Leveraging Business Intelligence and Analytics to Improve Decision-making and Organisational Success

A dissertation presented to the

Department of Information Systems

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By

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ABSTRACT

In a complex and dynamic organisational environment, challenges and dilemmas exist on how to maximise the value of Business Intelligence and Analytics (BI&A). The expectation of BI&A is to improve decision-making for core business processes that drive business performance. A multi-disciplinary review of theories from the domains of strategic management, technology adoption and economics claims that tasks, technology, people and structures (TTPS) need to be aligned for BI&A to add value to decision-making. However, these imperatives interplay, making it difficult to determine how they are configured. Whilst the links between TTPS have been previously recognised in the Socio-Technical Systems theory, no studies have delved into the issue of their configuration. This configuration is addressed in this study by adopting the fit as Gestalts approach, which examines the relationships among these elements and also determines how best to align them. A Gestalt looks at configurations that arise based on the level of coherence and helps determine the level of alignment amongst complex relationships.

This study builds on an online quantitative survey tool based on a conceptual model for aligning TTPS. The alignment model contributes to the conceptual development of alignment of TTPS. Data was collected from organisations in a South African context. Individuals who participated in the survey came from the retail, insurance, banking, telecommunications and manufacturing industry sectors.

This study's results show that there is close alignment that emerges between TTPS in Cluster 6 which comprises of IT experts and financial planners. Adequate training, coupled with structures encouraging usage of Business Intelligence and Analytics (BI&A), result in higher organisational success. This is because BI&A technology is in sync with the tasks it is being used for and users have high self-efficacy. Further analysis shows that poor organisational performance can be linked to gaps in alignment and the lack of an organisational culture that motivates usage of BI&A tools. This is because there is misalignment; therefore respondents do not find any value in using BI&A, thus impacting organisational performance.

Applying a configurational approach helps researchers and practitioners identify coherent patterns that work well cohesively and comprehensively. The tangible contribution of this study is the conceptual model presented to achieve alignment. In essence, organisations can use the model for aligning tasks, technology, people and structures to better identify ideal configurations of the factors which are working cohesively and consequently find ways of leveraging Business intelligence and Analytics.

Keywords: Business intelligence, Data analytics, Decision-making, Alignment

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DEDICATION

I would like to dedicate this dissertation to my family (Joseph Mushore, Loice Mushore, Gwinyai Mushore, Tino Mushore and Tawanda Mushore). God bless you all for your support and encouragement.

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LIST OF ACCRONYMS

AST ....Adaptive Structuration Theory

BI…………………………………………………..Business Intelligence

BI&A………………………………………………Business Intelligence and Analytics

DSS…………………………………………………Decision Support Systems

FSS………………………………………………….Financial Services Sector

IDT………………………………………………….Innovation Diffusion Theory

IT…………………………………………………….Information Technology

IS…………………………………………………….Information Systems

SIS……………………………………………………Strategic Information Systems

STS………………………………………………….Socio Technical Systems Theory

SMME………………………………………………Small, Medium and Micro-sized Enterprise

TAM…………………………………………………..Technology Acceptance Model

TPB………………………………………………….Theory of Planned Behaviour

TRA…………………………………………………Theory of Reasoned Action

TTF…………………………………………………..Task Technology Fit

TTPS………………………………………………Tasks, Technology, People and Structure

CHAPTER 1: INTRODUCTION

Chapter 1 introduces the research study by giving the background of the problem, the primary research purpose and the objectives of the study. This chapter also discusses why the research is significant, outlines the research questions and ends with a discussion of assumptions of the study.

1.1. BACKGROUND AND STATEMENT OF THE PROBLEM

The competitive business environment makes decision-making more important than ever. The role of decision-making is to ensure improved business performance (Schlafke, Silvi & Moller, 2012; Smith, Wilson & Clark, 2006). This has resulted in tremendous developments towards automating technologies that are interfacing with data in order to improve decision-making (Schlafke et al., 2012). One key technology is Business Intelligence (BI), which is widely known for its "*ability to present business information in a fast, simple and efficient way so that users can understand the logic and meaning of business information by employing a wide range of analytical possibilities and ad-hoc queries*" (Hocevar & Jaklic, 2008, p. 89).

BI is also important because of the rapid growth in data. As data continues to grow, managing and analysing it in an optimal way is a critical success factor in creating competitive advantage (Isik, Jones & Sidorova, 2013). According to Bhat & Quadri (2015), growth in data presents opportunities as well as challenges in data analytics. Challenges arise from legacy systems, silo applications and fragmented processes that limit the potential for data analytics optimisation (Bose, 2009; Chaudhuri, Dayal & Narasayy, 2011). Opportunities lie in the ability to synthesise data and critically analyse it so as to draw useful insights (Schlafke et al., 2012; Isik et al., 2013). Resultantly, BI and data analytics tools have emerged as critical applications that can be used to improve decision-making in organisations (Chaudhuri et al., 2011). In this study, BI and data analytics are collectively referred to as Business Intelligence & Analytics (BI&A). BI&A is a set of tools and technologies which are used in enhancing decision-making processes for competitive advantage (Chen, Chiang & Storey, 2012; Davenport, 2010).

As much as technologies continue to advance, a key challenge that remains is the real value obtained from these technologies. Goodhue & Thompson (1995) found that in some cases of successful Information Systems (IS) implementation, organisations still find it difficult to extract full value from their enterprise systems. Observations by Strong & Volkoff (2010) attribute these challenges to a misfit between enterprise applications and different domains of technology implementation. This challenge also affects BI as it does not always add value after implementation (Boyton, Ayscough, Kaveri & Chiong, 2015; Corte-Real, Ruivo & Oliveira, 2014). Reasons cited by Boyton et al. (2015) include poor integration between systems, BI analytics which are not appropriate for the majority of users in an organisation, the solution being run by Information Technology (IT), lack of delegation and poor governance. Importantly, they cite that technological, organisational and cultural issues are not properly addressed, thus contributing towards BI implementation failure.

To curb Information Technology/Information Systems (IT/IS) implementation failure, literature suggests that organisations need their business and information technology strategies to be aligned (Avison et al., 2004; Chan & Reich, 2007; Rashidirad, Soltani & Syed, 2013). Therefore, this notion can also be applied to deal with BI implementation failure. However, it is difficult to reach alignment because strategy is not a clear concept due to various turbulent and unpredictable circumstances (Chan & Reich, 2007). For instance, the alignment between technology, usage, and organisational performance remains unclear and this consequently results in problematic gaps in both industry and academia (Chan, 2002). This problem escalates when companies focus more on the technology component when implementing new technology tools. Furthermore, there is a gap between the business requirements and actual solutions being delivered by BI (Chaudhuri et al., 2011). Lahrmann, Marx, Winter & Wortmann (2011) note that BI topics like efficiency, organisational structures, people and strategy are rarely addressed in research studies. As a result, challenges typified by dilemmas exist in leveraging technologies such as BI&A tools mainly because organisations have not adequately addressed and designed successful artefacts required in implementing technology. From a theoretical perspective, this requires a deep understanding of influencing factors and the ability to properly align these factors (Popovic et al., 2012).

According to Chan (2002, p. 97), alignment is more likely to be achieved "*by emphasizing the management of specific components of alignment, rather than aiming for the seemingly unreachable target of multifaceted, overall alignment*." To date, manifold competing models exist in empirical research, which highlight inconsistent views. Whilst these models have been proposed to ensure implementation success, preliminary review of literature shows little attention is being paid to the interplay between tasks, technology, people and structures. Tasks are work activities that need to be completed (Ammeenwerth, Iller & Mahler, 2006). Technology is the tools and equipment internal or external to an organisation, which in this case is BI, for gathering and analysing data (Ranjan, 2009). People are individuals that implicitly determine adoption and usage of technology based on their behaviour, attitude and skills (Ramdani et al., 2013). Structures are distinct organisational contexts such as firm size, policies, management and culture (Venkatesh, Thong & Xu, 2012).

Statement of the problem: While organisations implement BI&A technology to enhance organisational success through decision-making, they are struggling to extract its full value because they have not adequately addressed the alignment of artefacts required to ensure its success. Little attention is being paid to the interplay between tasks, technology, people and structure. To close the gap of BI&A not adding value, these factors are critical and need to be aligned in order to achieve success.

1.2. RESEARCH OBJECTIVES AND PURPOSE

The primary objective of this study is to identify ways to leverage the value obtained from BI&A, which in turn improves decision-making and organisational success. This is achieved by examining the configuration and nature of alignment between TTPS.

Secondary objectives of the study include:

1. To examine the performance effects and the value created by BI&A based on the configuration and nature of alignment that arises from TTPS
2. To explore the challenges of BI&A utilisation when there is lack of alignment between TTPS

Research purpose classifications include explanatory and exploratory. However, these concepts are not mutually exclusive (Saunders, 2009). According to Shmueli and Koppius (2011), IS research can also be predictive. The emphasis of this study is to explore ways in which organisations can benefit from BI&A through testing a conceptual model in order to clarify and validate the ideal combinations or configurations of TTPS that work cohesively. This is achieved by showing significant interaction in the configurations of TTPS and answering research questions through the application of scientific procedures.

1.3. RESEARCH QUESTIONS

The primary research question is:

PRQ1. How can BI&A be leveraged by alignment of TTPS to improve decision-making and organisational success? This question attempts to confirm whether alignment of TTPS can result in BI&A influencing improved decision-making, which in turn leads to increased organisational success. According to Williams & Williams (2003, p. 5), "*while the alignment process is straightforward conceptually, there are a wide variety of challenges that must be overcome, as with any endeavour in IT*." This study adopts the alignment as Gestalts notion to assess the interrelationships between TTPS and to show their synergies and level of coherence, which can lead to improved organisational performance.

The secondary research questions are:

SRQ1. How does alignment of TTPS impact the relationship between usage of BI&A and organisational success? BI&A success is realised through key benefits, in the form of faster flows and easier access to information, which create increased efficiency and effectiveness of the organisation (Hocevar & Jaklic, 2008; Schlafke et al., 2012). According to Isik et al. (2013), success is related to the positive value an organization obtains from BI investment. As a result, BI has become a critical foundation of competition for many organisations (Shollo, 2010). This question therefore seeks to verify the importance of aligning TTPS in order to leverage the value of BI&A. A proposal can be made that where there is alignment, BI&A has the potential to create learning routines which can improve the effectiveness and efficiency of the business and create value by achieving competitive advantage.

SRQ2. What are the challenges faced by organisations when using BI&A for decision-making when there is no alignment of TTPS? This question aims to provide empirical evidence on the challenges organisations are currently facing. As mentioned earlier, organisations sometimes find it difficult to extract full value from their enterprise systems. Reasons for this include poor integration between systems, BI analytics that are not appropriate for the majority of users, the solution being run by IT, lack of delegation and poor governance (Boyton et al., 2015).

SRQ3. How can strategy implementation and execution be improved to achieve alignment of TTPS so that BI&A can be leveraged as a key technology in analysing data? This question looks at how the configurations that arise from TTPS can be used to leverage BI&A. As mentioned earlier, Lahrmann, Marx, Winter & Wortmann (2011) highlight that BI topics such as efficiency, organisational structures, people and strategy are rarely addressed in research studies. As a result, challenges and dilemmas exist on how to leverage technologies such as BI&A tools mainly, because organisations have not adequately addressed and designed successful artefacts required to leverage the technology.

