beneficiation of their big data strategies and gain competitive advantages in an era of discontinuous change. By understanding the dynamic interplay between exploitative and explorative capabilities and their effect on the big data environment, organisations can effectively improve their decisions making processes and enhance the structural and organisational configurations.

This research study intends to provide a deeper and malleable understanding on the application and deployment of BDAC and to provide guidance to organisations on the necessary organisational interactions that give rise to superior performance. The following Chapter provides the theoretical background regarding the big data environment, BDAC, exploitative and explorative capabilities and a view on the entanglement of capabilities and their effect on FPer.

Chapter 2: Literature review

2.1 Introduction

The literature review in this research is directed at illustrating the outlook of big data and the entanglement of higher order capabilities in the current dynamic environment and its impact on organisations. A reoccurring theme based on positions in organisational academia is that successful organisations create value through enabling and deploying higher order capabilities in dynamic environments, but the path dependencies and causal ambiguities are not properly understood as theoretical underpinnings in big data is in its relative infancy. As such, the research builds on distinct relationships under the concept of sociomaterialism to develop series of hypothesised positions to explain the distinct interplay between different types of higher order capabilities in a data driven ecosystem.

To address these positions, this study focusses on recent literature on big data and views on dynamic capability under the typologies of complementarities and co-specialisations. The literature review is structured as follows: firstly, a definition of big data is provided followed by the evolving nature of big data which gave rise to value potentials and finally an entanglement view of higher order capabilities under the dynamic capability view is presented and discussed. Of interest in this study was the relationships and influencing factors that enable organisations to create sustained competitive and performance level value through the potential of big data by exploiting and exploring attributes in the dynamic ecosystem. Focus was paid to the construct constituents of both big data and distinct capabilities to effectively annotate the reflective nature of the higher order capabilities to juxtapose path dependencies and direct and indirect effects. As such, the literature review intends to describe the relevance and importance of these artefacts as a basis for this study to understand the value potential and realisation path dependencies and causal ambiguities from big data through the proposed research model to create firm level performance.

2.2 Definition of big data

In the current era of discontinuous change and dynamic organisational interplays, organisations and individuals are generating a large amount of data at a fast rate. This data is accumulating at an exabyte rate (Akoka, Comyn-Wattiau, & Laoufi, 2017). Khan, Liu, Shakil and Alam (2017) refer to this data explosion as a data deluge which describes the increasingly growing amount of data in the world. These large sets of data are almost impossible to administer and process using traditional tools for data management (Akoka et al., 2017; Chen et al., 2014). Given this position, there needs to be a differentiation between traditional datasets and enormous datasets. Big data has been a buzzword in organisational and social ecologies for over a decade and has generated global attention (Khan et al., 2017; Garmaki et al., 2016; Wamba et al., 2015). Chen et al. (2014) and Wamba et al. (2015) posit this phenomenon is due to the proliferation of adoption and diffusion in smart technologies, social platforms, RFID technologies and strategic data driven by organisational value chains. However, considering that big data is still an emerging genre, several definitions currently exist. The difference in defining big data is based on the different perspectives of "scientific and technological institutions, research scholars, data analysts and technical practitioners" (Chen et al., 2014, p. 173). Whilst there is no widespread consensus on how big data is defined, the term was initially introduced to describe the large amount of data born from the utilisation of new anatomies of technology (Akoka et al., 2017; Gupta & George, 2016). However, what is agreed upon is that a true definition needs to encapsulate the social, economic and technical aspects of big data.

The dimension of 'V' has been adopted by certain academic scholars in their articulation of big data. Gandomi and Haider (2015), Kwon et al. (2014) and Mcafee and Brynjolfsson (2012) define big data in terms of the 3 V dimensions (Volume, Velocity and Variety). Whereby 'Volume' refers to the enormous amount of data that is either stored or collected (Chen et al., 2014; Lee, 2017). 'Velocity' is described as the speed or frequency of delivery required to analyse and collect data (Lee, 2017). 'Variety' speaks to the various sources and formats of the data that is collected ranging from structured to unstructured data forms (Chen et al., 2014). In addition to the core 3 V dimensions, White (2012) and Elgendy and Elragal (2016) proposed a further two dimensions. These include the dimension of 'Value' which relates to the generation of "economically worthy insights" through the transformation of the data (Wamba et al., 2015, p. 236) and lastly 'Veracity' which describes the unpredictability and unreliability of the data which would require further analysis to achieve accurate prognostications (Elgendy & Elragal, 2016; Wamba et al., 2015).

There are also a set of definitions that emphasise other artefacts of big data which have been summarised by Ozkose et al. (2015) and Wamba et al. (2015) where the commonalities focus on the size and the technological and infrastructure requirements for the storage, analysis, processing and management of the data. Wang, Xu, Fujita, and Liu (2016) provided a more overarching definition for the concept of big data that covers four perspectives. Firstly, they put forward a product-oriented perspective which focuses on the core dimensions of big data as described by the structure, volume and speed. Secondly, they add a process-oriented perspective, which focusses on the technological infrastructure and tools that are required to process, store and manage the data. Thirdly, they characterise big data as exceeding the current traditional data processing and storing infrastructure limits through the cognition-based perspective. Lastly, they emphasise the potential of big data to revolutionise and create major transformation through the social movement perspective. Though these four perspectives can be utilised and adopted within certain defined areas, there is a need to maintain a more structured and overarching definition which can characterise big data not only in analytical and capability terms. It is for this reason the researcher has adopted the following definition of big data in this research study. Herein, big data can be defined as a “holistic approach to manage, process and analyse 5 V’s (i.e., volume, variety, velocity, veracity and value) in order to create actionable insights for sustained value delivery, measuring performance and establishing competitive advantages” (Wamba et al., 2015, p. 235).

2.3 The rise of big data

Mcabee, Landis and Burke (2017) and Provost and Fawcett (2013) posit that data driven decision making by obtaining and analysing big data are the strategic goals of organisations today. Whilst big data has only since been emerged as an organisational evangelising asset, the theme has evolved since the advent of big data being reported as early as 1994 to determine usage behaviour from web content whereby organisations using online platforms where the main drivers of data and web content (Lee, 2017). The 3 V dimensions as discussed previously that described the challenges and opportunities of big data were being considered as early as 2001 (Chen et al., 2014). Thereby inferring the perceived importance of the big data artefact at infancy. As the social media phenomenon during the 2005-2014 period took shape this gave rise to the next wave of big data (Lee, 2017; Provost & Fawcett, 2013). This evolved wave created a continuum shift in the way that organisations operated. As more data was being made available as web users could now interact and contribute to web content which contrasts with the first wave. This rapid growth of data gave rise to challenges with managing the data and in 2007 a new generation of tools to engage and manage with this increasingly growing amount of data was required (Chen et al., 2014). Even though there had been increased veneration during this period, big data had only seen an increase in organisational application since 2011 (Lee, 2017; Mcabee et al., 2017). The current wave of big data began in 2015 and encompasses the first two waves and has arguably become an economic asset for driving value (Gupta & George, 2016; Lee, 2017). This current wave was evolved by the collaboration of data driven needs and opportunities through the interconnectivity of technology and borderless economies (Mcabee et al., 2017).The classifications of big data waves have been driven by technical depictions in academia with being classified as potentially transforming organisational practices and management theory (Akter et al., 2016), which could perhaps explain the various definitions of the big data artefact. Additionally, practical and academic implications of big data have largely being ignored even though big data initiatives are becoming mainstream (Mazzei & Noble, 2017). The value of big data exists beyond the technological paradigm and isn't only about the size and processing requirements but need to also include the insights that can be leveraged for organisations to create value. Even though big data has proliferated in recent years, there is a lack of conformity and clarity on avenues that are required to create appropriate applications of Big Data Analytics (BDA) in organisations (Akter et al., 2016; Elgendy & Elragal, 2016; Mazzei & Noble, 2017).

2.4 Big data as a value driver

By referring to the definition of big data adopted by the researcher, big data can create actionable insights for organisations to create organisational value and performance. Wamba et al., (2015) further state that big data has tremendous potential to transform organisational level ideologies in generating business value. Furthermore, Gupta and George (2016), Khan et al., (2017) and Yaqoob et al., (2016) describe a definite link between harnessing data and information that is available to organisations with knowledge management and organisational performance. This value has been illustrated through the indirect impacts generated by enhanced decision making and improvements in process efficiencies as reported by Chen et al., 2012, Lee, 2017 and Wamba et al., 2017. Even though the application of big data platforms has been assessed in different organisational settings (Yaqoob et al., 2016) they do not describe a sustained form of value or organisational performance (Elgendi & Elragal, 2016; Mazzei & Noble, 2017; Mcabee et al., 2016). This can be attributed to ineffective big data associated applications (Wang et al., 2016) and a poor understanding by early adopters of the big data concept (Wamba et al., 2015).

Although organisations may exhibit the potential to create value from their data, not all organisations can do so. This delineation can be attributed to a poor data driven transformation as big data requires a higher set of capabilities (Akter et al., 2016;

Ghasemaghaei et al., 2017). However, there are academic references to big data creating value to organisations by creating inflection points ranging from competitive artefacts (Mikalef & Pateli, 2017, Ozkose et al., 2015), developing new enhanced organisational capabilities (Mazzei & Noble, 2017, Mikalef, Pappas, Krogstie, & Giannakos, 2018; Wamba et al., 2017), enabling a new breed of scientific management (Chen et al., 2012; Mazzei & Noble, 2017), enhancing decision making processes (Mcabee et al., 2017; Mcafee & Brynjolfsson, 2012; Wang et al., 2016) amongst other organisational levers. The potential to create value for organisations given the breadth of big data applications (5 V's) and the depth of the direct and indirect organisational inflection points are quite formidable. Furthermore, the value that big data extends goes beyond just traditional organisational capabilities as illustrated by the three-tier value creation framework by Mazzei and Noble (2017), refer to Table 1.

Table 1

Three tiers of value creation through big data

Tier	Category	Description
1	Data as a tool	Allows for the traditional organisational functions and value chains to be improved. Additionally, the improvements are more efficient and effective using the current processes and capabilities of the organisation. This is an operational view where many organisations find themselves as it is relatively easy to achieve with a stepwise operative through real-time and customised decision-making focuses.
2	Data as an industry	As many organisations do not have the internal capability to process and leverage their data, many insource the acquisition, analysis, infrastructure construction and software development to manage big data.
3	Data as a strategy	Organisations dedicate building of data resources which can create radical or innovative changes that link traditional and modern strategic intent.

Note. Adapted from "Big data dream: A framework for corporate strategy," by M.J. Mazzei and D. Noble, 2017, *Business Horizons*, 60, p. 408. Copyright 2017 by Elsevier Inc.

As organisations progress through each tier, data drives more strategic intent and decision-making processes become more prominent. This follows the assertions of Mcabee et al. (2017) and Mcafee and Brynjolfsson (2012), who posit the organisational value intertwined with organisational strategy when enabling data strategies. Core functionalities and capabilities are enhanced by facilitating effectiveness and efficiencies in the first-tier when organisations apply data as a tool (Mazzei & Noble, 2017). Whereby, organisations identify data in terms of resources and data analytics as an organisational capability to resolve traditional organisational dilemmas more effectively (Mazzei & Noble, 2017). The competencies and capabilities are uplifted thus movement throughout the tiers can redirect organisational activities driven from data insights (Akter et al., 2016; Mazzei & Noble, 2017).

The second-tier depicts big data as a stimulus for industries. As the proliferation of big data takes shape, many organisations do not yet have the internal capability to create actionable value from their data. Thus, affirming a poor understanding of the concept of big data as organisations assess their internal value chains as argued by Wamba et al. (2015). This results in the creation of a data industry which is focussed on data driven platforms formed for infrastructure, processing and managing of big data (Mazzei & Noble, 2017). Inflection points have already been created in this tier by organisations such as Amazon, Cloudera, Microsoft, Pivotal and consulting houses.

The third-tier describes big data as driver of competitive strategy and arguably allows a monumental potential of big data for organisations by creating organisational performance at a strategic level (Mcabee et al., 2017). Actionable insights drawn from data is absorbed by organisations to influence their internal value chains, create differentiated advantages and develop ecosystems which redirect resources and knowledge processes as accumulation and access to data increases (Mazzei & Noble, 2017).

Most organisations confine themselves to tier one and do not realise the value of their data driven processes and strategies. In some cases, organisations lack the capability and understanding (Wamba et al., 2016) or actionable insights are not interpretable or incorrectly done so due to a lack of enhanced capabilities and resources (Baldwin, 2015; Ghasemaghaei et al., 2017). Capabilities have been identified as critical artefacts in the deployment of big data initiatives as organisations need to enable an authentic alignment to create value from data (Akter et al., 2016; Mcabee et al., 2017; Pappas et al., 2017).

2.5 Big data challenges

Routine and complex business functions can be effectively enhanced and simplified through the use of informed and structured insights from a data driven decision-making strategy (Janssen, van der Voort, & Wahyudi, 2017; Jagadish et al., 2014; McAfee & Brynjolfsson, 2012; Pigni, Piccoli, & Watson, 2016). Yet achieving the promise of big data value has been a challenge for organisations (Alharti et al., 2017). Gunther et al. (2017) report that not many organisations are analysing their insights from their big data platforms and in addition many big data projects are not fully implemented by organisations. Literature in big data posits this phenomenon to various technical and non-technical big data related challenges (Akter et al., 2016; Chen et al., 2014; Khan et al., 2017; Lee, 2017; Wamba et al., 2017; Wang et al., 2016; Yaqoob et al., 2016). Technical challenges in the big data dilemma relate to the data and infrastructure characteristics such as complexity, storage, visualisation, resource capability, analytical tools and processes, compliance and security (Lee, 2017; Wang et al., 2016). Non-technical challenges in the big data dilemma include big data skills and knowledge, management support, business processes, strategy alignment, decision making constraints, change management and implementation processes (Khan et al., 2017; Yaqoob et al., 2016).

Gunther et al. (2017) presented a detailed study, focusing on current academic debates around the issues of the big data paradigm and found that three core themes have been reported. The first theme, which is arguably the most critical reported issues on the lack of capabilities and skills in the organisational environment that cannot take advantage of big data strategies. Alharthi et al. (2017) further reported that the lack of big data specific skills inhibits organisations from effectively embracing big data. Gunther et al. (2017), further presented that organisational business models further constrain big data strategies and proposes the inclusion of a diverse set of skills and perspectives to embrace big data into the organisational structures and business models.

The second theme had a focus on the regulatory and privacy aspects of data. As organisations are reliant on both the exchange of internal and external data, data governance has become a prevalent area of concern for organisations (Alharthi et al., 2017; Gunther et al., 2017). Alharthi et al. (2017) argues that social risks are inherently becoming a factor for organisations to consider when aiming to realise value from big data.

The third theme focussed on the inherent integration of tangible and intangible organisational resources and their interactions over time. Mcabee et al. (2017) posits that the big data phenomenon is not properly understood by academia and an inductive approach is necessary to gain deeper insights into the mechanisms and autonomy of big data. As few organisations have been successful in deploying and realising value from big data implementations, Elgendy and Elragel (2016) and Mazzei and Noble (2017) posit value can only be realised through big data over a period of time, as this requires iterative configurations and capabilities which constantly evolve. This perspective relates back to the resource-based view of an organisation which will be discussed later sections.

2.6 An entanglement view of capabilities

Drawing from previous research, this study views the value creation associated with big data through an entanglement view (Gupta & George, 2016; Koryak et al., 2018; Smith, 2015; Wamba et al., 2017). An entanglement perspective infers the flow of information and synergy between connected artefacts. Drawing from the theory of quantum entanglement under a strategic management perspective, an entangled system of capabilities cannot be independently interpreted, instead they should be fully described as a whole Streltsov, Singh, Dhar, Bera and Adesso (2015)

2.6.1 Dynamic capabilities in organisations

Research on the concept of Dynamic Capability Theory (DCT) created conscious attention through the seminal positions of Teece, Rumelt, Dosi and Winter (1994) and Teece, Pisano and Shuen (1997). Interest in the field of DCT stems from its potential to enhance performance outcomes for organisations (Schilke, 2014; Teece & Leih, 2016) and as such has been a key topic of interest in management and IT fields (Corte-Real et al., 2016; Mikalef & Pateli, 2017; Lin & Wu, 2017). Given the interest in this field and very similar to that of big data, there is no consensus in terms of defining a dynamic capability. This could be attributed to the evolving nature of the concept (Helfat & Peteraf, 2009). Helfat et al. (2007) states that dynamic capabilities links to the capacity to purposefully mould and enhance an organisations resource base in dynamic environments. Where the resource base refers to the tangible and intangible resources and capabilities that an organisation control's (Helfat et al., 2007).

The DCT is an extension of the Resource Based View (RBV) of an organisation (Helfat & Peteraf, 2009) which postulates organisational performance as functions of the endogenous features of organisations referred to as the resources, capabilities and competencies (Barney, Wright, & Ketchen, 2001). This frame of reference originates from the seminal work of Penrose (1959) whereby the organisation is referred to as an agglomeration of its resources which shape its competitive position. This perspective explains the heterogeneity that exists between organisations in their focus to create inflection points in their competitive performance by establishing resources that embed the characteristics of Valuable, Rare, Inimitable and Non-substitutable (VRIN) (Barney, 1991). Where 'Valuable' refers to the sustainable value creation as an output from resources, 'Rare' refers to the level of scarcity in the resources, 'Inimitable' refers to the low level of isomorphism of the resources, and 'Non-substitutable' refers to the nontransferability of the resources (Barney, 1991; Wade & Hulland, 2004). Additionally, Wade and Hulland (2004) stated that an organisation should exhibit characteristics that are useful in navigating in dynamic environments through their resources, firm attributes and knowledge. Thus, inferring that competitive advantages stems from organisations having differentiated advantages based on their distinct tangible and intangible resources. This view is further enhanced by the Firm Specific Advantage (FSA) perspective whereby organisations develop unique capabilities which are costly to imitate by competitors (Rugman, Verbeke, & Nguyen, 2011). The RBV view was extended to include the influences under a dynamic perspective where the significance of organisational capabilities is required to integrate and reconfigure resources for organisations to navigate under a dynamic continuum (Birkinshaw et al., 2016; Helfat & Peteraf, 2003). Therefore, placing dynamic capabilities as a source of differentiated advantage for organisations in dynamic environments.

The viewpoints of DCT have evolved since the seminal identification's and due to the various types of dynamic capabilities in organisations (Helfat & Peteraf, 2009). Dynamic capabilities have been viewed in terms of an organisations systematic activity patterns which enhance an organisations effectiveness (Zollo & Winter, 2002), as strategic routines of organisations which reconfigure resources as market outlooks change (Eisenhardt & Martin, 2000) and as distinct factors that allow organisations to create sustainable performance in dynamic environments (Teece et al., 1997). Although there are differences in these viewpoints, there is however consensus that dynamic capabilities are embedded processes within an organisational setting with the key premise of creating competitive advantages by enhancing capabilities. This consensus presents an appropriate description in the context of this research as it suggests the enablement of outputs of tangible and intangible organisational assets directly impacting organisational performance and competitiveness. Which explains the need to effectively use the insights from BDA platforms to create value. Furthermore, it describes the proactive propensity of an organisation to address dynamic changes in its organisational ecology by altering its capabilities (Birkinshaw et al., 2016; Lin & Wu, 2014; Teece & Leih, 2016). It is important to note that a dynamic capability is not a resource as defined by the RBV, but a process which is forward looking that effectuates, enables and develops a resource base (Ambrosini, Bowman & Collier, 2009; Barney,1991; Birkinshaw et al., 2016).

However, some researchers are divided on the type of dynamism that is relevant for dynamic capabilities (Helfat & Peteraf, 2009), some accept that DCT is relevant for both stable and dynamic environments (Birkinshaw et al., 2016) and some who choose to ignore the external environment (Zollo & Winter, 2002). As discussed earlier, this research applied the base position that organisational ecologies are in a state of discontinuous change and require effective, efficient and rapid assimilation of tangible and intangible organisational assets to create value. This has become more prominent in the face of hyper competition (Porter & Heppelmann, 2014) and rapidly advancing peripheral industries as described in the second tier of big data value (Mazzei & Noble, 2017). There is therefore a need for higher and evolved states of organisational capabilities. In this regard, Collis (1994) proposed four typologies of organisational capabilities. The first level exists as ordinary capabilities, that perform basic organisational tasks and activities (Collis, 1994; Winter 2003), the second and third level are difficult to differentiate as both are concerned with internal dynamic improvements with the no only difference in that the third level modifies or enhances value on lower level capabilities (Collis, 1994; Winter, 2003) and the fourth level is termed higher order capabilities which renew, re-learn and adapt (Collis, 1994). The second to fourth level represent dynamic order capabilities from Teece et al's. (1997) original definition (Schilke, 2014).

Despite the varying viewpoints of DCT, there is commonality on the five sub-dimensions that constitute dynamic capabilities (Mikalef & Pateli, 2017). This is further enhanced by the different types of dynamic capabilities as previously discussed. These capabilities include 'Sensing' which is the ability to identify, analyse and filter opportunities and threats in the organisational ecology (Mikalef & Pateli, 2017; Teece et al., 1997), 'Coordinating' refers to the synchronisation of internal resources and activities to internal and external artefacts to improve collaboration (Mikalef & Pateli, 2017; Teece et al., 1997), 'Learning' refers to the capability and capacity to obtain, comprehend and exploit new knowledge types which allow effective decision making (Mikalef & Pateli; Teece et al., 1997), 'Integrating' refers to the process of evaluating, combining and exploiting resources and capabilities (Mikalef & Pateli, 2017; Teece et al., 1997) and 'Reconfiguring' refers to the capacity to enable strategic decision making and rapidly act on them to effect change and create a new configuration (Ambrosini et al., 2009; Mikalef & Pateli; Teece et al., 1997). However, these capabilities are only internal to an organisation and Ambrosini et al. (2009) and Birkinshaw et al. (2016) argue that extrinsic factors could also act as enablers of dynamic capabilities. This viewpoint stems from an organisation having control and exploiting intrinsic factors and having the ability to explore extrinsic factors that are within or external to its organisational ecology.

Of considerable interest in the context of this research is that DCT covers numerous aspects which influence the assimilation of capabilities and dynamics of an organisation.

These provide more insight into the effectuation and enablement of decision-making attributes through the big data environment. As the DCT and RBV embed tangible assets such as human capital and the resulting output and impact on organisational performance and competitiveness, these characteristics can be taken into consideration through its practice in organisational big data transformations (Akter et al., 2016; Ghasemaghaei et al., 2017; Gupta & George, 2016; Mikalef & Pateli, 2017; Wamba et al., 2017). Birkinshaw et al. (2016), Lin and Wu (2014) and Paliokaite and Pacesa (2015) furthermore describe the interrelation between dynamic capabilities, strategic foresight, innovation and learning. These linkages are key characteristics of resultant organisational performance outcomes through data driven decision making, internal organisational agility and organisational innovation (Chien & Tsai, 2012; Teece et al., 2016; Wu & Chen, 2014). In this regard dynamic capability is applied as a synthesis of organisational capability outcomes which describe an organisations ability to enable responses to intrinsic and extrinsic factors and embed that capability to create value, competitive and performance level outcomes. This research goes further by proposing the relationship between two key dynamic capabilities for the big data environment to effectuate organisational level performance metrics.

2.6.2 Big data analytics capabilities and IT capabilities

The role of Information Technology (IT) capabilities in organisational settings and academia is not a new phenomenon (Bharadwaj, 2000; Kim, Shin, & Kwon, 2012; Mikalef & Pateli, 2017). The IT capability concept stems from the DCT and RBV frameworks whereby resources can be imitated but a set of organisational distinctive capabilities are not easily replicable and create competitive level advantages for organisations (Bharadwaj, 2000; Kim et al., 2012). Information Systems (IS) research has seen a proliferation depicting the value of IT capabilities in organisations (Mcafee & Brynjolfsson, 2012; Mikalef & Pateli, 2017) where empirical research has reported both direct and indirect organisational performance gains (Bhatt & Grover, 2005; Kim, Shin, Kim, & Lee, 2011).

Despite the wide spread popularity of the capability based on the changing technological landscape in the IS environment, there has been no consensus on what constitutes an IT capability and through which causal path flows it creates organisational value (Kim et al., 2012; Mikalef & Pateli, 2017). Grant (1991) proposed a resource classification methodology for organisations whereby understanding the key mechanisms of sustaining competitive advantage is crucial. This is based on understanding the relationship between an organisation’s internal tangible and intangible assets. Given the evolving nature of the IS environment which includes the big data environment, many researchers, in alignment with Grant's (1991) resource classification method, view IT capabilities in terms of an organisations knowledge, tangible and intangible assets which include IT infrastructure and relational resources (Garrison, Wakefield, & Kim, 2015; Kim et al., 2011; Rai & Tang, 2010; Stoel & Muhanna, 2009). Furthermore, Aral & Weill (2007) argue that an organisations investment in various IT assets create value through performance dimensions in alignment with their strategic intent and are guided by the organisation's strategies. Under this perspective, IT capabilities are regarded as higher order fundamental organisational dynamic capabilities, which has been defined as an organisations capacity to stimulate, arrange and integrate IT based resources to enhance and support strategies and processes (Bharadwaj, 2000; Mikalef & Pateli, 2017). Davenport et al. (2012) positioned IT capabilities as key artefacts in the big data environment. Furthermore, recent research has shown to adopt IT capability dimensions to discuss capabilities in the big data environment (Akter et al., 2016; Ghasemaghaei et al., 2017; Gupta & George, 2016, Mikalef et al., 2016; Wamba et al., 2017). However, the nature the big data capability has been debated. Kim et al. (2012) position the big data capability as a purely technical capability, whereas other academics viewed the big data capability as a diverse integration of technical and knowledge artefacts (Gupta & George (2016).

In the big data environment, organisations require effective and efficient processes to unlock the potential value and derive significant insights (Garmaki et al., 2016). Furthermore, in conducting big data processes, organisations are presented with complex big data dimensions (5V's). This complexity arises, as previously discussed, by the lack of capability and understanding of the big data concept. A response to these challenges is the notion of a higher order dynamic capability which is an entanglement of human capital, tangible and intangible assets (Akter et al., 2016; Gupta & George, 2016; Wamba et al., 2017). Wherein, Akter et al., (2016) and Kiron et al. (2014) refer to this higher order capability as Big Data Analytics Capability (BDAC) and broadly define it as a capability of an organisation to derive insights from data management, technological infrastructure and organisational resources which transforms an organisation into a competitive position. Mikalef and Pateli (2016) and Wixom, Yen and Relich (2013) also link BDAC to organisational strategies that create sustainable organisational value by emphasising data driven decision making. This higher order capability stems from the theoretical underpinnings of Grant (1991) and the concept of sociomateriality which posits the importance of the integration and linkages between technology, innovation, strategy and the internal organisational processes and activities

(Akter et al., 2016; Orlikowski & Scott, 2008; Scott & Orlikowski, 2013). By adopting the concept of sociomateriality, BDAC can be interpreted as not just an individual capability but as a manifestation of critical building blocks with complementary and co-specialisation attributes. This interpretation follows the fundamental underpinnings of DCT and RBV whereby Powell & Dent-Micallef (1997) refer to the term complimentary as the enhanced of a resource in the presence of a higher order capability or resource and Williams (1997) refer to co-specialisation as the dormancy of one resource in the absence of another resource. Thus, BDAC can be identified through three critical typologies which constitute organisational artefacts and tangible and intangible assets of an organisation, which is very similar to that of IT capabilities using the concept of sociomateriality and DCT.

Wamba et al. (2017) measured BDAC through the three primary dimensions of BDA Personnel Expertise Capability (BDAPEC), BDA Management Capability (BDAMC) and BDA Infrastructure Flexibility (BDAIF). This follows viewpoints on the importance of critical attributes required to effectively derive insights and create organisational advantages focussing on organisational management capabilities across core business functions (Davenport et al., 2012, Kim et al., 2012), talent management (Davenport et al., 2012; Mcafee & Brynjolfsson, 2012), IT assets and infrastructure (Mcafee & Brynjolfsson, 2012; Kim et al., 2012; Kiron et al., 2014) and decision making capabilities (Davenport et al., 2012; Gupta & George, 2016; Wixom et al., 2013). Akter et al., (2016) views the BDAC dimensions as an entangled and distinct set of capabilities that support, complement and enhance each other in the big data environment which is congruent with the BDAC interpretation as being complimentary and co-specialising. BDAMC refers to the ability to manage and handle structured routines utilising IT specific resources to for organisational needs (Akter et al., 2016), BDAIF refers to the ability of the big data infrastructure to enable big data resources to effectively deploy, support and develop resources and system artefacts (Kim et al., 2012) and BDAPEC refers to the skills and knowledge ability of the big data resources to perform specific tasks (Akter et al., 2016).

For this research, BDAC is positioned as a higher order dynamic capability used to achieve strategic organisational assimilation by supporting and synergistically enabling organisational strategies through the co-specialisation and complementary nature of its dimensions.

2.6.3 Distinct dynamic capabilities

The distinctive capability concept put forward by Kay (1993), refers to the organisational process of enabling a successful alignment to achieve competitive level advantages by developing and deploying a unique set of distinctive relationships both intrinsic and extrinsic to an organisation. Snow and Hrebiniak (1980) and Teece and Pisano (1994) referred to the concept of distinct capabilities as those which are difficult to imitate, and which organisations excel in when compared to competitors. These viewpoints are identified with the concept of core competencies, which refer to the harmonious integration of resources and skills that differentiate an organisation through collective learning processes (Prahalad & Hamel, 1990). However, Kay (1993) argues that a truly distinctive capability for the basis of competitive advantages needs to meet two criterions. A distinctive capability needs to be developed faster through learning and innovation processes to maintain the distinctiveness and differentiation thus creating a level of sustainability (Kay, 1993). Additionally, the capability needs to exert benefits to the organisation and display high levels of appropriability (Kay, 1993).

