Competitive Advantage through Big Data Analytics

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CERTIFICATE OF ORIGINAL AUTHORSHIP

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as part of the collaborative doctoral degree and/or fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

Usarat Thirathon

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LIST OF ABBREVIATIONS

ABDM	Analytics-Based Decision-Making
BDA	Big Data Analytics
BI	Business Intelligence
BI&A	Business Intelligence and Analytics
DSS	Decision Support Systems
ERP	Enterprise Resource Planning
FTE	Full-Time Equivalent
IS	Information Systems
OAC	Organisational Analytic Culture
PLS	Partial Least Squares
PLS-SEM	Partial Least Squares Structural Equation Modelling
RBT	Resource-Based Theory

ABSTRACT

'Big Data' has become a major topic of interest and discussion for both academics and professionals in the IT and business disciplines, and evidence from case studies suggests that companies which have invested in Big Data outperform others. It has to be noted though that 'Bigger' Data as such does not provide any benefits, but rather how organisations make sense of data and gain insights from analysing it. Analytic capabilities and practices are required to gain insights from Big Data, and thereby arguably improving decision-making and gaining competitive advantage. While protagonists of such Big Data Analytics (BDA) imply that those effects exist, so far they have not been confirmed by rigorous empirical research.

The research questions in this thesis are: *can BDA create competitive advantage,* and *what mechanisms drive analytic organisations to achieve competitive advantage?* To explore the mechanisms, it is necessary to find out to what extent managers actually understand the implications of the analytic outputs and have capabilities and willingness to uncover and base their decisions on insights from BDA. In addition, the role of organisational culture in the context of BDA is also investigated.

Data was obtained using a cross-sectional online survey which targeted Chief Information Officers and senior IT managers of medium-to-large Australian for-profit organisations. The survey yielded 163 complete responses which showed no presence of common method and non-response biases, and met the standard criteria for measurement reliability and validity. Partial least squares structural equation modelling (PLS-SEM) and multiple bootstrapping methods were used to test the hypotheses.

The empirical results verify anecdotal claims made in the literature that Big Data and related analytics do actually lead to competitive advantage, partly directly and partly indirectly. The study reveals that such benefits are achieved primarily because BDA creates additional incentives for managers to base their strategic or operational decisions on analytics, and that more analytics-based decision-making actually leads to competitive advantage. Furthermore, the results also suggest that organisational culture, in contrast to BDA tools and methods, is a valuable, rare, inimitable and non-substitutable resource (as it cannot be changed easily or quickly), thereby indirectly driving and sustaining competitive advantage.

CHAPTER 1 - INTRODUCTION

1.1 Research Background

During the past decade, the words ‘Big Data’ and ‘Big Data Analytics’ have become increasingly important for both academics and business professionals in information technology (IT)-related fields and other disciplines. Furthermore, executives increasingly acknowledge the potential benefits associated with Big Data (Accenture 2013; NewVantage Partners 2014; Schroeck et al. 2012) and global private and public investment in Big Data has reached billions of dollars per annum (Gartner Research 2015; Palaskas 2015; Rossino 2015; Weldon 2017). During 2012–2017, the Australian Government has invested $250 million to transform the Australian Bureau of Statistics infrastructure to effectively and efficiently exploit Big Data sources (Australian Bureau of Statistics 2017). Big Data has become a popular term which represents the fact that data generated and available today is ‘big’ in terms of volume, variety and velocity (CGMA 2013; Chen et al. 2012; Davenport 2014; McAfee and Brynjolfsson 2012).

But being ‘big’ does not per se make data useful. It is rather the *insights* gained from analysing the data which provide benefits (Gartner Research 2011; King 2013) – this in turn requires organisations to develop or acquire analytic capabilities (Davenport 2014). The claimed power of Big Data does not replace the need for human insight (McAfee and Brynjolfsson 2012). Equipped with Big Data Analytics (BDA) experts (Davenport and Patil 2012), who can provide such insights from data (NewVantage Partners 2016), organisations are deemed to achieve competitive advantage (Barton and Court 2012; CGMA 2013; Chen et al. 2012; Davenport 2014).

It has been claimed that BDA can lead to better decision-making and improved organisational performance and competitive advantage (Bange and Janoschek 2014); it provides managers with insights to better understand their businesses, customers and environments, as well as enables them to base their decisions on facts rather than intuition (Barské-Erdogan 2014; Davenport 2014). High-performing organisations believe that BDA is a critical differentiator and key to growth (Deloitte 2014b; IBM Software 2013; LaValle et al. 2011; Schroeck et al. 2012). It has even been claimed that Big Data is a paradigm shift that changes the way organisations deal with data and the way they run their businesses (Vasarhelyi et al. 2015). However, none of these claims have so far been substantiated by large-scale empirical research.

The anecdotal ‘evidence’ of the benefits associated with BDA also often ignores that they come at a cost. Executives still struggle to understand and implement BDA strategies effectively (CGMA 2013). Considering the many well-documented cases of unsuccessful deployment of enterprise resource planning (ERP) and business intelligence (BI) systems (Grabski et al. 2011), one has to question how organisations can really make sense of Big Data (Abbasi et al. 2016). In addition, it is unclear to what extent managers actually use the available output of BDA to support their decisions. Early research has shown that personal attributes can affect the degree managers accept new technology, but very little is known precisely what factors encourage *analytics-based* decision-making (ABDM) in the Big Data context.

1.2 Research Questions

BDA is often praised as a promising source of benefits or even competitive advantage; however, apart from case evidence in the practitioner literature, very little is known about such effects. This prompts the main research question: *Can BDA create competitive advantages?*

To answer this question requires a clarification of what constitutes ‘Big Data Analytics’ and how it can be operationalised (and measured). Apart from data, the core ‘ingredients’ for BDA are *analytic methods* and *analytic tools* (Acito and Khatri 2014; Davenport 2014; Stubbs 2014). Numerous analytic methods have been developed and applied, and there are many analytic software tools available on the market. However, does the (increased) use of those methods and tools lead to superior organisational performance? What level of BDA sophistication is required to achieve such benefits?

Furthermore, it is worthwhile investigating whether ABDM influences the relationship between BDA and competitive advantage. Davenport (2014) claims that (higher levels of) BDA can have a positive impact on (the quality of) managerial decision-making. In addition, research shows that in high-performing organisations, important decisions are made rationally and involve less intuition than in low-performing organisations (Guillemette et al. 2014).

Research also shows that organisational culture has an influence on competitive advantage (Davenport and Harris 2007; Davenport et al. 2001). Organisational culture refers to an aggregation of values, beliefs, knowledge, attitudes, tasks, habits, morals, customs and norms which are shared and strongly held by members of an organisation, so as to provide a frame of reference that indicates organisational practices, behaviour, and goals (Barney 1986; Hofstede et al. 1990; Leidner and Kayworth 2006). Organisations develop an analytic culture by investing in data analytic capabilities in terms of tools, methods and people (Davenport et al. 2001; Ramakrishna et al. 2011).

Therefore, the second research question is *what mechanisms drive analytic organisations to achieve competitive advantage?* For the purpose of this research, two possible mechanisms are considered: ABDM and organisational analytic culture (OAC).

1.3 Objectives

The proposed research questions lead to two main research objectives. The *first* research objective is to empirically verify claims made primarily in the practitioner literature that Big Data and its analytics (BDA) lead to better performance and competitive advantage. A theoretical model is developed and tested to identify the impact of BDA on competitive advantage.

To achieve the main objective, it is necessary to operationalise Big Data and BDA. Practitioners have described various constituents of Big Data and BDA, yet there is no agreement on a generally accepted definition. This study is one of the first to measure these constructs.

The *second* objective of our research is to verify to what extent any such benefits are achieved because BDA creates additional incentives for managers to base their decisions more on analytics (ABDM). The role of OAC in the context of BDA and decision-making is also verified. Another research model is proposed to explain the direct and indirect relationships between these four constructs.

1.4 Motivation

The motivation for this study is twofold. *First*, many claims have been made that BDA will improve business performance and competitive advantage (Bange and Janoschek 2014). Industry surveys have been conducted to identify various benefits from Big Data and BDA (Accenture 2014; Deloitte 2014a; EY 2014; KPMG 2014; PWC 2012) and case-evidence confirms that some organisations actually achieve such benefits (Bakhshi et al. 2014), but so far no large-scale research has been conducted to analyse whether and how BDA can create competitive advantage.

Furthermore, there are no generally accepted definitions – let alone measurement scales – for Big Data and BDA. Organisations realise the existence and importance of Big Data (Accenture 2013; NewVantage Partners 2014; Schroeck et al. 2012); nonetheless, no empirical studies have attempted to operationalise Big Data and BDA.

Second, very little is known about whether managers actually use analytics output for decision-making and the role of organisational culture in the BDA context. Industry studies have claimed that BDA improves organisational performance through better managerial decisions (Accenture 2014; EY 2014; WSJ and Oracle 2015). Furthermore, Bange and Janoschek (2014) claim that BDA improves managerial decision-making. Whether ABDM positively influences the relationship between BDA and competitive advantage is still unclear.

1.5 Research Method

The research method is a cross-sectional online survey, based on developed constructs and measurement instruments. The survey targets Chief Information Officers (CIO) and senior IT managers, who have worked with their current employer for at least three months. The survey was sent to Australian for-profit organisations in any industry with more than 50 full-time equivalent (FTE) employees. There were 163 complete responses, which represents a 12.24% response rate. The sample is larger than the minimum sample size required for partial least squares (PLS) analysis and there is no indicator for a presence of potential method and non-response bias.

Data is not normally distributed and is therefore analysed using contemporary data analysis techniques and tools (PLS-SEM, Smart PLS, SPSS). The PLS procedures are used to test the path model and hypotheses using direct and indirect effect analysis. All indicators and constructs in the PLS model are tested and fulfilled validity and reliability criteria.

1.6 Results and Key Findings

This study provides models which (a) identify the overall impact (total effect) of BDA on competitive advantage, (b) analyse any mediating impact of ABDM on this relationship, (c) explore the moderating effect of Big Data intensity in the relationship between BDA and ABDM, and (d) examine the indirect effects of OAC on competitive advantage, via BDA and ABDM.

The hypothesised total effect between BDA and competitive advantage is strongly supported. Furthermore, the mediating effect from ABDM also strengthens the relationship between BDA and competitive advantage. BDA enhances competitive advantage *directly* and *indirectly* via ABDM. Managers in organisations with more sophisticated BDA base more of their decisions on analytics.

However, there is no moderating effect of Big Data in the relationship between BDA and ABDM. High levels of Big Data intensity and BDA sophistication drive ABDM in their own right, rather than in combination.

In a mediator model, the indirect effects of OAC on competitive advantage, via both BDA and ABDM, are significant. In an organisation with an analytic culture, there is a higher level of competitive advantage *indirectly* via higher levels of BDA sophistication and higher levels of managerial decisions based on analytics. Organisational culture is still a factor that can sustain competitive advantage, even in the Big Data era.

1.7 Contributions

This study contributes to the previous literature and professional practice in four important ways.

First, this study provides a better understanding of the effects of BDA on competitive advantage. It also provides the first empirical evidence on whether the hype about BDA is justified. Furthermore, it provides a better understanding of constituents of Big Data and BDA, in particular how to operationalise them in empirical research. Based on prior research and industry papers, measurements of Big Data and BDA are formulated and tested.

Second, this study is also one of the earliest research projects to synthesise major elements mentioned in prior literature, including analytic methods and tools, Big Data characteristics, managerial decision-making and organisational analytic culture. Therefore, this study identifies indirect contributors or mediators of BDA's impact on competitive advantage. Furthermore, this study contributes to the management accounting and information systems (IS) literatures on the impact of BDA on managerial decision-making and competitive advantage using a cross-sectional and large-sample approach.

Third, this study offers a significant opportunity to obtain a better understanding of what level of BDA is required to improve decision-making and competitive advantage. The result of this study can therefore provide valuable information for academic institutions around the world which are attempting to produce more analytic professionals by offering new courses in BDA, Data Science and ABDM (Chiang et al. 2012).

Fourth, the research method developed in this study and the results can help inform the work of a range of stakeholders. Academia can perform future research in other settings or test the relationship between BDA and other organisational perspectives (such as business model, management style) or other Big Data features (such as governance, privacy, security, architecture). Practitioners can benefit from new insights into the impact of BD and BDA on their organisations. Educational institutions can tailor their courses to better meet practical needs of future managers and researchers. Software vendors can benchmark the analytic functionality of their products and provide better guidance on how to use them.

1.8 Thesis Structure

The remainder of this thesis is organised as follows. Chapter 2 describes the background of the main constructs and related previous literature. Chapter 3 explores the theoretical background and presents the hypotheses of this study. Chapter 4 presents how the research is designed, how each construct is measured, and which methods are used to collect and analyse data. Chapter 5 shows quantitative data analysis and results of hypotheses testing; i.e. the hypothesised total, direct and indirect effects between main constructs. Chapter 6 concludes the study with research implications, limitations and possibilities for future research.

CHAPTER 2 – LITERATURE REVIEW

Big Data and BDA have been discussed in academic literature particularly in the areas of IS and business disciplines. Also, there are practitioners' publications stating various benefits from BDA. The acclaimed benefits are that BDA improves managerial decision-making and creates competitive advantage.

In this chapter, first, the two key terms Big Data and BDA are elaborated upon to provide a background understanding of what constitutes them, how they differ from the traditional database and analytics, and what their benefits are. Next, the chapter reviews prior literature which explains how managers make decisions. Finally, the last section explores how organisations recognise the value of analytics.

2.1 Big Data

Big Data refers to a set of techniques and technologies that require new forms of integration in order to uncover hidden value from large datasets that are diverse, complex, and of a very large scale. Big Data is a term characterised by its three "Vs": volume, variety and velocity (CGMA 2013; Chen et al. 2012; Davenport 2014; McAfee and Brynjolfsson 2012).

a) Volume: The volume of Big Data is massive, so conventional hardware and software are incapable of handling it within a suitable time-frame (Moffitt and Vasarhelyi 2013). Data volume has increased dramatically (CGMA 2013) and the unit of measuring data will change from zettabytes (10^{21} bytes) in 2012 (Davenport 2014) to yottabytes (10^{24} bytes) by 2030 (IEEE 2013). By contrast to this increase in available data, the percentage of that data used in analytics is decreasing (Davenport 2014; Zikopoulos et al. 2011).

Analytics has been performed on data since the emergence of IS. ERP systems have generated and stored large volumes of organisational internal transaction data and this, along with easier access to the Internet, cheaper computers and sensor devices, has helped expedite the growth of available data.

b) Variety: Data used for analytics has become more complex, because it includes not only traditional relational data, but also raw, semi-structured, and unstructured data from various sources. Unstructured data cannot be stored easily within a standard relational database (CGMA 2013). Examples of such data include emails, text-based documents, images, videos, call centre recordings, and sensor-generated, user-generated and systems auto-generated data.

Even though these various types of data have been available for some time, they have not been used extensively in analytics until the emergence of new BDA techniques and tools. Data scope is expanding, and research shows that data from a broader range of sources would enrich an organisation's analytics (Moffitt and Vasarhelyi 2013). Since the early 2000's, communication companies have gathered data such as activities and locations of their mobile phone users. However, it has only been recently that they have used or even sold this data for analytics (Davenport 2014). Most people have their smart phones with them or at least close-by everywhere they go, even while asleep, thereby providing another dimension of data and generating new opportunities for communication companies to understand their customers' behaviour (Kridel 2016).

Unstructured data makes up approximately 80 percent of all business information (Deloitte 2014b); however, it is fragmented and has no clear format across organisations. Cao et al. (2015) and Stubbs (2014) suggest that many organisations have difficulties utilising such vast unstructured data, while some organisations clean and/or organise their unstructured data for more efficient use and validation.

From the IS perspective, variety is the most interesting dimension of Big Data (Goes 2014). Pulling together data from sensors, the Web, the Internet of Things, social media, mobile platforms and enterprise systems, allows researchers to explain and predict individual behaviour and detect behavioural trends. Organisations have also found that non-traditional data and new analytic techniques has brought changes to many traditional business processes and environments (Moffitt and Vasarhelyi 2013).

c) Velocity: Velocity refers to the speed of both data generation and data processing. Data generation is rapidly increasing as a result of widely-used mobile and Internet-enabled devices. Real-time or near real-time information enables organisations to be more agile than their competitors (McAfee and Brynjolfsson 2012). Data today is generated, changed and removed more frequently (Zikopoulos et al. 2011) – consequently, organisations need new platforms and tools for analysing it.

Recent developments in IT infrastructure have also increased velocity. With faster computer processors and in-memory analytics, even larger data of various types can be quickly processed and analysed. BDA techniques and tools allow automatic interpretation of large amounts of data which can be uploaded and updated more frequently to generate close to real-time reports or to automatically forecast customer behaviours. For example, while online customers are browsing through the

Amazon website, Amazon automatically collates '*customers who bought this item also bought*', '*what other items do customers buy after viewing this item?*' and '*your recently viewed items and featured recommendations*' all personalised in real-time, thereby increasing the chances of customers purchasing more books and/or products (Wills 2014).

Big Data is also referred to by other characteristics such as veracity, variability, visualisation and value (Abbasi et al. 2016; McNulty 2014; Saporito 2014; Turban et al. 2011). To date, a generally accepted definition of Big Data has not been developed. Even though many new 'V's have been proposed in addition to the initial 3 Vs, their validity is questionable and has not been empirically confirmed. 'Value', for example, is a very broad term to describe the suggested benefits ('output') associated with Big Data, which is inconsistent with the original three Vs which depict inherent characteristics of the data itself ('input'). Therefore, only the original three Vs are used to measure Big Data.

2.2 Big Data Analytics (BDA)

2.2.1 Definition

Data analytics has been practised by both academics and professionals for some time. "Analytics is the science of analysis" (Turban et al. 2008, p. 435). Data analytics uses data for quantitative and/or qualitative analysis to help an organisation better understand its business and markets and to inform timely business decisions (Chen et al. 2012; Holsapple et al. 2014; Ramakrishna et al. 2011). Data analytics involves multiple disciplines, in particular, mathematics and statistics, but also data mining, BI, machine learning, pattern recognition and data visualisation.

Characteristics and objectives of different types of analytics are identified in a broad range of literature. First, analytics can be categorised into three broad types: descriptive, predictive and prescriptive (Chen et al. 2012; Davenport 2014; IBM Software 2013; Minelli et al. 2012). *Descriptive analytics* drills down into past or current data to discover trends or patterns to support managerial decisions. *Predictive analytics* supports organisational decisions and strategies by gathering historical data, forecasting, and simulating to anticipate possible future situations. *Prescriptive analytics* refers to descriptive and predictive analysis of data that suggests a set of potential actions to managers considering rules, constraints, thresholds, risks and uncertainty. The trend in analytics is moving from describing what happened to forward-looking (predictive) and prescriptive analytics (Hagel 2015).

Second, Davenport (2014) arranges analytics into three historical stages. *Analytics 1.0* focused primarily on descriptive analytics using small and structured data for internal purposes. *Analytics 2.0* expanded the scope, included unstructured data, and focused both on descriptive and predictive analytics; many organisations used this type of analytics to search for new business opportunities such as new products or services. In the Big Data era, *Analytics 3.0* focuses on prescriptive analytics and involves a combination of various data types and formats to support decision-making.

Third, Chen et al. (2012) identify three eras of business intelligence and analytics (BI&A) evolution. In *BI&A 1.0*, most data was in row-and-column format so it could be managed by relational database management systems. With the emergence of the Internet, data content became more unstructured and web-based (*BI&A 2.0*). The third era, *BI&A 3.0*, relates to data with a higher portion of mobile and sensor-based content.

Finally, Cao et al. (2015) define BDA as the procedure used to discover and manage useful information, patterns, or conclusions from Big Data so as to support managerial decisions. Present trends are moving towards Analytics 3.0/BI&A 3.0 which suggests that organisations are moving towards predictive and prescriptive analytics using increasing amounts of unstructured data.

Data analytics in the Big Data environment is different from conventional data analytics in several ways (McAfee and Brynjolfsson 2012). Computer storage and processing units are more powerful and can be obtained at lower cost. More personal information is being generated and made available due to the development and uptake of smart phones and sensor-based tracking devices, used by people to share their locations, opinions and feedback via social media applications in real-time. In these scenarios, BDA has an important impact on decision-making processes. Analysing a greater amount and various types of data now becomes possible. BDA applies scientific methods to solve problems that were previously impossible to solve, either because the data or the analytic tools did not exist (Davenport 2014; Parmar et al. 2014). When new advanced analytic tools are used, organisations can generate considerably better business opportunities (Agarwal and Dhar 2014).