1.4. RESEARCH SIGNIFICANCE

Managers are challenged by an increase in complexity, uncertainty, volatility and continuous growth in the amount of data in the business environment (Hocevar & Jaklic, 2008; Schlafke, et al., 2012). In order to improve organisational performance, these challenges can be alleviated through alignment of TTPS. According to Chan (2002), studies have demonstrated that alignment and organisational performance are correlated. Therefore, the fundamental importance of alignment is to ensure that imperatives are working in harmony to ensure organisational effectiveness. In this study a conceptual model is proposed to examine the alignment between TTPS. The model is empirically tested using the fit as Gestalts theory, producing new insights regarding Information Systems (IS) and business alignment that have not yet been discovered. This is significant in closing the gap of BI&A not adding value because of a silo approach which disregards a holistic view of influencing factors necessary for BI&A success. Configurations that form between TTPS show their level of alignment and can help predict combinations that allow for BI&A value generation. Researchers and practitioners will benefit by having the ability to identify coherent patterns of association in which TTPS can best reinforce each other comprehensively to enhance organisational success. Organisations can also use the results from this study to create opportunities for learning by creating a distinct understating of how to ensure success through alignment.

1.5. ASSUMPTIONS

Assumptions:

- The researcher assumes that the respondents participating in the study use business intelligence and data analytics tools in their organisations. Traditionally organisations used Excel spreadsheets. However, spreadsheets do not work well with complex data originating from disparate sources. Many organisations have since adopted proprietary and in-house developed Business Intelligence tools spread over databases and visualisation platforms.
- The researcher assumes that the respondents will answer truthfully because of the confidentiality and anonymity clause offered for those participating in the survey.
- Based on the paradigmatic stance adopted, the researcher assumes that reality of the study is objective and therefore the researcher will be separated from the topic under investigation.
- The final assumption is that the study is generalisable and can be replicated.

1.6. DISSERTATION OUTLINE

The rest of the dissertation is organised as follows:

Chapter 2 (Literature Review): This chapter presents a review of peer reviewed academic literature. This section also covers the concepts of BI, data analytics, decision-making and alignment. Four imperatives are extracted from the Socio-Technical Systems theory and their alignment is also discussed. In this chapter, a conceptual model is also developed and discussed.

Chapter 3 (Research Design and Methodology): Chapter 3 describes the research design in terms of the philosophy, approach, strategy and methodology followed during the data collection process. This chapter also explains how the research instrument was developed and used to obtain data from the sample.

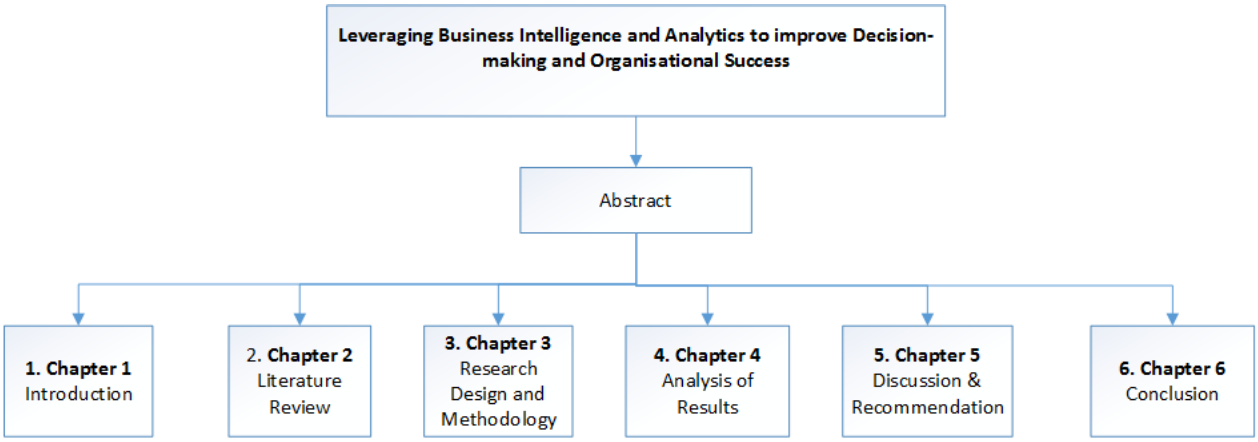
Chapter 4 (Analysis of Results): Chapter 4 presents the data analysis methods used on the data collected and interpretations made from the data analysis process.

Chapter 5 (Discussion and Recommendation): This chapter discusses the implications of the research study and gives contributions for Information Technology (IT) practitioners and researchers.

Chapter 6 (Conclusion): Concludes the thesis and suggests directions for future research.

Prior to the appendices, the work cited in this study is shown in the references section. This is followed by Appendix A, B, C and D which show additional material relevant in conducting this study. Figure 1 below shows the high level dissertation overview.

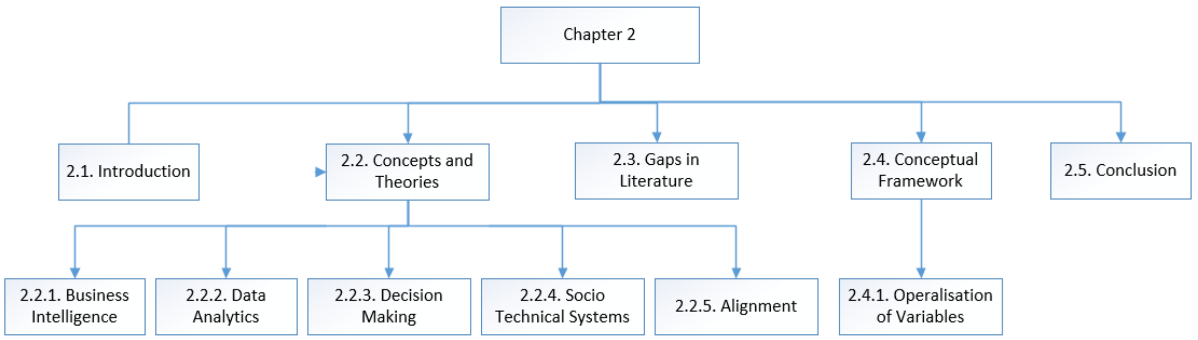
Figure 1: High level dissertation overview



CHAPTER 2: LITERATURE RIVIEW

This chapter provides structure and context to the study. A literature survey was conducted from online academic databases to draw upon knowledge from concepts and theories. Key words used to identify relevant literature included business intelligence, data analytics, decision-making and alignment. Selected literature was grouped; after which a detailed analysis and synthesis of literature was done. A collection of theories from the fields of strategic management, economics and technology adoption were used to help explore the concepts of alignment, decision-making, business intelligence and data analytics. Readings used for this literature survey include peer reviewed conference reports, books, journal papers and abstracts. The structure and layout of the literature review is as follows

Figure 2: High level Literature Review overview



2.1. INTRODUCTION

As data is becoming increasingly abundant, its value is found in contributing towards greater strategic agility and operational efficiency (Barone, Yu, Won, Jiang & Mylopoulos, 2010). This is achieved through the ability of BI to analyse data and facilitate decision-making (Arefin, Hoque & Bao, 2015). However, the benefits of BI can be elusive because of the conceptual gap between IT implementations and business people involved in decision making (Barone et al., 2010). To bridge this gap, this study looks at BI&A as a Socio-Technical System (STS) which involves interacting relationships between TTPS.

STS is made up of a social subsystem and a technical subsystem. The social subsystem comprises of people and structures, and is experienced through organisational culture, roles, common patterns, as well as behavioural patterns that develop (Hester, 2014;

Fuenfschilling & Truffer, 2016). The technical subsystem comprises of tasks and technology (Hester, 2014; Reich & Benbasat, 2000). The dominant view of STS is that technology failure is mostly due to social subsystem components (Hester, 2014). However, a long-time challenge has been the alignment of TTPS (Earl, 1996; Hester, 2014). Some scholars have studied alignment by examining strategies, structures and planning methodologies in organisations while others have looked at the actors in organisations, examining their values, communication with each other, and ultimately their understanding of each other's domains (Miller, 1987). This study proposes that proper alignment between TTPS will result in BI&A providing improved organisational success.

The organisation of the rest of this chapter is as follows. First, a discussion of the concepts of business intelligence, data analytics and decision-making is presented. Theory is used to reinforce, discuss and extract TTPS as the elements that interplay and need to be aligned for BI&A to add value in organisations. Literature is then summarized and a conceptual model is proposed to assess the configurations and level of alignment that will result in BI&A providing improved organisational success.

2.2. CONCEPTS AND THEORIES

2.2.1. BUSINESS INTELLIGENCE

BI is a set of technologies used by people, aimed at providing strategic and tactical information systems that support business strategy (Arefin et al., 2015). Strategic Information Systems (SIS) are defined as tools using knowledge, knowledge transformation and knowledge communication to support business strategy (Ucakturk & Villard, 2013). SIS are important because decision-making situations have become complex and knowledge requirements continue to grow (Koscielniaka & Putoa, 2015; Ucakturk & Villard, 2013). The expectation from BI has always been to improve the effectiveness of the core business processes that drive business performance (Schlafke et al., 2012). However, BI sometimes fails to meet the strategic expectation of accelerating the decision-making process for organisations (Boyton et al., 2015; Shollo, 2011). This could be because the discipline of BI is defined and interpreted differently. BI is sometimes seen as a method of analysing the business environment for example, competitor analyses and market studies (Chaudhuri et al., 2011). Other times, it is taken to mean Information Technology (IT) applications with which the information contained in the company's knowledge systems is refined into visual reports for management (Duan & Xu, 2012). For the purposes of this study, a definition by Chen & Zhang (2014) that describes BI as a set of methodologies, processes, architectures and technologies that leverage the output of information management and decision-making is adopted.

Besides the contrasting definitions, other reasons for BI not meeting strategic expectations include the misfit between enterprise applications and different domains of technology implementation (Strong & Volkoff, 2010). Boyton et al. (2015) note that poor integration between systems, BI analytics which are not appropriate for the majority of users in an organisation, BI solutions being run by Information Technology (IT), lack of delegation and poor governance impact the value obtained from BI. Importantly, they cite that technological, organisational and cultural issues are not properly addressed, thus contributing towards BI implementation failure. This shows that BI has many points of failure from a socio and technical perspective. BI, therefore, encapsulates integrated technology tools with a number of characteristics (Ranjan, 2009).

2.2.1.1. CHARACTERISTICS OF BUSINESS INTELLIGENCE

Distinct Technologies: BI includes architectures, tools, databases, applications and methodologies which converge with the common goal of having access to data for analysis (Moro, Cortez & Rita, 2015; Kasemsap, 2016). It includes a wide variety of concepts and techniques for example Online Analytical Processing (OLAP), data mining, data warehouses and Decision Support Systems (DSS) (Chaudhuri et al., 2011). OLAP allows for dynamic consolidation and analysis of large volumes of information (Williams and Williams, 2003). Data mining is a data extraction method which includes techniques such as correlation analysis and clustering, to detect relational patterns among data entities by using BI tools (Hedgebeth, 2007). These methods identify relationships between dependent and one or more independent variables based on hypothesised estimates (Chen & Zhang, 2014). Application of these techniques in data analysis has been successful to a large extent, but there are critical limitations. For instance, users require domain knowledge of the subject being investigated (Bhat & Quadri, 2014). Data warehouses deal with issues of data storage and information delivery in order to provide an integrated view of vast amounts of transactional data (Moro et al., 2015). Lastly, DSS perform simulations and computations that support decision-making (Kościelniaka & Putoa, 2015). They comprise of computer-based information systems supporting business and organisational decision-making activities (Zhaoa et al., 2012). They rely on a collection of data models, reporting and analysis tools coupled with supporting hardware and software (Kościelniaka & Putoa, 2015).