A key research stream in management academia has examined the predictors and interactions of organisational capabilities that are adopted during times of discontinuous change involving technology, learning and competitive advantage (Levinthal & March, 1993; Lin & Wu, 2014; Koryak et al., 2018; Raisch & Zimmerman, 2017; Teece et al., 2016). Levinthal and March (1993) recognised that organisations need to "engage in enough exploitation to ensure the organisations current viability and engage in enough exploration to ensure its future viability" (p. 105). These positions make significant reference to the current state of discontinuous change that organisations find themselves in. The phenomenon of organisational distinct capabilities has produced a rich set of viewpoints on examining how organisations manage two sets of contradictory dilemmas simultaneously. In this research two theoretical frame of references are brought together to provide a focus on the significant challenges that organisations face in operating under discontinuous change. The capabilities of exploitation and exploration have been linked to an organisation's performance (Koryak et al., 2018) and adoption in discontinuous environments (Teece et al., 2016). Additionally, these capabilities stem from the organisation learning capability where Teece et al. (2016) argue that organisational exploitation and exploration are critical dynamic capabilities under the theme of organisational searching and learning which posits the identification of external opportunities and threats and an internal focus on internal efficiencies and processes. Organisational learning can be viewed as the cognitive assimilation and process of knowledge imbrication in organisations (Andreu & Ciborra, 1996). An organisation's learning capability can be articulated as the potential to create, assimilate and integrate knowledge artefacts to modify and enhance resource capability and performance (Dibella, Nevis, & Gould, 1996). This is critical for an organisation to assess internal processes and understand their organisational ecologies especially under discontinuous change.

The learning capability of an organisation has been further identified as a distinctive capability in academia through absorptive capacity mechanisms (Paliokaite & Pacesa, 2015; Sutonto, 2017; Wu & Chen, 2014). This perspective stems from positions argued by Levinthal and March (1993) and Zahra and George (2002) wherein they refer to absorptive capacity as the organisational processes and activities that "acquire, assimilate, transform and exploit knowledge to produce a dynamic organisational capability" (p. 186). Zahra and George (2002) go further and identify four mechanisms through which absorptive capacity manifests itself in organisations. These mechanisms embed themselves in organisational processes and strategies as they are idiosyncratic in ways that organisations deploy and manage them. The first mechanism, 'Acquisition', refers to the ability to identify and obtain external knowledge which is fundamental to the organisation and is enhanced by previous ecological knowledge (Zahra & George, 2002). 'Assimilation', the second mechanism refers to the organisational processes that analyse, interpret and comprehend the acquired knowledge (Zahra & George, 2002). During the third mechanism, 'Transformation', the current organisational knowledge is integrated with the new knowledge and a synergy is created (Zahra & George, 2002). The last mechanism, 'Exploitation', refers to the organisational ability to embed the synergised knowledge to refine, enhance and create new processes and capabilities (Levinthal & March, 1993; Zahra & George, 2002). These perspectives allow both exploitative and explorative capabilities to be considered as dynamic distinct capabilities as they embed learning mechanisms and create organisational level advantages, in congruence with Kay's (1993) additional criterions of sustainability and appropriability.

Exploitative capability refers to an organisations ability to improve and develop new applications for current knowledge, skills and resources that signify evolutionary change and improved efficiency (Levinthal & March, 1993; He & Wong, 2004; Papachroni, Heracleous, & Paroutis, 2016). Exploitative capabilities place emphasise on "efficiency, increased productivity, control, certainty and variance reduction" (O'Reilly & Tushman, 2008, p. 189). It relies on repetitive and combinative learning mechanisms within an organisation's knowledge ecosystem reliant on existing competencies (Korak et al., 2018; O'Reilly & Tushman, 2013). However, organisations who purely focus on exploitative capabilities run the risk of falling into the routine trap lacking any forms of agility and run the risk of obsolescence in a constantly evolving ecosystem (O’Reilly & Tushman, 2013). This has been evident with the rise of radical innovations and peripheral markets disrupting business models and the bias for organisations to focus on short-term success due to the prognosticating effects and risks presented in success through exploration (Birkinshaw et al., 2016; O’Reilly & Tushman, 2013; Teece et al., 2016).

The effectiveness of organisational strategies in pursuit of competitive and differential advantages depends on an organisation’s capacity for both exploration and exploitation (Birkinshaw et al., 2016; Koryak et al., 2018; Raisch, Birkinshaw, Probst, & Tushman, 2009; Simsek, Heavey, Veiga, & Souder, 2009). Explorative capability refers to an organisations ability to acquire, assimilate and apply new knowledge artefacts (Papachroni et al., 2016). Explorative capabilities places emphasis on “search, discovery, autonomy, innovation and embracing variation” (O’Reilly & Tushman, 2008, p. 189). It relies on the establishment of new combinative learning mechanisms and improves the breadth of organisational knowledge systems (Korak et al., 2018). However, although radical changes through new knowledge assets are enabled, organisations with a pure focus on explorative capabilities run the risk of falling into the failure trap as they do not exploit these ideations fully and they may fail to be realised (O’Reilly & Tushman, 2013).

Hence, explorative and exploitative capabilities are distinct dynamic capabilities that place emphasis on different organisational processes and structures. Traditional and contingent views guided organisations to place full emphasise on either one capability (Alverez & Barney, 2007) but some academics have postulated inherent risks by adopting this perspective (Birkinshaw et al., 2016; O’Reilly & Tushman, 2013; Teece et al., 2016). Subsequently, the perspective of balancing both these activities at the organisational level has gained attention (Koryak et al., 2018; O’Reilly & Tushman, 2013; Raisch et al., 2009). However, even though exploitative and explorative capabilities are complementary organisational processes (Raisch et al., 2009) with each requiring different organisational modes they create inherent tensions (Andriopoulos & Lewis, 2009; Koryak et al., 2018). This is attributed to certain contradictions between the two capabilities. These tensions and contradictions include alignment and adaptability, stability and change, efficiency and openness to change and static and dynamism (Papachroni et al., 2016). Thus, creating a challenge when developing the higher order capability for a Dynamic Distinct Capability (DDC) under the learning capability mechanisms of explorative and exploitative capability. Under this perspective, organisations who have falling levels of competitive advantage fall into the trap of a tunnel vision focus as their orientations are either forward looking or backward looking as per the traditional and contingent views.

A growing academic concept in dealing with organisational tensions is the meta-theory of paradox (Lewis & Smith, 2014; Miron-Spektor, Ingram, Keller, Smith, & Lewis, 2017; Papachroni et al., 2014). Smith and Lewis (2011) define a paradox as “contradictory yet interrelated elements (dualities) that exist simultaneously and persist over time; such elements seem logical when considered in isolation, but irrational, inconsistent, and absurd when juxtaposed” (p. 387). The paradox view identifies with the complexities facing organisations today and posits a shifting and re-balancing continuum focus with each iteration reaching a new dynamic equilibrium. Where the traditional approach seeks to rectify the tension between exploitative and explorative capabilities through a single and separate focus the paradox theory enables both capabilities to be enabled simultaneously (Lewis & Smith, 2014; Miron-Spektor et al., 2017).

Birkinshaw et al. (2016) describes three possible modes of managing a paradox. The first mode being defined as ‘Structural separation’ refers to the traditional approach which places exploitative and explorative capabilities as separate focal points (Birkinshaw et al., 2016). The second mode, ‘Behavioural integration’, integrates both capabilities and finally the third mode, ‘Sequential alternation’, involves oscillating between the two capabilities over time (Birkinshaw et al., 2016). The first mode is indicative of the contingent and traditional approaches to adopting exploitative and explorative capabilities in organisations, whilst the third mode presents a dynamism view between the capabilities but reduces the sustainability and appropriability of the distinct capability characteristic. The second mode speaks to concept of dynamic management of exploitative and explorative capabilities which Smith (2015) posits through both differentiation and integration organisational strategic paradoxes can be sustained. This is based on the notion that when an organisation is faced with complexity a dynamic and antithetical approach enables lucidity and supports inconsistencies through being consistent (Smith, 2015).

By differentiating between exploitative and explorative capabilities, an organisation can separate unique elements and create distinct aspects whilst integrating enables path linkages and synergies (Koryak et al., 2018). Differentiating without integrating the two capabilities creates the traditional approaches shortfalls, integrating without differentiating creates a false sense of synergy and combined they enable a dynamic decision-making synergy and are characterised as complementary and necessary (Smith, 2015).

This study therefore proposes that exploitative and explorative capabilities are two distinct yet complementary capabilities that are synergistic and non-substitutable. In addition, in managing the two DDC's organisations will require to adopt a paradox perspective to enable the dynamic shift between the distinct aspects to be realised and effectuated.

2.7 Direct and indirect effects on firm performance

Barney (1991) argued that valuable and rare resources created competitive advantages for organisations and these organisations enjoyed short term firm performance. He further stated that to sustain these advantages an organisations resource's need to be inimitable and non-substitutable (Barney, 1991). Newbert (2007), drawing from DCT theory established a relationship between an organisation's dynamic capabilities and competitive advantage which created firm performance. Thus, indicating the organisational value through enabling dynamic capabilities in organisations.

In the context of IS research, Rai, Patnayakuni and Seth (2006) and Wu et al. (2014) define firm performance as the magnitude that an organisation is able to achieve superior performance over their competitors. Wixom et al. (2013) acknowledged the role BDAC has on positive organisational objectives. This is achieved through the facilitation of data driven insights to create tangible and intangible organisational benefits (Akter et al., 2016). Chen et al. (2014) further reported that an organisations IT capability has a positive relationship with a firm's performance. As previously discussed, BDAC and IT capabilities are both measured through the concept of sociomateriality and Akter et al. (2016) and Wamba et al. (2017) described a direct interaction between the higher order dynamic capability of BDAC and firm level performance. Gupta and George (2016) reported that as BDAC enables organisations through data driven decision making it provides superior performance over IT capabilities in effectuating firm performance. These perspectives suggest that big data organisations should adopt, deploy and enable higher order BDAC's as a critical strategic tool to achieve superior firm performance.

The paradox view of managing both exploitative and explorative capabilities in organisations has been previously discussed. In a constantly evolving ecosystem organisations need to simultaneously exploit and explore opportunities internally and externally. Birkinshaw et al. (2016), Koryak et al. (2018) and Raisch et al. (2009) posit the importance of these capabilities for long term firm performance. Koryak et al. (2018)

further elaborate on the long-term reinforcing and synergistic effects that the dynamic management of exploitative and explorative capabilities can have on firm performance. Through the concept of agility, which is a mechanism of the dynamic management of exploitative and explorative capabilities (Smith, 2015), Janssen et al. (2017) and Wassmer, Li and Madhok (2017) through empirical research reported the increase in firm performance influenced by agility.

In a data driven ecosystem which is constantly evolving due to external effects of discontinuous change, it needs to be acknowledged that data driven insights under strategic intent need to be effectively utilised for the success and survival of an organisation. This perspective stems from the notion of distinct capabilities being a transformer for converting, evolving and enabling resources and capabilities into enhanced firm performance (Lin & Wu, 2014) under discontinuous change (Birkinshaw et al., 2016, Koryak et al., 2018; Teece et al., 2016). Mikalef and Pateli (2017), Wamba et al., (2017) underline the importance of leveraging dynamic capabilities as a source of sustainable competitive and firm level performance in discontinuous environments.

IT enabled dynamic capabilities were found to reinforce the structurally separated (mode one classification of paradox management) capabilities of organisational agility under the concept of evolutionary fitness (Mikalef & Pateli, 2017). Dynamic capabilities can in turn act as an accelerator for organisational proactiveness and indirectly improve firm performance in dynamic environments (Mikalef & Pateli, 2017). Wamba et al. (2017) further posit that in the absence of a strategic leverage mechanism, BDAC may create competitive advantages for an organisation in the short term but this advantage maybe lost due to the dynamic nature of the organisational ecology. Akter et al. (2016) and Wamba et al. (2017) reported the significant interaction effects of organisational processes on the BDAC-FPer relationship. Although the organisational processes were process-oriented and focussed on internal exploitation strategies, the findings do provide insight into the strategic alignment between big data and organisational strategies. As previously discussed, dominant organisational structures and models hinder the big data value potential (Gunther et al., 2017). New or evolved business processes are required to effectively improve the adoption and success rates of data driven decision making through big data projects. This perspective thus infers that in dynamic environments, IT and Big data capabilities alone may not be a source of differentiated advantages for organisations, rather they contribute to the strategic leverage mechanisms and activities employed by organisations. Summarily, it can be inferred that under discontinuous change, a DDC through the organisational strategic mechanisms of exploitative and explorative capabilities is supported by BDAC to enhance firm competitiveness and performance.

2.8 Conclusion

Emerging literature in Information System research has positioned big data as an enabler for organisational competitive advantage (Mazzei & Noble, 2017; Mcabee et al., 2017; Wamba et al., 2015; Wang et al., 2016). Yet the mechanisms through which big data functions is not properly understood as organisations are finding difficulty in realising the potential value (McAbee et al., 2017; Gunther et al., 2017). Big data needs to be understood in terms of the environment in which it exists, both big data and the environment are in a state of constant change. This provides additional challenges for organisations who seek to use traditional intuitive insights to generate strategic foresight rather than big data driven insights (Alharthi et al., 2017).

This literature review confirmed the importance of understanding the autonomy of BDAC as an enabler for competitive advantage. Furthermore, the researcher posits that BDAC cannot exist in isolation in an organisation. As the state of organisational ecologies are discontinuous, traditional business processes need to evolve and a commitment to one strategic organisational mechanism can have deleterious effects for the long-term survival of an organisation. Thus, this research seeks to add to the theories of big data and dynamic capabilities by creating an understanding of the complex interactions between higher order organisational capabilities and competitive advantages for organisations. By applying a sociomaterialism and dynamic management view to BDAC and DDC respectively, this study provides an entangled view of the relationships that enable firm performance in a big data environment.

Chapter 3: Research questions

3.1 Introduction

The previous chapters highlighted the main objectives of understanding the value creation of big data through the entanglement of capabilities under theoretical and management perspectives. Drawing on recent literature in the big data and learning capabilities under dynamic context fields, this research proposed the hypothesised model shown in Figure 1. In line with previous research, a third-order reflective model for BDAC was developed under the theory of sociomaterialism. Herein, big data was posited as an enabler through the entanglement of capabilities view proposed in this study. The main aim of this research was to gain an enhanced understanding of the influence of DDC in leveraging BDAC to effectuate firm performance in discontinuous environments.

3.2 Research questions

The research questions proposed in this study were hypothesised as four individual hypotheses as described below.

3.2.1 Research question 1

Is there a positive relationship between Big Data Analytics Capability (BDAC) and Firm Performance (FPer)?

Research question 1 aimed to confirm the direct relationship between BDAC (independent variable) and FPer (dependent variable). Prior research proposed DCT to explain the difference in competitive advantages between organisations (Birkinshaw et al., 2016; Mikalef & Pateli, 2017; Teece et al., 1997; Teece et al., 2016). Lin & Wu (2014) further reported that an organisations dynamic capability enhances long term firm performance in dynamic environments.

A review of literature in the IS field identified a positive association between IT capabilities and FPer (Chen et al., 2014) and BDAC and FPer (Akter et al., 2016; Gupta & George, 2016; Wamba et al., 2017). The first research question was hypothesised as:

H_1: BDAC has a significant positive relationship with FPer.

3.2.2 Research question 2

Is there a positive relationship between Distinct Dynamic Capabilities (DDC) and Firm Performance (FPer)?

Research question 2 focussed on the relationship between DDC and FPer. Through theory of paradox, DDC was developed as a higher order construct to assess the dynamic management between the distinct constructs of exploitative and explorative capabilities. Koryak et al. (2018) and Smith (2015) described links between the integration of exploitative and explorative capabilities, under the paradox view, and FPer. This describes the impact of an organisations strategic leverage mechanisms to create superior performance, independent of BDAC under dynamic systems. The second research question was hypothesised as:

H_2: DDC has a significant positive relationship with FPer.

3.3.3 Research question 3

Is there a positive relationship between Big Data Analytics Capability (BDAC) and Distinct Dynamic Capabilities (DDC)?

Research question 3 aimed to assess the relationship between BDAC and DDC. This research argued that big data as a higher order dynamic capability creates insights which uniquely enable strategic mechanisms such as DDC (Ghasemaghaei et al., 2017; Mikalef & Pateli, 2017; Wamba et al., 2017). The third research question was hypothesised as:

H_3: BDAC has a significant positive relationship with DDC.

3.3.4 Research question 4

Does Dynamic Distinct Capabilities (DDC) mediate the relationship between Big Data Analytics (BDAC) and Firm Performance (FPer)?

Research question 4 focussed on evaluating the mediating effect of DDC on the relationship between BDAC and FPer. Drawing on recent theory which focuses on organisations in dynamic contexts, this research argued that BDAC supports strategic organisational mechanisms such as DDC which simultaneously exploit and explore opportunities and threats to enhance firm performance (Koryak et al., 2018; Mikalef & Pateli, 2017; Smith, 2015). Additionally, given the evolving nature of the current organisational ecology in which organisations exist, this research further argued that

BDAC alone can only provide short term firm performance. The fourth research question was hypothesised as:

H_4: DDC has a significant mediating effect on the relationship between BDAC and FPer.

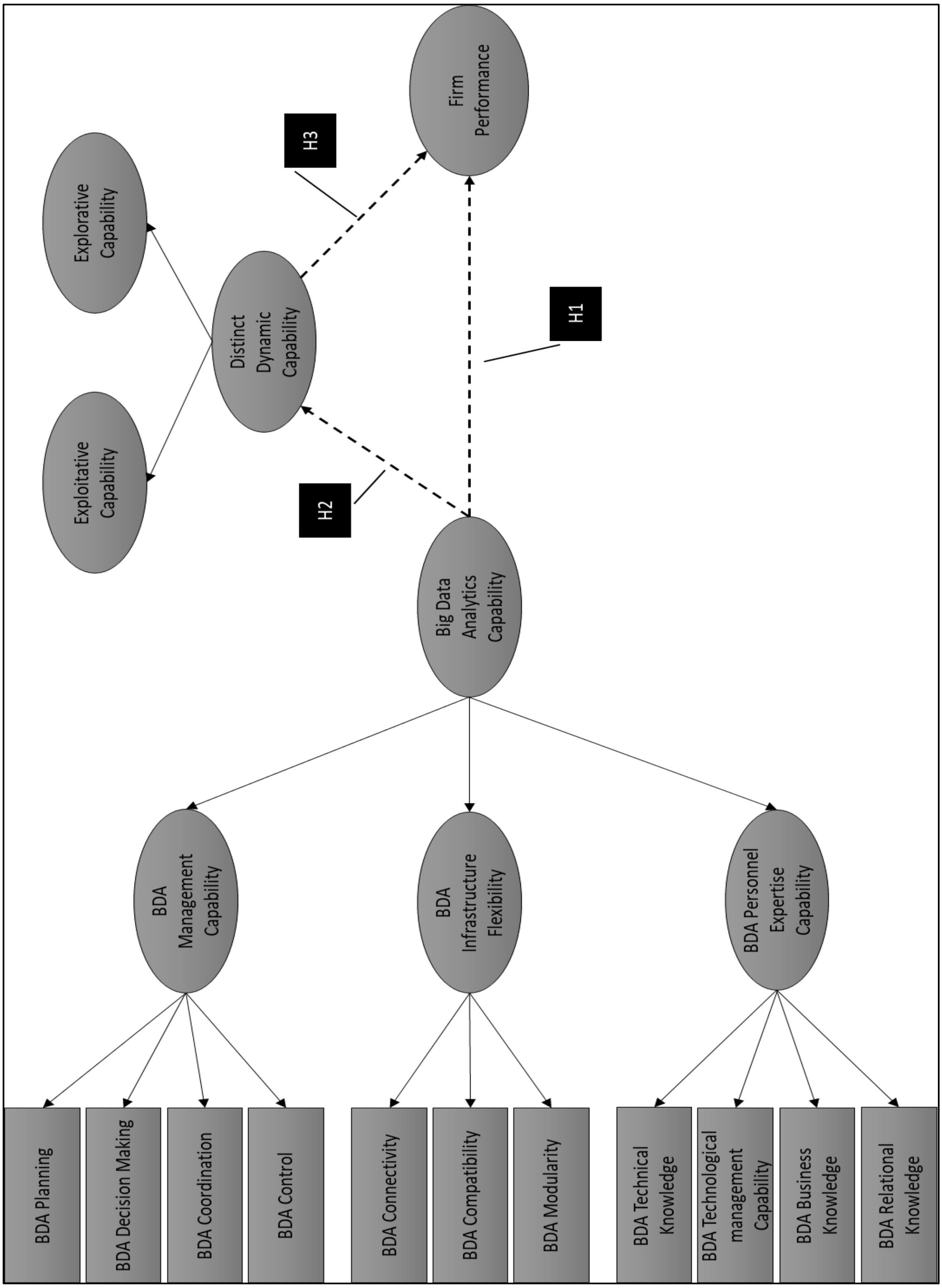


Figure 1. Hypothesised research model. Adapted from "Big data analytics and firm performance: Effects of dynamic capabilities," by Wamba et al., 2017, *Journal of Business Research*, 70, p. 363. Copyright 2017 by Elsevier Inc.

Chapter 4: Research methodology

4.1 Introduction

Research is a systematic process of “collecting, analysing, and interpreting data in order to understand a phenomenon” (Williams, 2007, p. 65). As previously described in Chapter 2, there is a developing interest in literature that describes the influence of both distinct dynamic capabilities and the internal ecosystem of an organisation to assimilate and create organisational advantages by utilising BDAC.

This section will discuss the research methodologies that were used by the researcher in order to test the hypotheses that were developed and described in Chapter 3.

4.2 Research design

The purpose of the research design is to confirm that any evidence obtained allows the researcher to effectively address the research problems developed (Bordens & Abbott, 2010). The research intention of this study was to assess the influence of the factors DDC and BDAC on FPer. Chapter 2 provided theoretical positions that the researcher used to develop, and test research questions that were set out in Chapter 3. It is on this position that the researcher sought to evaluate the relationship between DDC, BDAC and FPer as described in Chapter 3. In addition, the research study intent sought to empirically evaluate the measured variables put forward from theory (BDAC → FPer) and assess if their relationship was mediated by DDC. Given this, and the approach taken the research was centred on a positivist philosophy (Saunders & Lewis, 2012; Wamba et al., 2017). A positivist philosophy values objectivity in phenomena and tends to measure relationships between two or more variables through proving or disproving hypotheses (Gemma, 2018; Straub, Boudreau, & Gefen, 2004). This approach was validated by the nature of the study referring to philosophical positions that emphasise structured questioning and empirical methods to quantify relationships between the variables DDC, BDAC and FPer. Objectivity in the research findings was verified using statistical methods which is well suited for making generalisations and allows for independence on the part of the researcher (Bernard, 2006; Wamba et al., 2017). Given that the researchers own philosophy is based on scientific experimentation and statistical analysis, there is alignment between the research philosophy and the researchers own philosophy. This alignment postulates less bias whereas when they are not aligned, this may lead to research bias and can could undermine the nature of the study (Holden & Lynch, 2004).

The research study intended to expand the understanding of the influence of DDC on the ability of BDAC to create FPer and make a priori generalisations. The theoretical positions of the RBV and IT capabilities have been extensively researched in academia and constructs and measures currently exist for DDC, BDAC and FPer. Given that theoretical artefacts currently exist, this informed the approach of the research study to be deductive rather than inductive. This approach was substantiated by the need to test theoretical positions from developed hypotheses and confirm or disconfirm utilising quantitative methods (Saunders & Lewis, 2012; Trochim & Donnely, 2006).

Research using the themes of information systems such as BDAC has been dominated by a positivist philosophy (Abbasi, Sarker, & Chiang, 2016). It is normally accepted that positivists rely heavily on experimental and correlational techniques to test theoretical artefacts using quantitative research approaches (Bernard, 2006; Williams, 2007). A quantitative research approach embodies statistical methodologies and is "specific in its surveying or experimentation, as it builds upon existing theories" (Williams, 2007, p. 66). The researcher adopted a quantitative approach as the research intention was to assess the influence of existing theoretical artefacts and to statistically quantify relationships between the study variables. A qualitative approach was found not to be not suitable as it is built on inductive rather than deductive philosophies to develop new theory and "no attempt is made to mathematically specify the nature of the relationships between variables" (Bordens & Abbot, 2010, p. 54). Creswell (2014) states that a quantitative approach uses experimental and survey strategies of inquiry and data is collected from a predetermined or existing measurement instrument that yields statistical information.

In alignment with Ghasemaghaei et al. (2017) and Wamba et al. (2017), the researcher adopted the survey method design to gather responses from respondents. The survey strategy is a non-experimental, explanatory research method which is used to sample a population (Gable, 1994; Myers, 1997; Zikmund, Babib, Carr, & Griffin, 2013). Given that an explanatory method is used to assess a sample at a specific point in time without making causal statements but rather seeking to explain the relationship between hypothesised interactions, the research followed a predictive approach to determine what relationships exist between the independent variables – DDC and BDAC and the dependent variable – FPer (Bordens & Abbot, 2010). Secondary data was found to be unsuitable for the research intent as the data that could be obtained may not suit the hypotheses.

The scope of the survey design strategy was limited to the hypothesised variables of DDC, BDAC and FPer as well as specific demographic details as mentioned later in Section 4.5. The quantitative nature of the study allowed for replicable and statistical objectivity to explain and quantify the hypotheses as per Chapter 3. The survey strategy, in line with the explanatory method assessed the sample population at a single point in time, indicative of a cross-sectional time horizon (Zikmund et al., 2013). This method also allows for a large sample size which enhances the generalisability to the population and is easy to use and administer (Bordens & Abbott, 2010; Wamba et al., 2017).

As the research intent was to establish and describe the characteristics of a sample population and test hypotheses developed under theoretical underpinnings, the research intent and research design were in alignment (Bordens & Abbot, 2010; Williams, 2007). In addition, the research strategy adopted by the researcher followed similar research strategies to that of BDA and DC studies adopted by Ghasemaghaei et al. (2017), Koryak et al. (2018) and Wamba et al. (2017).

4.3 Population

Zikmund et al. (2013) defines a research universe (population) as, "Any complete group of entities that share some common set of characteristics" (p. 682). Given that industries are currently experiencing the proliferation of BD, the population of organisations adopting or that have adopted BD is not known. Finding this information would be costly and time consuming as it would require the need for a census. The researcher, in accordance with the research intent of assessing the influence of the factors DDC and BDAC on FPer proposed a research population of organisations that actively use BD in their decision making. Thus, the common characteristics that these organisations would share are the use of BD, data capabilities and specialist roles and functions. No limitation was made on the size of the organisation, on the volume of data stored. This is due the notion that there is a rapidly expanding volume of data being produced in the global ecosystem with the data volume expected to grow 50 times by 2020 (Yaqoob et al., 2016). A limitation on the size of the organisation and volume of data stored would limit the insights and research sample as organisations today utilise BD through onsite, cloud and outsourced mediums (Jagadish et al., 2014; Lee, 2017). Previous studies have limited the breadth of roles and responsibilities to just IT managers and business analysts (Ghasemaghaei et al., 2017; Koryak et al., 2018; Wamba et al., 2017). In addition, these previous studies have also limited the populations to specific organisational sectors. BDA has affects from CEO's to general users of data and effects a multitude of industries (Davenport et al., 2012; Khan et al., 2017). Thus, placing a limit on the BD organisation would limit the insights that can be drawn. The researcher, through opening the population to other industry sectors and varying levels of management and skills in the BD organisation has allowed for the findings to be generalised with relation to DDC, BDAC and FPer as well as allowing for a broader and more robust sample size and generalisation.

4.4 Unit of analysis

Zikmund et al. (2013) states that the unit of analysis for a research study "indicates what or who should provide the data and at what level of aggregation" (p. 146) to which the researcher may generalise. The unit of analysis for this study was identified as an organisation that utilises BD. In congruence with this identification, the research questions posed characteristics of the organisation which had to be reported from an individuals perspective. This premise is futher justified by the notion that a research problem can be evaluated or tested at more than one element of analysis (Zikmund et al., 2013). Salkind (2010), states that the unit of analysis needs to be informed by the data that is being collected. The research intent sought to quantify the relationships between the research constructs of DDC, BDAC and FPer and was adopted from existing measured variables under fields for BD and DC. As identified in the research population, the research intent needs to be aligned to the population identified. The researcher therefore believes that the data sought informed the need for the unit of analysis to be identified as an organisation which utilises BD. As posited in Section 4.3, the characteristics of the organisation were generalised across the population and not to a specific sector, industry or a single organisation.

4.5 Sampling method

Zikmund et. al (2013), state that probability sampling is prefered in research due to true randomness however, due to the research population size and number of individuals utilising BD not being known, a non-probability sampling method was adopted as probability sampling would be impossible (Saunders & Lewis, 2012; Trochim & Donnelly, 2006). Based on the research constructs and population dynamics the researcher identified specific individuals whom are congruent with the research attributes. The reseacher, due to studying the various literature on the research topic can be considered as an experienced individual around the research topic (Creswell, 2014). Zikmund et al. (2013) and Saunders and Lewis (2012), attribute this technique as a purposive sampling technique.

The purposive sampling technique satisified the researchers specific purpose and understanding to make logical genaralisations (Etiken, Musa, & Alkassim, 2016; Saunders & Lewis, 2012; Zikmund et al., 2013). The researcher made use of convenience sampling to leverage individuals in the researchers professional network whom fitted the characteristics of the research purpose under the assumption that "members of the target population are homogenous" (Etiken et al., 2016, p. 4). This method proves viable due to the foreseen difficulty of connecting with correct organisational individuals and firms in the research population and the associated cost of locating these individuals. Convenience sampling therefore offers a cost effective method of obtaining respondents from the researched population (Saunders & Lewis, 2012; Zikmund et al., 2013). Etiken et al. (2016), further elaborate that convenience sampling methodologies adopted place emphasis on generalising data obtained from the sample population to the research population.

Based on the difficulty to access individuals in the target population the snowball sampling techniques were adopted. Individuals in the researchers professional network would identify other sample members and pass the research instrument on to them to complete. Due to the complexity in the research literature these individuals are rare and the initial research respondents will refer these other individuals with the same traits as them (Trochim & Donnelly, 2006; Saunders & Lewis, 2012; Saunders, Lewis, & Thornhill, 2009; Zikmund et al., 2013).