BDA is a potential benefit-generator for any organisation in the Big Data information age (McAfee and Brynjolfsson 2012). In a recent survey of businesses and technology decision-makers in Fortune 1000 organisations, 70 percent of the respondents reported that Big Data was essential for the success of their organisations (NewVantage Partners 2016). Managers believed that they could make better decisions by analysing Big Data to gain insights into their businesses, customers, competitors and markets, so as to improve their organisations' performance (Bange and Janoschek 2014) and even outperform their competitors (competitive advantage) (Chen et al. 2012; Davenport 2014).

But successful implementation of BDA requires people with skills to handle Big Data, extract meaning and develop insights (Davenport and Patil 2012; Stubbs 2014). BDA needs to be managed to gain insights, and to communicate the results to managers in order for them to understand the results and take appropriate action (Accenture 2013; Schroeck et al. 2012).

However, it is also argued that managers have difficulty understanding the roles of BDA during this expeditious shift towards Big Data technology and unstructured data (Deloitte 2014b). A number of managers are also concerned about their ability to uncover and take advantage of meaningful insights (Deloitte 2014b). There are managers who lack understanding of how to use BDA outputs to improve business performance (IBM Software 2013). The biggest challenge is that managers do not comprehend the potential of BDA and how to gain benefits from it (LaValle et al. 2011).

In order to compete using analytics, organisations are required to make a significant investment in advanced technology and techniques, the accumulation and strategic manipulation of Big Data (Davenport 2006), as well as technologies to deal with large amounts of diverse, unstructured, and semi-structured data (Dyché 2014). BDA no longer involves just traditional hypothesis-based statistical analysis, but also machine learning, predictive modelling, faster processing tools, high-performance analytics environments and visual analytics (Chen et al. 2012; Dhar 2013; Dyché 2014). Many aspects of unstructured data, which have never been quantified before in traditional data mining, can be rendered by new BDA techniques (Alles and Gray 2014). In the Big Data context, various sources of data are identified, managed and combined (Barton and Court 2012). Furthermore, advanced analytics, using statistical methods and/or mathematical optimisation, is needed to generate better decision support and improve operational performance (Chae et al. 2014; Liberatore and Luo 2013).

Kaushik (2010) emphasises the importance of analytic resources by recommending the 10/90 investment rule. Ten percent of any investment in analytics should be allocated to tools, while the remaining 90 percent should be assigned to improve other organisational analytic resources, primarily intelligence resources and analysts. Analytic expertise, appropriate hardware and software analytic tools are all required for high-quality analytics (Cao et al. 2015).

2.2.2 Analytic Tools and Methods

The range of BDA tools and methods available is broad. They vary in terms of functionality, scope and level of sophistication. Since the emergence of BDA, the trend has been towards more sophisticated data analytic tools to support decisions (Chaudhuri et al. 2011; Liu and Vasarhelyi 2014). In turn, the quality of analytic tools has had a significant impact on data quality, managerial decision-making and organisational performance (Wieder et al. 2012).

BDA tools are divided into three categories: information and knowledge discovery, decision support and intelligence systems, and visualisation (Turban et al. 2015). BDA tools are different from traditional data analytic tools in that they are more likely to involve machine learning (Dyché 2014). New BDA tools and methods improve the quality of decisions, providing more accurate predictions and broader scope of analysis (Chaudhuri et al. 2011; Liu and Vasarhelyi 2014). This trend has been expedited by a quicker generation of models to explain and predict relationships in fast-moving data, faster processing tools such as in-memory and high-performance analytics environments, and visual analytics (Dyché 2014).

Analytic *methods* refer to techniques and processes, whereas analytic *tools* refer to features and functions in analytic software. Organisations use analytic tools and methods to deal with (i) data management, (ii) data analysis, and (iii) data presentation.

(i) Data management starts when organisations gather accessible data, clean it and convert it into particular formats, and store it into a data depository, either in a traditional data warehouse or a streaming data warehouse (Considine et al. 2012; Turban et al. 2008). In the Big Data context, this means the virtual extraction, transformation and loading that operates with the abstracted representation of objects or entities gathered from relational, semi-structured, and unstructured data sources (Shaik 2008). In addition, new Big Data management technologies, e.g. Hadoop, and high performance computing tools are required to process greater volumes of semi-structured and unstructured data (Dyché 2014; Tambe 2014; Zikopoulos et al. 2011). Most Big Data technologies are used to either store Big Data or transform it from an unstructured or semi-structured format (Dyché 2014).

(ii) Data analysis ranges from applying basic statistical, financial and mathematical models, to more sophisticated domains such as multivariate regression analysis, optimisation, and nonlinear programming (Harris et al. 2013). Data analysis includes advanced analytic and artificial intelligence, which helps identify patterns and formulate models to assist managements to ask/answer questions, support decisions, visualise results in various formats, predict future trends, or highlight issues that require immediate action. In the Big Data context, data analysis also includes real-time text mining, which is used to discover actionable and meaningful patterns, profiles and trends from text/web resources (Linoff and Berry 2001), and to analyse data that is streaming continuously on social media (Chakraborty et al. 2013).

Furthermore, advanced data mining, which involves machine learning, is one of the analytic domains that differentiates BDA from its predecessors (Barské-Erdogan 2014). Rather than traditional statistical analysis, BDA involves machine learning to quickly define and predict relationships in Big Data (Dyché 2014). Popular techniques are vector machines, random forests, decision trees, cluster analysis, and neutral networks. In a data-driven business, machine learning is often an essential part of the business model (Dhar 2013).

(iii) Data presentation refers to reporting and visualisation used to provide answers/patterns to business questions (Turban et al. 2015). Reporting and visualisation should bring insights to end-users in the form of descriptions, graphs, or alerts. These tools can be generic reporting tools (e.g. spreadsheets) or more sophisticated tools (e.g. digital dashboards). They can be generated on both a routine and an ad-hoc basis. Visualisations include digital images, geographical information systems, graphical user interfaces, virtual reality, dimensional presentations, videos and animation (Turban et al. 2015).

2.2.3 The Analytic Professional

In order to make sense of data, organisations require various levels of analytic expertise, ranging from strategic to day-to-day operational decision support (Harris et al. 2010).[1] Analytic professionals are in high demand (Rexar Analytics 2013). A variety of position names are used to describe analytic professionals; e.g. data scientist, researcher, data analyst and business analyst (Rexar Analytics 2013). Furthermore, Harris et al. (2013) categorise various types of analytic professionals as data business-people, data creative personnel, data developer, and data researcher.[2] In this study, the generic term '*analytic professional*' is used to refer to aptitude and proficiency in general, rather than using position names that vary.

Davenport (2014) and Granville (2014) categorise analytic professionals into two categories: vertical and horizontal. *Vertical analytic professionals* specialise in a particular area whereas *horizontal analytic professionals* have general knowledge of many fields. The former may be statisticians who specialise, e.g. in multi-variate regression, but lack experience in how to apply the results to specific business problems. In contrast, the latter are able to identify a possible dataset to solve a business problem even though they have only basic quantitative skills. Analytic professionals who are specialised in advanced (vertical) analytics are less likely to have developed skills in any other analytic domain (Schoenherr and Speier-Pero

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[1] **Breakdown of Analytic Talent:** *Champions* are high-level managers who make business decisions based on data and analytics. *Professionals* know complex quantitative techniques, while *semi-professionals* link analytics to business-contents. *Amateurs* are operational-level staffs who require an understanding of analytics to perform their day-to-day jobs (Harris et al. 2010) .

[2] **The Variety of Analytic Professional (Data Scientists):** *Data Business-people* concentrate on the organisation and how data projects generate profit. *Data Creatives Personnel* perform every single step of data analytics by applying a variety of tools and techniques while *Data Developer*'s attention is on data management. *Data Researchers* have an academic research background and know how to manage data in various circumstances (Harris et al. 2013).

2015). It is held by some that horizontal capability is more preferable (Davenport 2014; Granville 2014).

In the Big Data context, organisations tend to rely on analytic professionals who have a mix of skills in mathematics, statistics and programming (Davenport et al. 2012). Analytic professionals should have statistical as well as other quantitative and analytical capabilities (Davenport 2014; Davenport and Harris 2007; Dhar 2013; Harris et al. 2013; Harris et al. 2010) such as skills in cleaning and organising large datasets, and visualisation tools and techniques (Harris et al. 2013; McAfee and Brynjolfsson 2012). An ability to write code may not be essential because programming tasks can be outsourced. Other required areas of expertise are knowledge of the latest analytic tools, and how to design and monitor experiments with data (Barton and Court 2012; Davenport 2014; Davenport and Patil 2012; McAfee and Brynjolfsson 2012).

Furthermore, analytic professionals should be fact-based, experimental, product-focused, and steady in their approach to analyse and act on data; they should be skilled in ongoing monitoring of data, and mining new and existing data sources for patterns, events and opportunities (Barton and Court 2012; Harris et al. 2013). Analytic professionals do not necessarily have university degrees in science-related areas. The Institute of Analytics Professionals of Australia found that the background of analysts is interdisciplinary (Stubbs 2014).

Davenport and Patil (2012) define analytic professionals as people with training and the curiosity to make discoveries in the world of Big Data. Tambe (2014) refers to them as professionals who can translate technologies into business outcomes.

Industry research attempts to identify core analytic skills (Lavastorm Analytics 2013), but which and to what extent each analytic skill is needed to generate competitive advantage remains undefined (Schoenherr and Speier-Pero 2015). There is also a problem of labour shortage in qualified analytic professionals (Accenture 2014; Gartner Research 2012; Stubbs 2014) and many organisations encounter challenges to find and manage the right analytic professionals (Deloitte 2014b; McAfee and Brynjolfsson 2012).

2.2.4 Benefits of Big Data Analytics

Organisations have realised the potential value of BDA in many ways, such as in better or more informed decision-making processes, better decision outcomes, improved operational effectiveness, generation of additional revenue, development of new markets, products and services, cost savings, enhanced customer experience, and better organisational performance overall (Davenport 2014; Deloitte 2014b; Holsapple et al. 2014). Information can improve organisational performance in three ways: improving organisational structure, identifying ways to outperform competitors, and identifying new business opportunities (Barton and Court 2012; Germann et al. 2014; Liberatore and Luo 2013; McAfee and Brynjolfsson 2012; Moffitt and Vasarhelyi 2013; Porter and Millar 1985; Schroeck et al. 2012).

The primary objective of data analytics is to support business activities such as decision-making and managerial actions (Holsapple et al. 2014). Most organisations that outperform their industry peers believe that analytics is a critical differentiator and key to growth (Deloitte 2014b; LaValle et al. 2011). Organisational leaders expect analytics to exploit their growing data and computational power to get smart and innovative in ways they never could before. A majority of executives believe that one of the main reasons for losing revenue is the ineffective management of business information (WSJ and Oracle 2015).

In the Big Data context, useful analytic tools and methods can improve the quality of decision-making in the context of structured, semi-structured, and unstructured data (Guillemette et al. 2014). "The use of analytics has been recognised as a crucial part of any decision-making process in businesses" (Hagel 2015, p. 24). By providing new technologies and approaches, BDA supports management decisions with real-time and continuous predictive evidence (Barské-Erdogan 2014; Davenport 2014). The goal of BDA is "to improve the efficiency and effectiveness of every decision and/or action" (EY 2014, p.6). In addition, when organisations design and embed fact-based insights into key processes, managers make smarter decisions, leading to better business outcomes (Accenture 2013). A number of case studies claim that organisations benefit from BDA mainly because it leads to better planning, forecasting, and decision making (Barton and Court 2012; McAfee and Brynjolfsson 2012; Moffitt and Vasarhelyi 2013).

2.3 Analytics-based Decision-Making (ABDM)

2.3.1 Decision-Making Theory

To study how BDA creates competitive advantage, it is necessary to understand how analytics supports organisational decision-making. The analysis of decision-making involves various disciplines: economics, philosophy, psychology, management science, mathematics, statistics and computer sciences. Research has attempted to explain what influences managerial decisions and how, but has yielded conflicting results. Decision-making is not a clear-cut concept; however, there are two main views regarding what influences decision-making. On the one hand, decision-making is seen as a solely rational and logical process (Eilon 1969; Eisenführ et al. 2010; Harrison 1999; Schoemaker 1982), while on the other hand, decisions are not all rational and are influenced by the beliefs and values of decision-makers (Jones 1999; Selten and Gigerenzer 2001; Simon 2000).

Decision theory in traditional economic science is based on the assumptions that decision makers are informed, have the capability to calculate, and apply rational procedures to identify all possible alternatives, thereby making optimal decisions (Eilon 1969; Eisenführ et al. 2010; Harrison 1999; Schoemaker 1982). *Expected utility theory* is the main paradigm in managerial decision analysis and it is helpful to evaluate and guide decisions (Schoemaker 1982). Information is an integral part of the decision process (Eilon 1969), and consequently many decision support techniques were developed analysing information using mathematical methods, such as multiple-criteria decision analysis, game theory, probability theory, hypothesis testing, and Bayesian statistics (Dyer et al. 1992; Eisenführ et al. 2010; Harrison 1999).

In addition, an *evidence-based approach* is developed based on economic decision theory, but with more focus on empirical evidence. It was popular initially in medical science and health care. Pfeffer and Sutton (2006a) refer to previous studies which showed that patients of evidence-based physicians received treatment with better results. In management, it is proposed that the more evidence used to support decisions, the better decisions and organisational performance are (Pfeffer and Sutton 2006a). *Evidence* is also information and refers to facts, reliable measurements, justified estimates, unbiased observations, or information, which provides a rationale, an assumption, or a standpoint to support the conclusion (Baba and HakemZadeh 2012; Holsapple et al. 2014). *Evidence-based management*, therefore, occurs when organisational practices are based on the best available evidence without being influenced by personal experience and preference (Rousseau 2006). Useful evidence is characterised by both rigorousness and relevance (Baba and HakemZadeh 2012).

Researchers observed, however, that behaviours of decision makers often deviate from this rational framework and that there are also other factors that influence decision-making. Decision makers are more or less rational (Eisenführ et al. 2010), so they differ in terms of their levels of rationality (Eisenhardt and Zbaracki 1992). People are not perfect Bayesian calculators (Basel and Brühl 2013) and their rationality is multi-dimensional (Eisenhardt and Zbaracki 1992). They cannot take all aspects into consideration, cannot execute all necessary calculations to eliminate unfavourable options, and have difficultly choosing between alternatives (Jones 1999).

Simon (1972) proposed a theory of *bounded rationality* by referring to individual decision-making in which rationality is limited by the information decision makers have available, the cognitive limitations of their minds, and the time available to make their decision. Managerial decisions are often influenced by personal experience and judgment, individual preferences and values, or feelings (March 1978). When output from quantitative analysis seems unpleasant, managers may override the analytic output (Pfeffer and Sutton 2006a; Rousseau 2006).

Literature extended the concept of bounded rationality from simple cognitive tools to include emotions, social norms, and organisational culture (Jones 1999; Selten and Gigerenzer 2001; Simon 2000). Limited cognitive capability leads people to use *heuristics* (Basel and Brühl 2013) which tend to be both domain specific and adapted to the structure of environments rather than aiming for optimisation or consistency

(Selten and Gigerenzer 2001). *Intuition* became more accepted as an influencer of management decision-making (Agor 1986; Dane and Pratt 2007; Sadler-Smith and Burke-Smalley 2015), meaning that managers do not make their decisions based solely on information or analytics provided.

In psychology, decision-making is regarded as a cognitive process of identifying and selecting alternatives or possibilities. Social science researchers performed laboratory and field experiments to develop a practical implementation which combines subjective utility and objective probabilities, namely *behavioural decision theory*, by including personality variables in the expected utility maximisation model (Edwards 1961; March 1978). They studied economic behaviour with emphasis on the psychological aspects of underlying judgment and choices, rather than logical reasoning (Einhorn and Hogarth 1981; Slovic et al. 1977). Decision-making is recognised as a form of alternative rationality which varies from optimality (Einhorn and Hogarth 1981) and depends on clarification and understanding of criteria (March 1978). While optimality is conditional on assumption and time, actual decisions are normally based on multiple assumptions and criteria which change over time (Einhorn and Hogarth 1981).

Furthermore, when too much information is present, human decision makers have difficulty understanding and processing it (Pfeffer and Sutton 2006a; Rousseau 2006; Yang et al. 2003), an effect known as '*information overload*.' Managers process information with limited capacity, depending on how fast they make decisions from information received (Kahneman 2011; Radner 1993).

2.3.2 *Structure of Decision Problems*

Decisions vary in terms of structure. A *structured decision* is an organised and inclusive approach to understanding a complicated problem, followed by generating and evaluating alternatives and possible consequences and outcomes (Gregory et al. 2012; Turban et al. 2015). It stems from the economic decision assumption that alternatives are identifiable and uncertainty is measurable (Gregory et al. 2012). Structured decisions have a well-defined process and necessary data (Turban et al. 2015) to improve the quality of decisions (Eisenführ et al. 2010).

In *unstructured decisions*, problems are not predetermined and have no explicit alternatives (Mintzberg et al. 1976); therefore different decision makers may use different datasets, different evaluation processes, and produce different decisions. Unstructured decisions, however, rely not only on data, but also decision makers' knowledge, expertise, experience, judgment and preferences (Turban et al. 2015). Unstructured decisions encounter the problem of limited resources and expertise, and involve data that cannot be defined completely in the business environment (Turban et al. 2015); for example, customer behaviours and competitors' reactions.

2.3.3 *Information Systems and Decision-Making*

One purpose of IS is to support managerial actions and decision-making (Clark et al. 2007). IS improve a manager's information load, by increasing the quantity of information dimensions they have available to them (Iselin 1988). IS make information available, from operations and other sources, to help managers make decisions (Markgraf 2016; O'Brien and Marakas 2006). The early development of management information systems targeted mainly structured decisions, because they are routine and repetitive (Watkins 1982). As managers require accurate, relevant and timely information to make strategic and operational decisions, IS help to formulate scenarios and suggest options (Considine et al. 2012).

The goal of decision analysis is to help decision makers to make the most rational decisions that are possible (Eisenführ et al. 2010). For many decades, *decision support systems* (DSS) have been discussed and developed. Many types of DSS have been generated including group DSS and intelligent DSS. DSS provide alternatives, problem-solving, methods to analyse alternatives, and suggestions for the best solution (Clark et al. 2007). DSS differ in terms of systems' objectives and information characteristics (Gorry and Morton 1971).

Managers use IS to support strategic decisions, tactical decisions, and also day-to-day operational decisions (Nowduri 2011). To support decision-making under uncertainty, probabilities should be measured quantitatively (Eisenführ et al. 2010). In structured decisions, IS aggregate and summarise information, thereby reduce uncertainty – as a result, they improve the quality of decisions (Iselin 1990; Meissner and Wulf 2014; Turban et al. 2015). In less structured decision contexts, not all possible information may be acquired and modelled (Watkins 1982), which requires databases with more flexibility (Courtney 2001) and techniques to handle incomplete information (Eisenführ et al. 2010). Many DSS have been developed to transform data to support and improve the timeliness and quality of decision-making (Holsapple et al. 2014).

The trend in IS is moving towards more commoditised, less expensive, larger storage, and higher computing power (Chang et al. 2014). With the emergence of Big Data, the algorithms of DSS have changed to enable them to react more quickly to the high volume, variety and velocity of data (Renu et al. 2013). A combination of Big Data and DSS provides managers with more useful and valuable information to support their decisions (Poleto et al. 2015).

BDA provides new opportunities for managers to benefit from evidence-based solutions, make predictions, and/or evaluations, so as to base their decisions on better quality information (Holsapple et al. 2014). Advanced BDA supports structured decisions by modelling unstructured or semi-structured data, estimating uncertainty, eliminating less preferable alternatives, and then representing post-auto selected alternatives in graphical forms such as a decision matrix or a decision tree (Eisenführ et al. 2010).

2.4 Organisational Analytic Culture

2.4.1 Definition and Characteristics

Organisational culture refers to an aggregation of values, beliefs, knowledge, attitudes, tasks, habits, morals, customs and norms which are shared and strongly held by members of an organisation, so as to provide a frame of reference that indicates organisational practices, behaviour and goals (Barney 1986; Guiso et al. 2015; Hofstede et al. 1990; Khazanchi et al. 2007; Leidner and Kayworth 2006). People can interpret organisational culture in various ways (Guiso et al. 2015) and define what is important to them and how they should act and feel in organisations. Organisational culture may vary across functions and geographical locations (Khazanchi et al. 2007). Organisations also reflect their culture through the interactions of their employees, customers, suppliers, and competitors (Nahm et al. 2004).

Prior studies have attempted to measure and operationalise organisational culture using quantitative empirical methods (Hofstede et al. 1990; Leidner and Kayworth 2006). Even though culture normally includes a set of beliefs as a soft factor, there are visible aspects of organisational culture, for example organisational practices and processes, strategies and goals (Nahm et al. 2004). An alignment between culture and organisational practices depends on the perceptions of people within an organisation (Hofstede et al. 1990; Khazanchi et al. 2007).