Fast Processing of data: Rapid availability of information and the ability of decision makers to manipulate information influences decision-making (Daradkeh, Churcher, & McKinnon, 2013). Managers face demands to process more information because of the continuous flow of data (Daradkeh et al., 2013; Metaxiotis et al., 2003). BI involves fast gathering, processing, analysing and transferring of large amounts of data for decision-making (Isik et al., 2013).

Intelligent Data Analysis: Extracting and managing useful knowledge from data sources is currently one of the most popular topics in computing research especially in areas such as data mining, machine learning and computational intelligence (Bello-Orgaz, Jung & Camacho, 2015). BI uses mathematical models for analysing data. Intersecting fields of research such as artificial intelligence, statistics, databases, and machine learning have all proposed building data driven models (Moro et al., 2015). As explained by Banerjee, Bandyopadhyay & Acharya (2013), there are four different models of analytics used for decision-making. The first one is Predictive Analytics. Predictive Analytics is the extensive use of data and mathematical models to uncover explanatory and predictive models of business performance. The second is Descriptive Analytics, which is a set of technologies and processes that use data to understand and analyse business performance. The third is diagnostic analytics which investigate why things happened. The last one is Prescriptive Analytics, which is a set of mathematical techniques that prescribe alternative actions or decisions given a complex set of objectives, requirements and constraints with the goal of improving business performance. It has been long argued that the value of analysing data is emphasised by the positive impact of the information provided on decision-making.

2.2.2. DATA ANALYTICS

Data analytics is a key organisational function used to find patterns, trends and anomalies in information (Arefin, Hoque & Bao, 2015). This requires organisations to properly capture, manage, analyse, understand and visualise the value of this information. Subsequently, this has led to the field of computerised data management (Chen & Zhang, 2014). Data analytics refers to the systematic computational analysis of raw data with the use of BI tools. Data analytics methods are used "*to understand relevant business dynamics, to effectively control key performance drivers and to actively increase organisational performance*" (Schlafke et al., 2012, p. 111). Data analytics is part of a wide ecosystem of acquiring, transforming and distributing information that can help improve decision-making, enhance organisational performance, and ultimately increase profitability (Schlafke et al., 2012).

According to Duan & Xu (2012), BI tools take raw data, and using data analytics methods, turn it into knowledge. Knowledge is intelligence that must be acted upon through decision-making. This is supported by Shollo (2010, p. 5), who says "…i*ntelligence is only produced through decision-making action.*" Therefore, advances in analytics are proving to be an efficient solution to cope with uncertainties and transforming data into business value (Jalolen, 2009). This argument explains why organisations need to invest in analytics technology. Investment in analytics technology is essential and stems from the economics of Information Technology. Bakos & Kemerer (1992) previously used the economic theory to explain the impact and value created by IT. The economic theory looks at economic benefits added by IT by assessing either reduced costs or increased benefits against the true cost of providing IT resources (Bakos & Kemerer, 1992). IT Resources enable the core capabilities of an organisation. Currently, analytics is creating value by making it easier and faster for firms to analyse large volumes of information, compared to other firms who do not use it. Value is also created by enhancing organisational performance (Early, 2014).

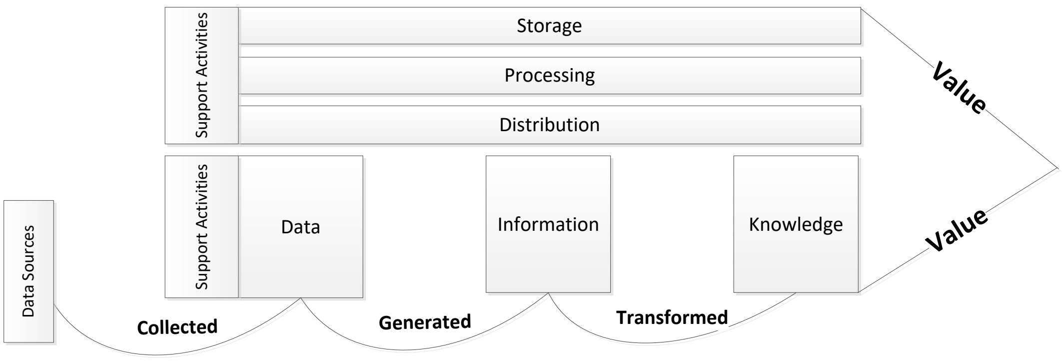
Using the theory of comparative advantage, organisations aiming to create value and business benefit have to identify their capabilities in comparison to what their competitors are not capable of doing despite their financial and human resource advantages (Alles, Kogan & Vasarhely, 2008). In this case, the competitive environment forces organisations to put more focus on BI tools and technology that facilitate faster decision-making (Zhaoa, Lia, Wang & Halanga, 2012).

Even though analytics technology has been around for many years, its application is still relatively underutilised (Early, 2014). This is because analytics "*is not an easy concept or technology for users to understand and use"* (Bose, 2009, p. 166). This could imply that potential adopters face uncertainties regarding the actual benefits of technology. These uncertainties exist even after technology has been deployed (Bakos & Kemerer, 1992). Underutilisation of analytics could also be related to the concept of user acceptance of technology. User acceptance is defined as the willingness within a user group to use IT for the tasks it is designed to support (Dillon & Morris, 1996). Besides user acceptance, organisations may not have the skills to utilise IT effectively or to its fullest potential (Tsiknakis & Kouroubali, 2009). Furthermore, the rate at which technology changes, evolves and advances, introduces challenges and an imbalance between technology and stable systems that are known to work (Bose, 2009, Chaudhuri et al., 2011). Nonetheless, "*businesses are leveraging their data asset aggressively by deploying and experimenting with sophisticated analysis techniques to drive business decisions*" (Chaudhuri et al., 2011, p. 88). The data analytics process inspects, cleans, transforms and models data with the intention of discovering useful information (Bose, 2009). Its success is dependent on a solid information value chain foundation.

An information value chain (see Figure 3) is a plan of how a business systematically manages raw data acquired through various stages and how value is added to that data (Abbasi, Sarker, & Chiang, 2016). It also has its origins rooted in the economic theory of using IT. It comprises of a set of value-adding activities necessary to convert data into information and subsequently transform information into knowledge (Soosay, Fearne & Dent, 2012). Each stage of the value chain is comprised of people, processes and technology, and operates in a context (Abbasi et al., 2016). These elements form an analytics ecosystem which comprises of entities such as data providers, analytics providers and end users (Schlafke et al., 2012). In the analytics ecosystem, data providers are those clients who have content requiring analytics. Analytics providers refer to technology vendors who offer analytics capabilities.

End users are the consumers of data and analytics capabilities (Chen, Kreulen, Campbell & Abrams, 2011).

Figure 3: Information Value Chain (Abbasi, Sarker, & Chiang, 2016)



The intention of analytics is to leverage data and analytics to maximise business value (Chen et al., 2011). As such, an effective analytics ecosystem involves interaction between intelligence, data and analytics to create business value (Soosay et al., 2012)). In this study, business intelligence and data analytics are closely related and collectively referred to as Business Intelligence & Analytics (BI&A).

2.2.3. DECISION-MAKING

Decision-making is a task that is part of organisational strategy (Daradkeh et al., 2013). It involves the process of coming up with decision alternatives, each of which can result in many possible outcomes (Daradkeh et al., 2013; Huang, Chen & Chang, 2015). As argued by Businska & Supulniece (2011), decision-making is an activity, that uses data reasoning to create information and knowledge in order to facilitate problem-solving. Decision-making has been widely researched by both academics and practitioners and can be grouped by decision types (Shollo, 2010). According to Bose (2009), the three broad categories of decision types that have emerged from studies are strategic, tactical and operational decision-making. Strategic decisions focus on the long term plans of an organisation, tactical decisions focus on the implementation of strategic decisions and lastly, operational decisions ensure that specific tasks are carried out effectively and efficiently whilst implementing strategic decision-making (Bose, 2009; Isik et al., 2013; Shollo, 2010). Isik et al. (2013) note that decision types impact the analytical methods used for decision-making.

However, decision types remain as one of the biggest challenges influencing the uptake of BI&A in many organisations (Shollo, 2011).

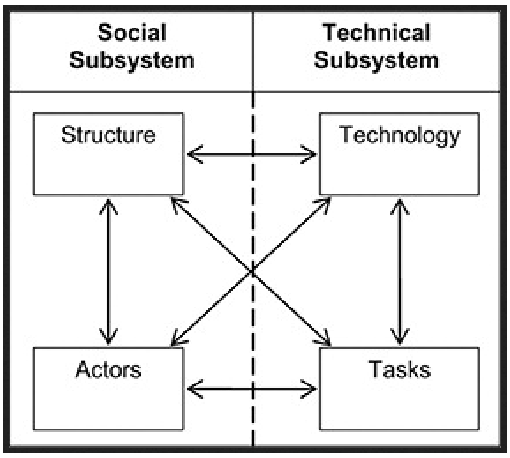
The importance of BI&A uptake is important in improving the value decision-making process (Smith et al., 2006; Davenport, 2010; Shollo, 2010). Value is the positive impact which permeates from getting the desired outcome after using a system (Tsiknakis & Kouroubali, 2009). However, organisations are complex social systems, thus various factors impact the value obtained from BI&A (Isik et al., 2013). Consequently, current corporate analytics processes are being challenged, forcing organisations to adapt to changes (Abbasi et al., 2016). It is therefore important to look at the Socio-technical systems theory (STS) and review factors that coexist in an analytics ecosystem. STS presents TTPS as the four interacting factors that offer an effective information management strategy (Hester 2014).

2.2.4. SOCIO-TECHNICAL SYSTEMS THEORY

Socio-technical systems (STS) present two pillars of a socio-technical system which are made up of a social subsystem (actors and structures) and a technical subsystem (tasks and technology) (Hester, 2014). According to Geels (2004), Socio-technical systems do not function autonomously; they are a result of the activities of human actors using technology. Human actors are embedded in social groups which share certain characteristics (e.g. roles, responsibilities, norms and perceptions). STS is widely used as an integrated approach in implementing technology changes (Appelbaum, 1997; Hester, 2014). Scholars have investigated the development of institutional and technological elements into a highly institutionalised configuration that enables the fulfilment of specific functions (Fuenfschilling & Truffer, 2015).

TTPS interact to form relationships between any two elements resulting in six separate relationships, for example actor to structure, actor to tasks, actor to technology, tasks to technology, tasks to structure, and technology to structure. Similar to STS is a model by Leavitt (1965) which is composed of the same four interactive elements that need to be considered for organisational change. These four elements are interdependent and any change in any one of them will influence the other three (Geels, 2004; Hester 2014). Figure 4 below shows the diagrammatic representation of STS.

Figure 4: Diagram depicting the Socio-technical Systems Theory



Leavitt (1965) also suggests that TTPS are critical factors that need to be reconciled in order to achieve successful change in an organisation. The technology facet is the process through which organisations accomplish key tasks and is used for collecting, organising, processing and storing data (Goodhue & Thompson, 1995). Structures come about as a result of the patterned elements and relationships amongst organisational participants (Calloway, 2010). People make contributions towards an organisation in exchange for rewards (Tsiknakis & Kouroubali, 2009). They are considered to have attributes such as skills, attitudes, behaviour, beliefs, training, motivation, roles and responsibilities (Goodhue & Thompson, 1995). Furthermore, through collective actions, people carry out functions and activities that seek to achieve goals. Tasks are functions that need to be completed (Tsiknakis & Kouroubali, 2009). The relationships that form from the linear interaction of TTPS are discussed below.