Although random sampling error is a problem associated with non-probability sampling techniques due to too many anomolous respondents, this was mitigated through initially extending the research instrument to a large number of first level respondents within the researchers network. Korak et al. (2018) and Wamba et al. (2017) made use of market research firms to submit their questionaires to obtain data from targeted organisations and individuals, this method proved impossible for the researcher due to the high cost implications.

4.6 Sample size

Bartlett, Kotrlik, and Higgins (2001) and Zikmund et al. (2013) reaffirm that obtaining data in research that can be generalised to the research population is a common purpose in survey strategies. Even though, properly selected sample frames may not perfectly represent the identified research population, they would generally provide a reliable estimation (Zikmund et al., 2013). This can be attributed to the previously mentioned sampling errors described in Section 4.5. Bartlett et al. (2001) further emphasise that one of the most consistent flaws in business research is the disregard for sampling errors when determining the sample size within a quantitative design. However, these sampling errors can be reduced with an increase in sample size due to their negative relationship (Bernard, 2006; Zikmund et al., 2013).

Given that the size of the population could not be validated, the researcher calculated the required sample size based on the statistical tests that would be conducted on the research model as described in Chapter 3. This position was corroborated by recent academia who also followed a similar approach for determining the minimum required sample size (Ghasemaghaei et al., 2017; Koryak et al., 2018; Wamba et al., 2017).

Sample size is also an important attribute when conducting a components-based Structural Equation Modelling (SEM) technique. Hair, Black, Babin, and Anderson (2010) suggest a sample size equivalent to10 times the number of links on the variable that has the most links in the research model. Kock and Hadaya (2018) and Roldan and Sanchez-Franco (2012) however, suggest that the sample size is not only dependent on the maximum number of model links on a latent variable but is also dependent on the need to include the effect size and minimum R^2 in the model respectively.

This position is based on the researcher knowing in advance whether the path coefficient's in the model will be either small, medium or large. Wamba et al. (2017) reported a path co-efficient of 0.235 in their mediated model. This reported value was used to calculate the minimum required sample size for the research. A summary of the required responses based on the suggested calculation methods is provided in Table 1. This study reported a final sample size of 155 responses which was assumed adequate based on the minimum sample size required.

Table 2

Minimum sample size required

Academic	Calculation method	Sample size required
Hair et al. (2010)	10x rule	70
Roldan and Sanchez-Franco (2012)	Effect size	~134
Kock and Hadaya (2018)	Gamma exponential method	~89
*Latent variable with maximum links - Fper (7 links)		

4.7 Measurement instrument

The adopted research philosophy informed the research strategy and data collection methodology that was applied to this research (Bordens & Abbott, 2010; Johnson, 2001).

The primary data that was required was determined by the research questions and research intent. As previously discussed in Section 4.2 with positivist philosophies and quantitative strategies in IS research, survey strategies are normally adopted (Straub et al., 2004). A cross-sectional survey method was applied for this research using a predetermined, self-administered online questionaire. The questionaire based survey strategy captures relationships between research variables and through its data gathering method can generalise findings to the research population (Pinsonneault & Kreamer, 1993). Survey strategies are recommended for explanatory research approaches which seek to assess relationships between research variables and predictive theory as they ensure a greater level of confidence and generalisation (Straub et al., 2004). In addition, Evans and Mathur (2005) and Zikmund et al. (2013), describe cost effectiveness, convenience, ease of use, high speed of data collection, anonymity, geographical flexibility and reach as some of the major advantages of adopting online based questionaires in research.

Previously published research questions based on multi-item scales with favourable applicable properties were used in the research questionnaire to provide objective confirmation and enable reproducibility. The questions adopted relate directly to the research variables of DDC, BDAC and FPer. The questionnaire was divided into seven sections (refer to Appendix A). The first section labelled - *context of organisation and respondent*, consisted of eight demographic questions and one screening question. A screening question was used to ensure that the correct unit of analysis completed the questionnaire. As previously explained, BD needs to be a characteristic of their organisation. The demographic questions allowed the researcher to provide descriptive information on the research sample as well as establish a level of sample diversity, whilst providing insight into the type of respondent on the survey, explained using descriptive analysis.

Sections two to four aimed to measure the BDAC within a BD organisation and were based on the research model described by Akter et al. (2016). These included 43 questions which covered the 11 first order constructs of BDACon, BDAComp, BDAMod, BDAP, BDADM, BDACoord, BDACont, BDATK, BDATMK, BDABK and BDARK. All the constructs made use of a seven - point Likert scale (ranging from strongly disagree to strongly agree), which were established measures from Akter et al. (2016) and Wamba et al. (2017). Sections five and six aimed to measure the various DDC's within the BD organisation – exploitative and explorative capabilities. To measure DDC, the researcher used the 12 - item scale from the model described by Koryak et al. (2018). The 12 items aimed to assess the BD organisations orientation during the past three years using the same seven - point Likert scale (ranging from strongly disagree to strongly agree) as the BDAC first order construct questions. Section seven aimed to measure FPer of the BD organisation and was based on the model described by Wamba et al. (2017). The seven – item scale aimed to assess the FPer during the past three years in alignment with DDC constructs using the same seven – point Likert scale (ranging from strongly disagree to strongly agree). The survey content and length were considered appropriate at a total of 71 questions (Appendix A). All completed questions and scales were transcribed into an online survey tool. SurveyMonkey was chosen as the survey tool of choice due to its ease of use, accessibility and the researcher's own experience in utilising the tool for previous.

To reduce non-response and social desirability biases, the researcher adopted recommendations by Gittelman et al. (2015) and Zikmund et al. (2013). The research questionnaire was subjected to a pre-test to verify the terminology, respondent understanding, ensure scale items were clear, and check for grammatical errors. Social desirability was also tested in the pre-test to verify if any questions came across as offensive and questions that could possibly result in exaggerated or false descriptions. According to Connelly (2008), a pre-test sample size should be at least 10% of the projected sample size required for the research.

However, Hertzog (2008) cautions that determining the pre-test sample size is not a simple process as the research is influenced by many factors. Nevertheless, Hill (1998) suggested a pre-test sample size between 10 – 30 and Perneger, Courvoisier, Hudelson and Gayet-Ageron (2015) stated that a pre-test sample size between 5 – 15 is most common in survey research. Based on the above arguments, the researcher decided on a pre-test sample size of between 15 and 20. A total of 17 responses were collected and analysed as the pre-test in this research through judgement sampling within the researcher's network. In addition, the pre-test respondents were advised to email the researcher if they experienced any issues with completing the survey as well as to comment on survey structure, grammatical errors as well as social desirability issues.

The feedback received highlighted a good understanding of the survey questions as respondents completed 100% of the questionnaire. Recommendations on the structure and grammatical errors in the survey were implemented. 35.3% of the pre-test respondents did advise that they felt the survey was too long and this was acknowledged by the researcher. However, the researcher maintained the survey design as these were based on adequate measured variables from previous research. No social desirability issues were commented on, possibly due to the researcher adding an introduction section and stipulated that the survey will remain confidential and no personal details will be requested.

4.8 Data gathering process

Two survey links were created on SurveyMonkey, a social media link and a weblink. The researcher submitted the weblink to respondents in the researcher's network via. WhatsApp and email. The social media link was posted on Facebook and Linkedin where individuals were tagged (thus being notified of the posting) from within the researcher's network. Individuals in the researcher's network were advised to distribute the survey links to other appropriate individuals on the researcher's behalf.

In addition, the researcher posted the social media link on three big data forums on Linkedin. Data was gathered through a cross-sectional approach over a period of one month (27 June 2018 to 27 July 2018). It was noted that the average time for survey completion was 11 minutes and the entire survey data had a completion rate of 81%. The survey attracted a raw sample size of 216 responses of which 35.19% and 64.81% were from social media and direct weblinks respectively. The raw survey data was exported into an XLS file for analysis.

4.9 Analysis approach

Since the raw data extracted from SurveyMonkey was not in a structure to analyse, the raw data required further processing. Zikmund et al. (2013) recommends that the data analysis process should consist of four stages – editing, coding, data file preparation and then data analysis. Since the data could be extracted in either text or numeric format from SurveyMonkey, the researcher opted to code the data set first.

4.9.1 Data coding

Data coding is the process of converting character symbols in survey data into numerical scores (Zikmund et al.,2013). The research survey made use of character symbols for all the seven sections. The character symbols were required to be converted to numeric scores to facilitate statistical analysis.

4.9.2 Data editing

Newman (2009), defines missing data as a statistical problem which is characterised by incomplete data. As informed by Brick and Kalton (1996) and Newman (2014), missing data in survey research occurs due to a respondent not participating in the survey (total non-response) and respondents failing to provide acceptable answers to one or more of the survey questions (item non-response). Newman (2014) further states that missing data in surveys correspond to three tiers namely item – level, construct – level and person – level (refer to Figure 2).

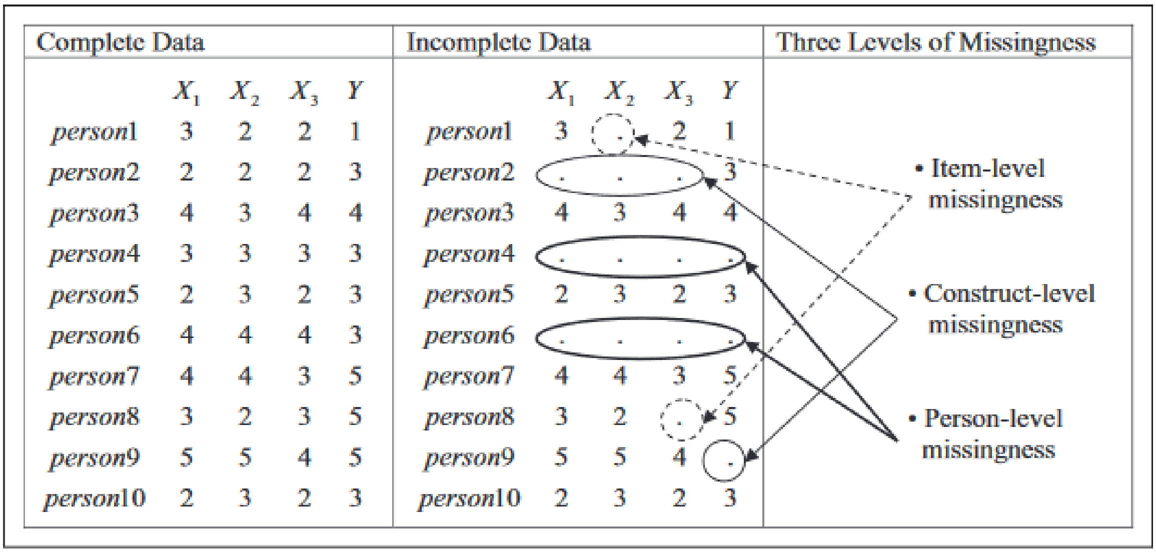


Figure 2. Three levels of missing data: Example (10-person sampling frame, three-item measure of construct. Adapted from “Missing Data: Five Practical Guidelines,” by D.A. Newman, 2014, *Organizational Research Methods,* 17(4), p. 375. Copyright 2014 D.A. Newman.

As described in Figure 2, missing values at the item – level occurs when a respondent does not compute a score to a multi – level scale, missing values at the construct – level occurs when a respondent does not compute any scores to a scale and missing values at the person – level occurs when a respondent does not compute any scores to the survey. The missing data can be missing by random or systematic effects through one of three methods (Little & Rubin, 1987; Schafer & Graham, 2002).

1. Missing completely at random (MCAR) – missingness of data that is not dependent on the variable of interest or is completely random (random),
2. Missing at random (MAR) – missingness of data that is dependent on other observed data and not the missing data in the dataset (systematic),
3. Missing not at random (MNAR) – Missingness of data that is dependent on other missing data (systematic).

The researcher has assumed that missing data in the research is due to MAR due to the length of the questionnaire, survey time considerations and lack of knowledge on the subject. The verification of this assumption could not be tested as all responses were anonymous. Thus, the researcher presumed the assumption for the missing data to be due to MAR to hold true. Newman (2009) recommends the Maximum Likelihood (ML) and Multiple Imputation (MI) technique to compute values in place of the missing values in the case that the data is missing due to MAR. This is based on the premise that data analysis is required to provide "unbiased estimates of population parameters, as well as to provide accurate (error – free) hypothesis testing" (Newman, 2014, p. 377). Both ML and MI provide unbiased and accurate errors to the missing mechanism.

The researcher computed for MAR by adopting the MI technique for respondents with less than a 100% and greater than a 50% completion rate (Hair et al., 2010; Scheffer, 2002). Imputation can be defined as a statistical method that provides a best guess value for missing responses based on information that is available (Zikmund et al., 2013). The missing data displayed a non-uniform scatter throughout the dataset. Therefore, the mean substitution to not represent enough variance was considered as a minimal impact (Schafer & Graham, 2002).

The data set was divided into sub-groups based on industry, and the mean of each question was calculated an imputed for the respondents that had missing data from a specific industry (Hair et al., 2010). 41 responses (18.98%) of the sample were screened out after question one of the research survey as they indicated that they were not aware or associated with big data in their organisations. 119 respondents (55.09%) of the raw data sample (216 responses) completed all the survey questions, whilst 20 of the responses (9.26%) had a completion rate of less than 50% and were rejected. Data was imputed for 36 responses at the person – level, who had a survey completion rate in excess of 50% but did not complete the entire survey. This left a final sample size of 155 responses.

4.9.3 Statistical analysis background

The data collected through the survey strategy was of a quantitative nature. Section one in the survey provided categorical data that informed descriptive statistical analysis. Sections two to seven in the survey provided ordinal data which was treated as continuous data for statistical analysis due to the scale containing more than five categories (Johnson & Creech, 1983; Norman, 2010; Sullivan & Artino, 2013; Zumbo & Zimmerman, 1993). The data imputation ensured that no missing data would affect the statistical analysis. This section explains the methods that the researcher used to provide descriptive and inferential statistics. A data file was created in XLS and CSV format after data imputation. These data files were imported into IBM SPSS and SmartPLS for further analysis.

4.9.3.1 Descriptive statistics

Descriptive statistics is defined as the decoding of raw data in a statistical process that allows the data to be described through its basic characteristics such as its mean, distribution and variance (Zikmund et al., 2013). The researcher included the raw data and data imputation results into the scope of the descriptive statistics as a separate section in Chapter five. The main descriptive analysis was analysed on the qualified sample only (155 responses). The assessment of categorical variables related to Section one of the research survey included frequency and percentage frequency to describe the data whereas assessments for ordinal data (treated as continuous data) from Section two to seven of the research survey included the mean, standard deviation, kurtosis and skewness to describe the data respectively. IBM SPSS was used to statistically analyse the descriptive statistics in this research study.

4.9.3.2 Inferential statistics

Multivariate Statistical Analysis (MSA) was used to test the hypothesis as well as validity and reliability of the data as it contained more than three variables (Zikmund et al., 2013). Hair et al. (2010) affirms that MSA not only influences analytical attributes of a research study, but its effects extend to the design and approach for decision making and problem solving. Selecting the correct MSA technique depends on three characteristics of a research study (Hair et al., 2010): (1) The ability to classify the variables as independent and dependant, (2) Knowing how many dependent variables are contained in the research study, and (3) The measurement classes of the variables.

A dependence technique was suitable as this research study contained dependent variables that had to be explained or predicted by independent variables (refer to Chapter three). The researcher found SEM as the most suitable MSA technique as the research study involved multiple relationships of independent and dependent variables (Hair et al., 2010). In addition, SEM is increasingly becoming a popular MSA approach for empirical research in academia (Hazen, Boone, & Overstreet, 2015; Ringle, Rigdon, & Sarstedt, 2018). SEM is a second generation MSA technique that combines the methodologies of factor analysis, path analysis and regression (Hair et al., 2010; Salkind, 2010). Although first generation MSA techniques such as linear regression could have been used to test the hypotheses in this research study, linear regression cannot assess the relationships between the latent variables and provide any test on the reliability of the latent variables (Hair et al., 2010). Moreover, there is a larger explanation of the variance in dependent variables in SEM techniques as it accounts for both direct and indirect effects versus linear regression methods (Lee, Petter, Fayard, & Robinson, 2011). Since this study consisted of theoretical and hypothesised relationships between constructs (refer to Chapter three), which were measured through observed indicators, SEM was suitable as the technique recognises error indicators and constructs unobserved latent variables (Hair et al., 2010).

Chin (2010), Hair et al. (2010) and Ringle et al. (2018), recommend two SEM methods for researchers to choose from – covariance-based SEM (CB – SEM) and variance-based partial least squares (PLS – SEM). Each method suits a different research perspective and understanding the differences is most important when adopting a specific technique for a research study. The CB – SEM method is primarily used for confirmatory studies – to confirm or reject theories, whereas PLS – SEM is used for both confirmatory and exploratory studies (Hair, Matthews, Matthews, & Sarstedt, 2017; Sarstedt, Becker, Ringle, & Schwaiger, 2011). The estimation procedure for CB – SEM is based on maximum likelihood whilst that of PLS – SEM is based on ordinary least squares (Hair et al., 2017). The CB – SEM thus requires normally distributed data to estimate a set of parameters for prediction whereas PLS – SEM estimates the coefficients in a linear regression model by minimising the sum of squares of the differences between fitted values and observed values regardless if the data is normally distributed (Chin, 2010; Hair et al., 2017).

The dichotomy between confirmatory and predictive research is overcome by PLS – SEM due to the combination of high predictive accuracy required by the researcher and the study being grounded in well-developed explanation of relationships. The interplay between predictive accuracy and explanation research strategies implies the understanding of the primary prediction and causes between theoretical and hypothesised relationships (Gregor, 2006; Hult et al., 2018). This perspective aligns well with the research intent which aims at testing the relationships between BDAC, DDC and FPer (explanation) whilst also offering management and academic recommendations (prediction). In addition to the above reasoning, the researcher chose to adopt the PLS – SEM technique in this study based on the following characteristics: (1) PLS – SEM does not require large sample size as that of CB – SEM and works well with complex models (Hair et al., 2017; Hult et al., 2018). This research study contains 14 first order constructs, four second order constructs, one third order construct and 155 qualified responses which was assumed suitable (refer to Section 4.5) whereas CB – SEM requires a sample size in excess of 200 (Bentler & Chou, 1987, Hu & Bentler, 1999; Wolf, Harrington, Clark, & Miller, 2013), (2) PLS – SEM is a recommended technique for estimating both formative and reflective constructs (Hair et al., 2014). Even though this study made use of only reflective constructs, PLS – SEM was more than adequate, (3) PLS – SEM is hugely efficient at parameter estimation which enhances its statistical power. Hair et al. (2014) states that higher statistical power generates significant relationships which can be generalised to the research population, and (4) The use of PLS – SEM with latent variables has proliferated in IS research studies (Hair, Ringle, & Sarstedt, 2011; Wamba et al., 2017).

The researcher used the SmartPLS 3.0 software package to analyse the PLS – SEM model due to the software being free over a period of 30 days. Furthemore, Akter et al. (2016) evaluated his research using the SmartPLS software and reported a similar sample size to that of this research. Hair et al. (2017) recommends the use of three algorithms for the evaluating PLS structural models. The 'Consistent PLS algorithm' is a sequence of regressions for the structural model and calculates path coefficients, path weights, reliability, validity and model fit measures for the model (Hair et al., 2017). The 'Consistent Bootstrapping algorithm' is a non-parametric statistical technique which tests the significance of all estimates from the 'Consistent PLS algorithm' (Hair et al., 2017). Finally, the 'Blindfolding algorithm' estimates the structural model's predictive relevance (Hair et al., 2017)

4.9.4 PLS – SEM model

A multi-stage process was required to apply the PLS – SEM model. This required the specification of the inner and outer models, overall model estimation and model evaluation. Prior to conducting the statistical analysis, the researcher found a need to address several statistical and theoretical issues in the study. These included the testing of PLS – SEM assumptions which Hair et al. (2017) and Hazen et al. (2015) reported have been overlooked in SEM studies. In addition, as discussed in Chapter 2, in line with recent academia, reflecting the researcher's arguments that the research variables of the second order reflective variable of DDC is measured by two non-substitutable and synergetic variables – exploitative and explorative capabilities (Benner & Tushman, 2015; Birkinshaw et al., 2016; Koryak et al., 2018; Smith, 2015). A principal component factor analysis (PCA) was required to confirm the measures of exploitative and explorative capabilities as well as to confirm if a multiplicative combination of the first order variables result in the DDC variable.

4.9.4.1 Priori test 1 - PCA analysis

PCA is a statistical method of processing data and extracting principal components (small number of synthetic variables) from a large set of measured variables which explain a certain phenomenon in research (Koryak, 2018; Pallant, 2007). Pallant (2007) affirms that PCA is a useful statistical technique for dimension reduction as the resultant components explain a large part of variation given by measured variables and are orthogonal. The principal components that are considered are those specific factors that explain the large amount of variance from the measured variables used in a study.

One of the most popular statistical approaches to determining the components that are retained in a study is Kaiser's eigenvalue one criterion (Braeken and van Assen, 2017; Hair et al., 2010; Kaiser, 1974). Only components with an eigenvalue of equal to or above one should be retained in a research model based on this criterion. The researcher sough to validate the measured variables for the second order construct of DDC using PCA to verify the exploitative and explorative capability component loadings, remove any unnecessary variables and reduce redundancy and multicollinearity as the PLS-SEM method is a second order regression MSA technique. For an improved interpretation of the PCA analysis, the varimax rotational method was adopted as recommended by Brown (2009), Costello and Osborne (2005) and Hair et al. (2010). The Varimax rotational method maximises and minimises high and low component loadings respectively. Hair et al. (2010) and Zikmund et al. (2013) specify four assumptions that are required to run a PCA test. The first assumption states that the measured variables need to be of a quantitative and continuous nature, within this study this assumption was met. The second assumption requires a linear relationship between the measured variables, this assumption was also met by analysing a correlation matrix (refer to Appendix D). The third assumption requires the data to not contain any outliers, this assumption was met as there a no data points in excess of three standard deviations from the mean. The fourth assumption requires a large enough sample size, this assumption was met as this research study had a final sample size of 155 which was deemed adequate (MacCallum, Widaman, Zhang, & Hong, 1999).

Hair et al. (2010) and Pallant (2007) affirm that a researcher should interpret the Kaiser Meyer Olkin (KMO), Bartlett's test for sphericity, inter-construct correlations in addition to the number of components extracted and the varimax rotation tests. The KMO is a measure of sampling fairness which indicates the proportion of variance in measured variables that are due to underlying factors. The KMO is measured on a scale of 0 to 1 where a measure greater than 0.5 is adequate (Hair et al., 2010; Pallant, 2007). The Bartlett's test for sphericity compares the correlation matrix of the assigned measured variables with its identity matrix. A PCA can only be performed if the result of the Bartlett's test for sphericity is significant ($p < 0.05$), meaning that the correlation and identity matrix need to be different and measured variables need to be correlated (Hair et al., 2010).

4.9.4.2 Priori test 2 – Measuring DDC

The researcher has previously argued that the measured variables of DDC – exploitative and explorative capabilities, are non-substitutable. This is based on the researcher's argument in Chapter two that exploitative and explorative capabilities are un-substitutable and independent. To develop the DDC variable, the researcher followed the approach recommended by Edwards (1994) for the most significant and interpretable computation for the measured variables of exploitative and explorative capabilities. This is in line with recent research arguing the various computation methods for exploitative and explorative capabilities under the RBV (Birkinshaw et al., 2016; Koryak et al., 2018).

Given the research hypotheses in Chapter three, whereby the researcher is testing the relationship between DDC and FPer, the most suitable test was against the dependent variable of FPer. Five regression models were tested where the first two models, tested explorative and exploitative as separate independent variables. The latter three models consisted of computing the addition of the two variables, the product of the two variables and finally testing the mean of the variables. The F – statistics and adjusted R^2 values were then compared for each model. The adjusted R^2 statistic is a measure of how well the model fits the measured data and the F – statistic is a good indicator of the path coefficients between the dependent and independent variables (Pallant, 2007). The mean computation reported the highest R^2 value and was thus adopted in this study.

4.9.5 Specifying the measurement model

The structural model in this study was required to be specified prior to conducting the PLS – SEM technique. The BDAC model specified by Akter et al. (2016) and theories of DC effects on FPer are the pillars of this research study. The research goal of this study was to explain the effects that DDC has on the relationship between BDAC and FPer. At the same time, the proposed model was developed to interpret the independent effects of the first order constructs of DDC – exploitative and explorative capabilities. Figure 1 shows the research constructs and their relationships which represent the structural model for this research by focussing on the BD organisation as the unit of analysis.

As defined by Akter et al. (2016), the hierarchical latent models in this study are characterised as reflective models. Reflective models identify the latent variable as the common measured variable behaviour whereby the causal action flows from the latent variable to the measured variables (arrows point from latent variable to measured variables) (Becker, Klein, & Wetzels, 2012; Edwards & Bagozzi, 2000). The research model in this study was composed of a third order latent model for BDAC, a second order latent model for DDC and a first order latent model for FPer. There are two stages in an assessment for a PLS – SEM analysis, namely the outer model assessment and the inner model assessment (Chin, 2010; Hair et al., 2010; Hazen et al., 2015).

Prior to conducting the assessment, the researcher modelled the hierarchical latent variables with their theoretical path model using the repeated indicator approach. Observed variables are required to estimate the higher order construct scores for hierarchical models and do not exist in this study as only measured variables for the first order latent variables where obtained in the survey design. There exist three statistical approaches to constructing the higher order latent variables in PLS: (1) the repeated indicator approach (Hair et al., 2017), (2) the two – stage approach (Ringle et al., 2018), and (3) the hybrid approach (Chin, 2010). The repeated indicator approach is widely adopted for reflective hierarchical latent models (Becker et al., 2012; van Riel, Henseler, Kemeny, & Sasovova, 2016). It has the advantage of estimating all latent constructs simultaneously and avoids interpretational confounding compared to the other two proposed methods (Becker et al., 2012). This is due to the repeated indicator method utilising all measured variables within the higher order constructs.

4.9.6 Outer model assessment

Measured variables in reflective models are linked to a higher order construct through their factor loadings. The outer model considers the relationships between each measured variable and their corresponding construct. The assessment of the outer model in reflective models focuses on the reliability and validity of these measured variables (Chin, 2010; Hair et al., 2014; Rolden & Sanchez-Franco, 2012; Wamba et al., 2017). By conducting the outer model assessment first, the researcher has ensured that the higher order constructs which constitute the inner model can be accurately represented. As previously mentioned, this research hypothesised three higher order latent constructs for the BDAC construct.

4.9.6.1 Reliability testing

Bland and Altman (1997) affirm that generalising a measure of interest in relation to a research population is often impossible to explicitly explain. In research, a composite value made up of a combination of a series of measured variables is used in place of this explicit measure to represent the measure of interest (Bland & Altman,1997; Tavakol & Dennick, 2011). Cronbach (1951) further states that these measured variables need to measure the same attribute and should be associated with each other. The presence of such an internal association provides statistical reliability and consistency in the measured variables (Trochim & Donnely, 2006). Cho and Kim (2015), Raykov (2018) and Zikmund et al. (2013) support the use of coefficient alpha (α) to estimate a multi – item scales reliability. More often known as Cronbach's coefficient alpha, this measure is most commonly adopted in research to assess scale internal consistency reliability (Zikmund et al., 2013). However, Becker et al. (2012) and Chin (2010) argue that Cronbach's alpha tends to underestimate the reliability PLS models. Hair et al. (2017) states that another measure of internal consistency reliability known as the Composite reliability is more consistent for PLS based research. This is due to Cronbach's alpha assuming that the measured variables are equally associated with a latent variable and are interchangeable whereas Composite reliability considers the varying factor loadings of the measured variables (Hair et al., 2017).

Although the PLS path model prioritises individual reliability on the latent variables which would assume that the Composite reliability would be superior to Cronbach's alpha, the researcher conducted both reliability tests as advised by Hazen et al. (2015) and Wamba et al. (2017). Both Cronbach alpha and Composite reliability scores vary between zero and one with higher scores indicating higher reliability. Hair et al. (2010) suggest reliability scores to be more than 0.7. If any scores fell below this threshold then measured variables would be deleted one at a time and the outer model iteration would be rerun.

4.9.6.2 Validity testing

The researcher assessed the reflective models' validity through convergent and discriminant validity tests (Hair et al., 2017). Convergent validity refers to the extent to which a measured variable is associated with other measured variables of the same construct (Hair et al., 2017). Measured variables of a specific construct need to converge or share a portion of high variance. Hulland (1999) states that convergent validity is required to ensure that the measured variables measure their theoretical construct and not another construct. Convergent validity is achieved when each measured variable has standardised factor loadings above 0.708 (Hair et al., 2017). Additionally, if each construct's average variance extracted (AVE) has a score greater than equal to 0.5 (Fornell & Larcker, 1981; Hair et al., 2017).

The value of the factor loading is commonly known as the indicator reliability in academia (Hair et al., 2017). The higher the indicator reliability indicates commonality of the measured variables on their specific construct. The square of a standardised indicator loading represents the amount of variance an indicator is explained by its specific construct and should explain greater than 50% of the variance (√0.708~0.5) (Chin, 2010; Hair et al., 2017). Although weak indicator loadings can be included in PLS path models, consideration by the researcher needs to be conducted to not effect the content validity if a measured variable with low loadings is deleted (Hair et al., 2011). However, indicator loadings below 0.4 should be removed as advised by Hair et al. (2017) and Roldan and Sanchez-Franco (2012). AVE is the mean value of the squared indicator loadings for a specific construct (Hair et al., 2014) and quantifies the amount of variance that a construct has from its measured variables relative to the measurement error (Fornell & Larker, 1981). An AVE of 0.5 or higher is indicative that the construct explains most of variance associated from its measured variables. Conversely, an AVE below 0.5 indicates that more errors remain on the measured variables than the variance that is extracted from the relative construct (Hair et al., 2017).