From an IS perspective, organisational culture is also a critical variable to describe the relationship between IS and people's behaviour (Leidner and Kayworth 2006). Organisational culture includes how senior managers associate with IS and contribute to its implementation and success by active involvement and provision of necessary resources (Bajwa et al. 1998; Leidner and Kayworth 2006). It also influences how people in organisations actually use IS and its outputs to support their operations and decisions (Chau et al. 2002).

One aspect of organisational culture is the attitude toward the use and benefits of analytics (Davenport et al. 2001). OAC is manifested in what people believe and how they make their decisions based on analytics. It is represented in how people in an organisation assess the value of analytics and therefore use data to support operations and decision-making, as well as sharing data within an organisation. OAC is also represented in a broader sense in the extent managers consider data analytics as a strategic resource to generate competitive advantage (Davenport et al. 2001).

2.4.2 Impacts of Organisational Analytic Culture

Since the emergence of computer-assisted systems such as expert systems, executive information systems, and DSS, there have been attempts to understand the relationship between organisational culture and the use of these IS (Chang et al. 2014). OAC affects how people respond to the adoption and implementation of IS in organisations. For example, if managers are involved with and support of the use of IS, this has an influence on the successful adoption of IS across the organisation (Bajwa et al. 1998).

The cultural context of how people in an organisation perceive value of data analytics influences how the decision-making process is configured (Davenport et al. 2001). In organisations that believe in the reliability and accuracy of their organisations' information, managers tend to use more information generated from data analytics to support their decisions (Garg et al. 2003). In addition, it is suggested that, in organisations that realise the value of analytics, managers should sponsor investment and support data analytics capabilities in terms of tools, methods and people (Davenport et al. 2001; Ramakrishna et al. 2011).

Organisational culture is also recognised as a source of sustained competitive advantage in *resource-based theory (RBT)*. The literature is based on assumptions that organisations compete in an imperfect market, are economically different, and have heterogeneous resources and capabilities. Consequently, organisations can gain higher returns from being the first mover, holding attractive resources, leading in technology, and having strong managerial values (Barney 1986; Nelson 1991; Wernerfelt 1984). The term *organisational resources* refers to both tangible and intangible *assets* that are controlled by an organisation so that it can appreciate and execute strategies to enhance its efficiency and effectiveness (Barney 1991; Barney 1995). They include financial, physical, human, or organisational capital resources such as capabilities, organisational processes, firm attributes, information and knowledge.

Four key characteristics that organisational resources and capabilities require to generate competitive advantage are: *valuable*, *rare*, *inimitable* and *non-substitutable* (VRIN) (Barney 1991). Resources are valuable when they can be used to exploit opportunities or neutralise threats in an organisational environment. However, valuable resources provide competitive advantage only when competing organisations cannot easily obtain or substitute them, i.e. when they are rare, inimitable and non-substitutable. Barney (1995) states that the specifics of organisational history and culture, a sequence of small correct decisions, and organisational reputation are difficult to imitate by competitors.

Later, Barney (1995) mentions *complementary resources* which are necessary to generate competitive advantage but have to work together with other resources and capabilities. Examples of complementary resources are formal reporting structures, explicit management control systems, and compensation policies.

2.5 Conclusion

Big Data is characterised by not only a high volume of data, but also a greater variety of types of data, and a high velocity. Research shows that the data available to organisations is significantly greater than what organisations use and know how to analyse. It is the insights gained from analysing Big Data that provide benefits (Gartner Research 2011; King 2013), improve managerial decision quality, and create competitive advantage.

Analysing Big Data requires new inventions of analytic tools and methods in order to handle high volume of not only structured data, but also semi-structured and unstructured data, in near real-time. Many new advanced BDA tools and methods are utilised, so organisations have greater opportunities to improve their performance (Agarwal and Dhar 2014; Bange and Janoschek 2014). In these scenarios, it is claimed that BDA is required to generate better or more informed decision-making processes and better decision outcomes (Davenport 2014; Parmar et al. 2014), improve operational performance, and create competitive advantage (Chae et al. 2014; Liberatore and Luo 2013). However, none of these claims have so far been confirmed by rigorous empirical research results.

To understand how BDA can create competitive advantage, it is necessary to understand to what extent managers make their decisions based on BDA outputs. How managers make their decisions has been studied for a long time by multiple disciplines, with inconsistent conclusions. Managers attempt to make their decisions rationally and based on information; however, they encounter either problems of information overload or insufficiently structured decision models. In the BDA environment, it is claimed that IS can overcome these boundaries but such claims have not been empirically validated yet.

Theoretical evidence shows that many factors influence the relationship between BDA and competitive advantage. For the purpose of this research, OAC is considered.

Prior literature has studied the influence of culture and capabilities on competitive advantage, but not specifically in the level of OAC, especially in the BDA context. Decisions at the organisational level are influenced primarily by people, structures, policies and culture (Guillemette et al. 2014). Organisational culture can affect the quality of management decisions (Davenport et al. 2005) and has an impact on managerial decision-making (Davenport et al. 2001).

CHAPTER 3 - HYPOTHESES DEVELOPMENT

The concepts Big Data, BDA, ABDM and OAC described in the previous chapter provide background that may help to answer the research questions: *Can Big Data Analytics create competitive advantage, and if so, what mechanisms drive analytic organisations to achieve competitive advantage?* To answer the research questions, an understanding of the mechanisms that drive an organisation to achieve a competitive advantage is required.

According to RBT, organisational value-creating resources, unlike assets, generate competitive advantage when they are valuable, rare, in-imitable, and non-substitutable (VRIN) (Barney 1991; Barney et al. 2011). The main objective of RBT research is to identify organisational characteristics that lead to sustainable competitive advantage in various settings. Resources are valuable when an organisation can utilise them to exploit opportunities or counteract threats. Competitors should not be able to easily obtain or substitute a firm's value-creating resources.

Sustained competitive advantage is different (Barney 1991; Mata et al. 1995). Competitive advantage concerns implementing a value creating strategy not simultaneously being implemented by any current or potential competitors. Sustained competitive advantage also requires that these competitors are unable to duplicate the benefits of this strategy. The word 'sustained' does not depend upon the period of calendar time but depends upon the possibility of competitive duplication – equilibrium definition.

A series of hypotheses are developed to identify the direct and/or indirect relationships between BDA and competitive advantage. Mediating effects of ABDM and OAC, as well as a moderating effect of BD, are also forecasted.

3.1 Big Data Analytics for Competitive Advantage

BDA generates benefits by enhancing organisational performance thereby potentially creating competitive advantage (Barton and Court 2012; Liberatore and Luo 2013; McAfee and Brynjolfsson 2012; Moffitt and Vasarhelyi 2013; Schroeck et al. 2012). Many organisations which outperform their industry peers believe that BDA is a critical differentiator and a key to growth (Deloitte 2014b; LaValle et al. 2011). Organisations have realised significant value from BDA when it is able to provide a new aspect of information for planning and forecasting (Barton and Court 2012; McAfee and Brynjolfsson 2012; Moffitt and Vasarhelyi 2013), leading to improvements in operational effectiveness, additional revenue generation, new market, products and service offerings, cost savings, and enhanced customer experience (Davenport 2014; Deloitte 2014b).

In order to compete using analytics, organisations are required to make a significant investment in advanced technology and techniques, the accumulation and strategic manipulation of Big Data (Davenport 2006), as well as technologies to deal with large amounts of diverse, unstructured, and semi-structured data (Dyché 2014). In the BDA era, there are new analytic tools and methods to explore and make sense of Big Data, and to define those that are important in supporting managerial decisions, thereby creating competitive advantage (Chang et al. 2014).

Furthermore, BDA can be used to directly improve and/or automate business processes; for example, in the form of recommender systems. Amazon reports that 29 percent of their sales increase is from its personalised recommendation systems (Mangalindan 2012). There are advanced data analytic tools and methods working behind the success of this integrated recommender system as it combines data from various perspectives and sources: purchase history, web browsing and search history, current item in shopping carts, other customers' purchase and browsing history, and related products available. Amazon calls it "item-to-item collaborative filtering", applying sophisticated mathematical algorithms to find proper suggestions to each individual whether they are existing or new customers (Linden et al. 2003).

On the basis of previous academic and practitioner literature, it is hypothesised that a higher level of BDA sophistication generates competitive advantage (Figure 1).

H1: Big Data Analytics (BDA) sophistication has a positive total effect on competitive advantage (COMP).

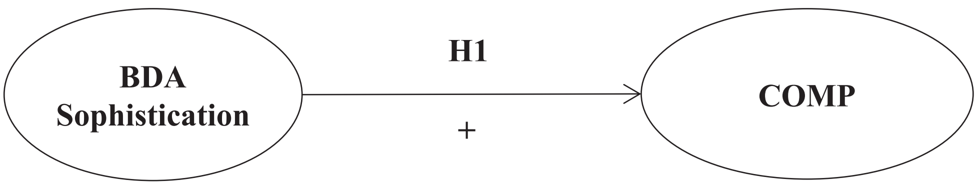


Figure 1 Hypothesis 1

3.2 Big Data Analytics and Competitive Advantage, mediated by Analytics-Based Decision-Making

BDA applies scientific methods to solve problems previously thought impossible to solve, because either the data or the analytic tools did not exist (Davenport 2014; Parmar et al. 2014). Big Data solutions help organisations create actionable strategies by providing constructive, predictive, and real-time analytics, to gain deeper insights to inform their business requirements and expansion plans (Barské-Erdogan 2014).

BDA has a significant impact on decision-making processes (Kościelniak and Puto 2015), and managers are more likely to use BDA outputs to support their decisions if they perceive that analytic outputs as useful (Davis 1989; Davis et al. 1989; Venkatesh et al. 2003). A higher level of BDA sophistication provides managers with better quality information on which to base their decisions and as a result they are able to better understand their businesses and customers (Chen et al. 2012; Ramakrishna et al. 2011).

The trend in BDA is toward a quicker model generation and faster data processing to explain and predict associations in Big Data (Dyché 2014). With more accurate and reliable forecasting, managers make better decisions (Park 2006; Wieder and Ossimitz 2015) and with this fact in mind, they tend to base more of their decisions on analytic outputs. By using advanced BDA techniques to analyse larger volumes of more timely and more diverse of data, BDA provides managers with 'new' insights, which previously either have not existed or have not been realised. By providing new technologies and approaches, BDA supports management decisions with real-time and continuous predictive evidence (Barské-Erdogan 2014; Davenport 2014).

Research is still inconsistent in terms of what managers make their decisions based on. Even when managers use a rational approach in their decision-making process, they may still use heuristics, which include intuition, to cope with bounded rationality at some point in this process (Guillemette et al. 2014). However, when data contradicts intuition, the majority of senior managers set aside their intuition and rely on data (McAfee and Brynjolfsson 2012).

Extended from Hypothesis 1, there are various mechanisms how BDA can help an organisation outperform its competitors. The relationship between BDA and competitive advantage is partly mediated by the extent to which managers make their decisions based on analytic outputs. BDA can help an organisation to better understand its business and market (Chen et al. 2012; Ramakrishna et al. 2011). With new technologies and analytic approaches, BDA can provide managers with information for real-time planning and continuous forecasting (Barské-Erdogan 2014; Barton and Court 2012; Davenport 2014; McAfee and Brynjolfsson 2012; Moffitt and Vasarhelyi 2013). BDA techniques are better able to analyse larger amounts of different types of data. With increasingly advanced algorithms, BDA can help improve decision efficiency and effectiveness (Brown-Liburd et al. 2015).

According to economic decision theory, if decisions are based on facts, the decision quality is higher (Eilon 1969; Eisenführ et al. 2010; Guillemette et al. 2014; Harrison 1999; Pfeffer and Sutton 2006b; Schoemaker 1982). Higher-quality information can improve the quality of decision-making (Park 2006; Wieder and Ossimitz 2015). In order to make high-quality managerial decisions, reliable information based on facts/evidence is needed (Rousseau 2006). For example, accurate managerial forecasts lead to high quality decisions in capital investment acquisitions (Goodman et al. 2014).

Making decisions based on information is expected to lead to better organisational performance and competitive advantage (Rogers and Blenko 2006). If managers make rational decisions, rather than intuitive decisions, it is expected that organisational performance will improve (Guillemette et al. 2014). For example, when managers make such decisions about a new marketing plan which reaches new customers, their organisation may increase revenue, profit margins, and market share.

It is therefore hypothesised that a higher level of BDA sophistication encourages a higher level of ABDM. When managers make more of their decisions based on information, their decision quality will be better and therefore more likely to create organisational competitive advantage. The next hypothesis, therefore, predicts a positive indirect relationship between BDA and competitive advantage via ABDM (Figure 2).

H2: Big Data Analytics (BDA) sophistication leads to competitive advantage (COMP) via analytics-based decision-making (ABDM).

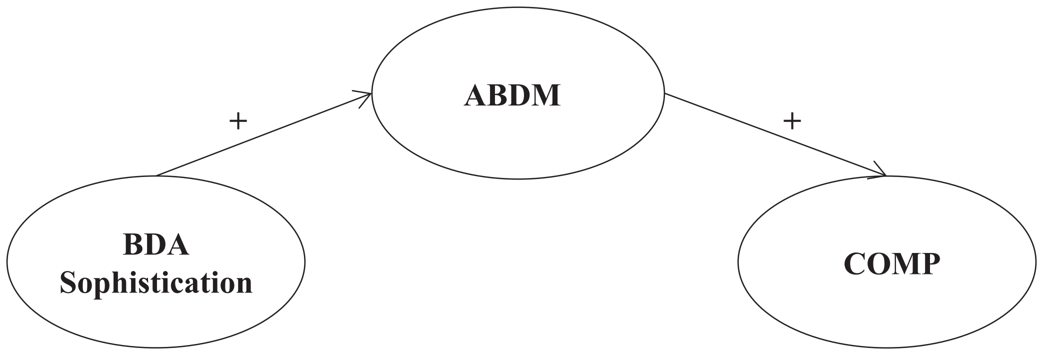


Figure 2 Hypothesis 2

3.3 Moderating Effect of Big Data

Some organisational resources are *complementary resources* which have to work together with other resources and capabilities to generate competitive advantage (Barney 1995). The relationship between Big Data intensity and BDA in affecting ABDM is proposed as an example of such complementarities (Masli et al. 2011). When more sophisticated analytic tools and methods are used with higher volume and variety of data, the analytic outputs are expected to be better quality.

Big Data intensity in itself is not expected to have a positive effect on ABDM. Just because an organisation has access to and uses a greater volume and variety of rapidly changing data will not per se create an incentive for managers to use that data for decision-making. Actually, it is more likely to be the reverse in that, in the absence of proper BDA, Big Data intensity will more likely result in information overload, which will make it more difficult to understand and process the data (Pfeffer and Sutton 2006a; Rousseau 2006; Yang et al. 2003), and more likely deter managers from using it.

However, when more sophisticated analytic tools and methods are used with 'bigger' data, the analytic outputs are expected to offer greater insights than BDA based on smaller and less diverse datasets, and will therefore be used more for decision-making. Managers will perceive the analytic outputs as of better quality and hence more useful. As a result, they will make more of their decisions based on analytic outputs. So while Big Data intensity is expected to have a weak direct impact on ABDM, its impact on ABDM in combination with BDA is expected to be significant.

It could be argued that sophisticated BDA is of little value for decision makers in organisations which use little data. Organisations which use Big Data are expected to benefit substantially from using advanced BDA tools and methods to gain insights from Big Data. In other words, the 'bigger' the data used by an organisation, the stronger the impact of BDA on ABDM.

It is therefore hypothesised that Big Data intensity has a positive moderating effect on the relationship between BDA and ABDM. With higher intensity of Big Data in an organisation, the positive influence of BDA on ABDM is expected to be stronger (Figure 3).

H3: The positive relationship between Big Data Analytics (BDA) sophistication and analytics-based decision-making (ABDM) is moderated by Big Data (BD) intensity.

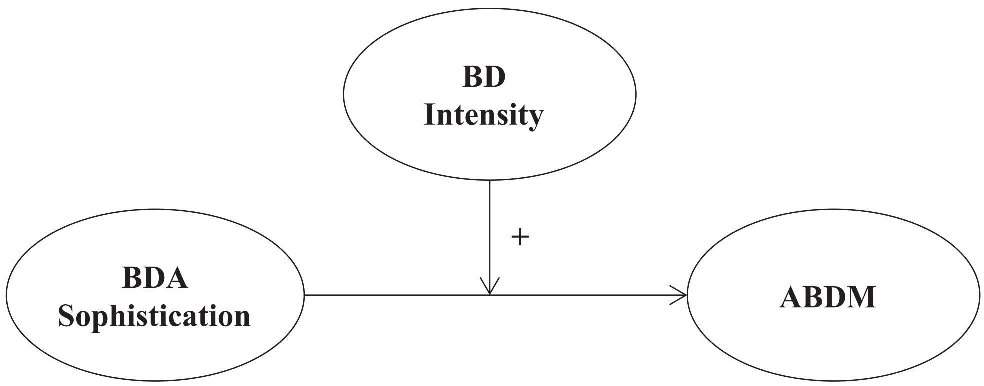


Figure 3 Hypothesis 3

3.4 Organisational Analytic Culture, Big Data Analytics, and Competitive Advantage

It is also debatable whether such competitive advantage is *sustainable* and what the underlying drivers of sustainable competitive advantage are. RBT research suggests that organisational resources create competitive advantage when they have VRIN components (Barney 1991).

This raises the question whether Big Data and BDA are just organisational assets or whether they are organisational resources. On the one hand, practitioners and researchers claim that BDA is valuable (Rexar Analytics 2013) and analytic expertise is rare (Davenport and Patil 2012). On the other hand, large amounts of data are available to most organisations and many analytic tools are available online for free. Analytic professionals can be recruited from the job market or sourced from consulting firms. Outsourcing also decreases the possibility of finding unique and non-substitutable resources. In this context, BDA does not comply with the VRIN requirement, so BDA might create competitive advantage, but it may not be sustainable.

Organisational culture is one of the organisational resources that cannot be imitated or duplicated easily by competitors (Barney 1991). To build organisational culture takes time and effort, something that other organisations cannot easily replicate, particularly not within a short period of time or through simple acquisition.

OAC refers to the extent organisations perceive data analytics to be beneficial. OAC is shown by how organisations recognise the value of analytics and whether or not fact-based decisions are encouraged and rewarded. OAC has been previously recognised as a source of competitive advantage (Leidner and Kayworth 2006; Naor et al. 2008) and something that enhances organisational and therefore financial performance (Marcoulides and Heck 1993). Senior management that is committed to analytics is also a primary driver for organisations to compete via analytics (Davenport et al. 2005).

OAC is reflected not only in the way people in organisations interact with analytics, but also how their managers support investment and operations related to analytics. Organisational culture bonds intelligence of an individual and organisation's core values in establishing a culture of excellence (Asiaei and Jusoh 2015).

Organisations with an analytic culture tend to support more investment in analytic assets such as Big Data, more sophisticated analytic tools, methods and skills. When an organisation has a culture that realises the importance of BDA, it also reflects on how an organisation designs analytic processes (Holsapple et al. 2014). As a result, the sophistication level of BDA tends to be higher if organisations have a culture that supports data-sharing and advanced analytics.

As stated in Hypothesis 1, a higher level of BDA sophistication is expected to enhance competitive advantage. It is further hypothesised that organisations with a strong analytic culture achieve competitive advantage via higher levels of BDA sophistication (Figure 4).

H4: Organisational analytic culture (OAC) has a positive indirect effect on competitive advantage (COMP) via Big Data Analytics (BDA).

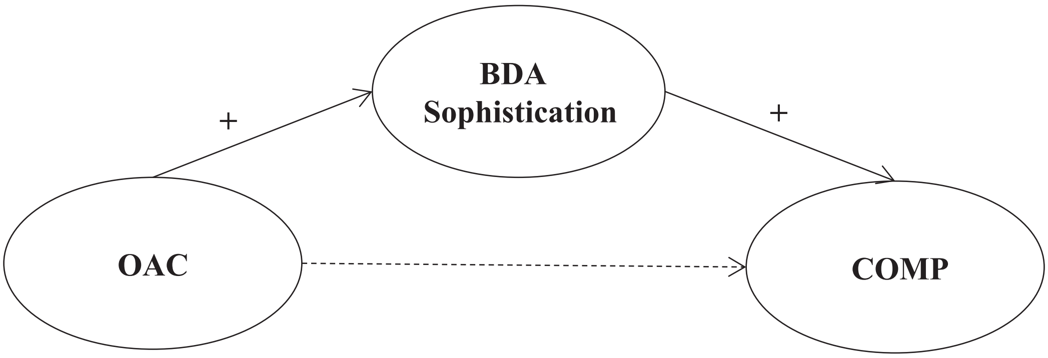


Figure 4 Hypothesis 4

3.5 Organisational Analytic Culture, Analytics-Based Decision-Making, and Competitive Advantage

OAC also influences the managerial decision process. One aspect of culture that should be emphasised is managerial attitude toward the benefits and use of analytics (Davenport et al. 2001). Managers in fact-based cultures may perceive information as more useful (Chakraborty et al. 2008). Analytic culture is reflected in organisations in such a way that senior managers perceive analytics as useful and beneficial, and they therefore seek advice from analysts before making decisions.