People – Technology: Humans interact with technology to deliver specific outcomes (Tsiknakis & Kouroubali, 2009). These two elements are embedded in a complex social structure which includes organisational goals, policies and culture (Hester, 2014). Many approaches have been used to highlight the relationship between people and technology. One approach is the Technology Acceptance Model (TAM) which shows the willingness within a user group to use information technology for the tasks it is designed to support. Separate studies have either used the Theory of Planned Behaviour (TPB) or Theory of Reasoned Action (TRA) to explain the relationship between people and technology. TPB, proposed by Ajzen (1991), stipulates that human action is guided by three considerations:

behavioural beliefs, normative beliefs and control beliefs. This was an extension to TRA by including the behavioural aspect, especially to predict an individual's intention to deliberately engage in behaviour at a certain place and time. Initially TRA suggested that behavioural intent is influenced by attitudes and our subjective norms (Tsiknakis & Kouroubali, 2009).

People – Structure: There is duality and interplay between structures and people. People have attributes such as attitudes, skills and values (Ajzen, 1991). People are normally guided by organisational characteristics (Tsiknakis & Kouroubali, 2009). Misalignment between people and structures leads to unhappy employees which may result in improper usage of technology.

People – Tasks: People have roles and responsibilities they need to fulfil. To fulfil these roles and responsibilities, people normally perform tasks, using technology (Ammeenwerth et al., 2006). For instance, the decision-making task uses BI&A with the hope of providing better analysis and decision-making processes to yield better decisions.

Technology- Structure and Structure - Tasks: Structure – Tasks and Technology – Structure have been grouped into one section. Currently, organisations face considerable challenges in fulfilling the decision-making task (Shollo, 2011). Technology tools have been made available for leveraging data for analysis (Isik et al., 2013). Diffusion of such technologies happens when top management perceive technology to have relative advantage over current organisational practices (Ramdani et al., 2013). This can be explained by using the Diffusion of Innovation theory (IDT). In IDT, innovation is an idea, practice or objective that is perceived as new and diffusion is the process by which innovation is communicated overtime through a population or social system (Rogers, 2003).

However, there exist complexities between technology and organisational structure relationships. The Adaptive Structuration Theory (AST) can be used to further illustrate how technology and structure exist in dual relationship and the role of technology in organisational structures. AST constitutes applied actions, decisions and constraints that prompt an organisation's behaviours to create norms and rules which are embedded in power arrangements or shared meanings (Niederman, Briggs & Vreede, 2008). Empirical studies by Hester (2014) show that alignment between technology and structure increase the use of technology. According to DeSanctis & Poole (1994), this can be viewed from two vantage points: (1) by looking at the types of structures that are provided by advanced technologies, and (2) the structures that actually emerge in human action as people interact with these technologies.

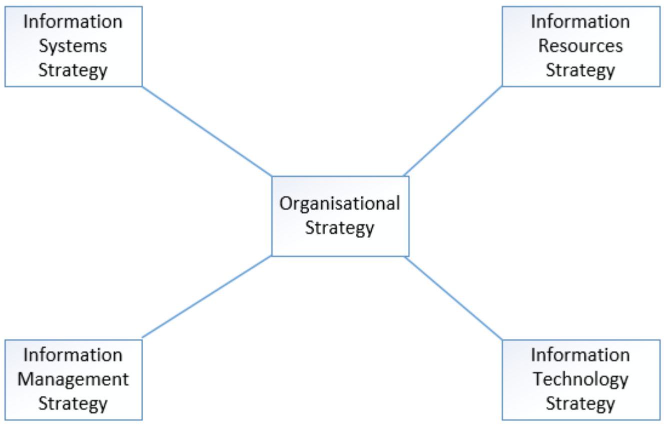
Technology – Tasks: Technology must have the ability to match the demands of a task (Goodhue & Thompson, 1995). As a result, technology is often developed in response to specific task requirements (Ammeenwerth, Iller & Mahler, 2006). There must be a fit between the task characteristics and system characteristics in order to not impede system performance. In this case, BI&A technology must fit the decision-making tasks. According to Goodhue & Thompson (1995), for technology to have a positive impact, it must be utilised and it must fit the task it is supporting. This is supported by Ahmad (2015) who notes that a fit between requirements and capabilities should be a key factor in closing the requirements gap in the processing ability of the organisation. However, Chen & Wang (2015), acknowledge that technology is developing rapidly. Resultantly, people's ideas fail to keep pace with it. March & Smith (1995) refer to Ferre (1988) who defines technology as practical implementations of intelligence, often developed in response to specific task requirements using practical reasoning and experimental knowledge. A gap currently exists between decision maker's requirements and the technology solution BI&A is offering (Shollo, 2010). There should be a fit between business decision needs and the BI&A technology solution (Hester, 2014). The Task Technology Fit model (TTF) has been widely used to explain the fit between task and technology in improving an individual's capabilities (Goodhue & Thompson, 1995).

As much as these theories and concepts have been used by researchers and practitioners, it is important to draw from STS and find out how TTPS can be used to achieve success in BI&A. As highlighted earlier, these factors interplay, making it difficult to determine how best they can be configured to support BI&A initiatives. However, STS is a linear model and is not enough to portray the extent of this interplay. To address this, the study draws from the concept of alignment by adopting the alignment as Gestalts notion.

2.2.5. ALIGNMENT

Delineations by Chan (2002, p. 98), describe alignment as broadly encompassing "*the fit between an organization and its strategy, structure, processes, technology and environment,*" whereas Levy, Powell & Yetton (2011), define alignment as the process of developing fit amongst key internal activities within an organisation and fit between the internal and external context. From a strategic perspective, Earl (1996) introduced an alignment model (see Figure 5) which denotes measures (information systems strategy, information resources strategy, information management strategy and information technology strategy) that can be used to ensure IS strategy is in line with business strategy. Chen, Mocker, Preston & Teubner (2010), define IS strategy as an organisational perspective on the investment, deployment, use, and management of information systems.

Figure 5: Earl's Model (Earl, 1996)



The information resources strategy is not limited to, but involves, people and other artefacts that can be regarded as resources. Implementation of BI has already been labelled complex, requiring a number of resources (Duan & Xu, 2012). In theory, the Resource Based Theory (RBT) can be used by a firm in deploying BI (Bharadwaj, 2000). Resources emphasise the capability of an organisation to foster significant relationships amongst unique internal resources such as information quality, quality systems, quality users and BI governance (Ahmad, 2015). Having unique resources is a way of creating competitive advantage (Peppard & Ward, 2004).

The information technology strategy identifies technology required to support business mission, goals and strategy (Henderson & Venkatraman, 1998). The technology strategy is used in close association with the information management strategy. The Information management strategy is about governing accountability for the structure, design, storage, security, movement, quality, delivery and usage of information required for management purposes (Ramdani et al., 2013). However, one challenge that can be associated with Earl's model is that strategies do not always develop in a logical sequence of analysis, choice and action. They tend to emerge as a result of adhoc, incremental or even accidental actions which may result in misalignment (Peppard & Ward, 2004). Misalignment of the five strategies in Earl's model can result in problems such as technology execution challenges.

The Management in the 90s (MIT90s) model is another alignment model that is popular in literature. Strategy and structure make up the MIT90s model where alignment amongst management, process, roles, skills and technology requires competences (Coltman, Tallon, Sharma & Queiroz, 2015). The MIT90s model resonates with alignment principles as it advocates for synergy amongst organisational elements in order to sustain their quality and inter-relationships so as to achieve competitive advantage (Levy et al., 2011).

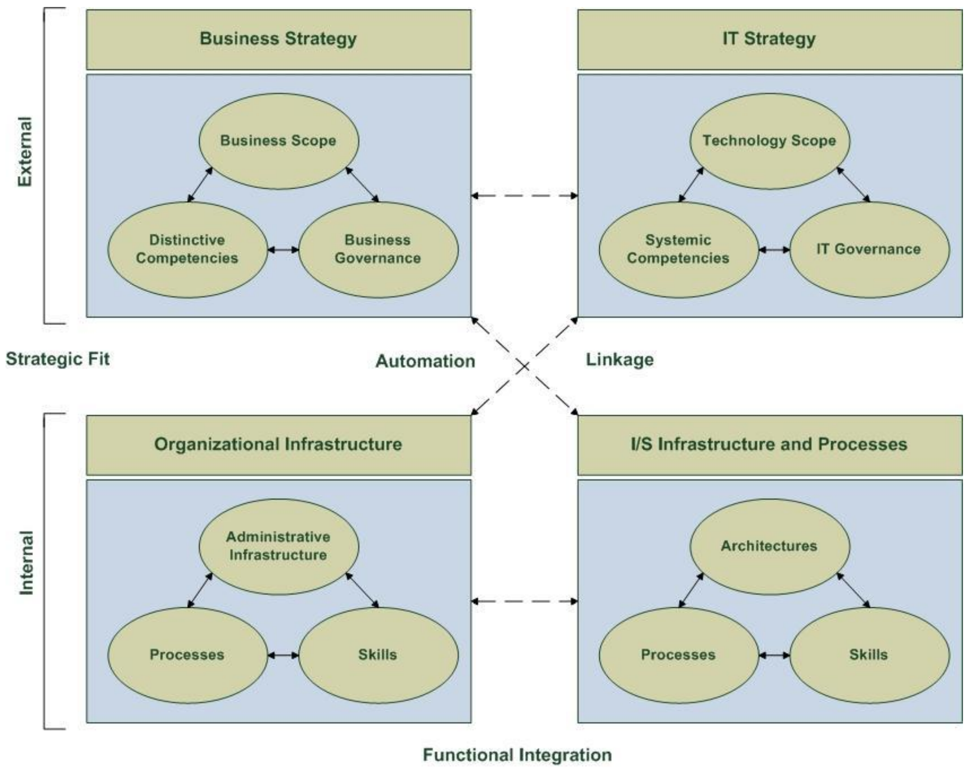
Figure 6 shows the Strategic Alignment Model (SAM) proposed by Henderson & Venkatraman (1998). This model is based on two vantage points. The first vantage point posits that "*the economic performance of an organisation depends on the strategic fit between strategy, organisation and technology.*" The second vantage point posits that "*strategic alignment relies on a dynamic process of adjustment between strategy and functional integration*" (Neuberta, Dominguez & Ageron, 2011, p. 1056).

SAM illustrates four quadrants in which the dynamic fit of four key domains, namely strategic fit, Information Communication Technology (ICT) strategy, Information Technology and Business need to be achieved (Henderson & Venkatraman, 1998). Each quadrant consists of three components: the anchor, the pivot and the impacted domain. The anchor is the domain that is considered to be the strongest area of the business and the change that the business is expected to undergo is directed based on this perspective. The pivot defines the area of the organisation that will serve as the support for change through re-alignment. The domain of impact is the area that will be directly affected through the changes made in the pivot domain through the re-alignment (Neuberta et al., 2011).

Alignment will promote and harness constructive synergies that lead to internal consistency or fit among patterns of relevant contextual, structural and strategic factors (Coltman, 2015). Of main concern is the distinction of the model into two parts, strategic fit and functional fit. Strategic fit involves the link between internal and external domains whereas functional fit shows how IT Strategy and business strategy influence each other, resulting in successful organisational performance (Neuberta et al., 2011).

At a macro level, literature has shown that there is interaction between business intelligence, data analytics and strategy which requires alignment to yield positive results. However, Henderson & Venkatraman (1998), note that it is difficult to achieve alignment and their model does not provide guidance on how to achieve good alignment.