In concluding the outer model assessment, the researcher verified the extent to which a given construct differs from other constructs in the research model. This is termed discriminant validity and "implies that a construct is unique and captures phenomena not represented by other constructs in the model" (Hair et al., 2017, p. 138). Following Chin (2010) and Wamba et al. (2017), the researcher confirmed discriminant validity by analysing the item cross loadings and Heterotrait-monotrait (HTMT) criterion.

The items cross loadings refer to a measured variables correlation with other constructs in the research model. A measured variable's loading on its associated construct should be larger than its loadings on other constructs in the research model (Chin, 2010). The presence of cross-loadings whereby a measured variables loading is higher on other constructs indicates a discriminant validity problem (Hair et al., 2017). Additionally, the Fornell-Larcker criterion adopted by Wamba et al. (2017) is a more traditional method in confirming discriminant validity as it compares the square root of the AVE with the correlation values of that variable with others in the same construct (Hair et al., 2011). The square root of a constructs AVE needs to be much higher than other correlation values in that matrix (Chin, 2010). This would indicate that the measured variables are measuring the same phenomenon. However, Henseler, Ringle and Sarstedt (2015), reported that in confirming discriminant validity for PLS-SEM the item cross loading and Fornell-Larcker criterion are inadequately sensitive when compared to the HTMT criterion when they compared 10,000 datasets as these methods are “largely unable to detect a lack of discriminant validity” p. 128. They reported that the Fornel-Larcker criterion reported discriminant validity issues on 10.66% of the datasets and the cross-loading method reported only 8.78% of the datasets whereas the HTMT criterion reported 14.66% of the datasets as having discriminant validity issues. The HTMT criterion assesses the interactions of measured variables across latent constructs measuring different constructs in the model against the interactions of measured variables within the same construct (Henseler et al., 2015). In addition to assessing item cross loadings, the researcher confirmed discriminant validity by evaluating the HTMT criterion which is an output of SmartPLS 3.0. Henseler et al. (2015) states that when HTMT values are below 0.9, then discriminant validity is confirmed for reflective models. Significance of the HTMT criterion test was established by running the bootstrap simulation in SmartPLS 3.0.

4.9.7 Inner model assessment

After concluding that the outer model achieved a satisfactory result based on the reliability and validity assessment, the researcher then evaluated the inner model (structural model) based on the recommendations by Chin (2010) and Hair et al. (2017). The inner model assessment is intended to provide “evidence supporting the theoretical model as exemplified” by the structural research model (Chin, 2010, p. 674). Figure 3 shows the systematic approach adopted by the researcher to analyse the results of the inner model (structural). The analysis examined the hypothesised relationships between the constructs (Hair et al., 2017).

4.9.7.1 Assessing collinearity

The PLS-SEM method is primarily focussed on prediction, with a goal of maximising the variance of dependent variables in a structural model. Additionally, as the PLS-SEM model estimates the path coefficients based on OLS regression methods based on each latent variable and their higher order constructs, collinearity must be tested (Hair et al., 2017).

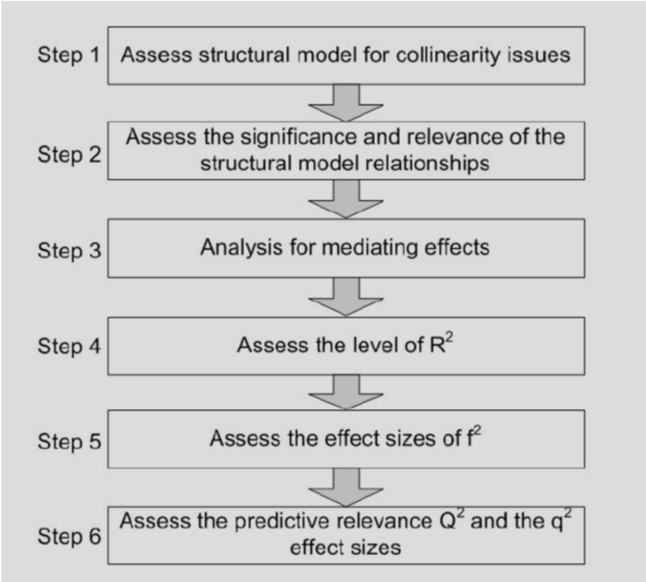


Figure 3. PLS model evaluation process. Adapted from "A primer on partial least squares structural equation modelling (PLS-SEM)," by J.A. Hair, G.T.M. Hult, C.M. Ringle and M. Sarstedt, 2017, Sage, edition 2, p. 202. Copyright 2017 J.A. Hair, G.T.M. Hult, C.M. Ringle and M. Sarstedt.

Collinearity issues in the PLS-SEM model may lead to bias amongst the predictor variables as it results in unstable path weight predictions which creates difficulty in evaluating the relationships when variables of different constructs are highly correlated (Hair et al., 2017).

O'Brien (2007) additionally states that the presence of collinearity can increase PLS-SEM path estimates when no variables has been proven to be statistically significant even with large R^2 values. Chen (2010), Hair et al. (2017) and Henseler et al. (2015) recommend that each construct on the PLS-SEM path inner model should be examined separately for collinearity through the Variance Inflation Factor (VIF). VIF is interpreted as the reciprocal of tolerance, which is based on the variance that an independent variable has that is not related to other independent variables in a model ($1-R^2$) (Hair et al., 2017; O'Brien, 2007).

The VIF thus quantifies the level of collinearity OLS statistical methods. Hair et al. (2017) states that the upper limit for VIF in assessing collinearity should be set at a threshold of 5, whereas Henseler et al. (2015) argue that the maximum level for VIF should be set at 10. O'Brien (2007) reported VIF limits as high as 20 in PLS-SEM related research. Due to no balanced consensus the researcher adopted a VIF threshold of 5 to evaluate if collinearity exists which was similarly adopted by Wamba et al., (2017). Hair et al. (2017) state that in dealing with collinearity issues a researcher can either delete problematic indicators, merge problematic indicators, or develop higher order constructs.

Due to the structural model being reflective, a deletion would not affect the meaning of the constructs as previously discussed. It is on this position that the researcher would delete any measured variables on constructs that reported a VIF greater than 5 by referring to the outer model VIF. This would ensure that no false inferences related to reporting path weight estimates and relationships in the inner model. It is important to note that during each evaluation, if items were removed the PLS-SEM model had to be rerun to re-establish all previous test conducted thus the researcher adopted a structured and iterative technique.

Since the structural model was evaluated and assessed and deemed adequate for significance and relationship testing after reliability, validity and collinearity testing, descriptive statistics of the constructs were evaluated using IBM SPSS 25. The researcher reported the mean, standard deviation, skewness and kurtosis statistics for each construct.

4.9.7.2 Assessing structural model path coefficients

The path coefficients in a structural model represent the hypothesised relationships for the research study as discussed in Chapter 3. The path coefficients are reported as standardised values between negative one and positive one. Path coefficients estimated from the SmartPLS 3.0 model close to positive one indicates a strong positive relationship and vice-versa for negative one (Hair et al., 2017). The path coefficients indicate the strength of the relationship between the hypothesised constructs (Chin, 2010; Hair et al., 2017). Based on the four hypotheses developed for this research the assessment of the path coefficients adopted a systematic approach (refer to Figure 3). The assessment of the first hypothesis was tested first by removing the mediation effects of DDC in the structural model. The second hypothesis was testing by including a path link from DDC to FPer, the third included the path link from BDAC to DDC and the fourth hypothesis was tested by including the mediation effects as the entire structural model. This was done as the PLS-SEM evaluates all path weightings as one structural model and if left as is the PLS algorithm would report on the overall model and not on the identified singular relationships as will be explained during the testing of mediation effects. This assessment is also required as a pre-requisite for mediation testing. The consistent bootstrapping algorithm was adopted by the researcher to assess the significance of the path coefficients. A t-statistic of 2.57 was chosen as the critical value to test for a 99% significance level as recommended by Hair et al. (2017). The hypotheses in this study were evaluated by statistical validation of the inner model path weightings. This was confirmed by evaluating the path weighting sign, strength and statistical significance between the hypothesised constructs in the research structural model.

4.9.7.3 Analysing for mediation effects

The research model in this study proposes a possible mediation effect as discussed in Chapter three, hypothesis four. Wamba et al., (2017) proposed a similar effect but based their test on the mediating effect of an internally oriented dynamic capability. As explained through Chapters one and two, this research posits that DDC is a much more robust capability considering the dynamic interplays in the current economic ecosystem. There are two possible interaction effects to test if a variable affects the relationship between established variables. These are termed moderation and mediation effects. A moderation analysis evaluates “whether the magnitude of a variables effect on some outcome variable of interest depends on a third variable” (Hayes, 2012, p. 4). In other words, a third variable might enhance or reduce the effect of a variable’s relationship between a variable of interest. Alternatively, mediator is a third variable that enables the relationship between a variable of interest (Baron & Kenny, 1986). In other words, a mediating effect involves a third variable that acts as an intermediate.

The mediation analysis can follow one of three statistical methodologies, Baron and Kenny’s (1986) mediation analysis, the Sobel test (Sobel, 1982) or the bootstrap method (Preacher & Hayes, 2008). Baron and Kenny’s (1986) analysis invloves a two step process by first testing the statistical significance of the associations between the independent, dependent and mediator variables and then assessing the direct effect after controlling for the mediator variable. Only when the mediator variable nullifies the direct relationship there is full mediation else it is absent or there is partial mediation. The Sobel test uses the product of the coefficients to evaluate the significance of a mediator effect (Sobel,1982). Hair et al., (2017) and Pardo and Roman (2013),challenge the use of mediation analysis through the methods proposed by Baron and Kenny (1986) and the Sobel test (Sobel, 1982). They state that mediation can occur even when there is no significance in the direct relationship (independent – dependent). Additionally, the Sobel test depends on distributional assumptions and this effects the applicability of the test (Hair et al., 2017). Based on these shortcomings the researcher adopted the Bootstrap mediation analysis proposed by Preacher and Hayes (2008).The Bootstrap method utilises a non-parametric test. The advantage of the Bootstrap test over the other two proposed methods is that it can assess mediation with significance.

Mediation through the SmartPLS 3.0 Bootstrapping algorithm was assessed using the guidelines proposed by Hair et al., (2017) and Zhao, Lynch and Chen (2010) as illustrated in Figure 4. The relationship between BDAC – FPer was first assessed for significance (Hypothesis 1), Hair et al., (2017) and Henseler et al. (2015) note that if this relationship is not significant (Hypothesis 1) then no mediation will exist. The indirect path, which include the mediator effect of DDC (Hypothesis 2 to 4) was then assessed for significance (path p2 and p3 in Figure 4). The researcher evaluated the two individual paths (BDAC → DDC and DDC → FPer) for significance which is required for mediation (Hair et al., 2017). Once significance on the indirect path was proved (p1 x p2 in Figure 4), the Variance Accounted For (VF) was calculated. The VAF is the addition of the indirect effect and the total effect (direct effect + indirect effect). This is computed as (p1 x p2) + p3) in Figure 4. Hair et al. (2017) recommend a VAF value in excess of 20% for mediation with values greater than 80% indicating full mediation and those between 20 – 80% indicating partial mediation.

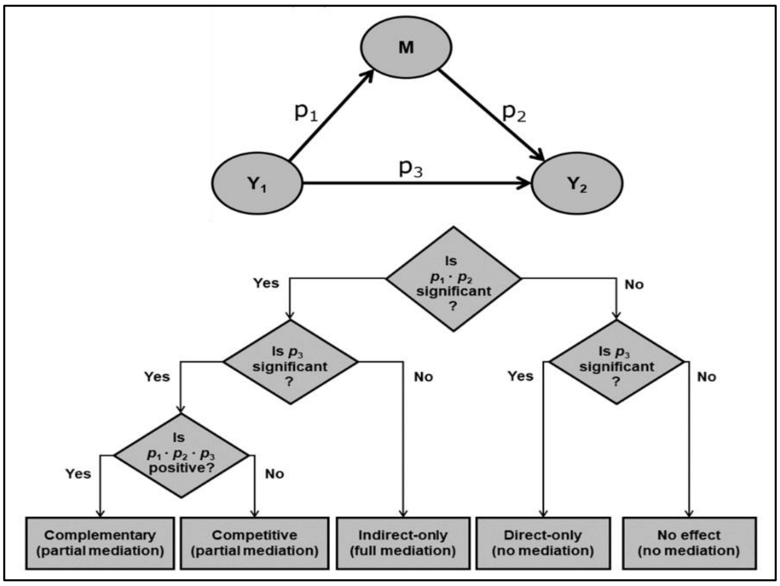


Figure 4. Mediation testing guidelines for PLS-SEM

4.9.7.4 Model fit and predictive assessment

The structural model including the hypothesis assessment was also evaluated by analysing the Coefficient of determination (R^2), Cohens f^2 and Stone-Geisser's Q^2. Where the R^2 value is indicative of the variance associated with a dependent variable that can be attributed by an independent variable and is a measure of predictive power of the model (Rolden & Sanchez-Franco, 2012). The R^2 value ranges from 0 – 1, with higher levels closer to 1 indicating higher levels of predicative power. Henseler et al. (2015), classifies R^2 values as weak (0.19), moderate (0.33) and substantial (0.67).

Cohens f^2 evaluates if the impact of predictor variable on a dependent variable is substantial. Hair et al. (2017) classifies the values as large (0.35), medium (0.15) and weak (0.02). Finally, Stone-Geisser's Q^2 is an indicator that assesses the predictive relevance of the independent variables in a reflective structural model (Rolden & Sanchez-Franco, 2012). Chin (2010) suggests the reporting of the cross-validated redundancy output in SmartPLS 3.0 by running the blindfolding algorithm to examine Stone-Geisser's Q^2. A value greater than 0 indicates that the research model has predictive power and follows the same recommendations as that of Cohens f^2 (Hair et al., 2017).

The Standardised Root Mean Square Residual (SRMR) was evaluated to assess the structural models fit for PLS-SEM as recommended by Hair et al. (2017) and Henseler et al. (2015). The SRMR evaluates the average discrepancies between the observed and expected interactions as a measure of model fit. Hair et al. (2017) and Hu and Bentler (1999) propose that a SRMR value less than 0.08 is considered as a good model fit. In addition, the researcher tested the SRMR value for significance by running the Bootstrap algorithm in the SmartPLS 3.0 programme.

4.9.8 Post-Hoc tests

To further verify the research findings, the researcher conducted further post-hoc analyses. Firstly, to understand the level of DDC in the respondent organisations. A graphical representation of the relationship between exploitative and explorative capabilities was developed.

Secondly, a statistical power analysis was conducted to validate the PLS model findings. The power value can verify if the null hypothesis is incorrectly rejected (Cohen, 1992; Faul, Erdfelder, Buchner, & Lang, 2009). This research evaluated the power test using the G*Power 3.1.9.2 software to confirm the hypothesised path linkages. Cohen (1992) recommends a power threshold of 0.8 which was adopted for this research.

Thirdly, to further evaluate the relationship between BDAC and FPer through the synergistic effect of DDC, a fuzzy set Qualitative Comparative analysis (fsQCA) was analysed by the researcher using the free fsQCA software by fs/QCA designed by Charles C. Ragin. The fsQCA evaluates the interplays between combinations of theoretical combinations that would lead to a desired outcome (Ragin, 2009). The adoption of fsQCA methods in quantitative research has been growing with the intention to evaluate causal relationships (Ragin, 2008; Woodside, 2016). fsQCA adopts Boolean perspectives to establish relationships on a specific outcome (Ragin, 2009). The entanglement view of capabilities presents a complex paradox when leveraging big data to create firm performance. As discussed in Chapter 2, it was argued that organisations require diverse resources and capabilities to deploy, manage and enable value creation which can be leveraged by DDC's to create firm performance. This fsQCA was evaluated in this research by using two key attributes within this perspective. The notion of an organisation's active years in pursuit of big data and the number of employees in an organisation form part of the learning capability and resource perspective. This was computed together with FPer as the outcome variable and BDAC, exploitative and explorative capabilities as the predictor outcomes. fsQCA evaluates the multiple cases and reports on the significant models based on coverage and consistency. '*Coverage*' refers to the valid number of cases for each configuration (Roig-Tierno, Gonzalez-Cruz, & Llopis-Martinez, 2017). In this research the five predictor variables gave rise to 21 possible configurations (these excluded the individual effects of each predictor variable). *'Consistency'* refers to the number of "causal configurations of similar composition which result in the same outcome value" (Riog-Tierno et al., 2017, p. 17). If a configurations consistency is below 0.75 it is disregarded as this value is regarded as a significance value (Ragin, 2009). fsQCA reports on the most significant configurations based on the hypothesised causal relationships. By analysing the fsQCA the researcher sought to gain a deeper understanding of the organisational configurations under the sociomaterialism and paradox views discussed in Chapter 2 that effectuate firm performance.

4.10 Limitations

This study adopted a non-probability sampling technique which included snowball and purposive sampling methods. A significant disadvantage of this method is the induced sampling bias due to the similarities of characteristics of the respondents under the referral mechanism and thus reducing the generalisation to the population (Zikmund et al., 2005). The research followed a survey strategy design to obtain responses. This assumed that the unit of analysis in this research would have access to internet facilities. The main drawback of online surveys is that it moves control away from the researcher and if the incorrect channel of distribution is adopted it creates sampling biases (Wright, 2017). Additionally, survey respondents are likely to lose interest if the survey is too long as in the case of this research (Wright, 2005).

The complexity of the concept of big data discussed in Chapter 2 could affect the survey responses and inferences as the respondents did not fully comprehend the study intent. Furthermore, the research questions adopted from Akter et al. (2016) and Wamba et al.

(2017) is relatively new and can be further refined as the literature on big data is in its infancy.

Due to the time constraints the research adopted a cross-sectional view. This only provided a snapshot of the data and the researcher could not create an understanding of the entanglement of capability view in the big data environment over time. The researcher posits that the mediating effect of DDC on the BDAC-FPer relationship will maintain its strength over time due to the learning capability effects.

Although PLS-SEM provides a more robust statistical method than first order MSA tests, it presents certain disadvantages. PLS-SEM only reports one model fit index (SRMR) and relies on bootstrapping and blindfolding techniques to assess the significance of the model's predictability (Hair et al., 2017). Although this was not an issue in this research, PLS-SEM tools are being improved to provide more model fit indices similar to CB-SEM methods. Furthermore, this research adopted the repeated indicator approach to model the interactions in congruence with Akter et al. (2016). van Riel et al. (2016) states that this method creates artificial residual correlations which could result in incorrect research conclusions if the model is not specified correctly.

Chapter 5: Research results

5.1 Introduction

This chapter presents the results of the research as described by the methodologies adopted by the researcher in Chapter four. This chapter begins by illustrating the descriptive characteristics to provide context from the sample obtained and describe the data from the survey method adopted. Following the descriptive statistics, the statistical analyses is presented as described in Chapter four which address the research questions for this study as hypothesised by the researcher in Chapter three.

5.2 Descriptive characteristics of sample data

5.2.1 Research sample

The researcher targeted a minimum of 250 responses as obtained by Koryak et al. (2018), Mikalef and Pateli (2017) and Wamba et al. (2017). This minimum value was envisaged due to the limitations of the study as discussed in Section 4.10. This was also to ensure that a minimum qualified sample size of 134 was obtained to conduct the PLS path model analysis as discussed in Section 4.6. A raw sample size of 216 was obtained of which 41 were screened out after the initial screening question which qualified respondents to enter the research survey with the question "*Are you aware of or associated with a Big Data Analytics Capability within the organisation being described in this questionnaire?*". Due to the sampling technique adopted, the response rate for the research survey could not be determined. However, the researcher posits that the response rate is well below the average response rate for online survey methods which is stated to be between 15% and 33% (Fricker, 2008; Nulty, 2008). This is justified as the researcher posted the survey links onto various LinkedIn big data groups. The Big Data and Analytics group boasts a membership of 340,766 and if only 1% viewed the survey this with equate to a response rate of 6.34%. However, Baruch and Holtom (2008) state that response rates in online surveys in quantitative academic research have been declining for some time.

This decline can be attributed to company policies, apathy amongst the respondents and unavailability (Baruch & Holtom, 2008). As previously discussed in Section 4.10, the complexity around the research topic could also provide a plausible reason for low response rates. In comparison with sampling methods adopted by Akter et al. (2016) and

Wamba et al. (2017) who achieved response rates in excess of 37%. The main difference was the use of market research firms with databases for the specific unit of analyses. As previously discussed in Section 4.5, this option was too costly for the researcher considering the time frame.

Of the 175 qualified responses, 20 were rejected as the completion rate was below 50% as discussed in Section 4.9.2. 36 responses had missing data which had to be imputed as per the MAR methodology discussed in Chapter 4.9.2. The data sample results are summarised in Table 3.

Table 3

Summary of data collected and imputed

	Total data set	% Total data
Raw data sample size	216	100%
Screened out respondents	41	18.98%
Respondents with less than 50% completion	20	9.26%
Respondents with 100% completion	119	55.09%
Respondents with >50% and <100% completion	36	16.67%
Qualified sample data set	**155**	71.76%
Total number of potential responses on qualified sample data set*	9610	100%
Total number of responses imputed	228	2.37%

*this only includes the measured variable questions and not the demographic questions

5.2.2 Descriptive characteristics of respondents

A total of eight descriptive questions were used in the research survey to profile the respondents which might influence any subsequent analyses (refer to Appendix A for descriptive questions). The researcher only used the 155 qualified responses for the descriptive and inferential statistics.

As illustrated in Figure 3, there were significantly more male respondents (66%) than female respondents (34%) who were qualified and completed the research survey. Figure 4 illustrates the age group split of the qualified respondents. Majority of the respondents fell into the 31 – 40 year age group category (54%), followed by the 41 – 50 year age group category (26%). The remaining 20% was split between the 20 – 30 year age group category (18%) and the 51 – 60 year age group category (2%). No respondents younger than 20 and older than 60 years of age were qualified in the final data set.

Figure 5: Respondent gender

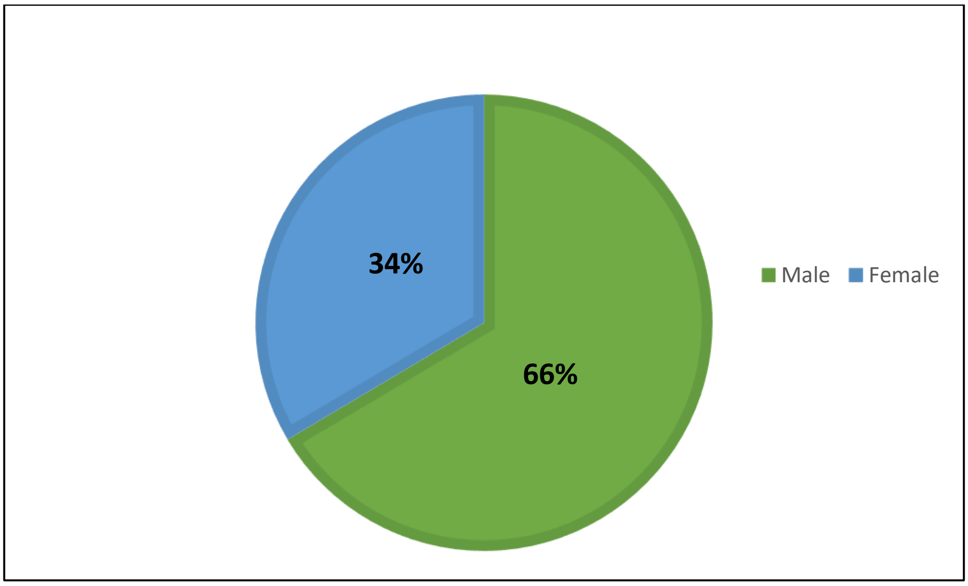
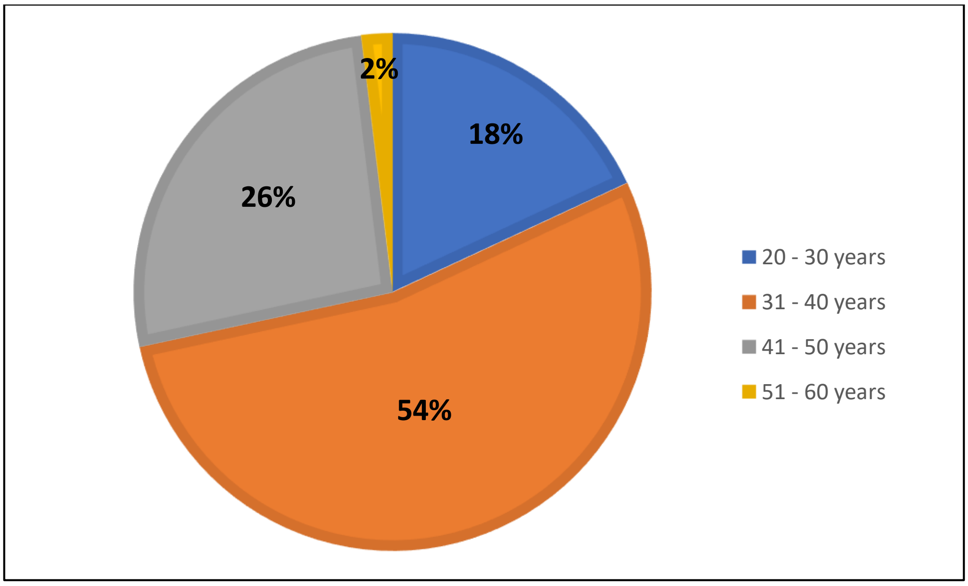


Figure 6: Respondent age



Most of the survey respondents in this research reside or are employed in South Africa (92.3%) as illustrated in Figure 5. 7.7% of the survey respondents are employed outside South Africa. The survey reach can be attributed to the usage of snowballing techniques as well as posting the research survey on social media platforms such as LinkedIn and Facebook.

Figure 6 illustrates the industries that the survey respondents represented. This is a key artefact under the notion that not every industry has adopted BDA and not all industries are currently positioned to apply BDA especially in the South African economic market.

Figure 7: Country in which respondents are employed

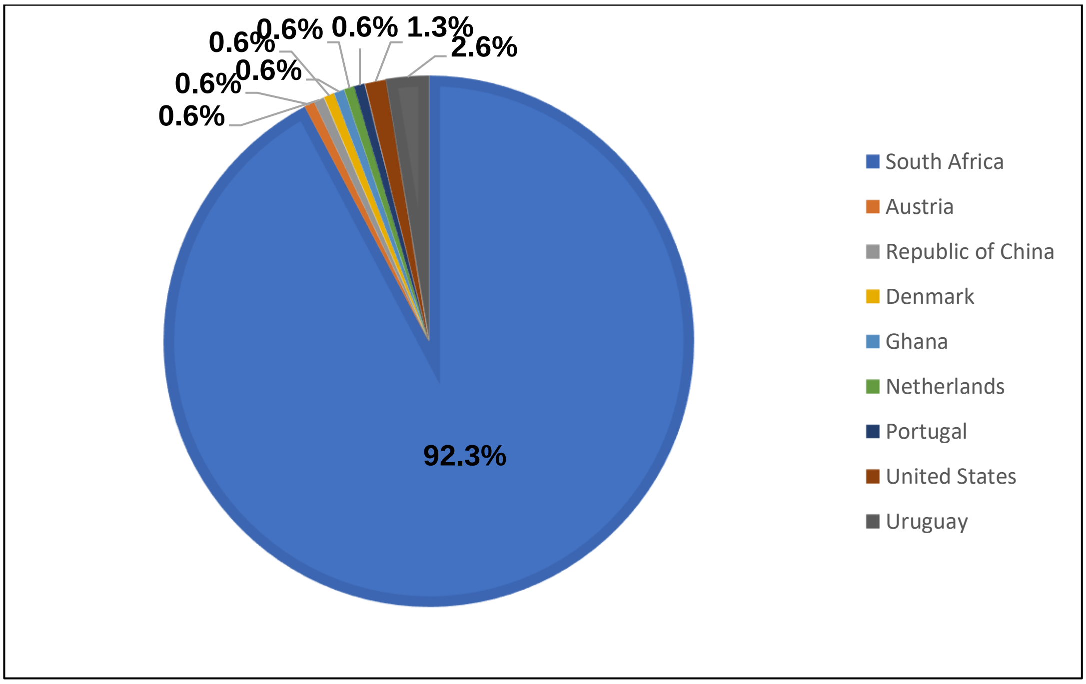


Figure 6 illustrates the industries that the survey respondents represented. This is a key artefact under the notion that not every industry has adopted BDA and not all industries are currently positioned to apply BDA especially in the South African economic market. The telecommunications and technology industry as well as the finance and insurance industry were two of the most ubiquitous industries represented in the research with 37% and 33% respectively. Akter et al. (2016) and Wamba et al. (2017) also reported their highest industries represented by their respondents as the telecommunication and technology industries under their definition of *'Information and communication'*. The transportation and warehousing industry followed with a 9% representation which was then followed by the retail industry with a 6% representation. The manufacturing industry represented just 4% in this research and when comparing to the figures reported by Akter et al. (2016) and Wamba et al. (2017), the manufacturing industry represented 10% and 14% respectively. 6% of the respondent's represented other industries which were not identified by the researcher as BDA capable.

The size of each organisation represented by each sector by the survey respondents were predominantly large organisations as illustrated in Figure 7. 54% of the respondents represented organisations with 1000 or more employees whilst a further 29% were represented by organisations with over 500 employees. Considering the amount of infrastructure and BDAC required to utilise and maintain BDA in organisations, this statistic was expected by the researcher. Although smaller organisations are finding other mediums to bring in and aggregate their data, large organisations driving BDA will still predominantly have larger teams to support the infrastructure and capabilities.