Across different organisational cultures, managers tend to behave and perceive benefits of analytics differently. If managers think that information is of better quality and can improve their work performance, they will perceive it as being more useful (Davis 1989). If organisations have a culture that acknowledges the benefits of BDA, managers will tend to use analytics to support their decisions, rather than using intuition.

It is hypothesised that there is a positive indirect influence between OAC and competitive advantage via ABDM (Figure 5). In organisations with a stronger OAC, managers support and realise the usefulness and quality of analytics. Therefore, they tend to make more of their decisions based on analytic outputs. When managers make more analytics-based decisions, their decision quality will be better in support of competitive advantage.

H5: Organisational analytic culture (OAC) has a positive indirect effect on competitive advantage (COMP) via analytics-based decision-making (ABDM).

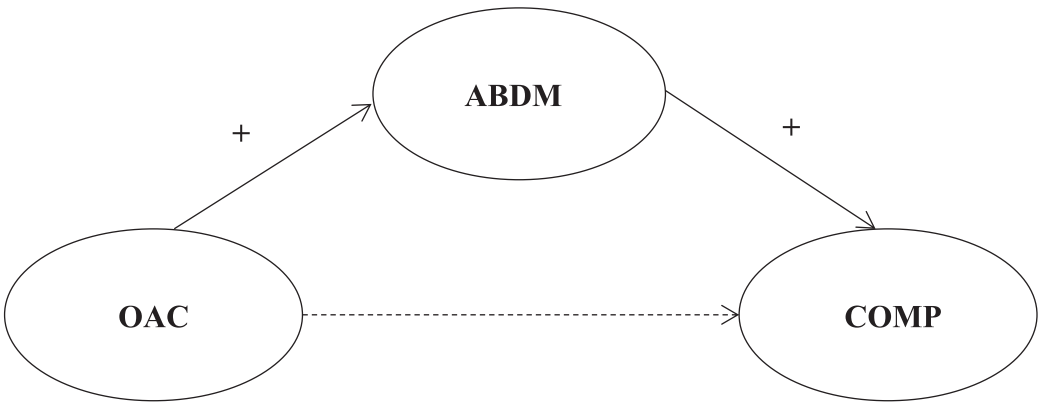
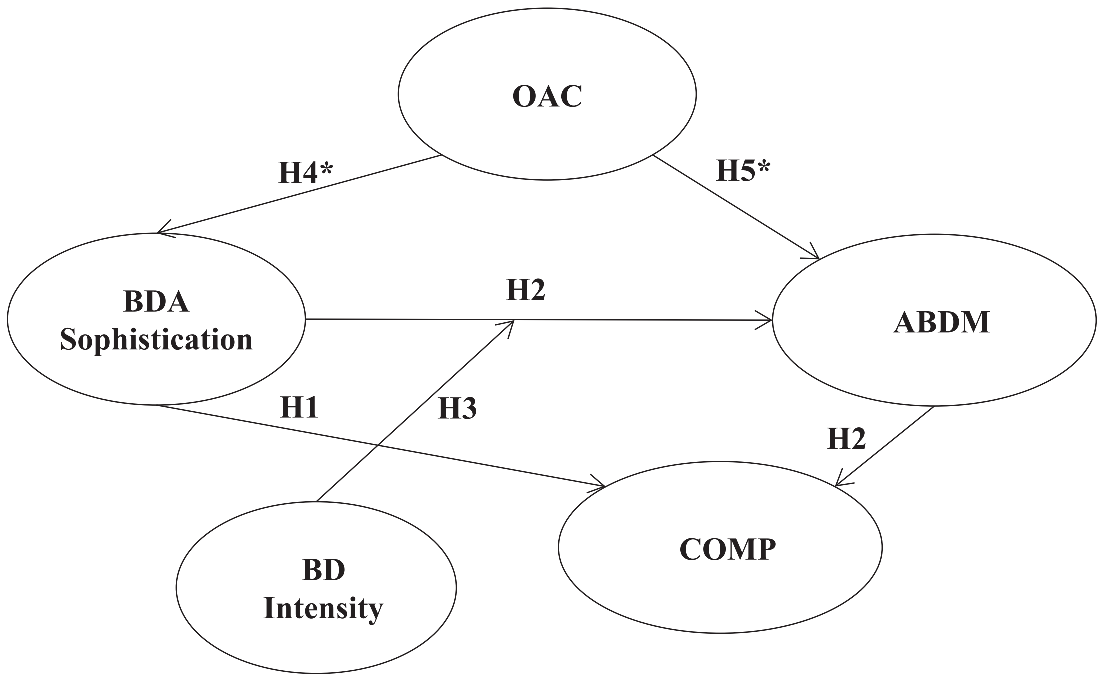


Figure 5 Hypothesis 5

3.6 Conclusion

All five hypotheses are shown in Figure 6. The first hypothesis expects that a higher level of BDA sophistication leads to better competitive advantage (H1). The second hypothesis adds a mechanism that is expected to enhance the previous relationship. To what extent managers make decisions based on analytic outputs – analytics-based decision-making (ABDM) – is hypothesised as a mediator in the relationship between a level of BDA sophistication and competitive advantage (H2). The third hypothesis expects that a high level of Big Data moderates a relationship between BDA and ABDM (H3).

Then, RBT is applied in an attempt to define mechanisms that drive analytic organisations to sustainable competitive advantage. OAC is hypothesised as a primary driver for organisations competing in analytics. The next hypotheses represent indirect relationships between OAC and competitive advantage via BDA (H4) and ABDM (H5).



* *Mediation Hypotheses*

Figure 6 Research Model

CHAPTER 4 – RESEARCH METHOD

This chapter discusses the research method used to test the hypotheses. Section 4.1 describes the rational for selecting an online cross-sectional survey as the data collection method. Section 4.2 explains the survey design and considerations to control or minimise any potential common method biases. Section 4.3 describes how the latent constructs are developed and measured. Last, Section 4.4 provides a rationale for the sample selection.

4.1 Data Collection Method

A *cross-sectional survey* was selected as the data collection method. There are two main reasons for this approach. First, surveys can be used to collect data from various contexts not previously available or observable, such as respondents' beliefs and preferences (Bloomfield et al. 2016; Nelson and Skinner 2013). Unobservable variables that cannot be measured directly, but can be inferred from other variables, are known as *latent variables* (Molloy et al. 2011). Surveys are appropriate to derive latent variables which are then analysed quantitatively (Bloomfield et al. 2016).

Second, this research is exploratory in nature by attempting to understand the associations between partly new constructs and those which have not yet been associated. Surveys are favoured when researchers try to explore and test for preliminary concepts (Pinsonneault and Kraemer 1993). They provide an opportunity to build new theory from previously not hypothesised associations between constructs.

Other data collection methods are less appropriate for a number of reasons. *Archival studies* involve a large amount of data and provide high statistical power to test for association (Bloomfield et al. 2016). However, no archival data is available to test the proposed hypotheses.[3] *A case study* was considered because it aims to study in depth and gain a better understanding of a certain phenomenon. It was later eliminated because the interpretation of case study research findings is limited in broader contexts. Even multi-case studies have small sample size thereby causing a lack of power for tests of association (Ahrens and Chapman 2006).

Big Data Analytics (BDA) is typically developed gradually over multiple smaller projects, rather than on one specific 'go-live' date. When the researched phenomenon does not have an explicit start and end date, Rindfleisch et al. (2008) recommend a cross-sectional rather than a longitudinal survey. The latter is only relevant when it is thought that the impact of the construct-of-interest occurs rapidly after the incident (Pinsonneault and Kraemer 1993). Differences across industries, especially in terms of BDA sophistication, are also not expected. Taking all these things into consideration, a cross-sectional survey is considered to be the most appropriate research method for the hypotheses studied in this research. The survey covers multiple industries and consequently research findings can be applied to organisations in general with less limitation than a study carried out in a specific industry.

Survey procedures used follow the suggestions of Dillman et al. (2014). A mixed mode survey was considered initially because it can reduce coverage error, improve response rates, reduce nonresponse error, and reduce measurement error (Dillman et al. 2014). However, an online survey is a survey medium with low cost, and it can reach the target respondents instantaneously. In addition, research shows that online survey results are not statistically different from paper surveys (Grandcolas et al. 2003). Therefore, this research uses an online survey only.

[3] Organisational performance data maybe available for publicly listed companies, but many of the responses are private companies.

4.2 Questionnaire Development

Each variable specified in the hypotheses is latent which is intangible and cannot be directly observed or quantified (Molloy et al. 2011). Constructing proper measurements/indicators for latent constructs which provide an indirect measurement of the original unobservable concepts is required (Borsboom et al. 2003). A questionnaire[4] was designed and constructed to capture the latent variables specified in the research model such as ABDM and OAC. The operationalisation of the constructs was based on prior academic literature (see section 4.3), but where required, practitioner literature was also consulted.

In designing the questionnaire, special consideration was given to the fact that there are several potential sources of common method bias. Data collected from a questionnaire can be influenced by the wording used as well as characteristics of respondents (Nelson and Skinner 2013). Common method bias can be either random or systematic and can arise from four potential sources: (a) common source or common rater, (b) item characteristics, (c) item context, (d) measurement context (Podsakoff et al. 2003). Necessary procedural remedies were applied, based on Podsakoff et al. (2003), to control for and minimise the impact from these common method biases (Appendix A).

There are many question types used in questionnaires e.g. multiple-choice, scales, matrix scales, as well as open questions. Each indicator statement was clearly defined and represented each construct properly. The matrix scale type of question is appropriate to capture multiple responses which have the same response categories,

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[4] This research project was approved by the UTS Human Research Ethics Committee (HREC) on 6th October 2015. The approval number is UTS HREC REF NO. 2015000619. Later, the amended application was approved by the UTS HREC on 1st December 2015.

thereby increasing the efficiency of the survey in terms of length and respondents' time (Schuman and Presser 1996).

In survey instruments, Likert scales are widely used to measure the extent of agreement or disagreement on a symmetric scale using a set of indicator statements (Albaum 1997; Dillman et al. 2014). Items should be designed based on the principle of symmetry and balance, and presented in plain English. The scales translate respondents' views on subjective dimensions into quantitative values.

The use of heterogeneous scales is recommended to prevent common method biases (Rindfleisch et al. 2008). To control for consistency and scale anchor bias, a mix of five-point and seven-point Likert scales were used. With this variety of scale formats and anchors, respondents are less likely to perceive the similarity or pattern of questions asked (Rindfleisch et al. 2008).

A draft questionnaire was developed, designed to be concise and simple in order to increase the likelihood of participation. The *face and content validity*, as well as the appropriateness of Likert scale endpoints of the survey instrument, were assessed (Podsakoff et al. 2003; Podsakoff et al. 2012). Five experts in survey research were invited to evaluate the draft research instrument and were asked for suggestions to improve it. Three of them were experts in survey research methods and have experience in questionnaire design. The other two experts were data analysts who have an in-depth of knowledge about analytic tools and methods. They were invited to assess the appropriateness of constructs related to Big Data, BDA, ABDM, OAC and competitive advantage, as well as the appropriateness of the survey instrument design and Likert scales. Their feedback was used to refine the design and content of the survey.

The revised version of the questionnaire was then delivered to a small sample group of experts for review and piloting. Fifteen data analysts and business/IT university lecturers were contacted via email and asked for their feedback. In the pilot test invitation email, the objective of the survey was explained. The assessors' feedback and any issues which arose during the piloting were taken into consideration.

4.3 Construct Measurement

4.3.1 Big Data Analytics

Chapter 2 explains how both academics and practitioners have attempted to define BDA. BDA refers to scientific methods and procedures used to discover and manage various types and formats of data (Accenture 2013; Conway 2010; Davenport and Patil 2012; Harris et al. 2010; McAfee and Brynjolfsson 2012; Minelli et al. 2012; Stubbs 2014; Tambe 2014). In the Big Data era, the sophistication level of BDA varies from basic to advanced analytic tools and methods.

In this research, BDA is conceptualised as a two-dimensional, second order construct, which refers to technical analytic tools and, indirectly, technical skills required to use these methods. BDA contains two components (Acito and Khatri 2014): (a) analytic tools and (b) analytic methods, so both of these have to be captured to indicate the level of BDA sophistication. In the next chapter, analytic tools and methods are grouped as sub-constructs to build a second order construct – BDA.

Analytic tools refer to software applications that analytic professionals use in data analytics. They range from basic to advanced quantitative tools represented in spreadsheets, BI tools, statistical packages, data mining suites, data visualisation tools, and high performance computing tools.

Prior to piloting the survey, the draft questionnaire contained nine indicator statements for analytic tools. Based on feedback received from the pilot, this section was revised to ensure that each indicator statement captures only one category of analytic tools. Therefore, fine-tuning of wording to clearly explain each indicator statement, and examples of each, were introduced to ensure that sophistication and complexity of analytic tools were captured properly. Eight indicator statements were retained in the final version (Table 1). Respondents were asked to rate their analytics expert or team using a seven-point Likert scale in terms of frequency of use of each analytic tool, with 1 = never and 7 = very frequently.

Table 1 Indicators for Analytic Tools

Indicator	Statement
Tool_1	Spreadsheets *(Excel)*
Tool_2	Business Intelligence Planning/Reporting Suites *(typically partly to fully centralised, client-server or cloud based applications built upon e.g. Business Objects, Cognos, etc.)*
Tool_3	Data Extraction/Cleaning/Loading/Management Solutions *(data warehouses e.g. SAP BI, Teradata, etc., but also tools like OpenRefine, DataWrangler, Sed, Awk)*
Tool_4	Statistical Suites – Basic Use *(use of user-friendly, menu-based statistical/mathematical software like SPSS, SmartPLS, etc. without programming or scripting)*
Tool_5	Statistical Suites – Advanced Use *(use of statistical/mathematical software like SAS, R, STATA, MatLAB, etc., with programming or scripting)*
Tool_6	Specialised Data Mining Suites *(e.g. SAS Enterprise Miner, Rapid Miner, KNIME, etc.)*
Tool_7	Data Visualisation Tools *(e.g. Tableau, LUMIRA by SAP, MatLAB, etc.)*
Tool_8	Big Data/High Performance Computing Tools *(e.g. Hadoop, SAP HANA, etc.)*

Analytic methods refer to quantitative methods that analytic professionals use in data analytics. They include statistical methods, machine learning, data mining, artificial intelligence, operations research, optimisation models, and path modelling (Dhar 2013).

Prior to piloting the survey, there were two sections for analytic practices: (a) analytic methods and (b) programming languages, with a total of three and nine indicator statements, respectively. Based on feedback from the pilot, it was decided that there were overlaps between the sections dealing with analytic methods and programming languages. Therefore, the latter section was dropped and just four indicator statements were retained in the final version (Table 2). Respondents were asked to rate their analytics expert/team on a seven-point Likert scale in terms of frequency of use of each analytic method, with 1 = never and 7 = very frequently.

Table 2 Indicators for Analytic Methods

Indicator	**Statement**
Method_1	Statistical Methods *(e.g. regression analysis, path modelling, factor analysis, Bayesian models, time series analysis, etc.)*
Method_2	Machine Learning, Data Mining, Artificial Intelligence *(e.g. support vector machines, random forests, decision trees, cluster analysis, neural networks, etc.)*
Method_3	Operations Research/Optimisation Models *(e.g. linear programming, Monte-Carlo simulation, data envelopment analysis, etc.)*
Method_4	Path Modelling *(PLS/SEM)*

4.3.2 Big Data

As pointed out in Chapter 2, Big Data is generally characterised by three Vs (volume, variety and velocity) (Chen et al. 2012; Davenport 2014; McAfee and Brynjolfsson 2012). Volume refers to both the amount of data that an organisation can access and its use in analytics. Variety relates to structured, semi-structured, and unstructured data. Velocity represents both the speed of data generation and data processing. In the next chapter, these three Vs are grouped as sub-constructs of a second order construct – Big Data.

Prior to piloting the survey, 17 indicator statements were proposed to capture various aspects of volume, variety and velocity. Based on the feedback received, these indicators were rearranged and used to capture mainly two aspects of each of the 3Vs – data availability and use (Table 3).

Table 3 Indicators for Big Data

Indicator	Statement
BD_1	The volume of all data we have access to has increased significantly over recent years.
BD_2	The volume of all data we use for analysis has increased significantly over recent years.
BD_3	The diversity of unstructured data (text, images, video, etc.) we have access to has increased significantly over recent years.
BD_4	The diversity of unstructured data (text, images, video, etc.) we use for analysis has increased significantly over recent years.
BD_5	The rate of change of all the data we have access to has increased significantly over recent years.
BD_6	The rate of change of all the data we use for analysis has increased significantly over recent years.

Organisations typically do not have a specific ‘go-live’ date when implementing BDA, but rather use a phased-in approach. Therefore, to identify changes which result from Big Data in organisations, it is difficult to refer to a specific point in time. Some organisations may spend just a few years on BDA implementation, while others may ‘implement’ BDA on an ongoing basis. Because each organisation is at a different stage of Big Data assimilation, the words ‘recent years’ were used. Respondents were asked to rate the level of increase of each V (volume, variety, velocity) in terms of (i) data they have access to, and (ii) data they use in analytics in their organisation over recent years, using a five-point Likert scale, in which 1 = strongly disagree and 5 = strongly agree.

4.3.3 Analytics-Based Decision-Making

ABDM refers to the extent to which managerial decisions are based on analytic outputs. According to economic decision theory, managers apply rational procedures to information available in making their decisions (Eisenführ et al. 2010). In the present Big Data era, managers are expected to make more of their decisions based on analytic outputs, where advanced BDA helps integrate the high volume of different types of data to reduce uncertainty (Iselin 1990; Meissner and Wulf 2014; Turban et al. 2015).

Prior to piloting the survey, indicator statements were proposed to capture how overall organisational decisions were made. Based on the feedback received, the questions failed to distinguish between different kinds of decision-making. In an organisation, decisions can be made at many levels: strategic, tactical and operational (Nowduri 2011). Strategic decisions involve how an organisation will initiate new products, services or market channels. They also represent decisions relating to major suppliers and business processes. Operational decisions involve day-to-day decisions in various business functions, e.g. marketing, operation and procurement.

Therefore, the indicator statements were adjusted to capture these different decision categories (Table 4). Tactical decisions were excluded because they were deemed to be in a 'grey area' between strategic and operational decisions. Respondents were asked to rate the level of their organisational decisions relying on insights derived from data analysis and analytics on a seven-point Likert scale, in which 1 = strongly disagree and 7 = strongly agree.

Table 4 Indicators for Analytics-Based Decision-Making

Indicator	Statement
ABDM_1	Our organisation relies heavily on insights derived from data analysis/analytics, when making decisions about *new products/ services/market channels*.
ABDM_2	Our organisation relies heavily on insights derived from data analysis/analytics, when making decisions about *strategic/key suppliers*.
ABDM_3	Our organisation relies heavily on insights derived from data analysis/analytics, when making decisions about *outsourcing/business processes management*.
ABDM_4	Our organisation relies heavily on insights derived from data analysis/analytics, when making *sales and marketing* decisions.
ABDM_5	Our organisation relies heavily on insights derived from data analysis/analytics, when making decisions about *operations*.
ABDM_6	Our organisation relies heavily on insights derived from data analysis/analytics, when making *procurement* decisions.
ABDM_7	Overall, our organisation acts on insights.

4.3.4 Organisational Analytic Culture

Organisational culture refers to a collection of values, beliefs, knowledge, attitudes and habits which are shared among members of an organisation, so as to provide a frame of reference that indicates organisational practices (Hofstede et al. 1990; Khazanchi et al. 2007; Leidner and Kayworth 2006). OAC is manifested in how people in an organisation assess the value of analytics, their use of data to support operations and decision-making, as well as sharing data within an organisation.

OAC is demonstrated in organisations in various ways. Analytic culture can be seen by how people in organisations recognise the value of analytics. It may be observed in the way senior managers perceive analytics as a strategic resource which helps to generate competitive advantage (Davenport et al. 2001). The more managers believe in the value of analytics, the more they tend to seek advice from analysts before making decisions (Garg et al. 2003).

In high-analytic organisations, OAC manifests itself in how people actually use analytics and its output (Chau et al. 2002). The use and sharing of data analytics is expected to be encouraged. Analytics-related investments should be made, e.g. hiring analytic professionals, purchasing analytic tools and new technology (Leidner and Kayworth 2006; Ramakrishna et al. 2011).