Figure 6: Strategic Alignment Model (Henderson & Venkatraman, 1998)



An empirical study performed by Ramdani et al. (2013) concluded that alignment of business and technology plans is important, but it differs with every context. The context of application poses challenges rooting from lack of knowledge and sufficient infrastructure, with the end result being BI implementation failure. Furthermore, Hanson, Melnyk & Calantone (2011) suggest that while the construct of alignment is conceptually clear, it is not clear how one might actually measure it. Six perspectives for achieving alignment where suggested by Venkatraman (1989).

1. Fit as mediation: explains the relationship between two variables. For example in a relationship between one variable (strategy) and another, (performance) there exists intervening variables such as organisational structure. According to Venkatraman (1989), complete mediation happens at the point where the effect between the strategy and organisational structure and the effect between organisational structure and performance is significant.

2. Fit as profile deviation: In this case, fit is measured by the degree of adherence to an externally defined profile. There exists an ideal strategy profile specified for a particular environment and deviations from that ideal profile imply a weakness in co-alignment, resulting in lower performance. Conversely, adherence to the ideal profile is expected to be associated with higher performance (Venkatraman, 1989).

3. Fit as co-variation: considers fit to be a pattern of internal consistency among a set of variables that have developed a relationship as a result of underlying theoretical explanation (Venkatraman, 1989).

4. Fit as moderation: explains a relationship that exists between a predictor and outcome variable. For example, the relationship between strategy and performance can be moderated by the organisational environment. Hence, the impact of strategy on performance is dependent on the influence of the environment (Venkatraman, 1989).

5. Alignment as matching: Here, there is a match between two related variables. For example, there would be alignment when an organisation matches its technology capabilities with its business strategy (Venkatraman, 1989).

6. Alignment as Gestalts: In the Gestalts theory, a configuration is a collection of patterns and concepts organised in a manner in which the collection operates as a unit in thought and behaviour. Alignment has its roots in the configuration theory (Rashidirad, Soltani &

Syed, 2013). A configurational approach therefore involves more than two variables which require some degree of coherence amongst a set of theoretical attributes.

Configuration theorists argue that ideal performance is only achieved when organisational attributes e.g. strategy, culture, environment and processes reach an adequate level of fit/alignment with one another (Miller, 1987). Therefore, by focusing on a configuration, one is looking at a representation of alignment among the elements of an organisation (Venkatraman, 1989).

Given the interplay between TTPS, and because alignment has its roots in the configuration theory, this study adopts the Gestalts theory. A Gestalt/configuration is a collection of patterns and concepts organised in a manner in which the collection operates as a unit and is characterised by temporal stability (Miller, 1987). Configuration theorists argue that ideal performance is only achieved when a number of organisational elements reach an adequate level of fit/alignment with one another (Venkatraman, 1989). A configurational approach therefore involves more than two variables which require some degree of coherence among a set of theoretical attributes.

2.3. GAPS IN LITERATURE

1. ***There is no clear indication of how TTPS can be aligned to influence success of BI&A:*** Literature shows that there is a lack of agreement as to how firms can achieve alignment. As mentioned above, the concept of alignment is not always clear, and there is no indication of how one might actually measure it (Hanson, Melnyk & Calantone, 2011). Reich and Benbasat (2000), note that there is no comprehensive model that is commonly used to reach alignment. This is also supported by Smaczny (2001) who states that even though there are some organisations which have tried, there are no specific guidelines that focus on how organisations actually achieve alignment.
2. ***There is misalignment between task requirements and what BI&A solutions offer. BI&A focuses more on technology implementation and neglects the interplay of various significant factors in the implementation of BI&A***: BI&A solutions focus more on technical implementation according to Boyton et al. (2015). Furthermore,

"the outputs of BI information, actionable insight or knowledge, do not by themselves guarantee its use by decision makers" (Shollo, 2010, p. 4). Isik et al. (2013, p. 13) also suggest that *"users do not necessarily make the connection between their BI capabilities and the decision environment."*

3. ***There is no validation on the value and positive impact created by BI&A in decision-making:*** Like the implementation of any IT technology, organisations are concerned with the tangible value generated from using BI (Williams and Williams, 2003). As far back as 2000s, Elbashir (2008) suggested the absence, in many organisations, of a rigorous method to measure the realised business value of BI.

2.4. CONCEPTUAL FRAMEWORK

Figure 7: Conceptual model for aligning Tasks, Technology, People and Structures

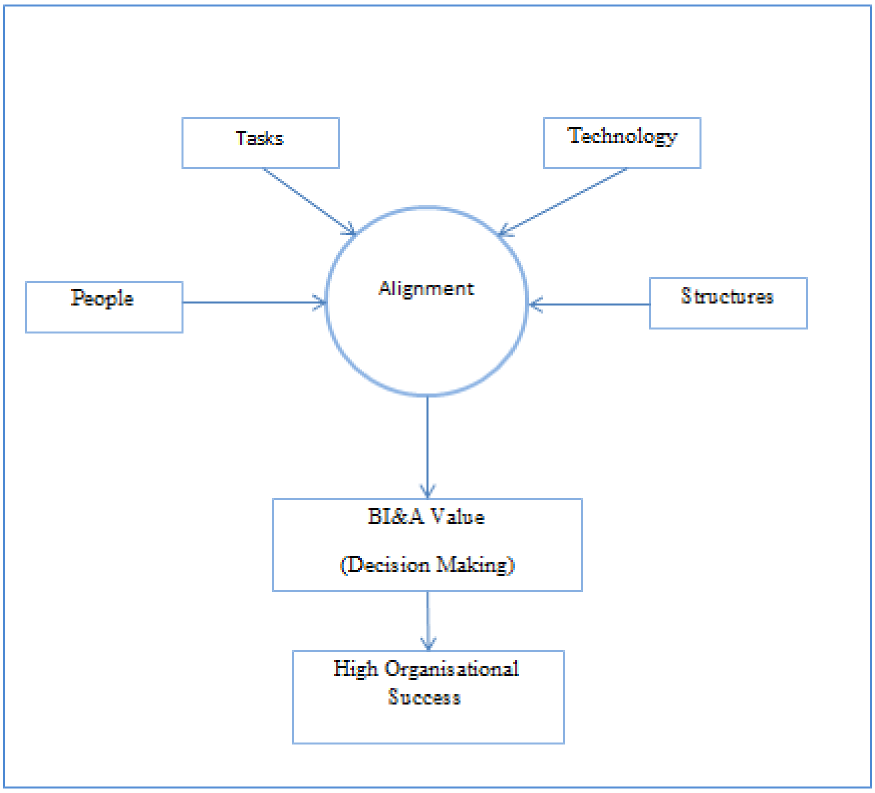


Figure 7 above shows a conceptual model which posits that TTPS are individual inter-related elements. The circle in the model suggests that when TTPS are put together, they have the ability to form configurations. These configurations, impact the value created by BI&A in decision making. The value created then results in high organisational success. The contribution of the alignment model is to the conceptual development of alignment between TTPS.

2.4.1. CONSTRUCTS AND OPERALISATION OF VARIABLES

According to Kimberlin & Winterstein (2008), measurement of constructs requires that the conceptual definition be translated into an operational definition. An operational definition of a construct links the conceptual or theoretical definition to more concrete indicators that have numbers applied to signify the amount of the construct (see Table 1). The ability to operationally define and quantify a construct is the core of measurement (Kimberlin & Winterstein, 2008).

Table 1: Description of Constructs

Variable	Description
Tasks	An activity or a piece of work that needs to be completed (Ammeenwerth et al., 2006). The ability of IT to support a task is expressed by the formal construct known as task–technology fit (TTF) (Dishaw& Strong, 1999)
Technology	The tools and equipment internal or external to the organisation and prove to be relevant to the organisation (Goodhue & Thompson, 1995).
People	Individuals that implicitly determine adoption and usage of technology based on their behaviour, attitude and skills (Ramdani et al., 2013).
Structure	Distinct organisational contextual characteristics such as firm size, policies, training, management and culture (Venkatesh, Thong & Xu, 2012).
Alignment	The process of developing fit amongst key internal activities within an organisation and fit between the internal and external context (Levy et al., 2011)
Value	Is the usefulness created by technology (Tsiknakis & Kouroubali, 2009), in this case, the value created by BI&A in decision-making.
Success	Is the positive impact of the BI&A solution on the organisation (DeLone & McLean, 2003).

2.4.1.1. OPERALISATION OF VARIABLES

From table 1 above, each construct is linked to one or more variables to allow for measurement. The variables where selected from previous studies that measure the same constructs. The following section describes the association between constructs and their variables in greater detail.

The people construct is denoted by the variables self-efficacy and training. Self-efficacy defines one's belief in one's ability to succeed in specific situations or accomplish a task. Positive self-efficacy is deemed to be important in influencing usage of information systems (Hester, 2014). Training defines the knowledge imparted to the users to develop and improve their competencies. Training ensures that users, having differing levels of computer skill, become comfortable with the software and use it successfully. Training is associated with higher levels of system usage and user satisfaction; and user expertise is strongly related to system usage (Hester, 2014).

Ease of use is linked to the technology construct. Ease of use is when a system is perceived to be easy to use if the user believes there is not much effort required to use the system (Venkatesh, Thong, & Xu, 2012).

The task construct is linked to the nature of tasks variable. Nature of tasks is the type of activity that is being completed (Giboney et al., 2015).

Top management support is linked to the structures construct. It is the stimulation and reinforcement of values through an articulated vision by managers (Ramdani et al., 2013). Top management therefore create a positive environment to facilitate adoption of new technologies by creating an appealing vision of how the adoption will benefit the firm, securing sufficient resources, and overcoming any member resistance to the change. In this study top management support refers to the degree to which top management understands the importance of BI&A technologies and the extent to which top management aware of BI&A benefits.

Value is denoted by efficiency and strategic performance. Efficiency is the amount of useful work that is completed by a user (Elbashir et al 2008). Strategic performance is the overall effectiveness and efficiency that can gauge company success (Elbashir et al 2008).

Organisational success is denoted by individual performance competitive advantage. Individual performance defines how well an individual executes their daily tasks (Elbashir et al 2008). Competitive advantage is the superiority gained by an organization compared to its competitors (Peters et al 2016).

Propositions made from the conceptual model are as follows:

Proposition 1: A strong level of alignment between TTPS positively affects the value of BI&A in decision-making: BI is considered as a socio-technical system. According to (Hester, 2014), socio and technical organisational elements coexist in both competitive and cooperative tension therefore they require alignment. Alignment leads to more focused and strategic use of IT which, in turn, leads to increased performance (Chan et al., 2007).

Proposition 2: The positive value created by BI&A results in high organisational success: Literature suggests that alignment is an important factor in ensuring competitiveness and success in organisations (Avison et al., 2004). Alignment achieves this by ensuring that information systems provide direction and flexibility to react to new opportunities thereby maximising return on IT investment by improving competitive advantage.

2.5. CONCLUSION

The purpose of this literature survey was to propose a conceptual model to ensure success of BI&A initiatives in supporting organisational success. An inter-disciplinary analysis of concepts and theory shows that TTPS interplay. These elements need to be aligned to result in improved business value in decision-making which in-turn results in increased organisational success. This study adopts the fit as Gestalts to assess cross-causality and configurations that arise among these factors. Propositions have also been suggested to confirm or disprove the premise of the conceptual model. The methodology that was followed in assessing these configurations is discussed in Chapter 3 below.