Figure 8: Industries represented by respondents

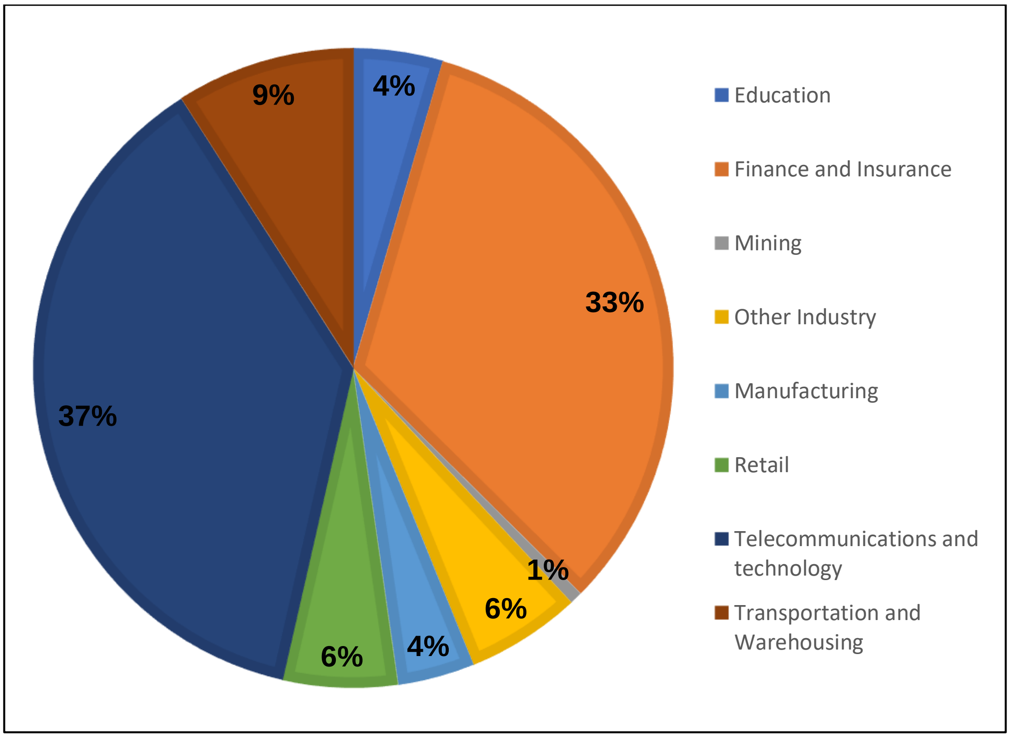


Figure 9: Number of employees in respondent organisations

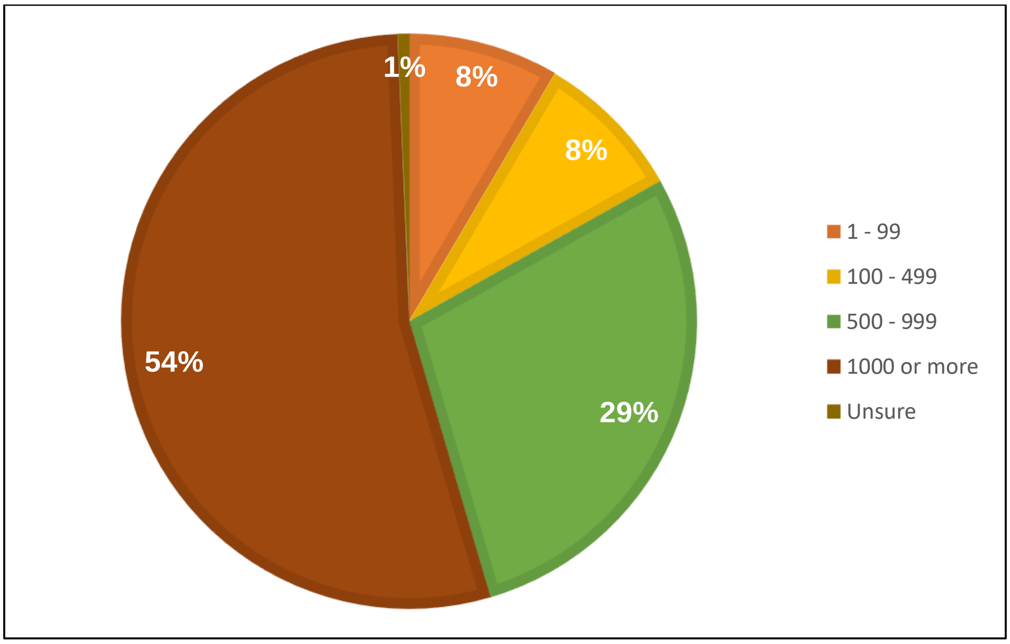
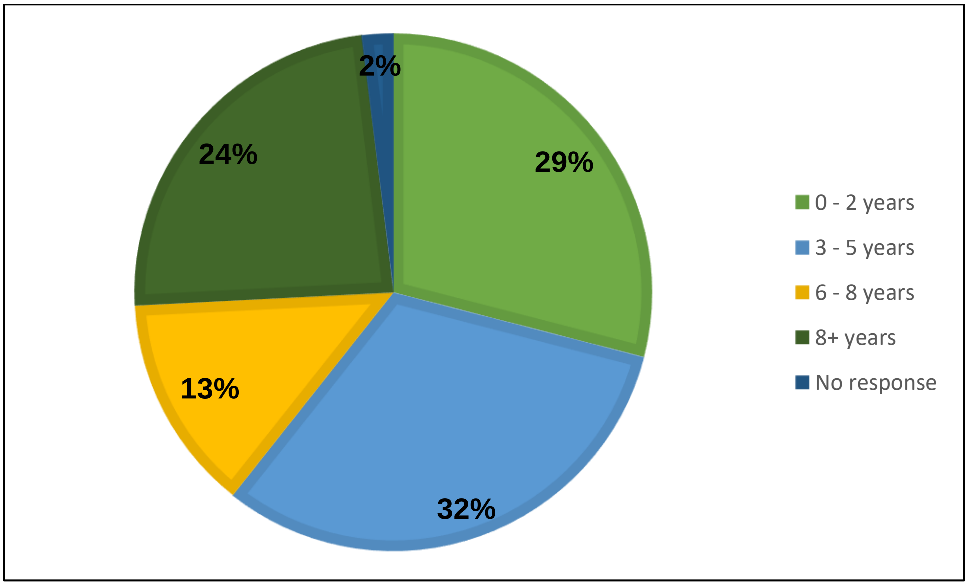


Figure 8 illustrates the organisations tenure in pursuing BDA. Therein, 32% of organisations reported to be within 3 and 5 years of their BDA deployments. 61% reported to be within their first 5 years of their BDA deployment. Thus, indicating the BDA infancy in South African organisations. A further 13% reported to be within 6 to 8 years of their BDA deployment and finally 24% of organisations reported that their BDA deployments have extended 8 years. This means that there has been an active pursuit of BDA in South Africa since the BDA tools had been developed in 2008 (Chen et al., 2014, Lee, 2017).

Figure 10: Organisations tenure in pursuing BDA



The level of seniority that the survey respondents themselves hold in their organisations is depicted in Figure 9. Only 6% of the respondents reported that they are employed in junior level positions in their organisations. This research aimed to obtain responses from individuals whom have the relative exposure in BDA to complete the survey. The researcher expected more senior level individuals to represent the unit of analysis. As evident in Figure 9, 3% reported themselves as executive level, 38% reported themselves as senior management level, 12% reported themselves as middle management and a further 32% reported themselves as specialists in their organisations.

In addition, the researcher sought to understand the respondent's association with BDA in their organisation. This would create context around the capabilities of the BDA organisations relevant to the research. As illustrated in Figure 10, 37% of respondents reported that their main association is being a user of analytics in their organisation. 25% reported their role as being drivers of big data applications (Big Data management). 16% reported as being direct processors of the data (Data analyst) and a further 15% reported as being involved in the data technology environment (IT infrastructure). 6% of the respondents reported themselves as being involved in other roles which were not identified by the researcher. Given the spread of the respondent's BDA association, the researcher considers the data set as being well balanced.

Figure 11: Respondent level of seniority in organisation

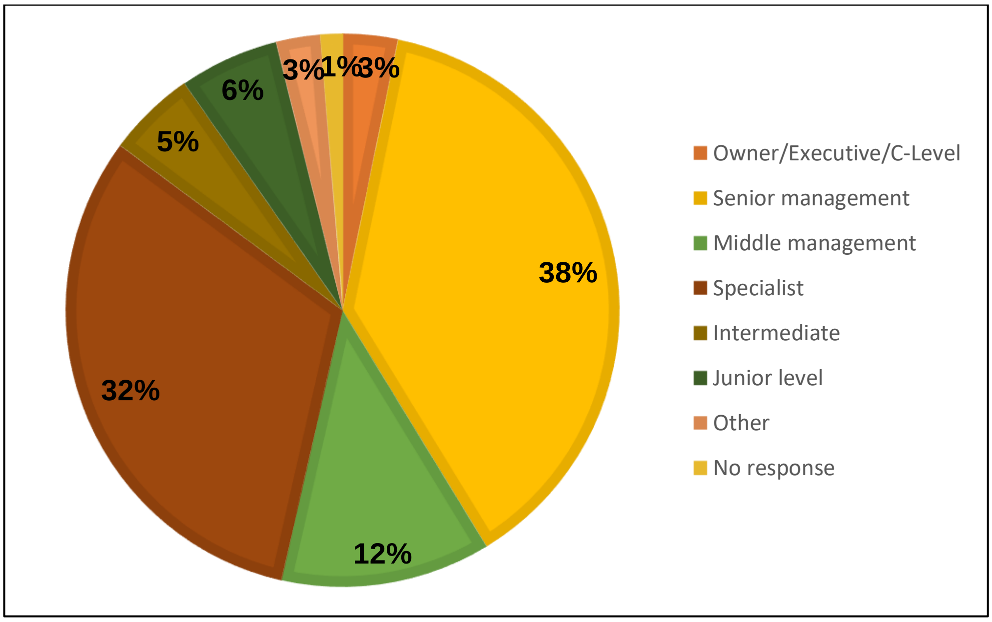
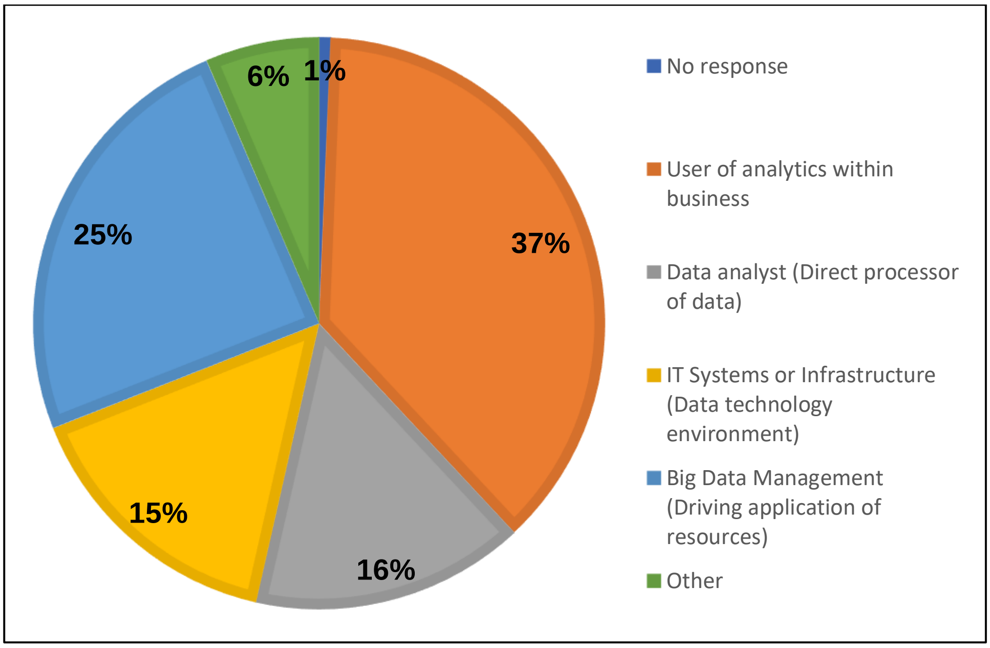


Figure 12: Respondent association with BDA



5.3 Priori tests

In the following sections an evaluation of the priori tests was analysed based on the process described in Chapter 4.

5.3.1 Factor analysis

As discussed in Section 4.9.4.1, PCA was performed on each of the survey constructs. In this research, the measurement scales were adapted from Akter et al. (2016), Koryak et al. (2018) and Wamba et al. (2017). Since the measurement scales were newly developed, the researcher sought to test the applicability in the current research context and test the construct validity. Suitability of the data to have a PCA analysis performed was addressed in Appendix D. The results of the PCA analysis by each construct is summarised in Table 3.

The overall KMO measure of sampling adequacy for all constructs tested was *'marvellous'* as they were greater than 0.9 (Kaiser, 1974). All constructs tested reported a Bartlett's test p value = 0.000, indicating that the data is factorisable and the data was suitable for PCA analysis (Zikmund et al. 2012). The extracted components were interpreted through a Varimax rotation, which resulted in measured variable groupings being applied in latter analysis.

As expected for the DDC construct, two components were extracted which explained a cumulative variance of 74.49% where questions for the exploitative and explorative capabilities loaded strongly on separate components. One component was extracted which cumulatively explained 89.95% variance for the FPer construct. The BDAC constructs as adapted from Akter et al. (2016) and Wamba et al. (2017) extracted two components each for the constructs of BDAMC, BDAIF and BDAPEC with a cumulative variance of 75.68%, 70.04% and 79.51% respectively.

Factor compositions thus differed from the BDAC model adopted from Akter et al. (2016) and Wamba et al. (2017) as depicted in Chapter 3, Figure 1. This was expected due to the variation in the survey question composition due to limitations on the research survey length. The new factor compositions for the constructs of BDAMC, BDAIF and BDAPEC were revised for the remainder of the analysis utilising the results of the PCA (refer to Appendix B). The BDAC factors still aligned with those of the model adopted from Akter et al. (2016) and Wamba et al. (2017).

Table 4

Summary results from PCA analysis

Construct	DDC	BDAMC	BDAIF	BDAPEC	FPer
Sample size	155	155	155	155	155
Number of Items	12	16	12	15	7
KMO measure of sampling adequacy	0.91	0.94	0.92	0.95	0.91
Bartlett's test of sphericity p value	0.00	0.00	0.00	0.00	0.00
Percentage of variance extracted	74.49	75.68	70.04	79.51	89.95
Number of factors extracted (eigenvalue≥1)	2	2	2	2	1

5.3.2 Measuring DDC

As described in Section 4.9.4.2, to compute for DDC five regression models were tested following the procedures recommended by Edwards (1994). The first unconstrained regression model treats exploitative and explorative capabilities as separate independent variables. The researcher then ran three constrained regression models in which exploitative and explorative capabilities were combined into one index, first by adding exploitative and explorative capabilities, second by multiplying exploitative and explorative capabilities and lastly by computing the mean of exploitative and explorative capabilities. Following the methodology by Edwards (1994), the R^2 and F-Value statistics from SPSS were analysed for each computation which is summarised in Table 4.

The mean computation method proved to be superior than the addition and multiplication method. The F-value for the mean computation method showed no significant reduction compared to the unconstrained regression models, and it's R^2 (0.52) is slightly higher than that of the multiplicative model (0.51). Given these results, based on Edwards (1994) methodology, the researcher measured DDC by calculating the mean between exploitative and explorative capabilities.

Table 5

Summary results for DDC computation method

Computation method	R^2	F-Value
Independent 1 Explorative	0.45	143.92
Independent 2 Exploitative	0.36	87.71
Addition	0.48	151.93
Multiplication	0.51	156.10
Mean	0.52	159.23

5.4 PLS outer model evaluation

As discussed in Section 4.9.4.4, the PLS outer model was evaluated for reliability and validity.

5.4.1 Reliability testing

In this research Cronbach alpha and the Composite reliability were assessed for the outer model reliability which was generated as an output in SmartPLS 3.0, the results are summarised in Table 6 and 7. Cronbach's alpha and Composite reliability threshold values based on Hair et al. (2017), confirm that all the research constructs have high levels of internal consistency reliability as they are greater than 0.7. Moreover, the composite reliability scores which is a more robust measure of internal reliability consistency exceeded the threshold value of 0.8 recommended by Hair et al. (2017). In addition, the researcher verified the Cronbach's alpha values on SPSS to establish if the removal of any indicators would lead to an increase in the Cronbach's alpha value.

The construct BDAMod reported an initial Cronbach's alpha of 0.84, with the deletion of item BDAMod4 the Cronbach's alpha score increased to 0.87. The researcher then verified the factor loading on the PLS-SEM output which reported a factor loading for the item BDAMod4 at 0.57 which is lower than the recommended threshold of 0.708 stated by Chin (2010) and Hair et al. (2017). The item BDAMod4 was deleted from the model for subsequent analysis. The reliability of the outer model was established as both reliability indices for the latent constructs exceeded the thresholds recommended by Hair et al. (2017)

5.4.2 Validity testing

Validity of the PLS outer model was assessed by convergent and discriminant validity. Convergent validity was established by analysing two methods as recommended by Chin (2010), Fornell & Larcker (1981) and Hair et al. (2017), the results of which are summarised in Tables 5, 6 and 7. The AVE values for all latent constructs ranged between 0.65 – 0.88, well above the 0.5 threshold recommended by Chin (2010) and Fornell & Larcker (1981). The factor loadings (indicator reliability) for the DDC construct (exploitative and explorative capabilities) ranged from 0.72 – 0.88, for the BDAC construct (BDAA, BDADM, BDAKT, BDAMod, BDATK and BDP) ranged from 0.74 – 0.9 and for FPer ranged from 0.91 – 0.97 (refer to Appendix C). All latent construct factor loadings exceeded the 0.708 threshold recommended by Chin (2010) and Hair et al.

(2017). Thus, confirming convergent validity of the outer model. Discriminant validity was confirmed by evaluating the item cross loading and the HTMT criterion as recommended by Chin (2010) and Henseler et al. (2015) as discussed in Section 4.9.4.4.

Table 6

Summary of the assessment of the higher order reflective model of BDAC

Model	Latent construct	AVE	CA	CR	Dimensions	B	R^2	t-Statistic
3rd order	BDAC	0.63	0.99	0.99	BDAMC	0.96	0.92	65.45
					BDAIF	0.94	0.89	43.34
					BDAPEC	0.96	0.93	67.82
2nd order	BDAMC	0.68	0.97	0.97	BDP	0.96	0.92	38.25
					BDADM	0.96	0.92	39.17
	BDAIF	0.63	0.95	0.95	BDAA	0.95	0.90	43.27
					BDAMod	0.95	0.90	51.53
	BDAPEC	0.71	0.97	0.97	BDATK	0.96	0.93	55.35
					BDAKT	0.96	0.93	53.58

The results of the HTMT criterion matrix is summarised in Table 7. There were no correlations exceeding 0.9 as per recommendation by Henseler et al. (2015) and the HTMT criterion was tested for significance by the bootstrap algorithm. An evaluation of the item cross loadings reported that all measured variables loaded higher on their own construct than on any other construct (refer to Appendix C). Additionally, the higher order reflect model of BDAC was also assessed as illustrated in Table 6. Based on these results, the researcher confirmed discriminant validity of the outer model.

5.5 PLS inner model evaluation

The researcher having established appropriateness of the outer model measures in the previous section, proceeded to evaluate the theoretical model by evaluating the PLS-SEM inner model by following the systematic approach recommended by Hair et al. (2017) as discussed in Section 4.9.4.5.

5.5.1 Assessment of collinearity

To assess for collinearity issues on the structural model, collinearity diagnostics through the evaluation of the VIF was interpreted as discussed in Section 4.9.4.5. The collinearity was assessed by evaluating the inner model VIF values reported by SmartPLS 3.0.

Table 7

Summary of reliability measures and HTMT results for measured variables

Construct	CA	CR	AVE	HTMT results								
				BDAA	BDADM	BDAKT	BDAMod	BDATK	BDP	Exploitative Cap	Explorative Cap	FPer
BDAA**	0.94	0.94	0.65	-								
BDADM**	0.96	0.96	0.71	0.86*	-							
BDAKT**	0.96	0.96	0.77	0.85*	0.86*	-						
BDAMod**	0.87	0.87	0.69	0.89*	0.85*	0.82*	-					
BDATK**	0.96	0.96	0.73	0.86*	0.86*	0.90*	0.82*	-				
BDP**	0.94	0.94	0.73	0.81*	0.88*	0.83*	0.79*	0.90*	-			
Exploitative Cap	0.93	0.93	0.68	0.51*	0.52*	0.52*	0.52*	0.44*	0.41*	-		
Explorative Cap	0.94	0.94	0.71	0.64*	0.60*	0.57*	0.61*	0.57*	0.57*	0.84*	-	
FPer	0.98	0.98	0.88	0.44*	0.51*	0.41*	0.48*	0.37*	0.34*	0.64*	0.74*	-

*Significant at the 99% level,

Table 8

Summary of latent construct factor loadings

Construct	Factor loadings
BDAA	0.74 – 0.85
BDADM	0.81 – 0.87
BDAKT	0.86 – 0.90
BDAMod	0.81 – 0.85
BDATK	0.80 – 0.88
BDP	0.84 – 0.88
Exploitative Cap	0.72 – 0.87
Explorative Cap	0.80 – 0.88
FPer	0.91 – 0.97

The inner model VIF was only evaluated as the structural model in this study was reflective. If the model contained any formative constructs, then the outer model VIF would also be evaluated. It is also important to note that if the inner model reported any VIF values that exceeded the threshold, the outer model VIF can be evaluated to verify which items have excess VIF values and can be deleted (Hair et al., 2017). Collinearity was not an issue in the study as the analysis of the collinearity indicator fell below the threshold adopted by the researcher (VIF < 5) (Hair et al., 2017). The inner model VIF values ranged between 1 – 1.58, clearly indicating that this study has no collinearity issues.

5.5.2 Structural model descriptive statistics

As discussed in Section 4.9.4.5, once the assessment of the outer model and collinearity was completed whereby all measured variables were confirmed, descriptive statistics for the constructs could then only be calculated. An assessment of descriptive statistics for the first and second order constructs is summarised in Table 9. The mean for the BDAC first order construct range between 4.32 – 4.77, suggesting a positive tendency of the survey respondents. The mean for the first order DDC constructs range between 5.11 – 5.29, also suggesting a positive tendency of the survey respondents. No significant outliers were reported after reviewing the Casewise Diagnostics output in IBM SPSS. The researcher reviewed the standardised residual values from the Casewise diagnostics table which reports the standardised residual value standard deviations. No standard deviations greater than ±3 were detected. Considering the PLS-SEM has no constraints against data with non-normal distribution, the researcher tested for normality by evaluating the Shapiro-Wilk test as a descriptive measure of the data (Shapiro & Wilk, 1965), refer to Table 10. The null hypothesis is rejected when $p<0.05$ for the Shapiro-Wilk test, which results in a statistical difference between the data set and normal distribution. As per Table 10, this infers that the data is not normally distributed with the exception of BDP and BDAMC.

5.5.3 Structural model relationship assessment

The revised model after assessing the priori and inner model evaluations is illustrated in Figure 13. The consistent PLS algorithm in SmartPLS 3.0 was used to calculate the relationships between the constructs for the hypothesised structural model. The R^2 values for the dependent variables were reported together with the path coefficients which refer to the strength and direction of the hypothesised relationships.

Table 9

Descriptive statistics for first and second order constructs

2nd order Construct	1st order Construct	N	Mean	Std. Deviation	Skewness		Kurtosis	
		Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
	BDP	155	4.77	1.11	-0.16	0.19	-0.22	0.39
	BDADM	155	4.47	1.13	0.03	0.19	-0.36	0.39
	BDAA	155	4.43	1.08	-0.10	0.19	0.26	0.39
	BDAMod	155	4.32	1.17	-0.12	0.19	-0.11	0.39
	BDATK	155	4.74	1.12	-0.32	0.19	0.56	0.39
	BDAKT	155	4.67	1.13	-0.19	0.19	0.18	0.39
	Exploitative Cap	155	5.29	1.05	-0.48	0.19	-0.30	0.39
	Explorative Cap	155	5.11	1.13	-0.54	0.19	0.31	0.39
	FPer	155	4.46	1.53	-0.52	0.19	-0.41	0.39
BDAMC	BDP BDADM	155	4.62	1.07	-0.06	0.19	-0.22	0.39
BDAIF	BDAA BDAMod	155	4.37	1.07	-0.07	0.19	0.11	0.39
BDAPEC	BDATK BDAKT	155	4.71	1.09	-0.27	0.19	0.55	0.39
DDC	Exploitative Cap Explorative Cap	155	5.20	1.03	-0.41	0.19	-0.32	0.39

Table 10

Summary of normality testing through the Shapiro-Wilk test

Construct	Shapiro-Wilk		
	Statistic	df	Sig.
BDP	0.98	155	**0.06**
BDADM	0.98	155	0.01
BDAA	0.97	155	0.00
BDAMod	0.98	155	0.01
BDATK	0.97	155	0.01
BDAKT	0.97	155	0.00
Exploitative Cap	0.97	155	0.00
Explorative Cap	0.97	155	0.00
FPer	0.96	155	0.00
BDAMC	0.98	155	**0.06**
BDAIF	0.98	155	0.01
BDAPEC	0.97	155	0.00
DDC	0.98	155	0.01

Since a reflective model was adopted in this research, and statistical inference and significance is crucial in validating the hypothesised relationships. The consistent PLS bootstrapping algorithm was used after the PLS algorithm to validate statistical significance of the path weightings and the R^2 results of the structural model. As discussed in Section 4.9.4.5 Hair et al. (2017) further state that bootstrapping allows inferences to be generalised to the research population, which is one of the research intents of this study. A systematic approach was adopted for the researcher to test each hypothesis as discussed in Section 4.9.4.5.

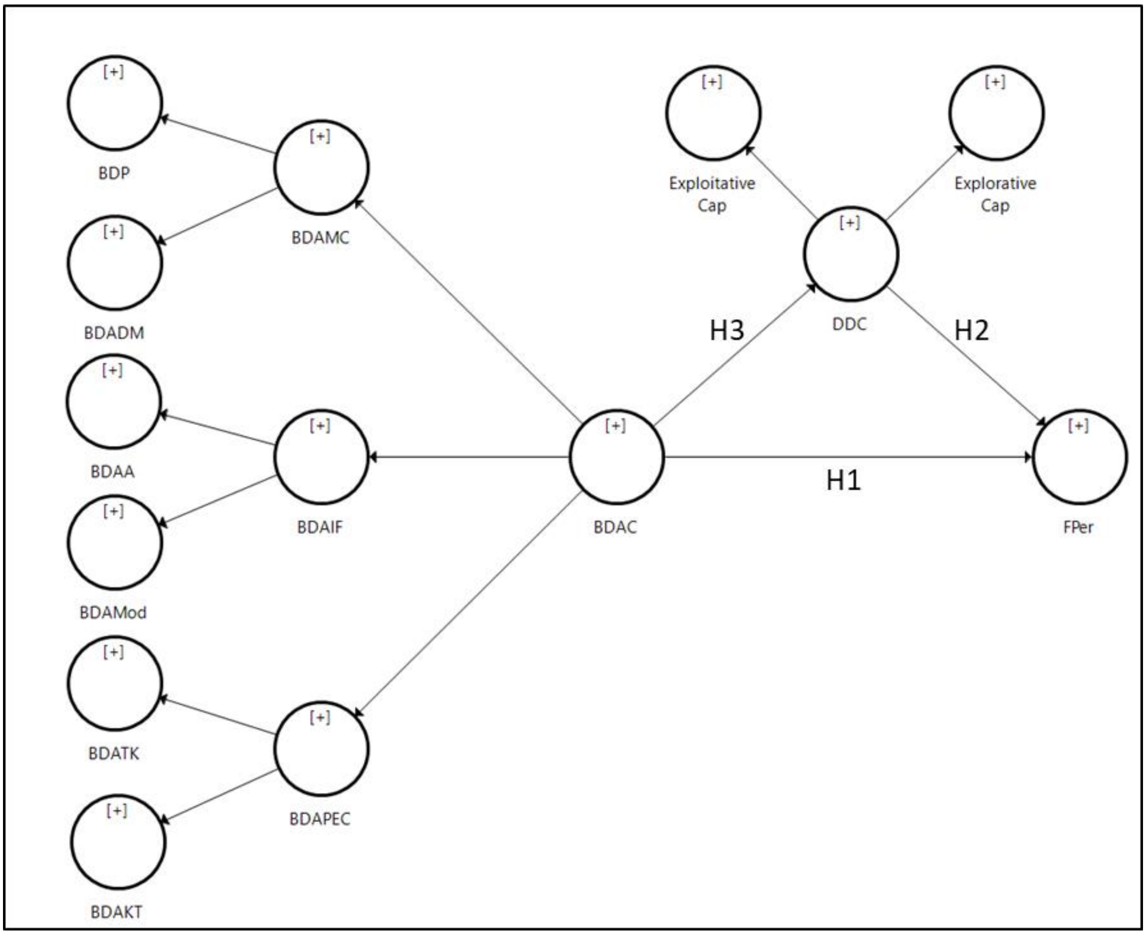


Figure 13. Revised research model applied in this study

5.5.3.1 Research question one

The first research question in this study followed that of Wamba et al., (2017), which sought to validate the relationship between BDAC and FPer. Hypothesis one (H_1) posited the presence of a positive relationship between BDAC (independent variable) and FPer (dependent variable). The proposed mediation effect of DDC was removed from this test as the hypothesis seeks to assess the relationship between BDAC and DDC with no third variable interaction. The result of the assessment for H_1 is shown in Figure 14.

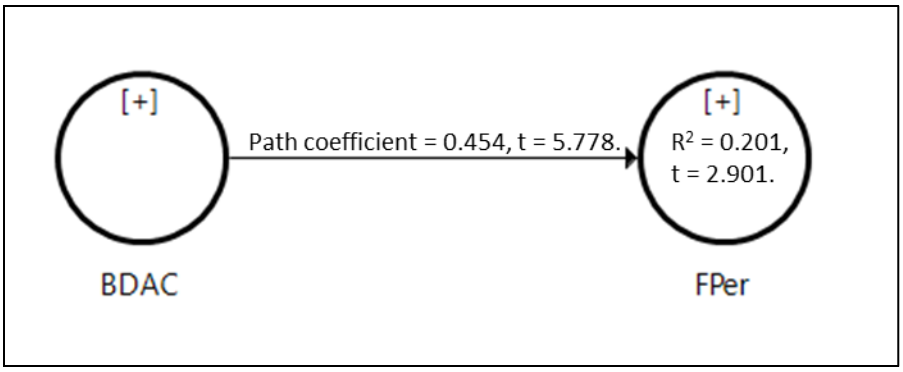


Figure 14. Path model for Hypothesis one

As illustrated in Figure 14, BDAC has a positive and significant path coefficient of 0.454 (t=5.78, p<0.01). Thus, the researcher rejected the null-hypothesis and confirmed H_1, showing that with the presence of BDAC in an organisation, FPer increases. This result concurs with that of Akter et al., (2016) and Wamba et al., (2017), who reported slightly higher path coefficients for the relationship between BDAC and FPer at 0.71 and 0.56 respectively. The coefficient of determination (R^2) value for FPer under the effect of BDAC was significant at 0.201 (t=2.90, p<0.01). This is the proportion of variance in FPer that can be explained by BDAC only. This represents a weak coefficient of determination (R^2) as stated by Hair et al. (2017). The result thus confirms that BDAC has a significant positive relationship with FPer (0.454) with a weak coefficient of determination (0.201) at the 99% level of significance.