Prior to piloting the survey, there were 13 indicator statements used to capture OAC. Based on feedback received, four indicators were removed because they were related to the resources available, rather than the attitude of the organisation. One indicator was added to highlight whether organisations acted upon an explicit Big Data strategy. After these adjustments, respondents were asked to rate the level of their organisations' analytic culture based on seven statements (Table 5), using a seven-point Likert scale, in which 1 = strongly disagree and 7 = strongly agree.

Table 5 Indicators for Organisational Analytic Culture

Indicator	Statement
OAC_1	Fact-based decision making is encouraged and rewarded.
OAC_2	It is easy to convince my organisation of the value of analytics.
OAC_3	Managers in general seek advice from analysts before making decisions.
OAC_4	My organisation has a culture which encourages the sharing of data.
OAC_5	Senior non-IT managers consider data analytics as a strategic resource and/or potential source of competitive advantage.
OAC_6	Senior non-IT managers support investment in people, tools, and technologies to support data analysis.
OAC_7	Our organisation acts upon an explicit Big Data strategy.

4.3.5 Competitive Advantage

Competitive advantage can be measured by comparing performance of an organisation with major competitors (Peteraf and Barney 2003). When using archival data, researchers usually measure performance either with market performance measures (stock market return, Tobin's q) or accounting performance measures (profit margin, turnover ratios) (Dehning and Richardson 2002). Performance can be measured either at the business process level (operational efficiency) or the organisation level (productivity, efficiency, profitability, market value) (Melville et al. 2004).

The pilot survey included three performance indicators: sales growth, market share, and profitability (Peters et al. 2016). Mixed feedback was received which ranged from the indicators being too specific, identifying a particular financial ratio, or too general so as to capture overall performance. As the target respondents were CIOs and senior IT managers, they were expected to have enough knowledge to answer general aspects of performance rather than be familiar with detailed accounting numbers. As a result of these comments, one additional indicator was added, resulting in four survey questions (Table 6). Respondents were asked to rate their organisational performance, relative to their competitors, in the past 12 months, using a seven-point Likert scale, in which 1 = much worse and 7 = much better.

Table 6 Indicators of Competitive Advantage

Indicator	Statement
COMP_1	Sales growth (relative to major competitor in the market)
COMP_2	Cost reductions (relative to major competitor in the market)
COMP_3	Market share (relative to major competitor in the market)
COMP_4	Profitability (relative to major competitor in the market)

4.4 Selection of Target Respondents and Survey Delivery

The target respondents had to have adequate subject-matter knowledge to answer all survey questions. This appeared challenging, considering the survey asked about both IT and financial performance. One option considered was to ask multiple people within the organisation to complete different parts of the survey and then join those parts together for analysis. This technique may reduce any self-reporting bias, but it is likely to result in a significantly lower response rate.

In this research, respondents needed to know: (a) the status of data analytics in their organisation, in particular the frequency and level of use of analytic tools and methods; (b) analytic culture; and (c) performance. The ideal target respondents were, therefore, analytic professionals, IT-related managers, or senior financial managers. Analytic professionals are difficult to locate in organisations, because they can be assigned to many different organisational units. Senior financial managers, such as CFOs, have good knowledge of organisational performance, but may have limited knowledge of technical aspects of BDA. Therefore, IT-related managers seemed a reasonable and reachable target. In addition, to ensure that respondents were able to answer questions about culture and organisational performance, only chief information officers (CIOs) and senior IT managers were targeted.

To facilitate and make indicator statements clear to CIOs and senior IT managers, the organisational performance questions avoided financial statement jargon. CIOs and senior IT managers were deemed to be able to identify the overall level of profitability improvement, but not specific financial statement jargon, e.g. Earnings Before Interest, Tax, Depreciation and Amortisation (EBITDA).

The target respondents should have worked for their organisations long enough to have knowledge about the recent history of Big Data, BDA, and organisational performance. Therefore, time in their current position was controlled, namely only respondents who had worked in their current position and in the organisation for more than three months were included in the final data analysis.

The questionnaire contained no questions which would require the respondents to reveal sensitive information about him/herself, but asked for the organisation's name. As far as the organisations are concerned, no sensitive information was asked for. The organisation name was required to potentially collect publicly available financial data as alternative measure of competitive advantage. Responses were assured that only aggregate data would be published.

The list of potential respondents was purchased from an Australian company which supplies business-to-business marketers targeting the mid to large company sector in Australia and New Zealand. The list contained the organisation's name, manager's name, position title, and email contacts. Because one of the constructs is organisational performance, only 'for-profit' organisations were selected, and government agencies and not-for-profit organisations were excluded.

To control for potential self-selection bias, contacts were selected from the dataset using simple random sampling. Only those who (a) have worked with their current employer for at least three months, and (b) in Australian organisations of more than 50 FTE employees in any industries, were included.

Considering all the above criteria for target respondents selection, a total of 1,837 email contacts were received from the marketing provider. However, later during validation of the email list, it was found that 57 of the contacts were duplicates. A further investigation based on a LinkedIn search also found that 185 of the contacts had already left their respective organisations. A total of 242 contacts were therefore excluded from the original email list (Table 7).

Table 7 Exclusion of Contacts

Total Contacts Provided	**1,837**
Contacts excluded due to same organisation as another contact	57
Contacts found to have left organisation	185
Total Contacts Excluded	**242**
Potential Survey Recipients	**1,595**

The first e-mail invitation with a link to the online survey was sent out to 1,595 contacts in August 2016. The survey was conducted in multiple rounds with two week intervals, each of which provided recipients with an opt-out option (Appendix B). The final reminder email was sent out in September 2016. The survey was open for eight weeks.

4.5 Summary

This research uses an online cross-sectional survey to explore the nature and associations between the constructs of interest. There are five constructs: BDA (analytic tools and analytic methods), Big Data, ABDM, OAC and competitive advantage. Each construct in the hypotheses is a latent variable. The questionnaire was designed and developed based on both academic and practitioner literature, with a mix of five-point and seven-point Likert scales. Proper procedures were applied to control for or minimise the potential of common method biases, for example keeping the questions precise and concise, providing examples where thought necessary, and avoiding complicated syntax or jargon. The draft questionnaire was reviewed and piloted, and the feedback was then used to refine construct measurement.

The target respondents were Chief Information Officers and senior IT managers.[5] Only those who have worked in their current role for at least three months, in Australian for-profit medium-to-large organisations (> 50 FTE employees), in any industries were selected.

[5] Senior IT managers included IT directors and IT managers.

CHAPTER 5 – DATA ANALYSIS AND RESULTS

This chapter begins with a quantitative analysis and a statistical description of the survey responses (Section 5.1) in order to provide a better understanding of the respondents' demographical data. Section 5.2 shows additional statistical tests performed to identify whether there is a potential non-response or common method bias. The section also presents statistical results of data validity and reliability tests to ensure that the measurement model is valid and reliable. After ensuring that each construct is valid and controlled for potential biases, a PLS model was developed and analysed (Section 5.3). Bootstrapping was then performed to determine the statistical significance of the construct loadings, and path coefficients of a structural model. Section 5.4 discusses the results of hypotheses testing, i.e. the hypothesised total, direct and indirect effects between the constructs.

5.1 Survey Response

The initial invitation was sent out to 1,595 potential respondents via email. Of which, 263 emails were rejected as the address was invalid. As a result, the actual number of survey recipients was 1,332.

Respondents were given the option to voluntarily provide their organisation's name with the initial plan to collect publicly available information of the respondents' organisations from a database for the purpose of measuring organisational performance. However, only 23 respondents provided the organisations' name and only 10 of those were public companies. Therefore, comparison with archival data was not possible.

A total of 174 responses were received during the survey period and all responses were examined to ensure that they met the required criteria. There were no incomplete surveys because all questions, excluding the organisational name, were completed as required. Responses where less than five minutes were spent completing the survey were excluded because it is substantially less than the expected time to complete the survey and it was concluded that no enough consideration had been given to the responses. Excluded from further analysis are respondents who: (a) had worked in their position for less than three months (1 response), (b) had worked in organisations which had less than 50 FTE employees (2 responses), or (c) spent less than five minutes to complete the survey (8 responses). The final usable responses were 163, which represents a 12.24% response rate (Table 8).

Table 8 Survey Responses

Target Sample	**1,595**
Emails returned undelivered	263
Total invitations delivered	**1,332**
Responses received after the first invitation	38
Responses received after the first reminder	50
Responses received after the second reminder	45
Responses received after the third reminder	41
Total Survey Responses Received	**174**
Excluded responses:	
Respondent time in current position (less than 3 months)	1
Size of organisation (less than 50 FTE employees)	2
Response time (less than 5 minutes)	8
Final Sample	**163**
Usable Response Rate (Final Sample/Total Surveys Delivered)	**12.24%**

The response rate may appear low but is not unusual in Australian business surveys, even more so on a topic which is emerging. However, response rates depend mostly on how the sample is selected (Sivo et al. 2006). According to an email list validation performed in

Chapter 4, many of the contacts were expired, indicating that the initial sample provided by the marketing provider was out of date.

Regardless of response rate, sample size is also important. In a structural model, a minimum sample size is 10 times the largest number of structural paths directed at a particular construct (Gefen and Straub 2005; Hair et al. 2016). The largest number of structural paths is three (Figure 6); therefore, the minimum sample size is 30. The sample of 163 is larger than the minimum size required for PLS, therefore the sample size is more than adequate.

Table 9 Industry Response

Industry	Responses	%
Agriculture	2	1.2
Mining	5	3.1
Manufacturing	23	14.1
Utilities	2	1.2
Construction	12	7.4
Wholesales	6	3.7
Retail	21	12.9
Transportation	10	6.1
Internet-Based Commerce/Services	13	8.0
Banking and Finance	12	7.4
Insurance	5	3.1
Real Estate	2	1.2
Consulting	8	4.9
Education	2	1.2
Medical and Health Care	18	11.0
Art and Recreation Services	2	1.2
Technology	11	6.7
Telecommunication	6	3.7
Other	3	1.8
Total	163	100.0

The characteristics of usable responses were reviewed to identify the respondents' background, and also to identify any evidence of certain respondents' characteristics that were over or under represented in the sample data. First, the sectional distribution was analysed (Table 9). Agriculture, utility, real estate, education, art and recreation services have low participation, approximately 1.2% of total responses each. High response industries are manufacturing, retail, medical and health care, with more than 10% responses.

As responses come from within business units of larger organisations, often from industries with different classification to their parent company, industry classification provided by the marketing provider may be inconsistent with the responses received. Therefore, industry comparison between initial contacts and responses was ignored.

The test of coefficient of variation (CoV) was performed to compare spread of the responses and Australian industry.[6] Results confirm that the spread of the responses reflects Australian industry, as shown by the CoV of survey responses is 0.844 while that of Australian industry is 0.843.

Firm size can affect decision-making rationality (Garg et al. 2003; Mintzberg and Waters 1982) and systematically influence organisational practices and organisational performance (Baum and Wally 2003; Garg et al. 2003). Especially small firms were not considered to have invested in BDA. Firm size was measured using the number of FTE employees. Organisations with less than 50 FTE employees are normally categorised as small organisations (IRS 2017) and were excluded.

[6] Australian industry is identified by total quarter income from sales of goods and services (http://www.abs.gov.au/ausstats/meisubs.NSF/log?openagent&5676004.xls&5676.0&Time%20Series%20Spreadsheet&4F30F3929062337ECA2580D1000BBBFB&0&Dec%202016&27.02.2017&Latest)

Organisations participating in the survey are medium to large organisations in terms of full-time equivalent employees (Table 10). In particular, 84% of responses came from organisations which have more than 100 FTE employees.

Table 10 Organisational Size

Size Category	Responses	%
50 – 100	26	16.0
101 – 500	67	41.1
More than 500	70	42.9
Total	163	100.0

Position levels of respondents in the organisations varied (Table 11). CIOs, chief technology officers, IT directors, and general managers–IT are classified as 'senior managers', whereas IT managers and other positions are classified as 'middle managers'. Other positions included analytics manager, network manager, and solution manager. Senior- and middle-level IT managers were almost equally represented (52.1% and 47.9%, respectively). When respondents are at a high enough level in the organisation, they have not only sufficient knowledge of the level of analytic tools and methods used in their organisations, but also a greater understanding of their organisational culture, managerial decision style, and organisational performance.

Table 11 Position Name

Position Name	Responses	%
Chief Information/Technology Officer	47	28.8
IT Director	32	19.6
General Manager – IT	6	3.7
IT Manager	70	43.0
Other	8	4.9
Total	163	100.0

Most of the respondents have worked in their organisations and positions for a relatively long time (Table 12): 81% of the respondents have worked in their organisations for more than three years, 63.8% of the respondents have been in the position for more than three years, while only 8% have been in the position for less than one year, but more than three months.

Table 12 Time in Organisation and Position

Time	Time in Organisation		Time in Position	
	Responses	%	Responses	%
3-12 months	7	4.3	13	8.0
1-3 years	24	14.7	46	28.2
More than 3 years	132	81.0	104	63.8
Total	163	100.0	163	100.0

In conclusion, the final respondents of 163 (12.24% response rate) are in relevant positions and have sufficient experience in the organisation to answer all survey questions. With their characteristics, it can infer that they know the status of data analytics in their organisations, OAC, as well as organisational performance.

5.2 Analysis of Data Characteristics and Data Quality

5.2.1 Test for Normality

It is not uncommon that survey data using Likert scales is not normally distributed (Zeis et al. 2001). Test for normality were conducted for both indicator data and latent constructs in order to determine appropriate analysis and testing techniques (parametric vs. non-parametric) (Bollen and Stine 1990; Kraska-Miller 2014; Ringle et al. 2012). IBM SPSS Statistics Version 24[7] was used to assess the statistical properties of the indicator and construct data.

[7] IBM Corp. Released 2016. IBM SPSS Statistics for Windows, Version 24.0. Armonk, NY: IBM Corp.

Skewness and kurtosis was analysed to confirm data distribution characteristics (West et al. 1995). The descriptive statistics of all indicators and constructs are presented in Appendix C (Table 21). They show that most variables have values of sample skewness (kurtosis) divided by standard error of skewness (kurtosis) either greater than 2 or less than –2, which suggests that data has significant positive or negative skewness (kurtosis) (Cramer 1997).

There are three indicators with high skew and kurtosis. Tool_1 (spreadsheets) and BD_1 (volume of data available) have significant negative skew and very high kurtosis. These values show that most respondents' organisations use spreadsheets frequently and have had access to significantly larger amounts of data over recent years. The values also show that Method_4 (path modelling) has a significant positive skew, with a mean value of 1.76. In addition, Tool_1 has a negative outer loading, while other indicators have positive values. The Tool_1 and Method_4 indicators were inconsistent with the other reflective indicators and were therefore both dropped from data analysis.

In addition, the *Shapiro-Wilk test* and the *Kolmogorov-Smirnov test* show that none of the indicators are normally distributed ($p \leq 0.05$) (Appendix C, Table 22). Therefore, distribution-free statistical tests such as non-parametric, PLS, and bootstrapping are considered appropriate data analysis techniques (Hair et al. 2014).

5.2.2 Method Bias

In addition to the procedural remedies applied during the development of the survey, post-hoc statistical remedies were used to test for potential method bias (Podsakoff et al. 2003). *Harman's single factor test* is used to determine the number of factors that are accounted for by the variance of indicator variables. The test was run across the set of 36 measurement indicators. The results show that there are eight factors with eigenvalues greater than 1 and the first of these factors explains 31.437% of the total variance (Appendix C, Table 23). These results indicate that common method variance due to method bias is not present.

5.2.3 Non-Response Bias

Non-response may answer differently from those who respond to a survey. Data collected from survey respondents can be systematically different from non-responses – known as *non-response bias* (Sax et al. 2003). In order to estimate any non-response bias, researchers often use the extrapolation method, which assumes that respondents who respond late have similar characteristics as non-respondents (Armstrong and Overton 1977).

Responses were tested for non-response bias by comparing early and late responses. The early response group (n = 83) comprises the replies received after the survey invitation and the first survey reminder, while the late group (n = 80) contains those received after the second and third survey reminders. Mean values of each group are compared by performing independent samples test (*Levene's Test for Equality of Variances and t-Test for Equality of Means*) (Appendix C, Table 24). The test results confirm that there are no significant differences in the indicator values between the early and late response group.

5.3 Partial Least Squares Analysis

PLS regression was selected to analyse the path model and test the hypotheses; this method is free from normal distribution assumptions and suitable for small data sets (Chin 1998). PLS is appropriate in exploratory research and when latent variable scores are used in higher order modelling. It is also suitable for indirect effect and moderator-mediator analysis (Gefen and Straub 2005; Hair et al. 2014; Hair et al. 2011). PLS is a variance-based statistical method that finds a linear regression (construct loading) of exogenous latent variables to predict endogenous latent variables in the pre-specified structural equation model.

PLS-SEM relies on the non-parametric bootstrapping procedure to determine the statistical significance of the outer weights, outer loadings, path coefficients, etc. (Hair et al. 2014, 2016). Bootstrapping refers to a resampling process where a number of subsamples are taken randomly from and then returned to the original sample (Efron and Tibshirani 1993). It enhances the reliability of estimations of standard error and confidence intervals. The bootstrapping resampling is random, so even though there is a chance that each process on the same dataset may produce different subsamples, its impact on reliability is not significant assuming a large number of samples.

'SmartPLS' version 3.2.6 (Ringle et al. 2015) was used for PLS analysis. All constructs in the PLS model were tested for convergent and discriminant validity (indicators and constructs) (Hulland 1999). Bootstrapping with 5,000 iterations was applied as the resampling technique to estimate the significance of the paths (Efron and Tibshirani 1993; Hair et al. 2014, 2016). Construct loadings were calculated in order to assess their significance. The structural model was then developed to determine direct and indirect effects.

5.3.1 Measurement Model Quality

A *reflective measurement model* was used to describe the relationships between the indicators and the constructs. Multiple indicators were used to measure a latent variable construct, assuming that they are more accurate and represent the different aspects of variable concepts, resulting in a higher level of measurement validity.

However, there is a chance that a construct and the value obtained from a measurement are different – known as a *measurement error*. In a reflective measurement model, as a rule of thumb (Hair et al. 2014, 2016), each indicator's loading should be higher than 0.70 to be acceptable – this shows that most of the variance observed in the indicator is explained by the latent variable. If the loadings are between 0.40 and 0.70, they should be justified for their theoretical relevance. Constructs should be removed only when the elimination of those indicators increases the measurement reliability. Indicators with loadings below 0.40 should be eliminated. Indicator loadings for each reflective construct were calculated with the PLS regression algorithm.

After the elimination of low-loadings and irrelevant indicators, all remaining indicators were calculated for their significances by a bootstrapping procedure (in SmartPLS). All indicators have a significance level of $p \leq 0.001$ and load primarily on their assigned construct (Appendix C, Table 25).

Table 26 in Appendix C shows *discriminant validity*, i.e. each indicator's loading on the associated constructs compared to the other constructs (cross-loadings). All indicators have an outer loading value on their own construct (theoretically associated) greater than all of its loadings on other constructs.

The measurement model was further assessed for the reliability and validity of the construct measures. Reflective measurement models are assessed for (i) the internal consistency (composite reliability), (ii) indicator reliability (composite reliability), (iii) convergent validity (average variance extracted and communality), and (iv) discriminant validity (Chin 1998; Hair et al. 2014, 2016).

Table 13 confirms that the first three of these criteria are fully met. *Internal consistency* and *indicator reliability* can be measured by either composite reliability or Cronbach's alpha. All constructs have high composite reliability ($\rho \geq 0.60$) and Cronbach's alpha ($\alpha \geq 0.70$). In terms of *convergent validity*, all constructs have an average variance extracted (AVE) and communality scores greater than 0.50, indicating that, they explain more than half of the variance of the indicators. However, communality values of Big Data's 3Vs are not statistically significant.

Table 13 Measures of Validity and Reliability

	Composite Reliability	**Cronbach's Alpha**	**Average Variance Extracted (AVE)**	**Communality (rho_A)**
Tools	0.861***	0.807***	0.508***	0.810***
Methods	0.911***	0.855***	0.774***	0.867***
Volume	0.868***	0.711***	0.768***	0.809
Variety	0.831***	0.595***	0.711***	0.603
Velocity	0.858***	0.691***	0.752***	0.839
ABDM	0.936***	0.918***	0.710***	0.920***
OAC	0.880***	0.828***	0.597***	0.836***
COMP	0.866***	0.787***	0.625***	0.827***

1-tailed: $p \leq 0.05$; $p \leq 0.01$**; $p \leq 0.001$****

Fornell-Larcker criterion was applied to assess for *discriminant validity* of latent constructs, i.e. comparing the square root of the AVE values of each construct against the highest Spearman correlations (ρ) with any other construct (Fornell and Larcker 1981). Table 14 demonstrates that all latent constructs meet the Fornell and Larcker (1981) criterion for discriminant validity.