CHAPTER 3: RESEARCH DESIGN AND METHODOLOGY

Chapter 3 is a discussion on the research design and methodology followed in conducting this study. The high level layout of the study is as follows

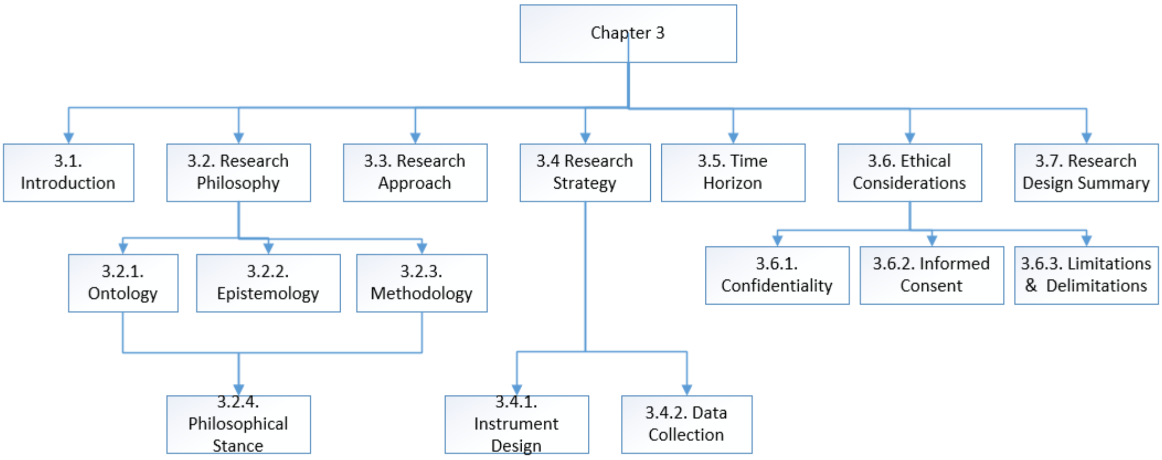
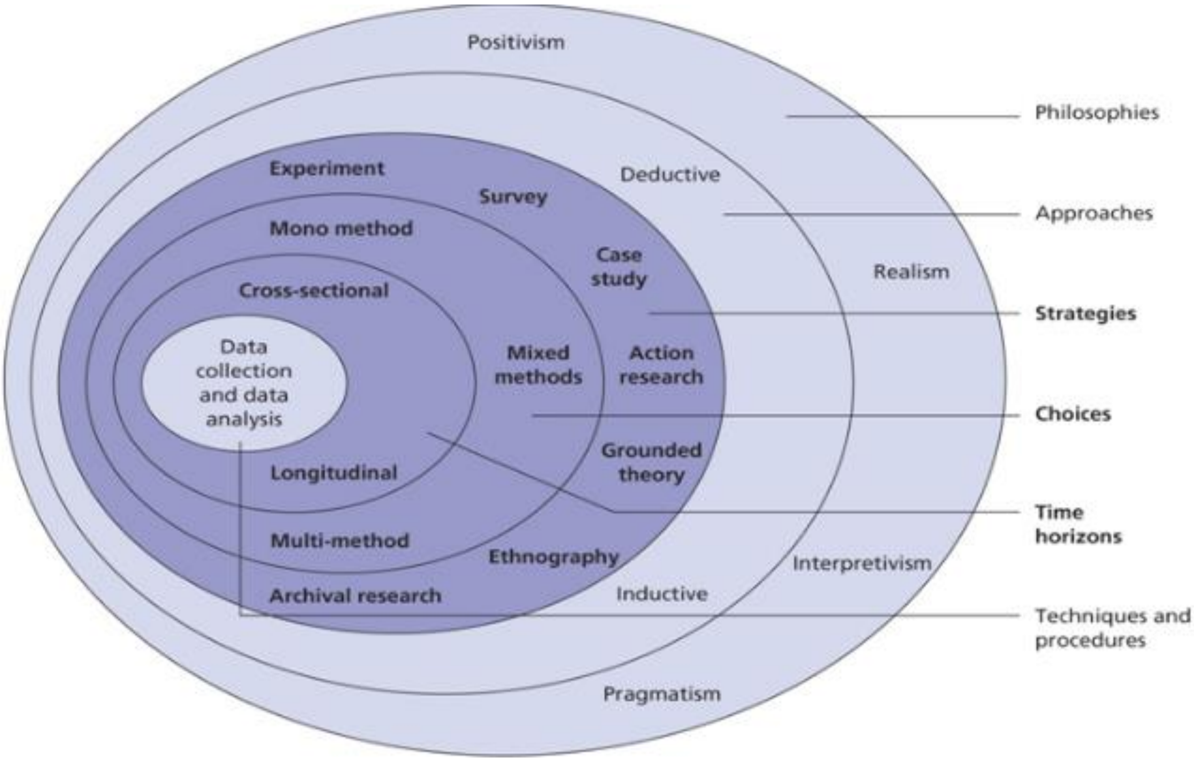


Figure 8: High Level Overview of Research Design

3.1. INTRODUCTION

According to Fisher et al. (2010), research methodology is a process of developing a unique approach on how to carry out a study. Saunders (2009) presented a framework of beliefs and values for investigating a research topic. This framework is known as a research onion and is presented in Figure 9. This framework shows stages that must be covered when developing and conducting research. It acts as a guideline for choosing suitable research methodology and strategies. From the research onion, the starting point for the researcher is to choose a suitable philosophy. The second step is to choose the research approach from underlying layers of the onion. The third step is to formulate a research strategy. The fourth step involves choosing the research method. Lastly, the fifth step involves outlining data collection methods. The selected design is considered the best to inform the research methodology that will best assist in answering research questions.

Figure 9: Research Onion



3.2. RESEARCH PHILOSOPHY

Research philosophy lays out the researcher's view of the world and how it is influenced by practical considerations (Saunders, 2009). Research philosophy is guided by epistemology and ontology (Diesing, 1966; Fisher et al., 2010; Saunders, 2009). Epistemology is the nature of knowledge, whereas ontology is the study of the nature of reality. Research philosophies differ in their goals and the way they achieve these goals (Cleland, 2015). The following section discusses the concepts of ontology, epistemology and methodology, after which, the philosophy adopted in completing this study is selected.

3.2.1. ONTOLOGY: OBJECTIVISM VS SUBJECTIVISM

Ontology deals with the nature of reality in terms of the types, properties, and interrelationships of the entities that fundamentally exist for a particular domain of discourse (Diesing, 1966). Two major streams of ontology in literature are objectivism and subjectivism. Objectivism involves a researcher adopting scientific methods that require publicly observable and replicable facts (Saunders, 2009). Objectivism is based on the notion that knowledge exists within the knower (Saunders, 2009). Furthermore, this knowledge is measureable and can be broken into variables (Wagner, 2012). The researcher's role is to discover this knowledge, independent of their interest (Mouton, 2005). This is supported by Saunders et al. (2009), who say that objectivism believes in a reality that exists without the interference of the social actors, meaning that there is no human interference.

Unlike objectivism, the subjective phenomenon seeks to understand action from the standpoint of the actor (Diesing, 1966; Saunders, 2009; Wagner, 2012). In subjectivism, there is no objective truth, meaning that reality is socially constructed (Diesing, 1966). A key feature of interpretive research is that you cannot understand how others make sense of things unless you have an insightful knowledge of your own values and thinking processes (Fisher, 2010). This has an advantage of creating better understanding of how and why a phenomenon is constructed by social actors (Saunders, 2009). However, data collection is considered time consuming and there is a potential threat of data analysis being challenging and complex (Creswell, 2013).

3.2.2. EPISTEMOLOGY: POSIVISTIC VS INTERPRETIVISM

The work of Scotland (2012) suggests that the meaning of knowledge in research is subjective. In research, the nature of the knowledge being sought and its development thereof can follow a positivistic paradigm, which implies the researcher will gather factual knowledge and meanings from what is learnt in literature and data analysed (Saunders, 2009). Positivism uses scientific methods which offer a better opportunity to establish the truth and objective reality (Saunders, 2009; Scotland, 2012). Contrary to the positivistic paradigm is the interpretive paradigm. With this paradigm, researchers seek to understand phenomena through accessing the meanings that participants assign to things, thereby adding understanding to the deeper structure of phenomenon (Orlikowski and Baroudi, 1991). This paradigm is not suitable for this study as it is not able to appropriately test propositions and answer the research questions.

3.2.3. METHODOLOGY: QUANTITATIVE VS QUALITATIVE

The methodologies followed by research studies can either be quantitative or qualitative. Quantitative and qualitative approaches make different assumptions about how scientific research should be conducted (Cleland, 2015). Qualitative research methodology is concerned with understanding processes, inclusive of the social and cultural contexts which shape various behavioural patterns (Saunders, 2009). It employs a wide range of data gathering techniques e.g. interviews, focus groups and observation. Qualitative research seeks insights through structured, in depth data analysis (Wagner et al., 2012). Quantitative research on the other hand, focuses on collecting data that is numerical (Saunders, 2009).

For the purposes of this study, a quantitative method with an inferential approach was chosen as the main methodology. This is because the data generated is in numerical form and analysis involved quantitative methods. The inferential approach is later used in Chapter 5 to infer the results from the sample population to a different or larger population that may have similar characteristics or relationships.

3.2.4. PHILOSOPHICAL STANCE CHOSEN FOR THIS STUDY

The foundation of the philosophical stance is guided by the fact that this study seeks to test theory and discover general principles. The underlying principles and belief systems that allow for this to be achieved are objectivism and positivism. The ontology chosen for this study is therefore objectivism, which asserts that knowledge can be observed and measured objectively with the researcher being independent from the research being conducted (Saunders, 2009). Objectivism was chosen because the main objective of this study is to identify ways to leverage BI&A in order to improve decision-making and organisational success. This is in line with objectivism principles which seek to understand phenomena so that we are able to predict and control it. This is supported by the positivistic epistemological stance.

It has been established that TTPS is embedded in organisations and need to be reconciled to ensure organisational success. As a result of their socio-technical nature, the way they interact forms an observable reality that is tangible and measurable. Tasks shape and are shaped by the use of machines and this is socialised through structures, roles and communication patterns (Leonardi, 2012). Positivism is therefore suited to collect factual data to best ascertain how TTPS interplay and form configurations of association in organisations. This then leads to discovering ways to leverage BI&A in order to improve decision-making and organisational success. However, some scholars find positivism inflexible as it is difficult to change direction once data collection has started. Furthermore, positivism is weak in understanding social processes and it is often difficult to discover the meanings people attach to social phenomena (Wagner et al., 2012).

The decision for choosing an appropriate methodology is generally informed by the philosophy (Wagner, 2012). In addition to objectivism and positivism, the study also takes a quantitative approach because concepts were operationalised in order to measure quantitative facts.

3.3. RESEARCH APPROACH: DEDUCTIVE VS INDUCTIVE

Research strategies can be deductive or inductive. A conceptual model was developed from theory and from there propositions to be tested were formed. This study therefore followed a deductive approach to confirm or disconfirm the propositions. A deductive approach works well when there is an abundance of sources (Saunders, 2009). Furthermore, the deductive approach is best suited when there is a short time available to complete a study. This is in line with the cross sectional time horizon (Wagner, 2012). An alternative to the deductive approach is the inductive approach. This approach aims to generate meanings from the data set collected in order to identify patterns and relationships to build a theory (Saunders, 2009; Wagner, 2012). The inductive approach does not prevent the researcher from using existing theory to formulate the research question to be explored (Saunders, 2009). The inductive approach was not chosen as it does not fit the process of developing hypothesis for testing.