5.5.3.2 Research question two

Research question two assessed the relationship between DDC and FPer. Although previous studies have described links between organisational capabilities and FPer (Akter et al., 2016; Wamba et al., 2017), the combination of exploitative and explorative capabilities have not been previously tested under the DDC construct. Hypothesis two (H_2), posited the presence of a positive relationship between DDC (independent variable) and FPer (dependent variable). The result of the assessment for H_2 is shown in Figure 15.

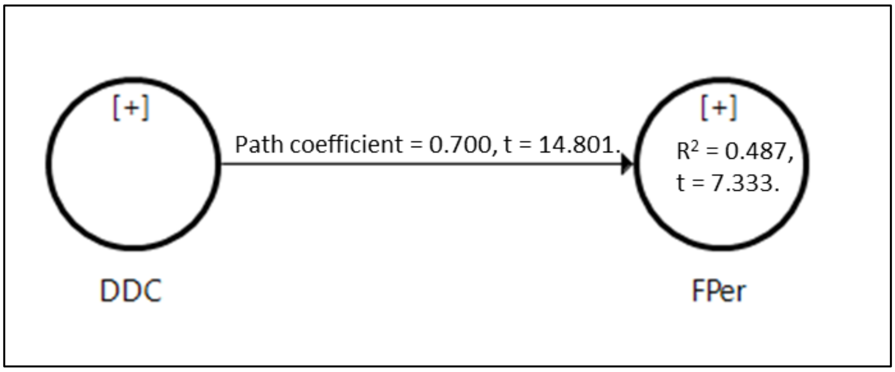


Figure 15. Path model for Hypothesis two

As illustrated in Figure 15, DDC has a positive and significant path coefficient of 0.700 (t=14.80, p<0.01). Thus, the researcher rejected the null-hypothesis and confirmed H_2, showing that with the presence of DDC in an organisation, FPer increases. The path coefficient for the relationship between DDC – FPer (0.700) was much larger than the relationship between BDAC – FPer (0.454). Thus, indicating that the effect of DDC on FPer is greater than that of BDAC. The coefficient of determination (R^2) value for FPer under the effect of DDC was significant at 0.487 (t=7.33, p<0.01). This represents a moderate R^2 as stated by Hair et al. (2017). The assessment for H_2, confirms that DDC has a significant positive relationship with Fper (0.700) with a moderate coefficient of determination (0.487) at the 99% significance level.

5.5.3.3 Research question three

The third research question sought to validate the relationship between BDAC and DDC. Hypothesis three (H_3) posited the presence of a positive relationship between BDAC (dependent variable) and DDC (dependent variable). Wamba et al. (2017) similarly tested the relationship between BDAC and PODC (an internal focussed capability), whereas the DDC construct in this study has not been previously tested with BDAC. The result of the assessment for H_3 is shown in Figure 16.

As illustrated in Figure 16, BDAC has a positive and significant path coefficient of 0.577 (t=8.40, p<0.01). Thus, the researcher rejected the null-hypothesis and confirmed H_3. The coefficient of determination (R^2) value for DDC under the effect of BDAC was significant at 0.328 (t=4.23, p<0.01). This represents a low effect size as stated by Hair et al. (2017). The path coefficient and R^2 for the relationship between BDAC – DDC (0.577, 0.328) was much greater than the relationship between BDAC – FPer (0.454, 0.201). Wamba et al. (2017) reported a higher path coefficient and effect size on the BDAC – PODC relationship at 0.84 and 0.70 respectively. It is important to note that the DDC construct used in this study covers aspects of internal and external dynamic capability orientations whereas PODC is only internally focussed. The assessment of H_3 confirms that BDAC has a significant positive relationship with DDC (0.58) with a low effect coefficient of determination (0.33) at the 99% significance level.

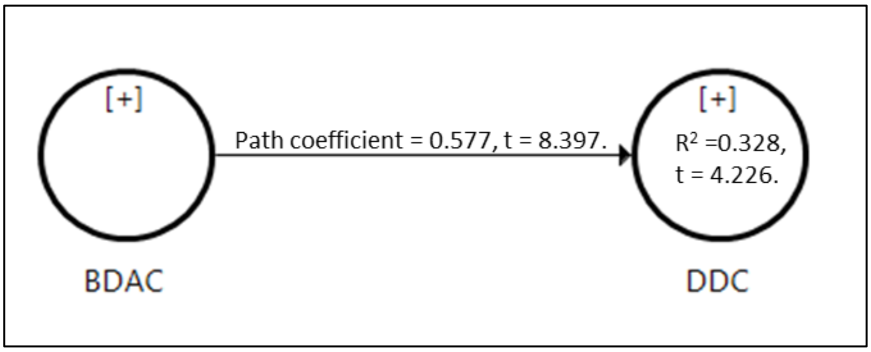


Figure 16. Path model for Hypothesis 3

5.5.3.4 Research question four

The proposed research model in this study proposed possible mediation interaction. Specifically, DDC may mediate the relationship between BDAC on FPer. Preacher and Hayes (2008) mediation analysis technique was used by the researcher to test and evaluate for mediation effects on this research. The verification of the path coefficients and significance for the direct effect was already conducted during the assessment of H_1. As per guidelines from Hair et al. (2017), since the direct effect showed significance (0.454, $p<0.01$), a mediating effect is possible. Additionally, through the evaluation of H_2 and H_3 the researcher confirmed the remaining conditions required for a mediation effect i.e. the relationship between the independent variable and the moderator (BDAC – DDC) and the relationship between the moderator and the dependent variable (DDC – FPer) was significant. Thus, it was concluded that a mediation effect is present. Table 11 summarises the results for the mediation analysis and Figure 17 illustrates the full structural model with inner and outer loadings of the study. The researcher evaluated the indirect effect by multiplying the coefficients of the two indirect paths (BDAC – DDC and DDC – FPer). SmartPLS 3.0 automatically calculates the indirect effect when the Consistent PLS algorithm is run. The indirect effect of BDAC (0.39, $p<0.01$) through the mediator construct DDC was significant, whereas the direct relationship between BDAC and FPer was insignificant (0.07, $P>0.01$). Significance was tested by running the Consistent PLS Bootstrapping algorithm. Thus, it was confirmed that BDAC has an indirect positive effect on FPer through DDC. Additionally, the value of the VAF for BDAC → FPer was reported at 85%. Hence, the researcher concluded that DDC fully mediates the relationship between BDAC and FPer (VAF > 80%). This mediation is regarded an indirect only (full mediation). The assessment of H_4 confirms that DDC mediates the relationship between BDAC and FPer, with an indirect effect of 0.39 with a moderate coefficient of determination (0.486) at the 99% significance level. DDC was also shown to have a full indirect mediation on the relationship between BDAC and FPer with a VAF of 85%, the null hypothesis was thus rejected.

Table 11

Summary analysis for mediating effects of DDC, H_4

Construct/indicator	Direct effect	Indirect effect	Total effect	t-statistic	VAF	Mediation type
H_4: BDAC > FPER (via DDC)	0.07	0.39***	0.46***	8.305	85.00%	Full mediation

(***p<0.01)

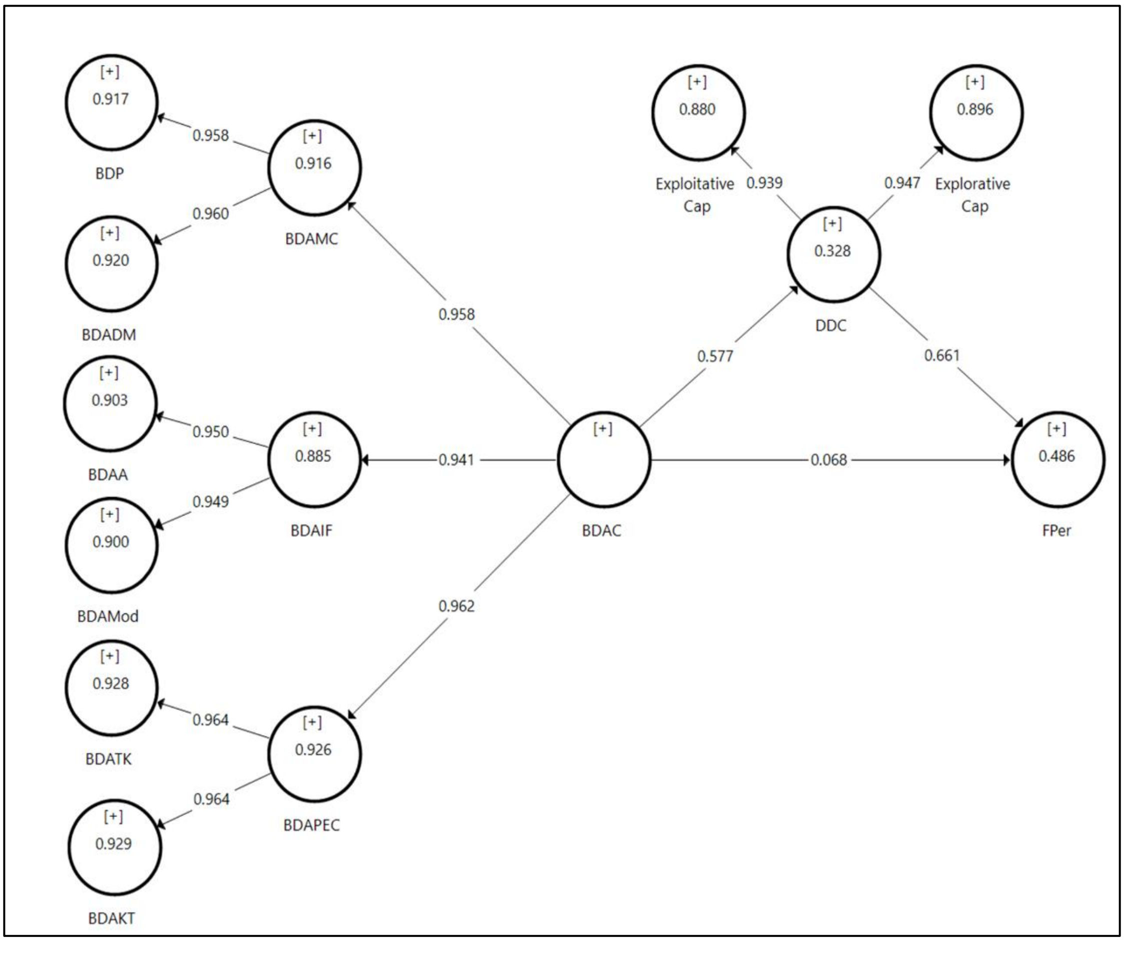


Figure 17. Research structural model with inner and outer loadings

5.5.4 Structural model fit assessment

The results of the bootstrap test for R^2 is summarised on Table 12 and indicates that the Coefficient of determination (R^2) for all the endogenous constructs are significant (p≤0.01). The bootstrap test for R^2, indicated that the predictive power of the hypothesised model was significant at the 99% level. All the R^2 values of the endogenous constructs in the model were greater than 0.1 as recommended by Hair et al. (2017). Additionally, the R^2 values for the 1st order constructs for BDAC and DDC, including the 2nd order BDAC constructs can be described as substantial (R^2>0.67) whilst that for DDC and Fper can be regarded as moderate (Hair et al., 2017).

Table 12

Results of the bootstrap test for the significance of R^2

Endogenous construct	R^2 value	T Statistic	P Values
BDP	0.917	37.596	0.000
BDADM	0.920	37.956	0.000
BDAA	0.903	41.031	0.000
BDAMod	0.900	49.005	0.000
BDATK	0.928	52.766	0.000
BDAKT	0.929	52.083	0.000
BDAMC	0.916	61.262	0.000
BDAIF	0.885	43.627	0.000
BDAPEC	0.926	65.972	0.000
Exploit	0.880	22.478	0.000
Explore	0.896	34.545	0.000
DDC	0.328	4.301	0.000
FPer	0.486	8.625	0.000

Table 13 summarises the effect size (f^2) for the independent variables in the structural model. As expected the effect size for DDC on FPer was much higher than BDAC on FPer. Additionally, the effect was of BDAC on FPer was not significant. The effect size of BDAC on DDC and DDC on FPer represented large effects (f^2>0.35) (Hair et al., 2017).

Table 13

Summary of effect size (f^2) analysis

Dependent variable	Independent variable	Effect size (f^2)	*t* Statistics	*p* Values
DDC	BDAC	0.53	2.54	0.01
FPer	BDAC	0.01	0.34	0.74
	DDC	0.57	2.77	0.01

The Stone-Geisser's Q^2 value evaluates the structural model's predictive relevance. The Q^2 value obtained for DDC indicates a medium predictive relevance (>0.15) whilst that of FPer indicates a large predictive relevance (>0.35) (Hair et al., 2017).

Table 14

Blindfolding procedure analysis – Q^2

Dependent variable	Q^2
DDC	0.33
FPer	0.47

The SRMR value was introduced as a measure of model fit for PLS-SEM by Henseler and Sarstedt (2014). An SRMR value less than 0.08 was adopted by the researcher as good model fit index (Hair et al., 2017). The SRMR value reported for this research model was 0.045 ($p \leq 0.01$) indicating that the hypothesised model meets the goodness of fit criteria.

5.5.3 Post-Hoc tests

Figure 18 shows the graphical output for the relationship between exploitative and explorative capabilities. This output highlights important features as there are very few respondents that rate their organisation low on both exploitative and explorative capabilities. Many respondents rated their organisations high on both exploitative and explorative organisations, indicating the dynamic organisational capability interplays within their organisations.

The results of the statistical power test using the study sample size of 155 (N), effect size of 0.57 and a 0.01 significance level (α) estimated the research model's power at 0.99. This value exceeded the threshold value recommended by Cohen (1992) confirming the validity and significance of the research model and the hypothesised path linkages based on the sample size obtained.

Outcomes of the fsQCA for achieving firm performance are presented in Table 14. Four solutions were extracted by the fsQCA programme showing an increase in the predictors would increase firm performance. All four solutions reported that for firm performance to be realised BDAC and both explorative and exploitative capabilities are required. Thus, BDAC and the dynamic management of explorative and exploitative capabilities are core constructs for the prediction of firm performance. One solution extracted years in pursuit of big data and number of employees in different solutions whilst the last solution model reported BDAC, exploitative capability, explorative capability, years in pursuit of big data and number of employees. The last model reported the highest consistency of 0.95.

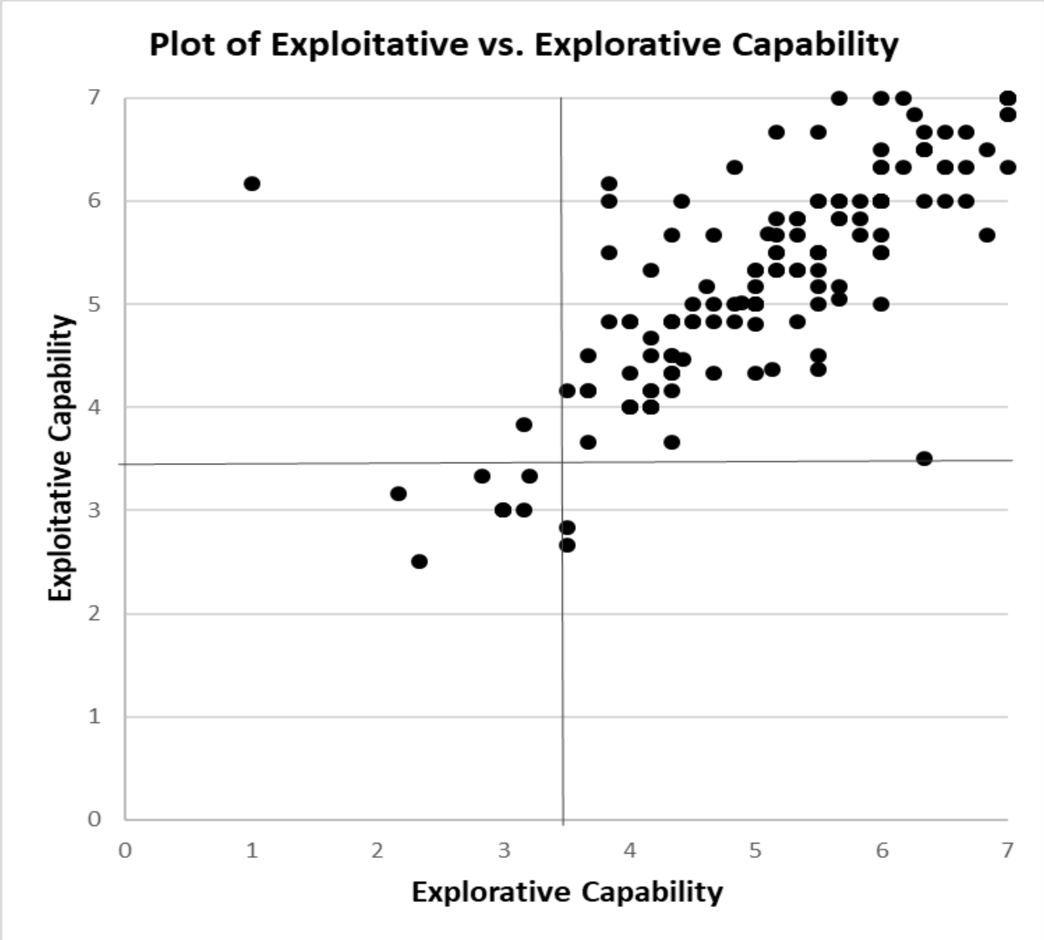


Figure 18. Plot of Exploitative vs. Explorative Capabilities

Table 15

Summary of fsQCA analysis

Configuration	Solution		
	Firm Performance		
	Raw Coverage	**Unique Coverage**	**Consistency**
BDAC*Exploit*Explore	0.89	0.89	0.89
BDAC*Exploit*Explore*Pursue	0.41	0.05	0.88
BDAC*Exploit*Explore*NE	0.75	0.34	0.90
BDAC*Exploit*Explore*Pursue*NE	0.15	0.00	0.95
Solution coverage: 0.80			
Solution consistency: 0.88			

BDAC: Big Data Analytics Capability, Exploit: Exploitative capability, Explore: Explorative capability, Pursue: Active years in pursuit of big data, NE: Number of employees in the organisation

Chapter 6: Discussion of results

6.1 Introduction

The aim of this research was to obtain a deeper insight and understanding of the value created by leveraging big data in a dynamic ecosystem through the entanglement of capabilities. The research proposed path linkages based on a theoretical evaluation of emerging research on the sociomateriality concept on big data and the paradox view on dynamic management of exploitative and explorative capabilities (Akter et al., 2016; Koryak et al., 2018; Lewis & Smith, 2014; Smith, 2015; Wamba et al., 2017). Primary intentions as outlined in Figure 1 of this research and discussed in Chapter 2 objectified the provision to clarify the mode of value creation as firm performance through the higher order dynamic constructs of BDAC and DDC. This was reified by addressing four research questions identified in Chapter 3. In addition, further post-hoc analyses were conducted to ensure the validity of the research findings as well as to determine the impact of other synergistic and antecedent mechanisms which shape the association between BDAC and FPer under the entanglement of capability view.

Under the entanglement view, this research positioned big data to effectuate data driven insights and support DDC in achieving firm performance. Whilst research question 1 sought to confirm the direct relationship between BDAC and FPer, research questions 2 to 4 sought to empirically evaluate the dynamic interplay between BDAC, DDC and FPer. This chapter discusses the research findings determined in Chapter 5 and is systematically structured.

6.2 Discussion of Research Question 1

The first research question sought to confirm the established theorised causal link between higher order capabilities in a big data environment and the effectuated value that is enabled. This research question was thus, articulated as:

Is there a positive relationship between Big Data Analytics Capability (BDAC) and Firm Performance (FPer)?

Big data has emerged as a critical resource for superior performance (Garmaki et al., 2016). Both Akter et al. (2016) and Wamba et al. (2017) highlighted the strategic and operational potential that can be effectuated through big data for organisations. Though, to reap the benefits and enable the potential of big data a sociomaterialism view is required (Akter et al., 2016). The link between IT capabilities and firm performance has provided researchers and organisations with a view on the importance of embedding this capability in an organisation (Mikalef & Pateli, 2017). This perspective stems from the DCT and RBV views which postulates IT capability through the VRIN concept and recognises the importance of leveraging, deploying, integrating and enabling IT based resources to effectuate value for organisations by directly and indirectly improving firm performance (Akter et al., 2016; Kim et al., 2012). Although IT capabilities have been posited to be a critical mechanism of BDAC (Akter et al., 2016; Gupta & George, 2016; Mikalef & Pateli; 2016), BDAC attaches many complexities due to the 5V's (Akoka et al., 2017; Wamba et al., 2017). In congruence with the entanglement view, a higher order capability was developed to measure BDAC as mechanisms of tangible, intangible and resource capabilities which do not act in isolation but rather as a synergy which under the sociomaterialism view manages tensions and creates consistency and dynamism (Akter et al., 2016; Smith, 2015). Similarly, to IT capabilities, BDAC draws on integrating, deploying and enabling big data resources which under the DCT view improves firm performance (Akter et al., 2016; Kim et al., 2012; Kiron et al., 2014; Mcafee & Brynjolfsson, 2012; Wamba et al., 2017).

This proposed association was tested using the PLS-SEM technique which reported a significant medium path coefficient of 0.45 between BDAC and FPer (refer to Figure 14). Additionally, BDAC explained approximately 20% of the variability in FPer. This infers that BDAC increases firm performance which emerges clearly in support of the views by Akter et al. (2016) and Wamba et al. (2017). Furthermore, as a higher order dynamic capability, this result is coherent with the perspective of dynamic capabilities being a distinctive influence which enables organisations to create competitive advantages which are inherently sustainable (Schilke, 2014; Teece et al., 2007). The path coefficient in this research was slightly lower than that reported by Akter et al. (2016), who reported a path coefficient of 0.71 between BDAC and FPer. This could be attributed to differentiation in the unit of analysis. Herein, this research reported a balanced sample between management levels and users of data analytics whereas Akter et al. (2016) reported a significant amount of IT managers and BDA managers whose main association is with the BDA infrastructure. Another factor could also be attributed to the breadth of survey questions per construct as this research reduced the original survey due to time constraints in the survey design. However, this result closely matches that of Wamba et al. (2017) who reported a path coefficient of 0.56 for the relationship between BDAC and FPer whereby the researchers reported similar unit of analyses to this research.

Based on the sociomaterialism view, it was also important to assess the hierarchical higher order model of BDAC as through its complementary and co-specialising lower order capabilities, BDAC can then only can create competitive advantages for organisations (Akter et al., 2016; Davenport et al., 2012; Gupta & George, 2016; Wixom et al., 2013). This research found BDAC to have significant positive associations with all its 2nd order elements (refer to Table 16), which was reported by previous studies (Akter et al., 2016; Gupta & George, 2016; Wamba et al., 2017). Though construct terminology differed between the three studies and the current research, the definitions and constituents were congruent. BDA personnel expertise capability (BDAPEC) was reported as the strongest path weighted construct (0.962), followed by BDA management capability (BDAMC) (0.958) and then BDA infrastructure capability (BDAIF) (0.941) in this study. Similarly, Akter et al. (2016) and Wamba et al., (2017) reported personnel expertise capability as the highest weighted 2nd order BDAC construct in their respective studies (refer to Table 16). Gupta and George (2016) reported lower path weightings for each of the 2nd order BDAC constructs and this could be attributed to the difference in research model, as they hypothesised a formative model for BDAC whereas the current study adopted a reflective higher model similar to that of Akter et al. (2016) and Wamba et al. (2017).

Table 16

Comparison of path weightings for BDAC 2nd order constructs from previous studies

Dimensions	**Current Study**		**Akter et al. (2016)**		**Wamba et al. (2017)**		**Gupta & George (2016)**	
	B	**R^2**	**B**	**R^2**	**B**	**R^2**	**B**	**R^2**
BDAMC	0.96	0.92	0.94	0.88	0.93	0.86	0.31	0.91
BDAIF	0.94	0.89	0.91	0.83	0.96	0.92	0.42	0.84
BDAPEC	0.96	0.93	0.95	0.90	0.96	0.93	0.37	0.88

These insights posit that greater potential in the overall BDAC can be achieved through BDAPEC. This occurs when an organisation has highly capable big data resources with strong competencies in problem solving, technical knowledge, business knowledge and management knowledge (Akter et al., 2016; Gupta & George, 2016) and are able to transfer and enhance other resources to support organisational strategies and big data goals. This perspective directly links with the broadly reported view on the influential role of resources under the RBV view in an organisation (Barney, 1991; Helfat et al., 1997; Wade & Hulland, 2004), as well as technical capabilities within the big data ecosystem (Akter et al., 2017; Khan et al., 2017; Mazzei & Noble, 2017; Yaqoob et al., 2016). This is not a surprising view given the technical nature of the big data ecosystem, and big data literature placing emphasise on big data skillsets (Alharthi et al., 2017; Chen et al., 2012) as a core characteristic in enabling BDAC (Kim et al., 2012; Gupta & George, 2016; Yaqoob et al., 2016). However, as discussed under the entanglement view this study prioritised the importance of all BDAC constructs to enable synergy, co-specialisation and complementarity for organisations. With an explained variance of 20%, BDAC is a significant predictor of FPer. Organisations that seek to achieve improved performance in a discontinuous environment can employ BDAC as a higher order capability to enable improved levels of firm performance.

6.3 Discussion of Research Question 2

The second research question focussed on the relationship between DDC as a higher order dynamic management of exploitive and explorative capabilities on FPer. The research question was articulated as:

Is there a positive relationship between Distinct Dynamic Capabilities (DDC) and Firm Performance (FPer)?

The effect of organisational dynamic capabilities and their influence on creating competitive advantages for organisations has been studied extensively (Birkinshaw et al., 2016; Kay, 1993; Raisch et al., 2009; Teece & Pisano, 1994). Under discontinuous change and constantly evolving organisational ecologies some researchers have contrarian views of the influence of dynamic capabilities (Birkinshaw et al., 2016; Helfat & Peteraf, 2009; Zollo & Winter, 2002). Although Birkinshaw et al. (2016) positioned dynamic capabilities as an organisational asset that is relevant in both stable and dynamic environments, Mazzei and Noble (2017) and Porter & Hepplemann (2014) argued the prominence of rapid advancement and hyper competition require inflection point strategies by organisations. Drawing on perspectives from Collis (1994) and Schilke (2014), through the lens of dynamic capabilities there exists higher order states of capabilities which influence, adapt, re-learn and renew themselves as well as lower order capabilities. Kay (1993) further states that these capabilities are distinct capabilities when they create sustainability and appropriability. The current discontinuous change parody was unbeknown when Levinthal & March (1993) posited that organisations need to “engage in enough exploitation to ensure the organisations current viability and engage in enough exploration to ensure its future viability" (p. 105). This gave rise to the perspectives of exploitative and explorative capabilities been linked to organisational survival and competitive performance as distinct organisational capabilities (Birkinshaw et al., 2016; Koryak et al., 2018; Teece et al., 2016). Given that exploitative and explorative capabilities stem from opposite learning capabilities (Korak et al., 2018) they require different organisational structures, processes and strategies as they would create tensions (Papachroni et al., 2016). Furthermore, by focussing on just one capability creates long term risks of not achieving sustainable competitive performance (Andriopoulos & Lewis, 2009; Birkinshaw et al., 2016; O'Reilly & Tushman, 2013). Thus, organisations face a trade-off between growth and survival by opting to focus on one mechanism, either through exploitation or exploration. It is on this premise that this study recognised explorative and exploitative capabilities as a paradoxical relationship (Lewis & Smith, 2014) which requires dynamic management to create synergies, readjustment and strategic linkages for organisational value creation (Koryak et al., 2018; Smith, 2015).

The measurement of DDC as a higher order distinct capability with exploitative and explorative as sub-dimensions in this research was verified by testing five regression models as per guidelines recommended by Edwards (1994). This method was adopted as Birkinshaw et al. (2016) highlighted three modes of managing the paradoxical relationship between exploitative and explorative capabilities.

Section 5.3.2 reported that the variance explained by measuring DDC as combinative mean of exploitative and explorative capabilities on their impact on FPer was the highest (R^2 - 0.51). Whilst treating the capabilities as separate influencers on FPer reported lower variance explained values for explorative and exploitative capabilities (R^2 - 0.45 for explorative and R^2 – 0.36 for exploitative). This finding is thus indicative of the dynamic interplay between explorative and exploitative capabilities due to structural tensions as argued by Smith (2015) who suggested the dynamic management of contradictory yet related artefacts under the differentiation and integration organisational design. This perspective also highlights the behavioural integration mode as proposed by Birkinshaw et al., (2016) which emphasises the integration of both capabilities in organisations.

Koryak et al. (2018) postulated the long-term synergistic effects that the dynamic management of exploitative and explorative capabilities have on organisations. As previously argued distinct capabilities enhance a firm's performance under discontinuous change due to their inherent characteristics of creating sustainability, appropriability, synergy, transformation and enabling other resources and capabilities (Birkinshaw et al., 2016; Janssen et al., 2012; Koryak et al., 2018; Lin & Wu, 2014; Mikalef & Pateli, 2017; Teece et al., 2016; Wassmer et al., 2017).