Table 14 Fornell Larcker Criterion for Discriminant Validity (First Order)

	Tools	Methods	Volume	Variety	Velocity	ABDM	OAC	COMP
Tools	**0.713**							
Methods	0.592	**0.880**						
Volume	0.339	0.337	**0.876**					
Variety	0.284	0.248	0.381	**0.843**				
Velocity	0.323	0.325	0.714	0.593	**0.867**			
ABDM	0.363	0.384	0.398	0.260	0.374	**0.842**		
OAC	0.453	0.394	0.400	0.145	0.353	0.616	**0.772**	
COMP	0.349	0.182	0.189	0.002	0.184	0.417	0.407	**0.791**

However, Henseler et al. (2015) find that both the Fornell-Larcker criterion and cross-loading examination are inadequate to detect the absence of discriminant validity in variance-based structural equation modelling. The heterotrait-monotrait (HTMT) ratio between the average of the heterotrait-heteromethod correlations and the average of the monotrait-heteromethod correlations (Henseler et al. 2015) is used to further ensure discriminant validity. An HTMT value of two latent constructs of less than 0.85 confirms discriminant validity between the pair.

Table 15 reveals that there are some measurement ‘overlaps’ between the ‘3 Vs’ of Big Data. Considering that they are used to form a second order formative construct, this minor lack of discriminant validity is not considered a concern.

Table 15 HTMT Values for Discriminant Validity (First Order)

	Tools	Methods	Volume	Variety	Velocity	ABDM	OAC
Methods	0.718						
Volume	0.432	0.418					
Variety	0.412	0.347	0.577				
Velocity	0.405	0.395	1.020	0.920			
ABDM	0.408	0.427	0.474	0.351	0.443		
OAC	0.556	0.474	0.488	0.226	0.425	0.703	
COMP	0.428	0.217	0.233	0.113	0.262	0.484	0.509

In summary, all constructs met the common quality criteria (Chin 1998; Hair et al. 2014, 2016; Henseler et al. 2015). The reflective measurement models are reliable and valid in terms of (i) the internal consistency, (ii) indicator reliability, (iii) convergent validity, and (iv) discriminant validity.

5.3.2 Structural Model

A structural path model depicts hypothesised connections between constructs based on theory and logic (Hair et al. 2014, 2016). The constructs to be examined can consist of multiple levels; therefore a higher-order model is required. In contrast to unidimensional constructs, second order constructs involve more than one dimension (Edwards 2001; Wetzels et al. 2009). The use of higher order constructs allows for more theoretical meaningfulness, less model complexity, better matching of the level of abstraction for predictor and criterion variables, and higher degree of reliability and validity.

The discriminant validity tests presented in Section 5.3.1 have identified that, except Big Data, all the first order constructs are distinct in their own right. Derived from the joint concepts of first-order constructs, in this study, BDA is operationalised as a second order construct based on analytic tools and analytic methods, and Big Data is a second order aggregate of volume, variety and velocity.

The second order formative latent variables were calculated following the two-stage approach (Ringle et al. 2012; Wetzels et al. 2009). Specifically the second order formative latent variables BDA and Big Data were constructed using the block of underlying first order indicators from the underlying first order reflective constructs. The weights and p-values of the respective sub-constructs calculated using the PLS algorithm are reported in Figure 7. In the final structural model analysis, the latent variable scores of the higher level formative constructs were used as single indicators of the higher order constructs in the structural model (Becker et al. 2012).

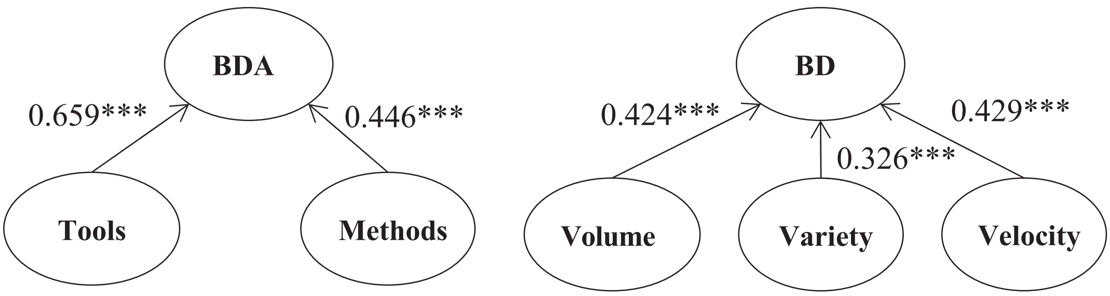

Figure 7 Formative Second Order Constructs and Weighting Values

In addition, to assess the discriminant validity of the final structural model, Fornell-Larcker criterion and HTMT ratio were assessed (Fornell and Larcker 1981; Henseler et al. 2015). Table 16 and Table 17 show that all constructs meet the Fornell-Larcker and HTML criterion for discriminant validity, respectively.

Table 16 Fornell Larcker Criterion for Discriminant Validity

	BDA	BD	ABDM	OAC	COMP
BDA	**0.699**				
BD	0.405	**0.732**			
ABDM	0.402	0.404	**0.843**		
OAC	0.481	0.353	0.615	**0.773**	
COMP	0.301	0.161	0.418	0.402	**0.791**

Table 17 HTMT Values for Discriminant Validity

	BDA	BD	ABDM	OAC
BD	0.471			
ABDM	0.451	0.455		
OAC	0.569	0.413	0.703	
COMP	0.376	0.220	0.484	0.509

To rule out multicollinearity, the variance inflation factor (VIF) values were calculated for formative second order constructs. Even though there is no precise criterion or cut-off value which identifies whether VIF is too large (Craney and Surles 2002; O'Brien 2007), the VIF values of both BDA and Big Data are low enough to conclude that there is no multicollinearity detected (Table 18).

Table 18 Collinearity Statistics

	BDA	BD
Tools	1.841	
Methods	1.712	
Volume		2.066
Variety		1.544
Velocity		2.717

Three alternative versions of the final structural model were developed. The first Structural Model (1a) was used to test Hypotheses 1 and 2, using the total and indirect effects between BDA and competitive advantage. The second Structural Model (1b) was developed to determine the moderating effect of Big Data intensity on the relationship between BDA and ABDM; to this end, Big Data and the interaction term BD*BDA were added to the model, as stated in Hypothesis 3. To investigate the mechanisms of how analytic organisations achieve competitive advantage, a third Structural Model (2) was developed. This represents the indirect influences of OAC via BDA and ABDM on competitive advantage (Hypotheses 4 and 5).

5.4 Hypotheses Testing

The results of the PLS analysis and bias-corrected bootstrapping are presented in Table 19. The *indirect effects* are estimated by the product of the coefficients (β) of each of the paths in a mediational chain (Baron and Kenny 1986). The *total effects* are the sum of the coefficients (β) of the direct and indirect path(s) between the explanatory and dependent variables. The *f*-square values demonstrate changes in R-square, which explain effect sizes of direct effects in the structural model.

Table 19 Hypotheses Testing

	Direct Effect (DE)	Indirect Effect (IE)	Total Effect (TE)	*f* Square (DE)
Model 1a				
ABDM → COMP	0.354***		0.354***	0.131
BD → ABDM	0.290***	0.115***	0.405***	0.092
BD → BDA	0.405***		0.405***	0.196**
BD → COMP		0.208***	0.208***	
BDA → ABDM	0.284***		0.284***	0.088*
BDA → COMP (H1, H2)	0.159*	0.101**	0.260***	0.027
R-squares				
ABDM	0.231***			
COMP	0.196***			
Model 1b				
ABDM → COMP	0.354***		0.354***	0.131
BD → ABDM	0.272***		0.272***	0.074
BD → COMP		0.096**	0.096**	
BD*BDA → ABDM (H3)	–0.065		–0.065	0.004
BD*BDA → COMP		–0.023	–0.023	
BDA → ABDM	0.306***		0.306***	0.091*
BDA → COMP	0.159*	0.108**	0.268***	0.027
R-squares				
ABDM	0.235***			
Model 2				
ABDM → COMP	0.354***		0.354***	0.131
BD → ABDM	0.213**		0.213**	0.069
BD → BDA	0.268***		0.268***	0.089*
BD → COMP		0.118***	0.118***	
BDA → COMP	0.159*		0.159*	0.026
OAC → ABDM	0.539***		0.539***	0.437***
OAC → BDA	0.387***		0.387***	0.186*
OAC → COMP (H4, H5)		0.253***	0.253***	
R-squares				
ABDM	0.418***			
COMP	0.196***			

1-tailed: $p \leq 0.05$; $p \leq 0.01$**; $p \leq 0.001$****

5.4.1 Effects of Big Data Analytics on Competitive Advantage (Hypotheses 1 and 2)

Hypothesis 1 proposes that BDA has a significant unmediated effect (total effect) on competitive advantage, and Hypothesis 2 predicts that this effect is achieved through ABDM. The PLS analysis results of the Structural Model 1a, displayed in Table 19 and Figure 8, support all of the hypothesised relationships between these constructs (Hypotheses 1 and 2).

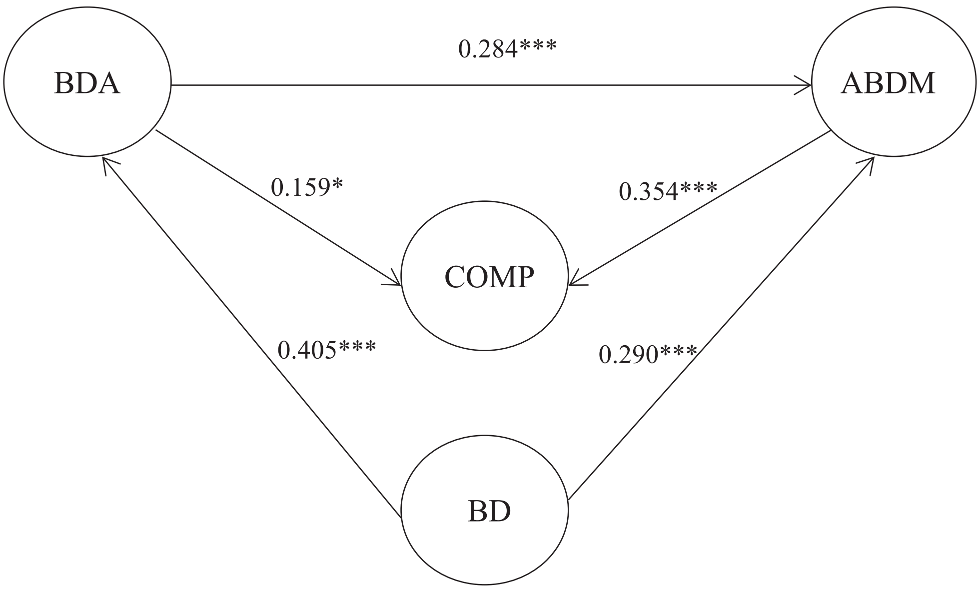

Figure 8 Structural Model 1a

As predicted in Hypothesis 1, there is a significant total effect of BDA on competitive advantage (β = 0.260, p $\leq$ 0.001). The result also confirms Hypothesis 2 that the indirect effect via ABDM is significant (β = 0.101, p $\leq$ 0.01). BDA impacts positively on competitive advantage, *overall* and *indirectly* through ABDM. Furthermore BDA also enhances competitive advantage *directly* (β = 0.159, p $\leq$ 0.05, f = 0.027), irrespective of the level of ABDM. Although the effect size (f square) is rather small, this is not surprising, considering there are many other factors contributing to competitive advantage.

In regards to the R-square values of the endogenous latent constructs, it is evident that the effect of BDA explains a moderate amount of the variation in ABDM (23.1%). The joint effects of ABDM and BDA explain 19.6% of the variance of competitive advantage.

5.4.2 Test of Moderating Effect of Big Data

Hypothesis 3 predicts that the relationship between BDA and ABDM is positively moderated by Big Data intensity. In a moderator model, the influence of the endogenous on the exogenous variable depends not only on the strength of the simple effect of an endogenous coefficient, but also on the product of the endogenous coefficient and moderator's coefficient. To identify moderation effects as proposed by Hypothesis 3, the specification of the simple effect of the exogenous latent variable, the simple effect of the moderator variable, and the interaction of the exogenous variable and the moderator were included (Henseler and Fassott 2010).

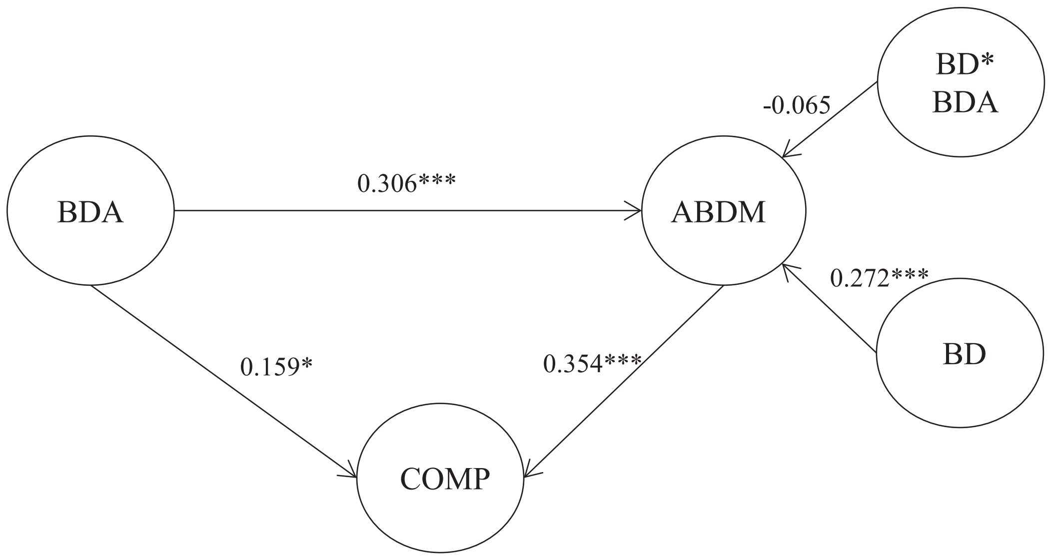

Figure 9 Structural Model 1b

The PLS analysis results of the Structural Model 1b, displayed in Table 19 and Figure 9, reject the hypothesised interaction effect of Big Data on a relationship between BDA and ABDM (Hypothesis 3). Even though the direct effect of an interaction of Big Data and BDA is not statistically significant, the direct effect of Big Data and ABDM is significant ($\beta = 0.272$, $p \leq 0.001$).

Rejecting Hypothesis 3, there is no moderating effect of Big Data on the relationship between BDA and ABDM (β = -0.065, p = 0.199). Even though the result is not statistically significant, the joint effects of BDA, Big Data, and an interaction term explain 23.5% of ABDM. However, this is an insignificant change from the results of Structural Model 1a (23.1%), as *f* square is equal to 0.004 (Table 19).

5.4.3 Test of Indirect Effects of Organisational Analytic Culture on Competitive Advantage

The *indirect effects* of OAC on competitive advantage are predicted to operate via BDA (Hypothesis 4), and via ABDM (Hypothesis 5). The PLS analysis results of the Structural Model 2, displayed in Table 19 and Figure 10, support both hypothesised relationships between the constructs (Hypotheses 4 and 5). The indirect effects of OAC on competitive advantage, via both BDA and ABDM, are significant

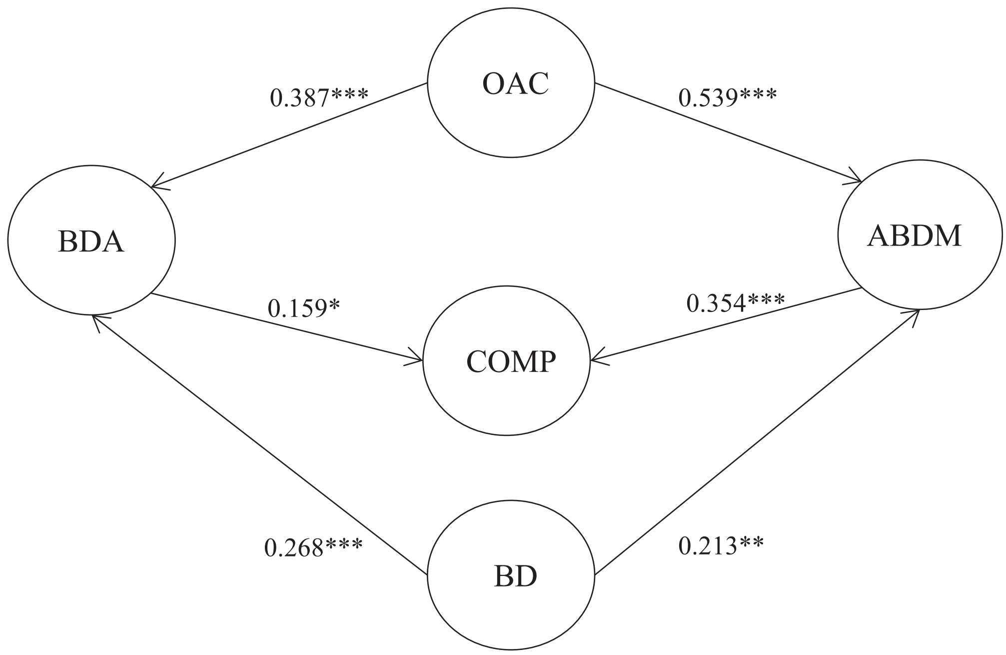

Figure 10 Structural Model 2

Initially the structural model included a path between BDA and ABDM; however, the high correlation between these two constructs causes a substantial suppression effect (zero or negative coefficient) to occur (Cheung and Lau 2008; Maassen and Bakker 2001). This suppression effect artificially inflates the strength of the relationship between OAC and ABDM. Therefore, the path between BDA and ABDM was eliminated in this structural model.

The indirect effect coefficients are calculated as the product of all direct effects in the path. In support of Hypothesis 4, there is a weak but significant indirect effect of OAC on competitive advantage via BDA ($\beta = 0.062$, $p \leq 0.001$), calculated from both strong direct effects between OAC and BDA ($\beta = 0.387$, $p \leq 0.001$) and between BDA and competitive advantage ($\beta = 0.159$, $p \leq 0.001$). The result also supports Hypothesis 5 that the indirect effect between OAC on competitive advantage via ABDM is significant ($\beta = 0.191$, $p \leq 0.001$), because of strong direct associations of OAC and ABDM ($\beta = 0.539$, $p \leq 0.001$) and between ABDM and competitive advantage ($\beta = 0.354$, $p \leq 0.001$). It is concluded that Hypotheses 4 and 5 are fully supported. OAC has an *indirect* positive effect on competitive advantage via BDA and via ABDM.

With regards to the R-square values of the endogenous latent constructs, it is evident that the effect of OAC explains a moderate amount of the variation in ABDM (41.8%).

5.5 Model Fit

Model fit approaches attempt to identify how well a hypothesised structural model fits the underlying data – model misspecifications, but should be interpreted with caution (Hair et al. 2016). The standardised root mean square residual (SRMR) has been recently recognised as a meaningful statistical measure to identify a good fit (Henseler et al. 2014). All SRMR values are less than 0.10 (Table 20), indicating that the three models are a good fit for the empirical data used for analysis (Henseler et al. 2014; Hu and Bentler 1998).

Table 20 Model Fit

	SRMR
Model 1a	0.058***
Model 1b	0.058***
Model 2	0.063***

1-tailed: $p \leq 0.05$; $p \leq 0.01$**; $p \leq 0.001$****

5.6 Summary

The final usable responses were 163, which represents a 12.24% response rate. The response rate may appear low but is not unusual in Australian business surveys. The sample size of 163 is larger than the minimum size required for PLS (Hair et al. 2016). The spread of the responses reflects Australian industry, as shown by the coefficient of variation.

Tests for normality were conducted for both indicator data and latent constructs, and results indicate that none of the indicators are normally distributed. Therefore, PLS-SEM and bootstrapping are used as data analysis and testing techniques. Tests for potential method bias and non-response bias were also performed and results confirm that none of these biases are present.

The measurement model was further assessed for reliability and validity of the construct measures. Results confirm that the models meet (a) internal consistency, (b) indicator reliability, (c) convergent validity and (d) discriminant validity requirements.

All hypotheses, except for Hypothesis 3, are supported. BDA enhances competitive advantage *directly* and *indirectly* via ABDM. A higher level of BDA sophistication has a positive *total* effect on competitive advantage. Also, this relationship is partly mediated by the extent to which managers make decisions based on analytics (ABDM). In addition, the effects of OAC flow through to competitive advantage through BDA and ABDM. In an organisation with analytic culture, there is a higher level of competitive advantage *indirectly* via higher level of BDA sophistication and higher level of managerial decisions based on analytics.