3.4. RESEARCH STRATEGY

The philosophical and methodological underpinnings chosen, result in a survey research study. A survey is described as the gathering of information about the characteristics, actions or opinions of a large group of people to advance scientific knowledge (Wagner, 2012). The purpose of a survey is to generate quantitative data of the sample population being studied (Saunders, 2009). Once data has been generated, analysis of data is concerned with establishing relationships between variables (Pinsonneault & Kraemer, 1993).

The survey strategy is also in line with the path of this research study, which follows the concept explication route. Concept explication is defined as the process of finding the meaning of a concept through clarification using the deductive approach whilst at the same time capturing various complexities (Mouton, 2005). A deductive approach empirically tests theory and answers research questions. Empirical findings make new factual discoveries or confirm or disconfirm a proposed phenomenon (Saunders, 2009) which is in line with this study.

3.4.1. INSTRUMENT DESIGN, MEASURES AND DATA VARIABLES

Literature is filled with multiple tools that measure TTPS in various environments. For the purposes of this research, an online survey tool was created based on the conceptual model in section 2.4. Questions were drawn from existing questionnaires that used a seven point Likert scale as the measuring scale. The seven point Likert scale was chosen even though it is considered to suffer from response style bias (Chun, Campbell & Yoo, 1974).

According to Paulhus (1991), response style bias is defined as the systematic tendency to respond to a range of questionnaire items on some basis other than the specific content outlined. However, it is considered that rating scales with more response categories transmit a greater amount of information and are therefore inherently more precise in their measurement (Alwin, 1997). The benefits of using an existing instrument are the greater chances of reliability and validity. This may, however, cause challenges of relevance to a South African context because most of the questionnaires used were developed in Europe, America and Asia. Caution therefore needs to be taken, as such instruments cannot be applied to the South African context without some adaptation (Mouton, 2005). As a result, some of the questions were re-phrased to ensure consistency. The questionnaire is shown in Appendix B.

The questionnaire is divided into two sections. The first section consists of questions about the demographic profile of the respondents. The second section consists of questions on the six main variables driving this study. All the questions were made mandatory to ensure a complete data set. Appendix C shows the constructs, summary of variables and the sources from where they are adopted.

3.4.2. DATA COLLECTION PROCESS

3.4.2.1. SOURCES OF DATA: SAMPLING

Sampling is the act of drawing individuals or entities from a population, which is representative enough to make generalisations about the phenomena of interest (Pinsonneault & Kraemer, 1993). The sample for this study was determined using non probability sampling. Purposive sampling is a type of non-probability sampling method usable with quantitative research techniques (Saunders, 2009). Purposive sampling was adopted to select respondents based on their profiles; for example, employees in BI, data analysis or decision-making positions. An analysis by Schoenherr, Ellram & Tate (2015), suggests that it is difficult to achieve statistically meaningful response rates because of the proliferation of empirical surveys to test business related theory. Purposive sampling mitigates this challenge by improving realised sample sizes and access to well-screened and targeted respondents. However, purposive sampling is considered to have a degree of bias which, however, contributes towards its efficiency of targeting informants who can best answer the research questions (Fisher et al., 2010). It is fundamental to the quality of data gathered for competent informants to be chosen. Another strength of purposive sampling is that it stays robust even when tested against random probability sampling.

Various domains have applied BI to inform decision-making (Aruldoss & Venkatesan, 2014). According to Arefin, Hoque & Bao (2015), BI has permeated various industries including banking, insurance, finance, retail, health care, telecommunications and manufacturing. This also applies in the South African context where it has been adopted widely in many industry sectors. An industry-wide (retail, insurance, banking, telecommunications and manufacturing sectors) data sample will therefore be chosen to better inform ways in which BI&A can be leveraged. The population considered for this study includes organisations that have implemented some form of BI&A technology. Table 2 shows the total number of participants in the study based on purposive sampling.

Table 2: Total Sample from which data was collected

Industry	Total
Retail & Manufacturing	20
Financial Services	30
IT & Telecommunications	30
Health	10
Mining & Engineering	10
Travel & Entertainment	10
Education	10
Total	**120**

3.4.2.2. DATA COLLECTION

Data collection methods vary and, in general, can be divided into qualitative methods which encompass unstructured interviews, unstructured focus groups and observation; and quantitative methods which encompass structured questionnaires. Each method has its own detailed procedure and has a specific purpose, as well as inherent disadvantages and advantages (Fisher, 2010; Wagner, 2012).

A combination of survey delivery and data collection methods were used to collect information across all industry sectors in South Africa. The primary delivery and collection method used was an online Google form which was sent via email. The secondary delivery and collection method involved printing the questionnaire and submitting it to the respondents for later collection. Both methods involved a questionnaire being administered to key respondents selected using purposive sampling. This survey method was chosen because data sources are more easily accessible, therefore allowing for a fairly good response rate. Furthermore, the survey method was chosen as it supports this study because it is theory-driven and aims to test hypothesis (Mouton, 2005).

This research study collected new data which is also known as primary data. According to Hox & Boeije (2005), the most important advantage of collecting own data is that the operalisation of the theoretical constructs, research design and data collection strategy can be tailored to research questions. This was done to further ensure that the study is coherent and that the information collected will indeed answer the research questions.

3.5. TIME HORIZON

The process of answering research questions can be completed using either a cross sectional survey or a longitudinal survey. A cross-sectional study collects data at a single point in time whereas longitudinal studies collect data over at least two periods of time (Pinsonneault & Kraemer, 1993). This study aims to examine how BI&A can be leveraged for business value at a single point in time. The research study is therefore cross sectional. However, this approach lacks the time element in determining if what works currently will work in future. Contrary to this limitation, a cross sectional study is less time consuming, inexpensive and gives a good picture of what is currently happening. One may argue that a longitudinal design is appropriate as it involves change over time and understanding of the sources and consequences of a phenomenon. As a one year study, this dissertation does not allow for a longitudinal design.

3.6. ETHICAL CONSIDERATIONS

Ethical considerations cover issues of confidentiality and informed consent. Confidentiality describes the methods incorporated in keeping information private, unless consent has been given to release the information (Saunders, 2009). Informed consent looks at permissions granted to gather information in the full knowledge of the possible consequences for the respondent (Saunders, 2009; Wagner, 2012). These issues are discussed below:

3.6.1. CONFIDENTIALITY

- To ensure privacy of data that can cause risk or harm, collected information was stored in a secure database.
- Confidentiality of identifiable data was offered to the respondents.
- Only the researcher had access and maintained the data collected.

3.6.2. INFORMED CONSENT

- Any person planning to undertake research requires clearance from a review board or a similar function at university level. Ethical issues concerning this study were reviewed by the Faculty of Commerce Ethics in Research committee at the University of Cape Town. The ethics form requesting permission to proceed with data collection is shown in Appendix D. The researcher only continued with data collection upon receiving confirmation to proceed from the Faculty of Commerce Ethics in Research committee.
- Permission was also requested to distribute the questionnaire to individuals who were willing to participate in the study. Appendix A shows the cover letter that was used to accompany the questionnaire.
- Voluntary consent was offered to those people who received the questionnaire (this is indicated in the cover letter in Appendix A). Therefore, respondents could choose to participate, refuse to participate or choose to exit the questionnaire at any given point.

3.6.3. LIMITATIONS AND DELIMITATIONS

Limitations of the study included:

- A convenience sample targeting the people who actively use, or have some knowledge of BI&A was selected to best answer the questionnaire.
- Not all the people from the selected sample were willing to participate in the study because of the fear that their views would be publicised.
- The study is cross-sectional, meaning that the results are dependent on the conditions occurring at that particular point in time and therefore are only a snapshot of what was happening at a single point in time.
- Respondents participated voluntarily and could withdraw from the survey at any particular time. As a result, the sample selected may have been insufficient and not fully representative.

- The research instrument was a combination of a number of instruments. Questions where therefore altered to ensure the flow and adequacy of the research instrument.

Delimitations of the study included the phenomenon of interest, sample choice and study design. The phenomenon of interest is Business Intelligence and Analytics and how alignment of task, technology, people and structures can contribute towards organisational success. To allow for an in depth understanding, this study was conducted across the various industry sectors and targeted users that interact with data and analytics at various levels. The decision to delimit the study to multiple industry sectors was intended to give a wider view of the subject under investigation.

3.7. RESEARCH DESIGN SUMMARY

Table 3 below shows a high level summary of the research design and methodology of the main areas of emphasis. The ontological stance of this study was objectivism because the researcher believes that knowledge exists within the knower and is observable, whilst the epistemological stance was positivistic because the researcher gathers factual knowledge and meanings from what is learnt in literature and the data analysed. The methodology predominantly follows a quantitative approach for both data collection and analysis.

Table 3: Research Design and Methodology Summary

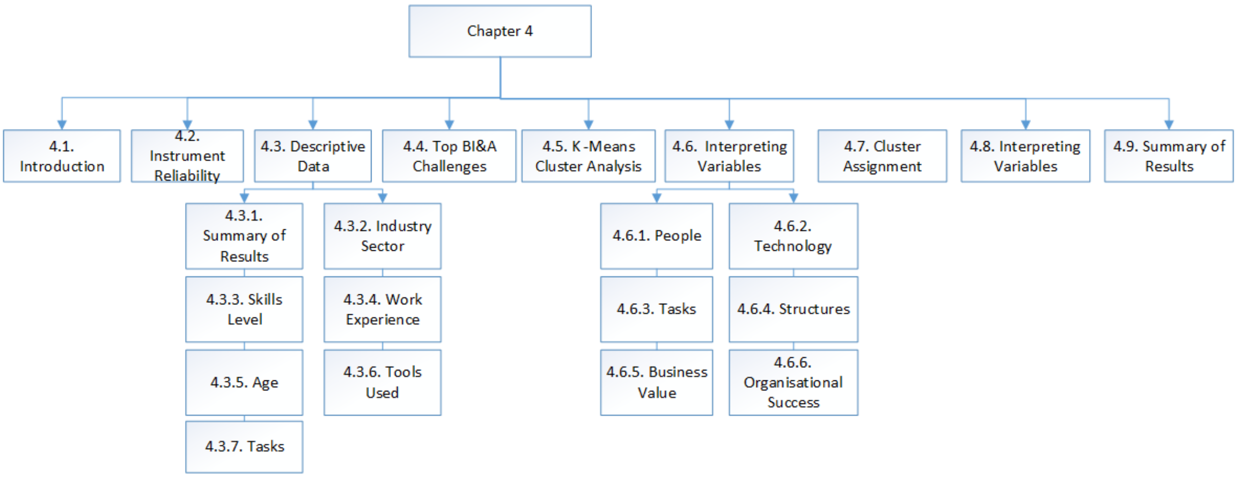
Research Design and Methodology Summary	
Research Philosophy	Ontology: Objectivism Epistemology: Positivistic Methodology: Quantitative
Research Approach	Deductive
Sampling Technique	Purposive
Data collection Method	Survey
Data collection instrument	Questionnaire
Data Analysis	Quantitative Methods
Time Horizon	Cross Sectional
Study Setting	Non-contrived

Unit of Analysis	South African Industry Sectors
Measures	Variables (7 point Likert scale)

CHAPTER 4: ANALYSIS OF RESULTS

This chapter presents the results and discusses the empirical findings from the data collected. The high level structure of the chapter is shown in Figure 10.