It is also imperative to note that these capabilities could exist in organisations in the absence of big data and the relationship must be considered for the relative impact to describe the environment in which big data is positioned. This is a critical as the dimensions of DDC has not been tested in the big data environment. Previous studies focussed on the interactions of process orientated dynamic capabilities and business strategy alignment through analytics enabled capabilities (Akter et al., 2016; Wamba et al., 2017).

The PLS-SEM model reported a positive large significant path coefficient of 0.70 between DDC and FPer (refer to Figure 15). Additionally, DDC explained 48.7% of the variability in FPer. This infers that DDC increases FPer which is in support of the views by various academics (Birkinshaw et al., 2016; Janssen et al., 2012; Koryak et al., 2018; Lin & Wu, 2014; Mikalef & Pateli, 2017; Teece et al., 2016; Wassmer et al., 2017). The paradox view of dynamically managing exploitative and explorative capabilities thus holds merit for organisations operating in environments of discontinuous change.

For DDC to create value for organisations it is imperative that the mechanisms of learning, integration and reconfiguration are effectively deployed. Organisations need to ensure strategies encapsulate both the external and competitive ecosystem as well as the internal environment for the enhanced integration of resources and capabilities (Levinthal & March, 1993; Lin & Wu, 2014; Wassmer et al., 2017).

DDC, under the learning and knowledge perspective, allows organisations to explore and assimilate new knowledge and transform to environmental changes whilst at the same time leveraging current resources and capabilities (O'Reilly & Tushman, 2013; Raisch et al., 2009). Additionally, the strong path coefficient linking DDC and FPer is indicative of the reinforced synergistic interaction that DDC creates for organisations.

This perspective extends the view on the paradoxical management of contradictory capabilities by providing empirical evidence of the synergistic interplays of two capabilities that traditionally were viewed in isolation. This involves an iterative mechanism in the dynamic management of DDC which creates distinct artefacts under the DCT and RBV view which enables sustainability and appropriability for organisations which enables firm performance (Koryak et al., 2018; Lewis & Smith, 2014; Smith, 2015).

The presence of these capabilities in organisations thus creates enhanced opportunities for big data which requires peripheral capabilities to be in place for organisations to continue to evolve and embed knowledge and learning artefacts.

6.4 Discussion of Research Question 3

A critical objective of this study was to understand the value creation mechanism of big data for organisations. Research question 3 sought to confirm a relationship between BDAC and FPer and was articulated as:

Is there a positive relationship between Big Data Analytics Capability (BDAC) and Distinct Dynamic Capabilities (DDC)?

Research has well documented the links between an organisation's ecosystem and the embedded organisational capabilities (Akter et al., 2016; Alharthi et al., 2017; Birkinshaw et al., 2016; Chen et al., 2014; Lin & Wu, 2014; O'Reilly & Tushman, 2013; Wamba et al., 2017). Although there is a large amount of research surrounding big data (Kim et al., 2012; Kiron et al., 2014) and exploitative and explorative capabilities (Levinthal & March, 1993; Birkinshaw et al., 2016; Koryak et al., 2018), a premise that is not well understood is the assimilation between BDAC and DDC. The promise of big data is the potential to "inform group and organisational – level phenomenon" (Mcabee et al., 2017, p. 278). These were identified as strategic inflection points through competitive artefacts, enhanced organisational capabilities, enhanced decision-making processes and competitive performance (Chen et al., 2012; Mcafee & Brynjolfsson, 2012; Mikalef & Pateli, 2017; Ozkose et al., 2015; Wang et al., 2016).

The value through big data is the inherent insights that can initiate a range of value (Gunther et al., 2017). However, this decoding may not be effectuated through an organisations existing models for business and strategy, thus requiring a shift or a transformation. This can be attributed to big data being constrained by dominant organisational structures and boundaries (Alharthi et al., 2017; Gunther et al., 2017; Khan et al., 2017; Yaqoob et al., 2016). A call of action in this research is the inclusion of a new perspective stemming from new organisational roles and resource's and embedded absorptive capacities to leverage and arrive at new organisational and strategic insights.

Under the paradoxical relationship between exploitative and explorative capabilities, there exists constant learning mechanisms which constantly evolve, thus providing a mechanism to challenge organisational constraints through dynamism, which is required under discontinuous change. IT capabilities through data analytics have been argued to enhance an organisations sensing, seizing and reconfiguring capabilities by enabling more rapid and informed decision making (Chen et al., 2014; Ghasemaghaei et al., 2017; Mcafee & Brynjolfsson, 2012). Building on the DCT view of an organisation, and in concurrence with the sociomaterialism and paradoxical views of BDAC and DDC, the researcher argues that BDAC, as a higher order capability constituted of tangible, intangible and resource elements, can potentially positively promote and support exploitative and explorative capabilities simultaneously under the higher order DDC.

The PLS-SEM model reported a positive significant large path coefficient of 0.577 between BDAC and DDC (refer to Figure 16). Additionally, BDAC explained 32.8% of the variability in DDC. This infers that BDAC positively promotes and enhances DDC as per the discussed linkages. More importantly, the path linkages from BDAC to DDC was more prominent than that of the path linkage from BDAC to FPer (0.454), which suggests that BDAC as a functional and higher order capability has a more direct impact on enabling and enhancing an organisations environment than it does as an output of the organisational activities and processes measured as FPer.

This research finding extends theorised positions on DCT and big data by empirically reporting that BDAC enables the dynamic management of exploitative and explorative capabilities under DDC. Studies on the impact of IT capabilities and an organisations ability to sense external triggers to rapidly reconfigure internal processes has shown mixed results (Lin & Wu, 2014). This is attributed to the poor understanding of the mechanisms through which IT investments and the use of data analytics can create positive outcomes for organisations (Ghasemaghaei et al., 2017; Mikalef & Pateli, 2017).

As this study proposed a higher order model for BDAC and a dynamically managed distinct construct for exploitative and explorative capabilities, under the entanglement of capabilities view, this provided a more in depth understanding of the dynamics and path linkages of the relationships. The relevancy and importance for organisations to adopt strategies to rapidly and effectively assimilate knowledge, capabilities and resources in dynamic ecosystem's has prevailed (Akoka et al., 2017; Lee, 2017; Mcabee et al., 2017). Big data has encompassed an evolving paradigm bringing with it, vast amounts of data and technological changes.

BDAC, as a higher order dynamic capability established through the concept of sociomateriality can be leveraged by organisations to simultaneously promote and enhance exploitative and explorative capabilities thus improving data driven informed insights. The significance of this for organisations, is the perspective that an organisations ecosystem which drives its strategic intent is impacted by the inputs, outputs and establishment of BDAC elements.

6.4 Discussion of Research Question 4

The main objective of this research was to investigate the leveraging mechanism of big data to indirectly effect firm performance by providing effective and formative insights to enable an organisations explorative and exploitative strategic intentions under discontinuous change to ensure survival and growth. Research question 3 was therefore articulated as:

Does Dynamic Distinct Capabilities (DDC) mediate the relationship between Big Data Analytics (BDAC) and Firm Performance (FPer)?

Previous studies in the IS domain have identified positive links between IT enabled dynamic capabilities and an organisations competitive performance (Chen et al., 2014; Mikalef & Pateli, 2017). Chen et al. (2014) assessed the role of an organisations business process in achieving firm performance through IT capabilities and reported both a direct and indirect link. Mikalef and Pateli (2017) reported that IT enabled dynamic capabilities enhanced an organisations internal agility which lead to competitive performance. Similarly, Wamba et al. (2017) reported the impact of leveraging BDAC in dynamic environments to improve and enhance organisational operational processes to create improved firm performance. Whilst these studies have provided a perspective of the indirect effects of dynamic organisational capabilities in the IS domain, they have done so by focusing on a structural separation perspective which postulates the focus of one critical organisational capability (Birkinshaw et al., 2016). Both studies reported the exploitative capability under different identifications as organisational processes that leverage big data to enhance firm performance. However, it has been positioned that an abject commitment to one strategic mechanism of either exploitative or explorative capabilities will lead to organisational absurdities.

Given that the reality of the big data environment is rapid and complex (Lee, 2017), understanding the modes of value creation is critical for organisations. This is attributed to various studies reporting inconsistent results through the effects of IT capabilities which points to a poor understanding of the underlying mechanisms of the capability. A fundamental presumption of both big data and the current organisational ecosystem are their evolving and dynamic nature, organisations that can assimilate and react to these rapid changes will clearly have competitive advantages (Davenport, 2012; Lee, 2017; Mcabee et al., 2017). It is on this premise that understanding the role of big data to effectuate both short-term and long-term firm performance as recommended by Levinthal & March (1993) are critical factors for organisations today.

This research reported that the predictive constructs of BDAC and DDC both significantly impacted FPer. It was further reported that BDAC enables and supports DDC as this relationship reported a positive large path coefficient. The PLS-SEM structural model reported a significant mediation effect of DDC on the relationship between BDAC and FPer reporting a significant indirect positive effect of 0.39 (refer to Table 11 and Figure 17). Using the method proposed by Preacher and Hayes (2008), it was further established that DDC has a full indirect mediating effect on the relationship between BDAC and FPer with a significant total effect of 0.46 and a VAF of 85%. The result reveals that 85% of the effect of BDAC on FPer is explained through DDC. The structural model further reported a combined explained variability of 48.6% on FPer. The findings further reveal that the impact of BDAC on FPer is an indirect one which is mediated through DDC. In other words, BDAC improves firm performance by enhancing and supporting the organisations dynamic management of exploitative and explorative capabilities, which in turn enables competitive performance. The entanglement view of capabilities also provided a level of complexity in hypothesising the research model through the multiple interactions of the higher order reflective constructs. PLS-SEM has been recommended as a statistical tool for complex models and as such the overall structural model for the study was validated with and an SRMR value of 0.045 and the research models predictive power estimated at 0.99 through post-hoc tests, thus validating the hypothesised model.

This finding further extends research by adopting the sociomaterialism and paradoxical view in the entanglement of capabilities, as it demonstrates the underlying mechanisms of the organisational ecosystem that serves as an important tenet for big data value creation. Wamba et al. (2017) reported a partial mediation effect of process-oriented dynamic capabilities on the BDAC and FPer relationship, where BDAC had a larger impact on FPer than it did on the process-oriented dynamic capabilities. Whereas this study reported a larger impact of BDAC on DDC than FPer and a full indirect effect on BDAC through DDC to create firm performance. The findings from Wamba et al. (2017) differ as process-oriented capabilities are but one strategic mechanism and processes for organisations. Additionally, Wamba et al. (2017) adopted research questions for process-oriented dynamic capabilities from Kim et al. (2011) which focused on comparing an organisations “competence to change existing business processes better than its competitors” (p. 496). This perspective is arguably an outcome of big data as “organisational models can be developed to create and appropriate value from big data” (Gunther et al., 2017, p. 198). Furthermore, the process-oriented approach falls part of the tier 1 big data value creation phenomenon in Table 1 depicted by Mazzei & Noble

(2017), which Kim et al. (2011) posited do not require complex systems to provide insights. This perspective provides insight into the relationship reported by Wamba et al. (2017) as the relative supporting nature of BDAC on process-oriented capabilities would be lower than the overall impact on FPer. In comparison, the current research adopted a view on the strategic internal structure, orientation and organisational processes that were viewed as antecedents to firm performance (Birkinshaw et al., 2016; Koryak et al., 2018). Under the paradoxical and dynamic management view of exploitative and explorative capabilities, this research embedded DDC as a tier 3 phenomenon depicted in Table 1 by Mazzei & Noble (2017). It is argued that this paradoxical relationship between exploitative and explorative capabilities is a complex arrangement with interwoven tensions (Birkinshaw et al., 2016; Koryak et al., 2018; Lewis & Smith, 2014), which can be managed by dynamic and complex strategies (Smith, 2015). This study therefore demonstrated the full understanding of the importance and effectiveness assimilated by DDC through BDAC under the sociomaterialism and paradoxical views. BDAC indirectly creates value for organisations by providing data driven insights to effectively enhance, support and inform the strategic processes of organisations through the process of simultaneously exploiting and exploring activities to create competitive performance.

6.5 Discussion of Post-Hoc analyses

Results from the post-hoc analysis also revealed insights for the entanglement of capabilities view under the big data environment. A review of Figure 18 suggests the dynamic interplay between exploitative and explorative capabilities in organisations. Respondents tended to view their organisations equally exploitative and explorative, thus linking with both the behavioural integration mode proposed by Birkinshaw et al. (2016) and the dynamic management view by Smith (2015). This finding suggests the strategic intentions of organisations operating in a discontinuous environment where both these capabilities have equal importance for the growth and survival for organisations today.

The fsQCA analysis provided an understanding into the patterns of configurations that enhance the value creation of big data under dynamic conditions. Alharthi et al. (2017), Gunther et al. (2017), Mazzei and Noble (2017) and Wang et al. (2016) raised the challenges of managing the technical aspect of big data, as this required a large capable resource base to maintain the complex infrastructure. As illustrated in Table 15, the '*number of employees*' in an organisation with a big data strategy was extracted in two of the four solution models together with BDAC, exploitative and explorative capabilities as predictors of firm performance. Thus, emphasising the importance of a large capable resource base for the deployment of big data strategies, these resources will eventually under the RBV view take the form of VRIN resources (Lin & Wu, 2014). Two of the four extracted solution configurations reported an organisations tenure in the big data environment together with BDAC, exploitative and explorative capabilities as predictors of firm performance (refer to Table 15). Elgendy and Elragal (2016) reported that an increased maturity of the big data environment requires improved capabilities to enhance the big data activities. This perspective also aligns with the constant learning mechanisms under the RBV view and signifies the importance of the evolving nature of capabilities to enhance competitive performance for organisations. Findings from the PLS-SEM for the hypothesised path linkages were also in congruence with the fsQCA solution model as all four models indicated BDAC, exploitative and explorative capabilities as core predictors of firm performance. The outcomes of the fSQCA enhance the results reported by the PLS-SEM structural model and provide a deeper insight into the structures and orientations required by organisations to effectuate value from big data.

6.6 Conclusion

The main objective of this research was to understand the mechanisms under which value can be realised and enabled through big data. The research further postulated that big data enhances firm performance indirectly through an organisations strategic activity to ensure survival and growth. The results presented in Chapter 5 and the discussion above verified and validated the researcher objectives herein. The hypotheses were statistically tested through a structural PLS-SEM model, considering the theorised complexity under the entanglement view of capabilities, and established all four hypotheses as statistically significant. The research results provide for a rich set of implications and insights for academia and management which is discussed in the postliminary chapter.

Chapter 7: Conclusion

7.1 Introduction

The research study sought to gain a deeper understanding into the organisational mechanisms and structures under the big data ecosystem that effectuate value. The main premise in this research was the discontinuous paradigm that organisation currently face. Whilst recent academia posits big data as an organisational tool to enable performance in complex and evolving environments (Davenport, 2012; Lee, 2017; Mcabee et al., 2017), both seminal and emerging research identify with organisational capabilities such as exploitative and explorative capabilities to ensure an organisations survival and growth (Birkinshaw et al., 2016; Kay, 1993; Levinthal & March, 1993; O'Reilly & Tushman, 2016). This research merged both academic perspectives by adopting the sociomaterialism and paradox meta-theory concepts to create an entanglement of capabilities view which was posited to influence an organisations competitive performance. This informed the development of hypothesised model illustrated in Figure 1.

As such, this Chapter summarises the principle findings presented in Chapter 5 and Chapter 6 through key contributions for academia and management. Furthermore, a discussion on the future research recommendations and limitations for this study is presented in this chapter.

7.2 Theoretical contributions

This study makes contributions to academic literature in the fields of Information Systems and Strategic Management as it contributes to both big data and dynamic capability research. The research study built on emerging literature on the potential value of big data for organisations, with specific influence on enhancing firm performance (Akter et al., 2016; Gupta & George, 2016; Wamba et al., 2017). One critical aspect of this research was to understand the organisational capabilities, processes and orientations that are required to effectively deploy and enable big data strategies to effectuate the value. Furthermore, the research sought to understand the organisational capabilities in the big data environment that can effectively leverage of big data to create superior competitive performance for organisations in dynamic environments.

Whilst there have been rich contributions to big data research, built on the foundations of IT capabilities (Chen et al., 2014; Kim et al., 2011; Mikalef & Pateli, 2017), there has been limited consensus on the nature of the BDAC construct. Whilst some researchers view BDAC as a purely technical capability (Lee, 2017), others view BDAC in terms of the technology, business and human interactions (Akter et al., 2016; Gupta & George, 2016; Wamba et al., 2017). This research makes an important contribution by building on DCT and RBV views to extend the conceptual and empirical findings of Kiron et al. (2014) who posit that effective big data strategies encompass talent, infrastructure and management processes. In doing so, a hierarchical reflective model for BDAC was hypothesised based on the theory of sociomateriality and was substantiated to have an influence on firm performance through the DCT lens. The research findings herein, agreed with this hypothesis and with Akter et al. (2016) and Wamba et al. (2017) who reported that effective big data strategies encapsulate capabilities in talent, management strategic processes and big data technology assets. Furthermore, the hierarchical BDAC model was able to positively impact the variability in firm performance in this research, thus agreeing with DCT views.

By applying an entanglement view, this research allowed for the integration of multiple theories which have been previously viewed in isolation to model the synergistic and co-specialisation effects of capabilities on firm performance. To better understand the mechanisms under which organisations can navigate through discontinuous change, the notion of simultaneous exploitation and exploration was adopted using the seminal works of Levinthal and March (1993). This study further argued that the exploitative and explorative capabilities have a paradoxical interaction (Koryak et al., 2018; Lewis & Smith, 2014), and need to be addressed using dynamic management and behavioural integration strategies to manage the structural tensions (Birkinshaw et al., 2016; Smith, 2015). This was based on the perspective that a commitment to only one strategy of exploitation or exploration will lead to organisational absurdities in dynamic environments (O'Reilly & Tushman, 2013). This study added further theoretical contribution by merging the sociomaterialism and paradoxical concepts to create an entangled phenomenon on capabilities to understand the strategic alignment of capabilities in data driven organisations. By analysing the parameters of exploitative and explorative capabilities through the dynamic management of DDC, and to the best of the researcher's knowledge, this research is the first one to consider the synergistic effects of the entanglement of capabilities on the BDAC – FPer relationship. Since the mechanisms of value creation theorised by the big data paradigm is in its relative infancy (Ozkose et al., 2015; Wamba et al., 2015), this research argued that big data value is indirectly assimilated through DDC to improve firm performance. The findings of this research supported this position and extended the theoretical contributions by providing a new frame for the impact of the hierarchical model for BDAC in its interactions with firm performance. Under the entanglement view of capabilities, the research model provided empirical evidence of its power under structural relevancy and by explaining the theorised interactions between higher order constructs.

Finally, this research made fundamental contributions of a methodological nature on reflective constructs. By adopting several empirical tests and theoretical perspectives, the research applied a systematic process to develop a complex model with theorised path linkages in PLS-SEM and fsQCA which has gained attention in Information System research.

7.3 Practical implications for management

Organisations today face numerous challenges from the evolving nature of their organisational ecologies. The findings in this research resonate with seminal and emerging literature in terms of organisational growth and survival (Birkinshaw et al., 2016; Levinthal & March, 1993). With the escalating enquiry into organisational structures, orientations and capabilities that can create sustained performance for organisations, informed data driven decision making is becoming an important organisational artefact (Akter et al., 2017; Koryak et al., 2018). This research accentuated the role of DDC in leveraging BDAC to effectuate sustained firm performance. These findings were congruent with previous studies reporting the importance of IT enabled dynamic capabilities supporting behaviourally separated strategies to ensure an organisations survival (Chen et al., 2014; Kim et al., 2011; Mikalef & Pateli, 2017) as well as process-oriented capabilities leveraging of BDAC to enhance firm performance (Wamba et al., 2017). This research also argued that BDAC may only present short-term competitive advantages in the absence of DDC, due to the dynamic nature of the big data environment, business environment and the importance of strategic learning mechanisms.

For BDAC to effectuate value for organisations, this research proposed the adoption of a sociomaterialism view. Deploying a big data strategy within organisation is a complex task (Mazzei & Noble, 2017), this study proposes a focus on the sub-dimensions and mechanisms of BDAC for organisations. The sub-dimensions of BDAC need to be effectively deployed and embedded (Akter et al., 2016; Kiron et al., 2014). The antecedents of BDAMC, BDAIF and BDAPEC exhibit a complementary and co-specialising relationship and are therefore equally important in providing a unified mechanism for organisations to leverage. Organisations need to also understand that effective big data deployments require a multiple and diversified resource base. Organisational managers and BDA managers should focus BDAMC initiatives on effective big data planning and big data analytics decision making. Similarly, BDAIF initiatives should focus on improving big data accessibility and modularity. Finally, BDAPEC initiatives should ensure that big data resources have big data technical knowledge and are effective in knowledge transfer to improve and re-learn. Although this sheds light on the associated complexity of deploying effective big data projects, organisations should view big data as an extension of their IT capabilities which they are more familiar with. The big data interactions with other business processes serve as a conduit for informed decision making and should not be underestimated by organisations.

7.4 Recommendations for future research

The complexity through which this research hypothesised the theorised linkages through the entanglement of capability view cannot be underestimated. Given the relative infancy of big data literature, there is significant potential for future research on both the direct and indirect effects of value created by embedding BDAC in organisations. Possible recommendations for future research are detailed below.

The research constructs adopted in this study are not exhaustive. The findings in this research extracted six first order constructs for BDAC whereas Akter et al. (2016) and Wamba et al. (2017) reported 11, indicating that refinement is required. As BDAPEC was reported as having the highest path coefficient with BDAC in this study, further research can disentangle the BDAC elements to discover the most suitable and effective arrangement for each construct to enable BDAC. This is further elaborated by the dynamic nature of both big data and the business environment in which they co-exist.

External factors such as regulation and legal aspects may also play a role in the big data environment. This has become a prominent and relevant feature of the sharing economy and could either enhance or reduce the potential of big data effectuating competitive advantages.

This research attracted 92.3% of its respondents from South Africa, whilst that of Akter et al. (2016) and Wamba et al. (2017) reported majority from the USA and China respectively. Big data deployments and maturity levels may exist at different levels and obtaining a diverse sample could provide enhanced findings for both practical and academic perspectives.

This study adopted a cross-sectional research design due to the time constraints. The researcher recommends a longitudinal study be conducted to understand the rate of big data value creation for organisations and if this interaction inherently evolves through the entanglement of capabilities view.

Organisational culture and management commitment are key artefacts in the successful implementation of business projects and changes. This was not represented in this study and would provide a moderating effect on the BDAC and FPer relationship.

As big data generated insights are different for each industry. A revision of the measured variables through scale validation procedures could allow BDAC to be effectively measured for different industries. This is critical as adopting measured variables designed for a specific unit of analysis could skew results and inferences if they are not found to be statistically and theoretically relevant for anther industry.

Given the paradoxical relationship between exploitative and explorative capabilities, it would be important for both business and academia to understand the key antecedents for both capabilities that give rise to the tensions between the capabilities and those that complement and co-specialise. Thus, providing insight into the differentiation and integration mechanisms that give rise to the dynamic balance between the two capabilities.

Following the method proposed by Edwards (1994), this study reported DDC as the mean computation between exploitative and explorative capabilities. The multiplicative computation for exploitative and explorative capabilities could provide a better understanding into the distinctness and non-substitutability characteristic which was argued in this research.

This study adopted a deductive approach which based the research strategy on testing theoretical positions (Saunders & Lewis, 2012; Trochim & Donnely, 2006). Mcabee et al. (2017) proposed that big data should follow an inductive approach due to gaining a better understanding of the concept since there has been no consensus on an effective definition for big data (Akoka et al., 2017; Gupta & George, 2016).

On a methodological note, this study proposed that BDAC and DDC are higher order reflective constructs. The study further reported findings from Gupta and George (2016) who reported the use of a formative construct for BDAC. Although the use of formative constructs is gaining attention in Information System research, it is not properly understood (Chin, 2010). A deeper analysis into the anatomy of BDAC could reveal mixture of reflective and formative, fully reflective or a fully formative nature and would provide effective insights into the mechanism of BDAC as a higher order dynamic capability.

7.5 Research limitations

As with any academic research, this study is not without any limitations. Various methodological and theoretical limitations were observed in this study. Firstly, the scope of this research was limited to interactions between BDAC, DDC and FPer. This study reported a combined explained variance of 50% on FPer explained by DDC and BDAC. The implications for both academia and business would appreciate the addition of other variables which theoretically interact on this model to improve the explained variance. Secondly, as discussed in Section 7.4 the BDAC construct has been recently developed and this study reported the exclusion of one measured variable (BDAMod 4) due to reliability issues. Thus, inferring that the dimensions of BDAC are not properly refined in a theoretical sense even under the application of BDAC as a reflective construct. Thirdly, various methodological limitations were discussed in Section 4.10 which include induced sampling biases due to the non-probability sampling technique and survey strategy adopted. Furthermore, the research adopted a cross-sectional view which only provided a snapshot of the data at a single point in time. Thus, the entanglement of capability view in the big data environment over time could be not understood. The researcher posits that the mediating effect of DDC on the BDAC-FPer relationship will maintain its strength over time due to the learning capability effects.

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Appendix A

Table 17

Research questionnaire

The effect of big data analytics and dynamic distinct capability on firm performance		
Section 1: Context of Organisation and Respondent		
1	Are you aware of or associated with Big Data Analytics within the organisation being described in this questionnaire?	• Yes • No
2	What is your gender?	• Male • Female
3	What is your age?	• <20 years • 20-30 years • 31-40 years • 41-50 years • 51-60 years • >60 years
4	Which of the following best describes the principal industry of your organisation?	Standard SurveyMonkey™ drop down menu of industries
5	How long has your organisation actively pursued or applied big data analytics to its business?	• 0-2 years • 2-4 years • 4-6 years • 6-8 years • 8+ years
6	What is your main association with the data analytics capability?	• User of analytics within business • Data analyst (Direct processor of data) • IT Systems or Infrastructure (Data technology environment) • Big Data Management (Driving application of resources)

7	What is the approximate total number of employees within your organisation?	• 1-99 • 100-499 • 500-999 • 1000 or more
8	Which of the following best describes your current job level?	• Owner/ Executive/ C-Level • Senior Management • Middle Management • Intermediate • Entry Level
9	In what country do you work?	Standard SurveyMonkey™ drop down menu of countries
Section 2: Big Data Analytics Management Capabilities		
Likert Scale (1-7) - Strongly disagree - Strongly Agree		
BDA Planning		
10	We continuously examine the innovative opportunities for the strategic use of big data analytics	Likert Scale (1-7)
11	We enforce adequate plans for the introduction and utilisation of big data analytics	Likert Scale (1-7)
12	We perform big data analytics planning processes in systematic and formalized ways	Likert Scale (1-7)
13	We frequently adjust big data analytics plans to better adapt to changing conditions	Likert Scale (1-7)
BDA Decision making		
14	When we make business analytics investment decisions, we estimate the time managers will need to spend overseeing the change	Likert Scale (1-7)
15	When we make big data analytics investment decisions, we project about how much these options will help end-users make quicker decisions	Likert Scale (1-7)
16	When we make investment decisions, we think about and estimate the cost of training that end-users will need.	Likert Scale (1-7)
17	When we make business analytics investment decisions, we think about and estimate the effect hey will have on the productivity of the employee's work. whether they will consolidate or eliminate jobs.	Likert Scale (1-7)

BDA Coordination		
18	In our organisation, business analysts and line people meet regularly to discuss important issues.	Likert Scale (1-7)
19	In our organisation, business analysts and line people from various departments regularly attend cross-functional meetings.	Likert Scale (1-7)
20	In our organisation, business analysts and line people co-ordinate their efforts harmoniously.	Likert Scale (1-7)
21	In our organisation, information is widely shared between business analysts and line people so that those who make decisions or perform jobs have access to all avail- able know-how.	Likert Scale (1-7)
BDA Control		
22	In our organisation, the responsibility for big data analytics development is clear.	Likert Scale (1-7)
23	We are confident that big data analytics project proposals are properly appraised.	Likert Scale (1-7)
24	We constantly monitor the performance of the big data analytics function.	Likert Scale (1-7)
25	Our analytics department is clear about its performance criteria.	Likert Scale (1-7)
Section 3: Big data analytics Infrastructure Flexibility		
BDA Connectivity		
26	Compared to rivals within our industry, our organisation has the foremost available analytics systems.	Likert Scale (1-7)
27	All other (e.g., remote, branch, and mobile) offices are connected to the central office for analytics.	Likert Scale (1-7)
28	Our organization utilises open systems network mechanisms to boost analytics connectivity.	Likert Scale (1-7)
29	There are no identifiable communications bottlenecks within our organization for sharing analytics insights.	Likert Scale (1-7)
BDA Compatibility		
30	Software applications can be easily used across multiple analytics platforms.	Likert Scale (1-7)
31	Our user interfaces provide transparent access to all platforms.	Likert Scale (1-7)

32	Our organisation provides multiple analytics interfaces or entry points for external end users.	Likert Scale (1-7)
33	Information is shared seamlessly across our organization, regardless of the location.	Likert Scale (1-7)
BDA Modularity		
34	Reusable software modules are widely used in new system development.	Likert Scale (1-7)
35	End users utilize object-oriented tools to create their own applications.	Likert Scale (1-7)
36	Analytics personnel utilize object-oriented technologies to minimize the development time for new applications.	Likert Scale (1-7)
37	The legacy system within our organization restricts the development of new applications.	Likert Scale (1-7)
Section 4: Big data analytics Personnel Expertise Capability		
BDA Technical Knowledge		
38	Our analytics personnel are very capable in terms of programming skills (e.g., structured programming, web-based application, CASE, tools, etc.).	Likert Scale (1-7)
39	Our analytics personnel are very capable in terms of managing project life cycles.	Likert Scale (1-7)
40	Our analytics personnel are very capable in the areas of data and network management and maintenance.	Likert Scale (1-7)
41	Our analytics personnel are very capable in data decision support systems (e.g., expert systems, artificial intelligence, warehousing, mining, marts, etc.).	Likert Scale (1-7)
BDA Technological Management Knowledge		
42	Our analytics personnel show superior understanding of technological trends.	Likert Scale (1-7)
43	Our analytics personnel show superior ability to learn new technologies.	Likert Scale (1-7)
44	Our analytics personnel are very knowledgeable about the critical factors for the success of our organisation	Likert Scale (1-7)
45	Our analytics personnel are very knowledgeable about the role of business analytics as a means, not an end.	Likert Scale (1-7)
Business Knowledge		