CHAPTER 6 - CONCLUSION

The concepts of 'Big Data' and 'BDA' have become a topic of discussion for both academics and business professionals, especially in IT-related and business fields. However, some practitioners argue that Big Data alone does not provide benefits, but rather it is how managers make sense of data and the insights gained from analysing the data that provides the benefits (Gartner Research 2011; King 2013). Analytic capabilities are required for organisations competing in analytics (Davenport 2014). It has been claimed that BDA leads to better decision-making, improved organisational performance and competitive advantage (Bange and Janoschek 2014). However, none of these claims have so far been confirmed by rigorous empirical research results.

This study explores the following research questions: *Can Big Data Analytics create competitive advantage,* and if so, *What are the mechanisms which drive analytic organisations to achieve this competitive advantage?* To answer these research questions, BDA is operationalised as a combination of analytic tools and methods. Furthermore, the study investigates whether managerial decisions, based on analytics, influence the relationship between BDA and competitive advantage. This study also explores whether OAC influences the relationship between BDA and competitive advantage.

Five hypotheses are developed to identify the direct and indirect relationships between BDA and competitive advantage. The first hypothesis expects that a higher level of BDA sophistication leads to competitive advantage (*H1*). The second hypothesis adds a mechanism that is expected to explain the previous relationship. To that effect, ABDM is hypothesised to be a mediator in the relationship between BDA sophistication and competitive advantage (*H2*). The third hypothesis anticipates that the volume, variety and velocity of Big Data moderate the relationship between BDA and ABDM (*H3*). Then, RBT is applied in an attempt to define the mechanisms that drive analytic organisations to achieve sustainable competitive advantage. It is hypothesised that OAC is one of the primary drivers for organisations competing in analytics. The remaining hypotheses represent the indirect relationships between OAC and competitive advantage via BDA (*H4*) and ABDM (*H5*).

6.1 Summary of Results

Hypothesis 1 suggests that a higher level of BDA sophistication generates competitive advantage (direct and total positive effect). The finding confirms previous anecdotal claims that BDA generates benefits by enhancing organisational performance, thereby creating competitive advantage. New analytic tools and methods make it possible to analyse a greater amount and variety of data, thereby helping to explore and make sense of Big Data. Real-time or near real-time information enables organisations to be more agile than their competitors. In some cases, BDA also directs and/or automates business processes and decision-making.

To find out whether this positive total effect is from both direct and indirect effects, a further investigation of a possible mechanism is proposed. There are inconsistencies in decision-making theory as to what managerial decisions are based on. It is held by some that when managers perceive analytic outputs as useful, they will use these outputs to support their decisions. One possible mechanism that helps BDA to create competitive advantage is therefore the extent to which managers make their decisions based on analytics (ABDM).

The results also confirm a positive indirect effect in *Hypothesis 2*, that is BDA can create incentives for managers to use analytic outputs to support their decisions, which in turn has a significant impact on competitive advantage. The findings support practitioners' claims that BDA solutions help organisations create actionable strategies by providing timely and deeper insights to better understand their customers and businesses. Using increasingly advanced algorithms, BDA can help improve decision efficiency and effectiveness. Thus, in summary, a higher level of BDA sophistication encourages a higher level of ABDM. When managers make more of their decisions based on high quality information, the quality of their decisions will be improved and therefore be more likely to create organisational competitive advantage.

It can therefore be concluded that BDA generates competitive advantage, both directly and indirectly. For the direct effect, the findings confirm practitioner's examples that BDA can be used to directly improve and/or automate business processes and decisions. BDA tools and methods allow automatic interpretation of Big Data. Thus, in summary, implementing BDA alone can benefit organisations in terms of better information triggers to enhance services and increase business opportunities.

However, it is surprising that the moderating effect predicted in *Hypothesis 3* is not significant (and has a negative sign). Big Data alone does not strengthen the relationship between BDA and ABDM, even though the direct effect of Big Data on ABDM is statistically significant. The results suggest the presence of mediating rather than moderating effects. Big Data is strongly related to BDA, confirming that using large and diverse data sets for analysis requires more sophisticated tools and methods, which in turn creates competitive advantage – directly and indirectly. So Big Data in itself positively impacts competitive advantage, but only indirectly. The absence of any moderating effects between Big Data and BDA on ABDM suggests that these resources influence decision making independently, i.e. the level of Big Data and BDA do not have to be 'balanced' to achieve the desired outcomes.

Thus in summary, the relationship between BDA and ABDM is not affected (moderated) by Big Data. In fact, the inclusion of the interaction term changes hardly any result compared to the values in Structural Model 1a. It appears that high levels of both Big Data and BDA drive ABDM 'in their own right', rather than in combination i.e. as complementary resources.

OAC then is considered as a factor that drives both BDA and ABDM, and therefore competitive advantage. The findings from *Hypotheses 4 and 5* indicate that OAC has the predicted effects on BDA and ABDM, thereby indirectly driving and sustaining competitive advantage. Organisations high on analytic culture achieve competitive advantage via higher levels of BDA sophistication. Managers in these organisations also tend to make their decisions based on analytics, rather than on intuition, leading to better decision quality and better performance.

In summary, organisations with high levels of analytic culture generate competitive advantage via two mechanisms: BDA and ABDM. The findings support the theorisation of OAC as an organisational resource, in line with RBT. OAC has an impact on both BDA and ABDM. Organisational culture is still a factor that can sustain competitive advantage, even in the Big Data era. It is argued that BDA is available in the market and can therefore confer competitive advantage only for a short period of time. However, if driven by OAC, a VRIN resource[8], organisations can achieve sustainable competitive advantage.

6.2 Theoretical Implications

This study makes five main contributions to the existing academic literature in relation to BDA, managerial decision-making, analytic culture, and competitive advantage. The *first* contribution relates to the measurement model. This research first focuses on operationalising BDA and Big Data. The operationalisation of the constructs is based on prior academic literature, but where required, practitioner literature is also consulted. This study is one of the earlier empirical research projects attempting to measure BDA and Big Data.

The *second* contribution relates to the research model. Even though a substantial amount of literature has been speculating about the benefits of BDA, so far no large-scale empirical study has been conducted to analyse how BDA can create competitive advantage. The research explains both the direct and indirect relationships between BDA and competitive advantage.

Third, very little is known about mechanisms contributing to the achievement of benefits from BDA, in particular whether managers actually use analytic outputs for decision-making. The findings demonstrate that managers in the Big Data era do 'listen' to analytics. Furthermore, they validate the claims that IS can help to overcome the information overload problem as increases in Big Data lead to more ABDM.

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[8] In RBT, four key characteristics that organisational resources and capabilities require, in order to generate sustainable competitive advantage, are:- valuable, rare, inimitable, and non-substitutable (VRIN).

Fourth, the findings suggest that the main underlying driver of ABDM is OAC, which also manifests in high levels of BDA sophistication. The study is also one of the earliest research projects which synthesises major elements mentioned in prior literature, including analytic tools and methods, Big Data characteristics, managerial decision-making, and analytic culture.

Fifth, the findings suggest that the impact of BDA investments is predominantly driven by culture and not the BDA investments themselves. In other words, organisations which invest in BDA, e.g. by employing advanced analytic professional, creating modern Big Data infrastructures and deploying BDA tools, may create an incentive for managers to 'listen' more to what analytic results suggest. However, in the absence of an analytic culture in the organisation, such impacts will remain marginal.

6.3 Practical Implications

The findings of this study broadly support the existing claims that BDA enhances organisational performance and creates competitive advantage. *First*, the findings empirically confirm the often unverified claims that BDA has an impact on managerial decision behaviour insofar as more advanced analytics creates an incentive for managers to base their decisions on the analytic insights. This research also confirms BDA as a second order construct, derived from two underlying dimensions: analytic tools and methods.

Second, the results provide an insight in how to deal with Big Data in practise and utilise BDA effectively. Managers in organisations which use sophisticated BDA tools and methods tend to base their decisions on analytics more than managers in low-

BDA organisations. However, the analytic culture in an organisation is a stronger predictor of ABDM than the sophistication of BDA practices.

Third, despite some apparent shortage of data analytic skills in the job market, BDA resources can be sourced from markets in a relatively short time. Culture, on the other hand, is generally considered a VRIN resource, because it cannot be changed easily and quickly. Organisations with a strong analytic culture are therefore in a good position to 'compete on analytics', whereas those which have a low analytic culture are well advised to start developing such culture, rather than investing 'blindly' into BDA assets.

6.4 Research Limitations

The findings should be interpreted with caution. While the analysis provides some interesting findings, it should be pointed out that there are a number of limitations to this study. The predominant limitation relates to the survey method and the responses. Despite the fact that several procedural and statistical remedies were deployed to avoid biases, survey-based research is not completely immune to biases. In addition, even though the sample size of 163 is sufficient for PLS-SEM analysis of the model presented, there is little capability for further analysis (e.g. sub-group analysis).

Second, decision-making quality or performance is not measured explicitly. It relies on prior research (Chaudhuri et al. 2011; Guillemette et al. 2014) which suggests that ABDM is associated with better decision-making.

6.5 Future Research Opportunities

There have been a number of issues identified in this study which may be appropriate for further investigation. The survey was based inevitably on IT-centric perspective because respondents were exclusively CIOs and senior IT managers. Future research could attempt to capture a more balanced perception, especially with managerial decision making.

Future research can also be performed in other settings or test the relationships between BDA and other organisational perspectives or other Big Data features. There are many possible organisational factors that could affect these relationships, e.g. business model and management style. In addition, there are a number of questions emerging around Big Data and related security and privacy issues.

APPENDIX A

Common Method Bias and Procedural Remedies

Common Method Bias (Podsakoff et al. 2003)

1. *Consistency motif* – When respondents perceive the similarities of questions asked, leading to produce consistent and rational responses, artificial relationships may have occurred.
2. *Implicit theories and illusory correlations* – Systematic falsification may be introduced if respondents form assumptions about the co-occurrence of survey items.
3. *Social desirability* – False relationships may occur if respondents answer with what they believe to be socially approved and acceptable answers.
4. *Leniency biases* – Relationships discovered may be higher than they should be if respondents answer about items that they know well.
5. *Item complexity and/or ambiguity* – When indicator statements are complex or the meaning is unclear.
6. *Scale format and scale anchors* – When presenting the same scale format and scale anchors, the relationships observed may result from scale properties, rather than from the content of the survey items.
7. *Intermixing items of different constructs on the survey* – When different constructs are mixed in one survey, it may increase the inter-construct correlations and reduce the scale reliability.
8. *Time and location of measurement* – Systematic co-variation may occur when measuring predictor and criterion variables at the same time in the same place.
9. *Use of a common medium to obtain measurement* – The use of different mediums used to gather data may lead to a different level of common method variance.

Procedural Remedies

In order to control for and minimise the impact from common method biases, the following remedies were applied:

1. *Consistency motif* – The survey questions do not ask for respondents' attitude, perception, or behaviour; therefore, it is expected that biases involving respondents' emotion, such as consistency motif, positive/negative affectivity, and transient mood state, are less likely to occur.
2. *Implicit theories and illusory correlations* – No research question was stated in the invitation email, so respondents perceive no direction or overall research questions. Also, using an online survey allowed the backtracking option to be made inactive, so respondents can only answer and continue.
3. *Social desirability* – Respondents were treated as anonymous so social desirability bias is expected to be minimal.

4. *Leniency biases* – Even though the respondents were IT professionals and they were asked IT-related questions, they were not provided the observable or non-observable links between the constructs of interest.
5. *Item complexity and/or ambiguity* – All indicator statements were reviewed and piloted to identify ambiguous or unfamiliar terms. If vague concepts were identified, examples of such concepts are provided. Therefore, questions were simple, specific and concise, and complicated syntax or jargon was avoided.
6. *Scale format and scale anchors* – The matrix format of question was chosen, enabling different indicators with the same scale to be easily measured. Furthermore, the mix between seven-point and five-point Likert scales and different scale endpoints were used. Both end-points and mid-points were labelled. No bipolar numerical scale value is used. These techniques were used to ensure that the co-variation captured by questionnaire results from the content of the item, rather than the scale properties.
7. *Intermixing items of different constructs in the questionnaire* – So as to prevent either confusion or cognitive displacement among respondents, the indicator statements were grouped, rather than mixed between different constructs.
8. *Time and location of measurement* – Predictor and criterion variables were not in the same place.
9. *Use of common medium to obtain measurement* – After trading off between the benefits and accessibility of online survey and potential medium bias, only the online survey was used.

APPENDIX B

Survey Instrument

UTS: BUSINESS

UNIVERSITY OF TECHNOLOGY SYDNEY

For the purpose of this survey, we define:

a) **your organisation** as either a group of companies, an individual company, or a sub-unit within a company *(at the end of the survey, you will have an opportunity to identify what you mean by 'your organisation');*

b) **analytics** as the discovery, interpretation, and communication process to gain insights from data;

c) **analytics expert/team** as the individual or all individuals in an organisation engaging in analytics.

A. Software Tools and Analytics Methods

1. How frequently does your analytics expert/team use the following categories of software?
('not applicable' = 'never')

	1 never	2	3	4 occasionaly	5	6	7 very frequently
a) Spreadsheets (Excel)							
b) Business Intelligence Planning/Reporting Suites (typically partly to fully centralised, client-server or cloud based applications built upon e.g. Business Objects, Cognos, etc.)							
c) Data Extraction/Cleaning/Loading/Management Solutions (data warehouses, e.g. SAP BI, Teradata, etc., but also tools like OpenRefine, DataWrangler, Sed, Awk)							
d) Statistical Suites – Basic Use (use of user-friendly, menu-based statistical/mathematical software like SPSS, SmartPLS, etc. without programming or scripting)							
e) Statistical Suites – Advanced Use (use of statistical/mathematical software like SAS, R, STATA, MatLAB etc., with programming or scripting)							
f) Specialised Data Mining Suites (e.g. SAS Enterprise Miner, Rapid Miner, KNIME, etc.)							
g) Data Visualisation Tools (e.g. Tableau, LUMIRA by SAP, Matlab, etc.)							
h) Big Data/High Performance Computing Tools (e.g. Hadoop, SAP HANA, etc.)							

2. How frequently does your analytics expert/team use methods from the following domains/disciplines?
('not applicable' = 'never')

	1 never	2	3	4 occasionaly	5	6	7 very frequently
a) Statistical Methods (e.g. regression analysis, path modeling, factor analysis, Bayesian models, time series analysis, etc.)							
b) Machine Learning, Data Mining, AI (e.g. support vector machines, random forests, decision trees, cluster analysis, neural networks, etc.)							
c) Operations Research/Optimisation Models (e.g. linear programming, Monte-Carlo simulation, data envelopment analysis, etc.)							
d) Path Modelling (PLS/SEM)							

Next >>

B. Generic Skills and Domain Knowledge

How do you rate the skills of your analytics expert/team in the following areas?

	1 very basic	2	3	4 average	5	6	7 expert
a) Reporting on progress & outcomes	○	○	○	○	○	○	○
b) Understanding the needs of (internal) customers/clients	○	○	○	○	○	○	○
c) Collaborating & contributing to team results	○	○	○	○	○	○	○
d) Developing creative, innovative and practical solutions	○	○	○	○	○	○	○
e) Solving problems	○	○	○	○	○	○	○
f) Liaising with stakeholders & sponsors	○	○	○	○	○	○	○
g) Being open to new ideas & techniques	○	○	○	○	○	○	○
h) Understanding organisational culture	○	○	○	○	○	○	○
i) Awareness of the strategy of the organisation	○	○	○	○	○	○	○
j) Understanding their organisation's performance measurement systems	○	○	○	○	○	○	○
k) Understanding of business processes	○	○	○	○	○	○	○
l) Effectively communicating problems and solutions	○	○	○	○	○	○	○

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C. Management Attributes

1. To what extent do you agree or disagree with each of the following statements about your organisation?
('not applicable' = 'strongly disagree')

	1 strongly disagree	2	3	4 neutral	5	6	7 strongly agree
a) Concerns about data security are a barrier to the greater use of data.	○	○	○	○	○	○	○
b) Concerns about privacy are a barrier to the greater use of data.	○	○	○	○	○	○	○
c) Data gate-keeping is a barrier to the greater use of data.	○	○	○	○	○	○	○
d) Fact-based decision making is encouraged and rewarded.	○	○	○	○	○	○	○
e) It is easy to convince my organisation of the value of analytics.	○	○	○	○	○	○	○
f) Managers in general seek advice from analysts before making decisions.	○	○	○	○	○	○	○
g) My organisation has a culture which encourages the sharing of data.	○	○	○	○	○	○	○
h) Senior non-IT managers considers data analytics as a strategic resource and/or potential source of competitive advantage.	○	○	○	○	○	○	○
i) Senior non-IT managers support investment in people, tools, and technology to support data analysis.	○	○	○	○	○	○	○
j) Our organisation acts upon an explicit Big Data strategy.	○	○	○	○	○	○	○

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C. Management Attributes (cont.)

2. To what extent do you agree or disagree with each of the following statements about managers in your organisation?

	1 strongly disagree	2	3	4 neutral	5	6	7 strongly agree
Senior non-IT managers in my organisation: a) ... have strong analytical skills.	○	○	○	○	○	○	○
b) ... have poor numeracy skills.	○	○	○	○	○	○	○
c) ... have substantial experience with the use of quantitative methods.	○	○	○	○	○	○	○
d) ... are competent in statistics.	○	○	○	○	○	○	○
Middle non-IT managers in my organisation: a) ... have strong analytical skills.	○	○	○	○	○	○	○
b) ... have poor numeracy skills.	○	○	○	○	○	○	○
c) ... have substantial experience with the use of quantitative methods.	○	○	○	○	○	○	○
d) ... are competent in statistics.	○	○	○	○	○	○	○

Next >>

C. Management Attributes (cont.)

3. To what extent do you agree or disagree with each of the following statements about your organisation?

	1 strongly disagree	2	3	4 neutral	5	6	7 strongly agree
Our organisation relies heavily on insights derived from data analysis/analytics: a) ... when making decisions about new products/ services/ market channels.	○	○	○	○	○	○	○
b) ... when making decisions about strategic/key suppliers.	○	○	○	○	○	○	○
c) ... when making decisions about outsourcing/business processes management.	○	○	○	○	○	○	○
d) ... when making sales and marketing decisions.	○	○	○	○	○	○	○
e) ... when making decisions about operations.	○	○	○	○	○	○	○
f) ... when making procurement decisions.	○	○	○	○	○	○	○
Overall, my organisation acts on insights.	○	○	○	○	○	○	○

Next >>

D. Big Data

To what extent do you agree or disagree with each of the following statements about your <u>organisation</u>?

	1 strongly disagree	2	3 neutral	4	5 strongly agree
a) The volume of all data we have <u>access</u> to has increased significantly over recent years.					
b) The volume of all data we <u>use</u> for analysis has increased significantly over recent years.					
c) The diversity of unstructured data (text, images, video, etc.) we have <u>access</u> to has increased significantly over recent years.					
d) The diversity of unstructured data (text, images, video, etc.) we <u>use</u> for analysis has increased significantly over recent years.					
e) The rate of change of all the data we have <u>access</u> to has increased significantly over recent years.					
f) The rate of change of all the data we <u>use</u> for analysis has increased significantly over recent years.					

Next >>

E. Organisational Performance

Refer to the situation in your organisation in the past 12 months. Relative to your competitors or benchmark organisations, how has your <u>organisation</u> performed in the following four areas:

	1 much worse	2	3	4	5	6	7 much better
a) **Sales growth** (relative)							
b) **Cost reductions** (relative)							
c) **Market share** (relative)							
d) **Profitability** (relative)							

Next >>

F. Demographics and Organisational Setting

1. What industry/primary activity is your organisation in?

- Bank and Finance
- Construction
- Consulting
- Education
- Insurance
- Internet-based Commerce/Services
- Manufacturing
- Marketing
- Medical
- Pharmaceutical
- Retail
- Technology
- Telecommunications
- Utilities
- Other, please specify:

2. What is the legal status of your organisation?

- A Publicly Listed Company
- A Private Company

3. 'Your organisation' as referred to in this survey is:

- A group of companies
- An individual company within a group of companies
- An individual company without affiliation
- A sub-unit within a company

4. How many people are employed (full-time equivalent) by your organisation?

- Less than 50
- 50 - 100
- 101 - 500
- More than 500

5. What is the name/title of your position?

- Chief Information Officer
- IT Director
- IT Services Manager
- IT Infrastructure Manager
- Systems/Network Administrator
- Other, please specify:

---

6. Do you currently work as employee or as consultant of your organisation?

- Employee
- Consultant

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7. For how long have you held your current position/role?

- Less than 3 months
- 3 - 12 months
- 1 - 3 years
- More than 3 years

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8. For how long have you been working for your organisation?