46	Our analytics personnel understand our organization's policies and plans at a very high level.	Likert Scale (1-7)
47	Our analytics personnel are very capable in interpreting business problems and developing appropriate solutions.	Likert Scale (1-7)
48	Our analytics personnel are very knowledgeable about business functions.	Likert Scale (1-7)
49	Our analytics personnel are very knowledgeable about the business environment.	Likert Scale (1-7)
Relational Knowledge		
50	Our analytics personnel are very capable in interpreting business problems and developing appropriate technical solutions.	Likert Scale (1-7)
51	Our analytics personnel are very capable in terms of planning and executing work in a collective environment.	Likert Scale (1-7)
52	Our analytics personnel are very capable in terms of teaching others in our business.	Likert Scale (1-7)
Section 5: Exploitative Capabilities		
53	My organisation commits to improve quality and lower cost.	Likert Scale (1-7)
54	My organisation continuously improves the reliability of its products/services.	Likert Scale (1-7)
55	My organisation increases the levels of efficiency in its operations.	Likert Scale (1-7)
56	My organisation constantly surveys existing customer's satisfaction.	Likert Scale (1-7)
57	My organisation fine-tunes what it offers to keep current customers satisfied.	Likert Scale (1-7)
58	My organisation penetrates more deeply into its current customer base.	Likert Scale (1-7)
Section 6: Explorative Capabilities		
59	My organisation looks for novel technological ideas by thinking "outside the box".	Likert Scale (1-7)
60	My organisation bases its success on its ability to explore new technologies.	Likert Scale (1-7)
61	My organisation creates products or services that are innovative to the company.	Likert Scale (1-7)

62	My organisation looks for creative ways to satisfy its customers' needs.	Likert Scale (1-7)
63	My organisation aggressively ventures into new market segments.	Likert Scale (1-7)
64	My organisation actively targets new customer groups.	Likert Scale (1-7)
Section 7: Firm Financial and Market Performance		
65	Using big data analytics improved customer retention during the last 3 years relative to competitors.	Likert Scale (1-7)
66	Using big data analytics improved Sales Growth during the last 3 years relative to competitors.	Likert Scale (1-7)
67	Using big data analytics improved Profitability during the last 3 years relative to competitors.	Likert Scale (1-7)
68	Using big data analytics improved Return on Investment (ROI) during the last 3 years relative to competitors.	Likert Scale (1-7)
69	Using big data analytics improved overall financial performance during the last 3 years relative to competitors.	Likert Scale (1-7)
70	Our success rate of new products or services has been higher than our competitors.	Likert Scale (1-7)
71	Using analytics our market share has exceeded that of our competitors.	Likert Scale (1-7)

Appendix B

Table 18

Summary of revised construct compositions

Survey Question	Original Model	Revised Model
10	BDP1	BDP1
11	BDP2	BDP2
12	BDP3	BDP3
13	BDP4	BDP4
14	BDAI1	BDP5
15	BDAI2	BDP6
16	BDAI3	BDADM1
17	BDAI4	BDADM2
18	BDCoord1	BDADM3
19	BDCoord2	BDADM4
20	BDCoord3	BDADM5
21	BDCoord4	BDADM6
22	BDACon1	BDADM7
23	BDACon2	BDADM8
24	BDACon3	BDADM9
25	BDACon4	BDADM10
26	BDAconnect1	BDAA1
27	BDAconnect2	BDAA2
28	BDAconnect3	BDAA3
29	BDAconnect4	BDAA4
30	BDACompat1	BDAA5
31	BDACompat2	BDAA6
32	BDACompat3	BDAA7
33	BDACompat4	BDAA8
34	BDAMod1	BDAMod1
35	BDAMod2	BDAMod2
36	BDAMod3	BDAMod3
37	BDAMod4	BDAMod4 (removed)
38	BDTK1	BDTK1
39	BDTK2	BDTK2
40	BDTK3	BDTK3
41	BDTK4	BDTK4
42	BDATMK1	BDTK5
43	BDATMK2	BDTK6
44	BDATMK3	BDTK7
45	BDATMK4	BDTK8
46	BK1	BDAKT1
47	BK2	BDAKT2
48	BK3	BDAKT3
49	BK4	BDAKT4
50	RK1	BDAKT5
51	RK2	BDAKT6
52	RK3	BDAKT7

Appendix C

Table 19

Summary of item loadings

	BDAA	BDADM	BDAKT	BDAMod	BDP	BDATK	Explore	Exploit	FPer
BDAA1	**0.74**	0.66	0.63	0.65	0.63	0.69	0.52	0.38	0.46
BDAA2	**0.79**	0.74	0.69	0.74	0.60	0.65	0.48	0.50	0.33
BDAA3	**0.85**	0.76	0.73	0.75	0.76	0.77	0.52	0.37	0.35
BDAA4	**0.73**	0.62	0.57	0.63	0.55	0.61	0.49	0.30	0.32
BDAA5	**0.85**	0.68	0.70	0.77	0.62	0.66	0.49	0.42	0.33
BDAA6	**0.83**	0.65	0.69	0.72	0.65	0.66	0.52	0.42	0.35
BDAA7	**0.82**	0.73	0.70	0.80	0.67	0.74	0.50	0.38	0.36
BDAA8	**0.82**	0.71	0.77	0.73	0.69	0.72	0.59	0.50	0.36
BDADM1	0.61	**0.81**	0.65	0.65	0.70	0.68	0.49	0.42	0.43
BDADM2	0.64	**0.84**	0.70	0.70	0.76	0.69	0.47	0.41	0.41
BDADM3	0.69	**0.85**	0.70	0.68	0.76	0.67	0.49	0.49	0.38
BDADM4	0.76	**0.85**	0.77	0.74	0.77	0.76	0.52	0.53	0.37
BDADM5	0.72	**0.87**	0.73	0.75	0.75	0.74	0.49	0.42	0.48
BDADM6	0.70	**0.81**	0.71	0.67	0.73	0.67	0.50	0.34	0.36
BDADM7	0.77	**0.86**	0.79	0.74	0.75	0.77	0.55	0.47	0.50
BDADM8	0.76	**0.82**	0.71	0.67	0.70	0.70	0.51	0.40	0.53
BDADM9	0.80	**0.87**	0.75	0.77	0.75	0.77	0.54	0.44	0.47
BDADM10	0.79	**0.84**	0.74	0.76	0.74	0.77	0.50	0.47	0.44
BDAKT1	0.76	0.80	**0.90**	0.73	0.79	0.83	0.57	0.54	0.45
BDAKT2	0.74	0.78	**0.90**	0.75	0.73	0.81	0.47	0.47	0.32
BDAKT3	0.73	0.72	**0.87**	0.71	0.67	0.76	0.44	0.40	0.32
BDAKT4	0.76	0.74	**0.86**	0.68	0.71	0.73	0.47	0.40	0.33
BDAKT5	0.80	0.76	**0.90**	0.76	0.78	0.82	0.55	0.43	0.37
BDAKT6	0.71	0.78	**0.86**	0.69	0.76	0.79	0.54	0.48	0.45
BDAKT7	0.75	0.74	**0.87**	0.75	0.71	0.79	0.51	0.44	0.38
BDAMod1	0.73	0.70	0.68	**0.81**	0.60	0.63	0.52	0.42	0.41
BDAMod2	0.77	0.71	0.69	**0.85**	0.67	0.67	0.49	0.47	0.41
BDAMod3	0.75	0.70	0.69	**0.83**	0.69	0.74	0.50	0.40	0.37
BDP1	0.70	0.75	0.71	0.64	**0.86**	0.82	0.44	0.28	0.22
BDP2	0.69	0.74	0.68	0.69	**0.85**	0.77	0.48	0.39	0.31
BDP3	0.69	0.74	0.68	0.69	**0.85**	0.78	0.52	0.40	0.35
BDP4	0.71	0.76	0.74	0.67	**0.88**	0.81	0.49	0.30	0.30
BDP5	0.65	0.76	0.70	0.64	**0.84**	0.73	0.52	0.36	0.35
BDP6	0.72	0.78	0.77	0.71	**0.86**	0.74	0.48	0.39	0.26
BDTK1	0.66	0.65	0.69	0.68	0.73	**0.80**	0.43	0.32	0.25
BDTK2	0.70	0.77	0.74	0.73	0.80	**0.84**	0.47	0.39	0.38
BDTK3	0.73	0.76	0.77	0.73	0.80	**0.88**	0.47	0.41	0.30
BDTK4	0.76	0.70	0.79	0.68	0.75	**0.88**	0.47	0.37	0.31
BDTK5	0.77	0.71	0.78	0.71	0.78	**0.85**	0.50	0.36	0.21
BDTK6	0.78	0.75	0.74	0.69	0.75	**0.85**	0.45	0.34	0.33
BDTK7	0.73	0.75	0.82	0.68	0.79	**0.88**	0.53	0.38	0.37
BDTK8	0.71	0.79	0.81	0.70	0.82	**0.87**	0.56	0.44	0.44

EXplr1	0.47	0.52	0.44	0.54	0.47	0.43	**0.85**	0.73	0.69
EXplr2	0.50	0.45	0.41	0.46	0.41	0.43	**0.80**	0.65	0.64
EXplr3	0.55	0.58	0.58	0.57	0.57	0.57	**0.88**	0.75	0.66
EXplr4	0.52	0.53	0.51	0.49	0.49	0.47	**0.88**	0.77	0.61
EXplr5	0.62	0.45	0.47	0.52	0.46	0.48	**0.81**	0.65	0.56
EXplr6	0.58	0.50	0.49	0.50	0.48	0.48	**0.84**	0.69	0.60
EXplt1	0.32	0.41	0.42	0.36	0.36	0.35	0.58	**0.72**	0.54
EXplt2	0.49	0.46	0.49	0.48	0.40	0.41	0.72	**0.87**	0.55
EXplt3	0.47	0.41	0.46	0.50	0.37	0.41	0.67	**0.82**	0.50
EXplt4	0.44	0.46	0.39	0.44	0.38	0.35	0.77	**0.85**	0.55
EXplt5	0.41	0.42	0.38	0.41	0.27	0.33	0.70	**0.85**	0.52
EXplt6	0.40	0.41	0.43	0.38	0.27	0.35	0.70	**0.85**	0.48
Fper1	0.41	0.50	0.40	0.49	0.35	0.37	0.67	0.58	**0.91**
Fper2	0.45	0.52	0.44	0.48	0.34	0.38	0.70	0.61	**0.96**
Fper3	0.41	0.48	0.41	0.42	0.33	0.36	0.70	0.59	**0.94**
Fper4	0.37	0.44	0.36	0.43	0.29	0.32	0.68	0.60	**0.93**
Fper5	0.42	0.51	0.40	0.45	0.32	0.35	0.69	0.60	**0.94**
Fper6	0.44	0.50	0.42	0.46	0.36	0.39	0.73	0.60	**0.97**
Fper7	0.41	0.45	0.35	0.42	0.28	0.32	0.70	0.57	**0.92**

Appendix D

Table 20

BDP item correlations

		BDP1	BDP2	BDP3	BDP4	BDP5	BDP6
BDP1	Pearson Correlation	1	.818**	.735**	.788**	.699**	.670**
	Sig. (2-tailed)		0.000	0.000	0.000	0.000	0.000
BDP2	Pearson Correlation	.818**	1	.827**	.795**	.648**	.655**
	Sig. (2-tailed)	0.000		0.000	0.000	0.000	0.000
BDP3	Pearson Correlation	.735**	.827**	1	.832**	.698**	.670**
	Sig. (2-tailed)	0.000	0.000		0.000	0.000	0.000
BDP4	Pearson Correlation	.788**	.795**	.832**	1	.740**	.729**
	Sig. (2-tailed)	0.000	0.000	0.000		0.000	0.000
BDP5	Pearson Correlation	.699**	.648**	.698**	.740**	1	.698**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000		0.000
BDP6	Pearson Correlation	.670**	.655**	.670**	.729**	.698**	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	

**. Correlation is significant at the 0.01 level (2-tailed).

Table 21

BDADM item correlations

		BDAD M1	BDAD M2	BDAD M3	BDAD M4	BDAD M5	BDAD M6	BDAD M7	BDAD M8	BDAD M9	BDAD M10
BDAD M1	Pearson Correlation	1	.782**	.742**	.669**	.702**	.596**	.689**	.650**	.686**	.633**
	Sig. (2-tailed)		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
BDAD M2	Pearson Correlation	.782**	1	.756**	.652**	.725**	.677**	.645**	.617**	.743**	.680**
	Sig. (2-tailed)	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
BDAD M3	Pearson Correlation	.742**	.756**	1	.758**	.774**	.632**	.689**	.719**	.688**	.654**
	Sig. (2-tailed)	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000
BDAD M4	Pearson Correlation	.669**	.652**	.758**	1	.785**	.677**	.735**	.672**	.695**	.714**
	Sig. (2-tailed)	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000
BDAD M5	Pearson Correlation	.702**	.725**	.774**	.785**	1	.745**	.737**	.759**	.724**	.711**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000
BDAD M6	Pearson Correlation	.596**	.677**	.632**	.677**	.745**	1	.708**	.647**	.641**	.619**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000
BDAD M7	Pearson Correlation	.689**	.645**	.689**	.735**	.737**	.708**	1	.768**	.840**	.759**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000
BDAD M8	Pearson Correlation	.650**	.617**	.719**	.672**	.759**	.647**	.768**	1	.788**	.705**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000
BDAD M9	Pearson Correlation	.686**	.743**	.688**	.695**	.724**	.641**	.840**	.788**	1	.853**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000
BDAD M10	Pearson Correlation	.633**	.680**	.654**	.714**	.711**	.619**	.759**	.705**	.853**	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	

**. Correlation is significant at the 0.01 level (2-tailed).

Table 22

BDAA item correlations

		BDAA 1	BDAA 2	BDAA 3	BDAA 4	BDAA 5	BDAA 6	BDAA 7	BDAA 8
BDAA 1	Pearson Correlation	1	.586**	.676**	.524**	.608**	.559**	.596**	.577**
	Sig. (2-tailed)		0.000	0.000	0.000	0.000	0.000	0.000	0.000
BDAA 2	Pearson Correlation	.586**	1	.713**	.574**	.623**	.577**	.591**	.651**
	Sig. (2-tailed)	0.000		0.000	0.000	0.000	0.000	0.000	0.000
BDAA 3	Pearson Correlation	.676**	.713**	1	.625**	.741**	.727**	.742**	.621**
	Sig. (2-tailed)	0.000	0.000		0.000	0.000	0.000	0.000	0.000
BDAA 4	Pearson Correlation	.524**	.574**	.625**	1	.601**	.609**	.538**	.640**
	Sig. (2-tailed)	0.000	0.000	0.000		0.000	0.000	0.000	0.000
BDAA 5	Pearson Correlation	.608**	.623**	.741**	.601**	1	.827**	.727**	.707**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000		0.000	0.000	0.000
BDAA 6	Pearson Correlation	.559**	.577**	.727**	.609**	.827**	1	.639**	.788**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000		0.000	0.000
BDAA 7	Pearson Correlation	.596**	.591**	.742**	.538**	.727**	.639**	1	.632**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000		0.000
BDAA 8	Pearson Correlation	.577**	.651**	.621**	.640**	.707**	.788**	.632**	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
**. Correlation is significant at the 0.01 level (2-tailed).									

Table 23

BDAMod item correlations

		BDAMod1	BDAMod2	BDAMod3
BDAMod1	Pearson Correlation	1	.694**	.637**
	Sig. (2-tailed)		0.000	0.000
BDAMod2	Pearson Correlation	.694**	1	.732**
	Sig. (2-tailed)	0.000		0.000
BDAMod3	Pearson Correlation	.637**	.732**	1
	Sig. (2-tailed)	0.000	0.000	
**. Correlation is significant at the 0.01 level (2-tailed).				

Table 24

BDATK item correlations

		BDTK1	BDTK2	BDTK3	BDTK4	BDTK5	BDTK6	BDTK7	BDTK8
BDTK1	Pearson Correlation	1	.734**	.743**	.737**	.752**	.702**	.680**	.613**
	Sig. (2-tailed)		0.000	0.000	0.000	0.000	0.000	0.000	0.000
BDTK2	Pearson Correlation	.734**	1	.801**	.712**	.640**	.771**	.681**	.729**
	Sig. (2-tailed)	0.000		0.000	0.000	0.000	0.000	0.000	0.000
BDTK3	Pearson Correlation	.743**	.801**	1	.833**	.732**	.788**	.724**	.749**
	Sig. (2-tailed)	0.000	0.000		0.000	0.000	0.000	0.000	0.000
BDTK4	Pearson Correlation	.737**	.712**	.833**	1	.748**	.776**	.734**	.661**
	Sig. (2-tailed)	0.000	0.000	0.000		0.000	0.000	0.000	0.000
BDTK5	Pearson Correlation	.752**	.640**	.732**	.748**	1	.730**	.721**	.673**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000		0.000	0.000	0.000
BDTK6	Pearson Correlation	.702**	.771**	.788**	.776**	.730**	1	.742**	.747**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000		0.000	0.000
BDTK7	Pearson Correlation	.680**	.681**	.724**	.734**	.721**	.742**	1	.839**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000		0.000
BDTK8	Pearson Correlation	.613**	.729**	.749**	.661**	.673**	.747**	.839**	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	

**. Correlation is significant at the 0.01 level (2-tailed).

Table 25

BDAKT item correlations

		BDAKT 1	BDAKT 2	BDAKT 3	BDAKT 4	BDAKT 5	BDAKT 6	BDAKT 7
BDAKT1	Pearson Correlation	1	.816**	.748**	.747**	.772**	.802**	.735**
	Sig. (2-tailed)		0.000	0.000	0.000	0.000	0.000	0.000
BDAKT2	Pearson Correlation	.816**	1	.846**	.844**	.780**	.722**	.774**
	Sig. (2-tailed)	0.000		0.000	0.000	0.000	0.000	0.000
BDAKT3	Pearson Correlation	.748**	.846**	1	.869**	.750**	.677**	.788**
	Sig. (2-tailed)	0.000	0.000		0.000	0.000	0.000	0.000
BDAKT4	Pearson Correlation	.747**	.844**	.869**	1	.803**	.719**	.757**
	Sig. (2-tailed)	0.000	0.000	0.000		0.000	0.000	0.000
BDAKT5	Pearson Correlation	.772**	.780**	.750**	.803**	1	.772**	.779**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000		0.000	0.000
BDAKT6	Pearson Correlation	.802**	.722**	.677**	.719**	.772**	1	.762**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000		0.000
BDAKT7	Pearson Correlation	.735**	.774**	.788**	.757**	.779**	.762**	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	
**. Correlation is significant at the 0.01 level (2-tailed).								

Table 26

Exploitative item correlations

Correlations							
		EXplt1	EXplt2	EXplt3	EXplt4	EXplt5	EXplt6
EXplt1	Pearson Correlation	1	.712**	.649**	.498**	.554**	.569**
	Sig. (2-tailed)		0.000	0.000	0.000	0.000	0.000
EXplt2	Pearson Correlation	.712**	1	.832**	.635**	.747**	.755**
	Sig. (2-tailed)	0.000		0.000	0.000	0.000	0.000
EXplt3	Pearson Correlation	.649**	.832**	1	.604**	.713**	.679**
	Sig. (2-tailed)	0.000	0.000		0.000	0.000	0.000
EXplt4	Pearson Correlation	.498**	.635**	.604**	1	.714**	.716**
	Sig. (2-tailed)	0.000	0.000	0.000		0.000	0.000
EXplt5	Pearson Correlation	.554**	.747**	.713**	.714**	1	.829**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000		0.000
EXplt6	Pearson Correlation	.569**	.755**	.679**	.716**	.829**	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	
**. Correlation is significant at the 0.01 level (2-tailed).							

Table 27

Explorative item correlations

Correlations							
		EXplr1	EXplr2	EXplr3	EXplr4	EXplr5	EXplr6
EXplr1	Pearson Correlation	1	.786**	.768**	.691**	.648**	.646**
	Sig. (2-tailed)		0.000	0.000	0.000	0.000	0.000
EXplr2	Pearson Correlation	.786**	1	.733**	.638**	.623**	.599**
	Sig. (2-tailed)	0.000		0.000	0.000	0.000	0.000
EXplr3	Pearson Correlation	.768**	.733**	1	.799**	.693**	.691**
	Sig. (2-tailed)	0.000	0.000		0.000	0.000	0.000
EXplr4	Pearson Correlation	.691**	.638**	.799**	1	.695**	.785**
	Sig. (2-tailed)	0.000	0.000	0.000		0.000	0.000
EXplr5	Pearson Correlation	.648**	.623**	.693**	.695**	1	.867**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000		0.000
EXplr6	Pearson Correlation	.646**	.599**	.691**	.785**	.867**	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	
**. Correlation is significant at the 0.01 level (2-tailed).							

Table 28

FPer item correlations

		Fper1	Fper2	Fper3	Fper4	Fper5	Fper6	Fper7
Fper1	Pearson Correlation	1	.898**	.834**	.867**	.872**	.851**	.824**
	Sig. (2-tailed)		0.000	0.000	0.000	0.000	0.000	0.000
Fper2	Pearson Correlation	.898**	1	.924**	.879**	.905**	.882**	.851**
	Sig. (2-tailed)	0.000		0.000	0.000	0.000	0.000	0.000
Fper3	Pearson Correlation	.834**	.924**	1	.906**	.905**	.890**	.851**
	Sig. (2-tailed)	0.000	0.000		0.000	0.000	0.000	0.000
Fper4	Pearson Correlation	.867**	.879**	.906**	1	.896**	.892**	.848**
	Sig. (2-tailed)	0.000	0.000	0.000		0.000	0.000	0.000
Fper5	Pearson Correlation	.872**	.905**	.905**	.896**	1	.906**	.876**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000		0.000	0.000
Fper6	Pearson Correlation	.851**	.882**	.890**	.892**	.906**	1	.911**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000		0.000
Fper7	Pearson Correlation	.824**	.851**	.851**	.848**	.876**	.911**	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	

**. Correlation is significant at the 0.01 level (2-tailed).

Appendix E

Table 29

Descriptive statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
BDP1	155	1.00	7.00	4.99	1.17	-0.38	0.19	0.15	0.39
BDP2	155	2.00	7.00	4.74	1.20	0.17	0.19	-0.76	0.39
BDP3	155	1.00	7.00	4.50	1.36	-0.16	0.19	-0.38	0.39
BDP4	155	1.00	7.00	4.80	1.26	-0.35	0.19	0.31	0.39
BDP5	155	1.00	7.00	4.72	1.35	-0.27	0.19	-0.33	0.39
BDP6	155	1.00	7.00	4.89	1.20	-0.42	0.19	-0.21	0.39
BDADM1	155	1.00	7.00	4.31	1.35	-0.07	0.19	-0.86	0.39
BDADM2	155	1.00	7.00	4.64	1.32	-0.33	0.19	-0.41	0.39
BDADM3	155	1.00	7.00	4.61	1.32	-0.22	0.19	-0.69	0.39
BDADM4	155	1.00	7.00	4.63	1.27	0.01	0.19	-0.51	0.39
BDADM5	155	1.00	7.00	4.37	1.26	0.13	0.19	-0.67	0.39
BDADM6	155	1.00	7.00	4.70	1.26	-0.08	0.19	-0.43	0.39
BDADM7	155	1.00	7.00	4.34	1.36	-0.01	0.19	-0.67	0.39
BDADM8	155	1.00	7.00	4.23	1.37	-0.02	0.19	-0.64	0.39
BDADM9	155	1.00	7.00	4.40	1.34	-0.21	0.19	-0.35	0.39
BDADM10	155	1.00	7.00	4.42	1.35	-0.14	0.19	-0.14	0.39
BDAA1	155	1.00	7.00	4.19	1.36	0.08	0.19	-0.31	0.39
BDAA2	155	1.00	7.00	4.56	1.30	-0.10	0.19	-0.22	0.39
BDAA3	155	1.00	7.00	4.45	1.21	-0.19	0.19	0.06	0.39
BDAA4	155	1.00	7.00	4.19	1.34	-0.04	0.19	-0.11	0.39
BDAA5	155	1.00	7.00	4.48	1.34	-0.25	0.19	-0.29	0.39
BDAA6	155	1.00	7.00	4.43	1.30	-0.37	0.19	-0.08	0.39
BDAA7	155	1.00	7.00	4.41	1.26	-0.17	0.19	-0.33	0.39
BDAA8	155	1.00	7.00	4.75	1.31	-0.38	0.19	0.01	0.39
BDAMod1	155	1.00	7.00	4.33	1.27	-0.15	0.19	-0.34	0.39
BDAMod2	155	1.00	7.00	4.31	1.36	-0.24	0.19	-0.41	0.39
BDAMod3	155	1.00	7.00	4.30	1.31	-0.30	0.19	-0.05	0.39
BDAMod4	155	1.00	7.00	4.44	1.22	-0.15	0.19	0.34	0.39
BDTK1	155	1.00	7.00	4.83	1.34	-0.58	0.19	-0.04	0.39
BDTK2	155	1.00	7.00	4.64	1.34	-0.46	0.19	-0.03	0.39
BDTK3	155	1.00	7.00	4.78	1.25	-0.36	0.19	0.27	0.39
BDTK4	155	1.00	7.00	4.69	1.21	-0.33	0.19	0.12	0.39
BDTK5	155	1.00	7.00	4.87	1.22	-0.47	0.19	0.26	0.39
BDTK6	155	1.00	7.00	4.82	1.25	-0.35	0.19	-0.02	0.39
BDTK7	155	1.00	7.00	4.69	1.31	-0.28	0.19	-0.05	0.39
BDTK8	155	1.00	7.00	4.64	1.36	-0.21	0.19	-0.37	0.39
BDAKT1	155	1.00	7.00	4.55	1.30	-0.16	0.19	-0.59	0.39
BDAKT2	155	1.00	7.00	4.73	1.29	-0.29	0.19	-0.34	0.39
BDAKT3	155	1.00	7.00	4.62	1.27	-0.18	0.19	-0.31	0.39
BDAKT4	155	1.00	7.00	4.74	1.26	-0.21	0.19	-0.20	0.39

BDAKT5	155	1.00	7.00	4.84	1.23	-0.44	0.19	0.05	0.39
BDAKT6	155	1.00	7.00	4.63	1.25	-0.17	0.19	-0.34	0.39
BDAKT7	155	1.00	7.00	4.57	1.22	0.02	0.19	-0.11	0.39
EXplt1	155	2.00	7.00	5.31	1.28	-0.50	0.19	-0.41	0.39
EXplt2	155	2.00	7.00	5.36	1.17	-0.61	0.19	0.11	0.39
EXplt3	155	2.00	7.00	5.26	1.25	-0.46	0.19	-0.50	0.39
EXplt4	155	2.00	7.00	5.30	1.24	-0.61	0.19	-0.19	0.39
EXplt5	155	2.00	7.00	5.31	1.17	-0.62	0.19	0.02	0.39
EXplt6	155	1.00	7.00	5.21	1.27	-0.67	0.19	-0.02	0.39
EXplr1	155	1.00	7.00	4.89	1.28	-0.46	0.19	-0.20	0.39
EXplr2	155	1.00	7.00	4.87	1.34	-0.48	0.19	-0.29	0.39
EXplr3	155	1.00	7.00	5.09	1.24	-0.53	0.19	0.22	0.39
EXplr4	155	1.00	7.00	5.31	1.20	-0.77	0.19	0.62	0.39
EXplr5	155	1.00	7.00	5.20	1.35	-0.85	0.19	0.45	0.39
EXplr6	155	1.00	7.00	5.32	1.36	-0.86	0.19	0.31	0.39
Fper1	155	1.00	7.00	4.57	1.60	-0.54	0.19	-0.64	0.39
Fper2	155	1.00	7.00	4.60	1.61	-0.55	0.19	-0.49	0.39
Fper3	155	1.00	7.00	4.48	1.64	-0.44	0.19	-0.64	0.39
Fper4	155	1.00	7.00	4.29	1.61	-0.35	0.19	-0.69	0.39
Fper5	155	1.00	7.00	4.43	1.67	-0.41	0.19	-0.66	0.39
Fper6	155	1.00	7.00	4.47	1.59	-0.47	0.19	-0.63	0.39
Fper7	155	1.00	7.00	4.41	1.56	-0.39	0.19	-0.51	0.39
BDP	155	1.39	7.00	4.77	1.11	-0.16	0.19	-0.22	0.39
BDADM	155	1.00	7.00	4.47	1.13	0.03	0.19	-0.36	0.39
BDAA	155	1.00	7.00	4.43	1.08	-0.10	0.19	0.26	0.39
Damon	155	1.00	7.00	4.32	1.17	-0.12	0.19	-0.11	0.39
BDATK	155	1.00	7.00	4.74	1.12	-0.32	0.19	0.56	0.39
BDAKT	155	1.00	7.00	4.67	1.13	-0.19	0.19	0.18	0.39
Exploitative Cap	155	2.50	7.00	5.29	1.05	-0.48	0.19	-0.30	0.39
Explorative Cap	155	1.00	7.00	5.11	1.13	-0.54	0.19	0.31	0.39
FPer	155	1.00	7.00	4.46	1.53	-0.52	0.19	-0.41	0.39
BDAMC	155	1.19	6.92	4.62	1.07	-0.06	0.19	-0.22	0.39
BDAIF	155	1.00	7.00	4.37	1.07	-0.07	0.19	0.11	0.39
BDAPEC	155	1.00	7.00	4.71	1.09	-0.27	0.19	0.55	0.39
BDAC	155	1.06	6.75	4.57	1.02	-0.07	0.19	0.04	0.39
DDC	155	2.42	7.00	5.20	1.03	-0.41	0.19	-0.32	0.39
Valid N (listwise)	155								