- Less than 3 months
- 3 - 12 months
- 1 - 3 years
- More than 3 years

---

9. What is the name of your organisation? (Optional)

This final, optional question, asks for the name of 'your organisation'. We collect this information to be able to use publicly available financial information about your organisation for our analysis. We respect that you may not want to provide such information and prefer to submit the questionnaire completely anonymously.

Next >>

Invitation Letter

Dear <<FirstName>> <<LastName>>,

Our research team is seeking your assistance with a **research study (PhD Project)** which investigates the **status, context and impact of Big Data Analytics in Australian organisations**. Your participation will contribute to a better understanding of the impact and success factors of Big Data Analytics.

The survey should take between 5 and 10 minutes to complete and consists of 6 sections:

a) Software Tools and Analytics Methods
b) Generic Skills and Domain Knowledge
c) Management Attributes
d) Big Data
e) Organisational Performance
f) Demographics and Organisational Setting

You are invited to participate by follow the link <<Survey Link>> or copy the URL <<SurveyURL>> and paste it into your web browser.

As a tangible outcome for completing the survey, we would like to offer you to receive a **Summary Report** before the general survey results are published.

On behalf of the research team, I would like to thank you for supporting our research in general and my PhD project in particular.

Your Sincerely,

Ann Usarat Thirathon
PhD Candidate
UTS Business School
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Main Supervisor:	Co-Supervisor:
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This study has been approved by the UTS Human Research Ethics Committee (approval number UTS HREC REP NO 2015000619). Further information on the study, including privacy and confidentiality details, are available in the Participant Information Sheet.

To unsubscribe: <<OptOutLink>>

First Reminder

Dear <<FirstName>> <<LastName>>,

Two weeks ago, we sent you a request to assist my **PhD project*** by participating in a short survey in relation to the **status, context and impact of (Big) Data Analytics in Australian organisations**. Your participation is valuable to us even if your organisation has not engaged in 'Big Data' initiatives. Your participation will contribute not only to a better understanding of data analytics in Australia, but also will be an essential contribution to my doctoral research.

If you have already completed and submitted the survey, thank you for your input.

If you have not had a chance to take the survey yet, please follow the link <<SurveyLink>>. This survey should take between 5 and 10 minutes to complete.

On behalf of the research team, I would like to thank you for supporting our research in general and my PhD project in particular.

Your Sincerely,

Ann Usarat Thirathon
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To unsubscribe: <<OptOutLink>>

Second Reminder

Dear <<FirstName>> <<LastName>>,

Earlier this month, I sent you a request to assist my PhD project* by participating in a short survey. The project is one of the earlier empirical research attempting to understand the status, context and impact of (Big) Data Analytics in Australian organisations. By completing this survey, you will not only help increase industry understanding and awareness of Big Data in Australia, but will also be an essential contribution to the progress of my doctoral research. Your participation is valuable to me even if your organisation has not engaged in Big Data initiatives.

If you have already completed and submitted the survey, thank you for your input.

If you have not already completed the survey, please follow the survey link <<Survey Link>>, which should take between 5 and 10 minutes to complete.

If you have any concern or queries, please feel free to contact me directly by replying to this email or contacting me by phone at 02 9514 3684. In appreciation for your time and contribution, I will send you a Summary Report before the general survey results are published.

Thank you and kind regards,
Ann

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To unsubscribe: <<OptOutLink>>

Third Reminder

Dear <<FirstName>> <<LastName>>,

Earlier last month, we sent you a request to assist my PhD project* by participating in a short survey. The project is one of the earlier empirical research studies attempting to understand the status, context and impact of (Big) Data Analytics in Australian organisations. By completing this survey, you will not only help to increase industry understanding and awareness of Big Data in Australia, but will also be an essential contribution to my doctoral research. Your participation is valuable to us even if your organisation has not engaged in Big Data initiatives.

If you have already completed and submitted the survey, thank you for your input.

If you have not already completed the survey, please follow the survey link <<Survey Link>>, which should take between 5 and 10 minutes to complete.

If you have any concern or queries, please feel free to contact me directly by replying to this email or contacting me by phone on 02 9514 3684. In appreciation for your time and contribution, we would like to offer to send you a Summary Report before the general survey results are published.

Thank you and Kind Regards,
Ann

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To unsubscribe: <<OptOutLink>>

Participant Information Sheet

Research Project: Big Data Analytics in Australia

UNIVERSITY OF TECHNOLOGY SYDNEY

Participant Information Statement

Background:
Industry and media praise Data Science and Big Data Analytics as the most promising trends for discovering business insight and improving business performance. However, reports show that most managers struggle keeping up with the rapid changes, and many lack understanding of how to use Big Data Analytics to improve business performance (Deloitte 2014, IBM 2013). This academic study is the first of its kind which intends to provide answers to many of the questions surrounding the practises, success factors, impediments and benefits of Data Science and Big Data Analytics in Australia.

Privacy and Confidentiality:
While your cooperation in completing the questionnaire is valued, your participation is voluntary. It is important to note that the results from this survey will be used only in an aggregated form and therefore your anonymity and the confidentiality of your responses are assured. The completed questionnaire will be securely stored and the only people to have access to the details of the questionnaires are the researchers and UTS.

Nature and Extent of Your Participation:
The questionnaire includes questions seeking information about:

a. Software tools and analytics methods
b. Generic skills and domain knowledge
c. Managerial attribute
d. Big Data
e. Organisational performance
f. Demographics and organisational setting

Your decision to complete and submit the questionnaire is taken as consent that you have read the information on this information sheet and that you understand the procedures, that your questions have been answered to your satisfaction, that you understand that you do not have to answer any question, and that you have voluntarily chosen to participate in this study.

Should you have any queries regarding the project or questionnaire, please feel free to contact the main researcher or co-researchers as mentioned in the cover sheet/email invitation.

Ethics and Complaints:
This study has been approved by the University of Technology Sydney Human Research Ethics Committee. If you have any complaints or reservations about any aspect of your participation in this research which you cannot resolve with the researcher, you may contact the Ethics Committee through the Research Ethics Secretariat (phone: +61 2 9514 9772, Research.Ethics@uts.edu.au). Any complaint you make will be treated in confidence and investigated fully and you will be informed of the outcome.

APPENDIX C

Table 21 Indicator and Construct Descriptive Statistics

	Mean	Std. Deviation	Skewness	Kurtosis	Skew/ SE	Kurtosis/ SE
Analytic Tools						
Tool_1	6.55	0.795	–1.831	2.699	–9.637	7.140
Tool_2	4.88	2.056	–0.730	–0.703	–3.842	–1.860
Tool_3	4.32	2.246	–0.263	–1.397	–1.384	–3.696
Tool_4	2.73	1.966	0.808	–0.665	4.253	–1.759
Tool_5	2.42	1.866	1.104	–0.088	5.811	–0.233
Tool_6	2.02	1.593	1.612	1.731	8.484	4.579
Tool_7	3.53	2.215	0.143	–1.456	0.753	–3.852
Tool_8	2.13	1.709	1.358	0.708	7.147	1.873
Analytic Methods						
Method_1	3.44	2.114	0.300	–1.253	1.579	–3.315
Method_2	2.45	1.846	0.965	–0.374	5.079	–0.989
Method_3	2.53	1.789	0.828	–0.587	4.358	–1.553
Method_4	1.76	1.285	1.923	3.490	10.121	9.233
Organisational Analytic Culture						
OAC_1	5.02	1.434	–0.898	0.589	–4.726	1.558
OAC_2	4.83	1.557	–0.635	–0.012	–3.342	–0.032
OAC_3	4.39	1.642	–0.411	–0.750	–2.163	–1.984
OAC_4	4.71	1.485	–0.476	–0.468	–2.505	–1.238
OAC_5	4.96	1.606	–0.682	–0.271	–3.589	–0.717
OAC_6	4.55	1.580	–0.591	–0.309	–3.111	–0.817
OAC_7	3.17	1.853	0.367	–0.995	1.932	–2.632
Analytics-Based Decision-Making						
ABDM_1	4.73	1.667	–0.697	–0.193	–3.668	–0.511
ABDM_2	4.46	1.508	–0.557	–0.073	–2.932	–0.193
ABDM_3	4.32	1.570	–0.542	–0.402	–2.853	–1.063
ABDM_4	4.80	1.576	–0.561	–0.338	–2.953	–0.894
ABDM_5	5.02	1.486	–0.819	0.334	–4.311	0.884
ABDM_6	4.52	1.446	–0.459	–0.137	–2.416	–0.362
ABDM_7	4.78	1.445	–0.664	0.121	–3.495	0.320
Volume						
BD_1	4.51	0.781	–1.962	4.680	–10.326	12.381
BD_2	4.13	0.972	–1.255	1.414	–6.605	3.741
Variety						
BD_3	4.04	0.974	–0.885	0.214	–4.658	0.566
BD_4	3.26	1.159	–0.266	–0.660	–1.400	–1.746
Velocity						
BD_5	4.16	0.831	–0.961	0.962	–5.058	2.545
BD_6	3.77	1.026	–0.676	–0.101	–3.558	–0.267

	Mean	Std. Deviation	Skewness	Kurtosis	Skew/ SE	Kurtosis/ SE
Competitive Advantage						
COMP_1	5.13	1.194	–0.572	0.587	–3.011	1.553
COMP_2	4.72	1.147	–0.050	0.417	–0.263	1.103
COMP_3	4.84	1.133	–0.352	0.617	–1.853	1.632
COMP_4	4.94	1.304	–0.596	0.406	–3.137	1.074

Table 22 Shapiro-Wilk and Kolmogorov-Smirnov Test

	Shapiro-Wilk		Kolmogorov-Smirnov	
	Statistic	**Sig.**	**Statistic**	**Sig.**
Tool_1	0.619	0.000	0.409	0.000
Tool_2	0.849	0.000	0.185	0.000
Tool_3	0.868	0.000	0.172	0.000
Tool_4	0.815	0.000	0.240	0.000
Tool_5	0.761	0.000	0.286	0.000
Tool_6	0.689	0.000	0.340	0.000
Tool_7	0.858	0.000	0.211	0.000
Tool_8	0.705	0.000	0.354	0.000
Method_1	0.880	0.000	0.170	0.000
Method_2	0.771	0.000	0.305	0.000
Method_3	0.805	0.000	0.270	0.000
Method_4	0.655	0.000	0.367	0.000
OAC_1	0.896	0.000	0.200	0.000
OAC_2	0.919	0.000	0.193	0.000
OAC_3	0.927	0.000	0.173	0.000
OAC_4	0.928	0.000	0.172	0.000
OAC_5	0.908	0.000	0.182	0.000
OAC_6	0.920	0.000	0.176	0.000
OAC_7	0.896	0.000	0.177	0.000
ABDM_1	0.908	0.000	0.190	0.000
ABDM_2	0.925	0.000	0.210	0.000
ABDM_3	0.922	0.000	0.183	0.000
ABDM_4	0.924	0.000	0.183	0.000
ABDM_5	0.903	0.000	0.199	0.000
ABDM_6	0.937	0.000	0.183	0.000
ABDM_7	0.920	0.000	0.205	0.000
BD_1	0.655	0.000	0.373	0.000
BD_2	0.788	0.000	0.255	0.000
BD_3	0.829	0.000	0.240	0.000
BD_4	0.910	0.000	0.179	0.000
BD_5	0.808	0.000	0.252	0.000
BD_6	0.868	0.000	0.256	0.000
COMP_1	0.911	0.000	0.189	0.000
COMP_2	0.909	0.000	0.201	0.000
COMP_3	0.916	0.000	0.188	0.000
COMP_4	0.919	0.000	0.187	0.000

Lilliefors Significance Correction, df = 162

Table 23 Harman's Single Factor Test

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	11.317	31.437	31.437	11.317	31.437	31.437
2	3.650	10.138	41.575	3.650	10.138	41.575
3	2.606	7.238	48.814	2.606	7.238	48.814
4	2.040	5.667	54.480	2.040	5.667	54.480
5	1.677	4.659	59.139	1.677	4.659	59.139
6	1.335	3.709	62.848	1.335	3.709	62.848
7	1.136	3.156	66.004	1.136	3.156	66.004
8	1.042	2.893	68.897	1.042	2.893	68.897

Table 24 Independent Sample Test

	Levene's Test for Equality of Variances		t-test for Equality of Means					
	F	Sig.	t	Sig. (2-tailed)	Mean Diff.	Std. Error Diff.	95% Confidence Interval of the Difference	
							Lower	Upper
Tool_1	1.795	0.182	–0.653	0.515	–0.081	0.125	–0.328	0.165
Tool_2	0.529	0.468	–1.868	0.064	–0.597	0.320	–1.228	0.034
Tool_3	0.261	0.610	–1.151	0.252	–0.405	0.352	–1.099	0.290
Tool_4	2.726	0.101	–0.524	0.601	–0.162	0.309	–0.772	0.448
Tool_5	0.807	0.370	–0.935	0.351	–0.273	0.292	–0.851	0.304
Tool_6	9.095	0.003	–1.228	0.221	–0.308	0.250	–0.802	0.187
Tool_7	0.001	0.973	–0.021	0.983	–0.007	0.348	–0.695	0.680
Tool_8	1.963	0.163	0.898	0.371	0.241	0.268	–0.289	0.770
Method_1	0.053	0.818	0.468	0.640	0.156	0.332	–0.500	0.811
Method_2	1.098	0.296	1.089	0.278	0.315	0.289	–0.256	0.886
Method_3	5.457	0.021	–1.206	0.230	–0.339	0.281	–0.893	0.216
Method_4	0.014	0.906	–0.017	0.986	–0.003	0.202	–0.402	0.395
OAC_1	1.260	0.263	–1.484	0.140	–0.332	0.224	–0.774	0.110
OAC_2	0.208	0.649	–1.134	0.259	–0.276	0.244	–0.757	0.205
OAC_3	0.085	0.772	–1.444	0.151	–0.370	0.256	–0.876	0.136
OAC_4	1.025	0.313	–0.639	0.524	–0.149	0.233	–0.609	0.311
OAC_5	0.191	0.663	–1.068	0.287	–0.269	0.251	–0.765	0.228
OAC_6	0.955	0.330	–0.181	0.857	–0.045	0.248	–0.535	0.445
OAC_7	0.739	0.391	0.866	0.388	0.252	0.291	–0.322	0.826
ABDM_1	0.002	0.966	–0.996	0.321	–0.260	0.261	–0.776	0.256
ABDM_2	0.031	0.860	–1.692	0.093	–0.397	0.235	–0.861	0.067
ABDM_3	0.520	0.472	–0.745	0.457	–0.184	0.246	–0.670	0.303
ABDM_4	1.353	0.246	–0.814	0.417	–0.201	0.247	–0.689	0.287
ABDM_5	0.094	0.760	–1.058	0.291	–0.246	0.233	–0.706	0.213
ABDM_6	1.497	0.223	–1.498	0.136	–0.338	0.226	–0.784	0.108
ABDM_7	0.297	0.587	–1.049	0.296	–0.237	0.226	–0.684	0.209
BD_1	0.750	0.388	–0.053	0.958	–0.006	0.123	–0.249	0.236
BD_2	0.161	0.689	–0.354	0.724	–0.054	0.153	–0.356	0.247
BD_3	0.207	0.650	–1.136	0.258	–0.173	0.153	–0.474	0.128
BD_4	0.167	0.684	–0.256	0.799	–0.047	0.182	–0.406	0.313
BD_5	0.251	0.617	–0.233	0.816	–0.030	0.131	–0.288	0.227
BD_6	0.133	0.716	–1.094	0.276	–0.176	0.161	–0.493	0.142
COMP_1	0.723	0.396	–0.419	0.676	–0.079	0.188	–0.449	0.292
COMP_2	0.148	0.701	0.740	0.460	0.133	0.180	–0.222	0.488
COMP_3	0.001	0.975	–0.796	0.427	–0.141	0.178	–0.492	0.209
COMP_4	0.909	0.342	–0.950	0.344	–0.194	0.204	–0.598	0.209

Table 25 Outer Loadings

	Original Sample	P Values
Tools		
Tool_2 ← Tools	0.645	0.000
Tool_3 ← Tools	0.727	0.000
Tool_4 ← Tools	0.747	0.000
Tool_5 ← Tools	0.745	0.000
Tool_6 ← Tools	0.742	0.000
Tool_7 ← Tools	0.664	0.000
Methods		
Method_1 ← Methods	0.887	0.000
Method_2 ← Methods	0.848	0.000
Method_3 ← Methods	0.904	0.000
Volume		
BD_1 ← Volume	0.819	0.000
BD_2 ← Volume	0.930	0.000
Variety		
BD_3 ← Variety	0.818	0.000
BD_4 ← Variety	0.867	0.000
Velocity		
BD_5 ← Velocity	0.792	0.000
BD_6 ← Velocity	0.936	0.000
Analytics-Based Decision-Making		
ABDM_1 ← ABDM	0.861	0.000
ABDM_2 ← ABDM	0.871	0.000
ABDM_3 ← ABDM	0.862	0.000
ABDM_4 ← ABDM	0.830	0.000
ABDM_5 ← ABDM	0.834	0.000
ABDM_6 ← ABDM	0.796	0.000
Organisational Analytic Culture		
OAC_1 ← OAC	0.639	0.000
OAC_2 ← OAC	0.791	0.000
OAC_4 ← OAC	0.737	0.000
OAC_5 ← OAC	0.844	0.000
OAC_6 ← OAC	0.833	0.000
Competitive Advantage		
COMP_1 ← COMP	0.847	0.000
COMP_2 ← COMP	0.527	0.000
COMP_3 ← COMP	0.850	0.000
COMP_4 ← COMP	0.885	0.000

Table 26 Cross Loadings

	Tools	Methods	Volume	Variety	Velocity	ABDM	OAC	COMP
Tool_2	**0.645**	0.198	0.227	0.099	0.103	0.288	0.250	0.281
Tool_3	**0.727**	0.282	0.271	0.112	0.166	0.241	0.266	0.292
Tool_4	**0.747**	0.604	0.275	0.298	0.368	0.303	0.396	0.241
Tool_5	**0.745**	0.546	0.252	0.244	0.272	0.207	0.352	0.232
Tool_6	**0.742**	0.516	0.175	0.251	0.233	0.298	0.340	0.243
Tool_7	**0.664**	0.411	0.261	0.235	0.269	0.173	0.353	0.171
Method_1	0.458	**0.887**	0.294	0.198	0.273	0.337	0.370	0.158
Method_2	0.516	**0.848**	0.302	0.235	0.272	0.284	0.347	0.161
Method_3	0.583	**0.904**	0.295	0.225	0.310	0.384	0.328	0.163
BD_1	0.220	0.228	**0.819**	0.317	0.624	0.263	0.222	0.129
BD_2	0.352	0.344	**0.930**	0.351	0.640	0.411	0.440	0.192
BD_3	0.191	0.189	0.236	**0.818**	0.481	0.203	0.005	0.001
BD_4	0.283	0.227	0.396	**0.867**	0.518	0.234	0.224	0.002
BD_5	0.160	0.189	0.553	0.474	**0.792**	0.225	0.172	0.141
BD_6	0.358	0.344	0.676	0.553	**0.936**	0.391	0.393	0.175
ABDM_1	0.337	0.384	0.399	0.245	0.365	**0.861**	0.557	0.345
ABDM_2	0.366	0.333	0.331	0.208	0.305	**0.871**	0.527	0.349
ABDM_3	0.278	0.343	0.286	0.225	0.332	**0.862**	0.481	0.315
ABDM_4	0.254	0.263	0.380	0.245	0.352	**0.830**	0.441	0.373
ABDM_5	0.303	0.336	0.304	0.179	0.278	**0.834**	0.587	0.388
ABDM_6	0.290	0.273	0.311	0.215	0.258	**0.796**	0.504	0.336
OAC_1	0.272	0.260	0.202	0.013	0.205	0.410	**0.639**	0.308
OAC_2	0.329	0.336	0.433	0.149	0.341	0.478	**0.791**	0.325
OAC_4	0.292	0.308	0.297	0.139	0.211	0.461	**0.737**	0.303
OAC_5	0.428	0.365	0.324	0.157	0.310	0.482	**0.844**	0.265
OAC_6	0.412	0.256	0.279	0.090	0.287	0.537	**0.833**	0.368
COMP_1	0.315	0.174	0.241	0.105	0.271	0.365	0.269	**0.847**
COMP_2	0.213	0.061	0.000	-0.052	-0.046	0.193	0.266	**0.527**
COMP_3	0.253	0.175	0.190	-0.010	0.172	0.367	0.310	**0.850**
COMP_4	0.311	0.145	0.120	-0.058	0.122	0.363	0.436	**0.885**

Note: Tool_1, Tool_8, Method_4, ABDM_7, OAC_3 and OAC_7 were excluded from analysis.

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