Figure 10: High Level overview of the Analysis of Results



4.1. INTRODUCTION

This study was aimed at examining the relationships between tasks, technology, people and structures to see how they can be used to leverage BI&A. Scientific methods were used to assess their level of alignment. Other aims included, exploring the concept of BI&A and its utilisation in decision-making. The theoretical foundation of this study posits that there is a relationship between TTPS. To allow for measurement, the research adopted quantitative techniques. The quantitative techniques adopted include statistical methods such as descriptive statistics, measures of central tendency, dispersion, instrument reliability analysis, Analysis of Variance (ANOVA) and cluster analysis.

The survey attracted a response rate of 62.5%. The initial steps of data analysis involved capturing data into Microsoft Excel for cleaning and sorting to highlight anomalies. No anomalies and outliers were observed in the dataset. Data was then uploaded into Statistica for further analysis. Preliminary tests conducted on the data include a statistical test for reliability as well as tests for descriptive statistics. Descriptive statistics were used to summarise the data using measures of central tendency and measures of spread (mean and standard deviation) to show patterns of data numerically and graphically. Inferential statistics were used to make generalisations about the population from which the sample was drawn. K-means cluster analysis was used as the main data analysis method and as a validity check.

Cluster analysis is best suited to discover structure and associations in the data. This is achieved by reviewing associations in the data and grouping variables into clusters, such that the elements within a cluster have a high degree of natural association among themselves whilst the clusters are relatively distinct from one another (Anderberg, 2014). However, one weakness of cluster analysis identified by Anderberg (2014) is that the set of results applies only to the sample on which they are based. Nevertheless, through appropriate modification, results can be extended to adequately describe the properties of other samples.

4.2. INSTRUMENT RELIABILITY

Research Instruments need to be scientifically checked for reliability and validity. To achieve this, researchers often determine the internal consistency reliability and construct validity.

Reliability measures consistency or the degree to which an instrument measures the same way each time it is used under the same conditions with the same subjects. "*Reliability coefficients range from 0.00 to 1.00, with higher coefficients indicating higher levels of reliability"* (Kimberlin & Winterstein, 2008, p. 2277). According to Kimberlin & Winterstein (2008), reliability measures stability, inter-rater reliability and internal consistency. Stability determines the correlation of results for the questionnaire administered to the same people at two different points in time. Inter-rater reliability determines the correlation of the scores from two or more raters. Internal consistency looks at three or four questions measuring the same concept and groups them into one to determine the reliability of the instrument.

Validity is defined as the extent to which an instrument measures what it is set out to measure. Validity measures how multiple constructs are related to one another. Validity is taken to mean different things in different contexts. As a result, there are a number of ways to assess validity. These include content validity, criterion validity and construct validity (Brown, 2010). Content validity analyses the content of the instrument whereas criterion validity computes the correlation between scores on the instrument. Investigating the particular characteristics or constructs measured by the instrument accounts for construct validity (Kimberlin & Winterstein, 2008). These three types of validity are seen as relatively separate and substitutable attributes of a measure, and have to be established independently (Streiner & Norman, 1995; Messick, 1995). However, these concepts have been the subject of notable challenges and confusion amongst theorists, educators, researchers and practitioners. These concepts tend to compartmentalise the thinking about validity, thus narrowing or limiting it to a checklist approach (Brown, 2010).

For this study, the Cronbach Alpha coefficient was calculated to measure construct reliability. One widely used method of testing for validity and adequacy of fit of the instrument is the confirmatory factor analysis (Bagozzi, Yi & Phillips, 1991). In this study the cluster analysis sufficed as the test for data validity. According to Anderberg (2014, p. 5), "*factor analysis is a strong competitor to cluster analysis.*" They share the same principles, for example they are both exploratory and they also group closely related items in the same factor (factor analysis) or cluster (cluster analysis). The main difference between the two is that factor analysis groups variables in some form of reduction whereas cluster analysis groups similar cases according to certain criteria.

The Cronbach Alpha function is a widely used method of determining consistency of the measuring scale. The Cronbach Alpha is the function of the average inter-correlations of the items in the scale. Cronbach (1951) suggested that reliability can be accepted for alpha values greater than 0.7. If the Cronbach Alpha test is run, values greater than 0.7 imply that there is internal consistency which is acceptable and satisfactory.

Table 4 below shows the results of the Cronbach alpha test that was conducted on the constructs. The alpha values for the constructs are above the 0.7 threshold and are therefore acceptable and satisfactory. This implies that the instrument is valid and cannot be affected by any changes to the context of study or the subjects under study (Brown, 2010).

Table 4: Cronbach Alpha Table

Reliability Table					
Construct	Variables	Number of questions	Mean	StdDev	Alpha Coefficient
People	self-efficacy and training	3	13.47	4.92	0.85
Technology	Ease of use	4	13.40	4.86	0.86
Tasks	nature of tasks	4	13.99	4.63	0.82
Structures	Top management support	3	14.23	4.52	0.84
Value	efficiency and strategic performance	7	14.50	4.45	0.80
Success	individual performance competitive advantage	4	14.32	4.57	0.82

4.3. DESCRIPTIVE DATA

4.3.1. SUMMARY OF RESPONSES

Figure 11 below shows the distribution order of the scores for the six constructs people (PE), technology (TE), task (TA), structure (ST), BI&A value (VA) and organisational success (SU). This figure is supported by Table 5 below.

Figure 11: Summary of Responses

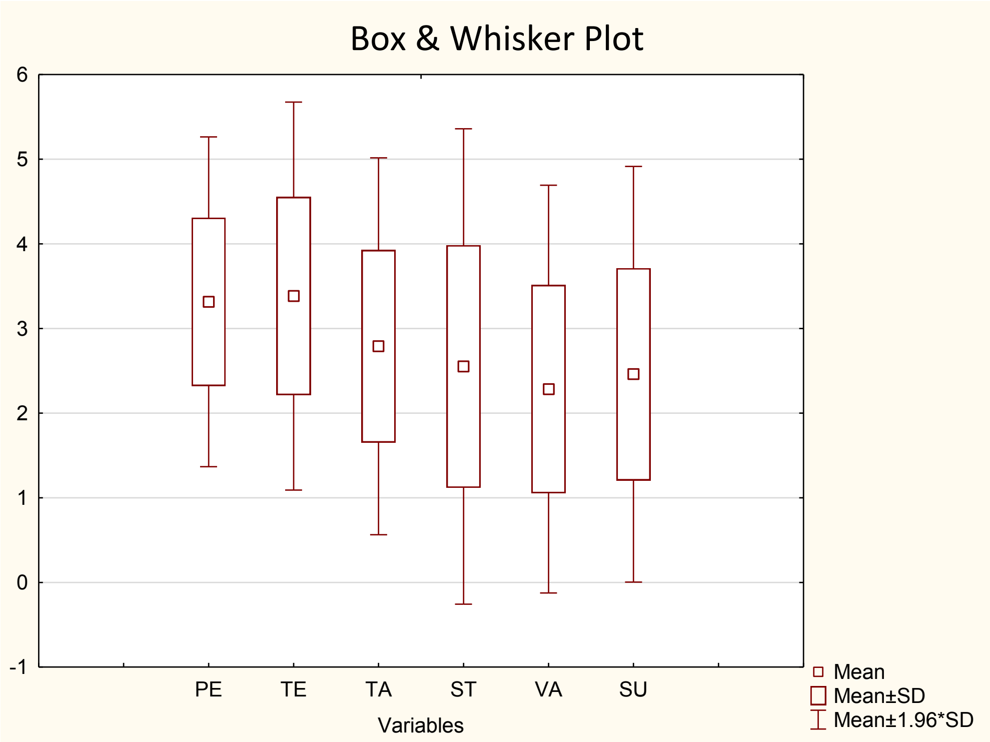


Table 5 shows the mean scores and the standard deviation values measured on the variables that represented the 6 constructs. The mean scores of the constructs range from a low of 2.28 to a high of 3.38. This shows that respondents generally agree that BI&A adds value and which results in organisational success. The standard deviation values are not too far from the mean as they range from 0.99 to 1.43.

Table 5: Mean Scores and Standard Deviation of Variables

Likert scale used: |1= Strongly Agree|2= Agree|3= Agree Somewhat|4= Neutral|5= Disagree Somewhat|6=Agree|7 =Strongly Disagree|

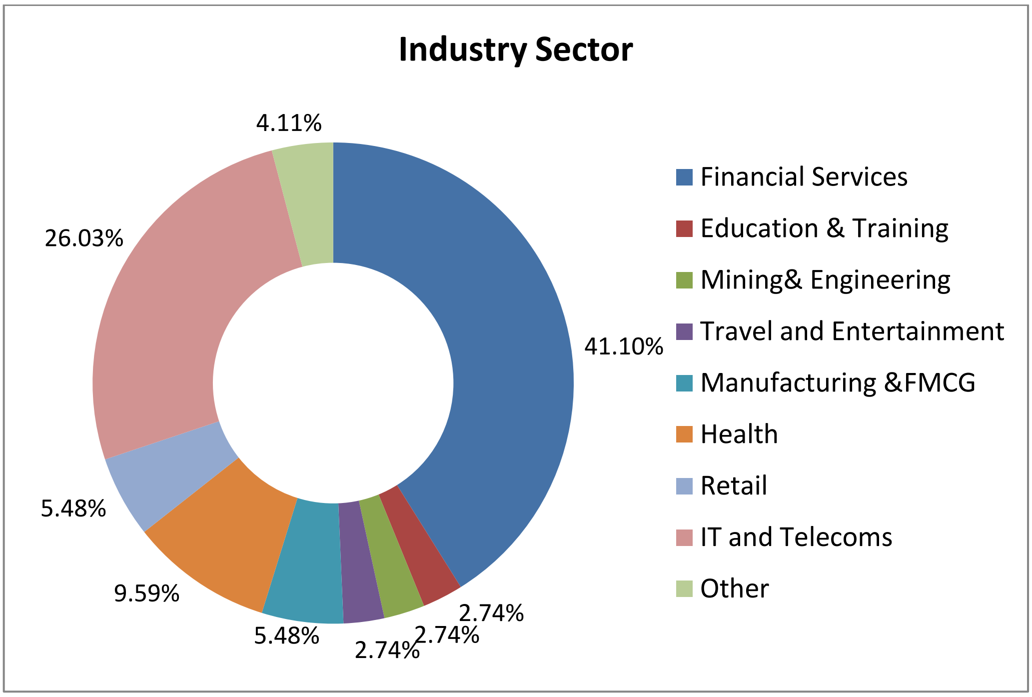
Variable	Descriptive Statistics for the variables				
	Valid N	Mean	Minimum	Maximum	Std.Dev.
People	75	3.32	1.00	6.33	0.99
Technology	75	3.38	1.00	6.75	1.17
Task	75	2.79	1.00	6.00	1.14
Structure	75	2.55	1.00	5.67	1.43
BI&A Value	75	2.28	1.00	5.71	1.23
Organisational Success	75	2.46	1.00	6.00	1.25

The discussion that follows is on descriptive data collected from the sample which includes industry sector, department, job title, skill level, work experience, age, common BI&A tools used and the tasks they are used for.

4.3.2. INDUSTRY SECTOR

As shown in Figure 12 below, 41.10% of the respondents are from the financial services sector. The financial services sector is considered as one of South Africa's biggest economic contributors. Respondents came from a range of financial services firms such as commercial banks, investment banks and insurance companies. The IT and telecommunications sector accounted for 26.03% of the respondents while 9.59% of the respondents came from the health sector. The manufacturing and FMCG sectors had the same number of respondents (5.33%) and the mining, travel and education sectors each had 2.74% of the respondents.

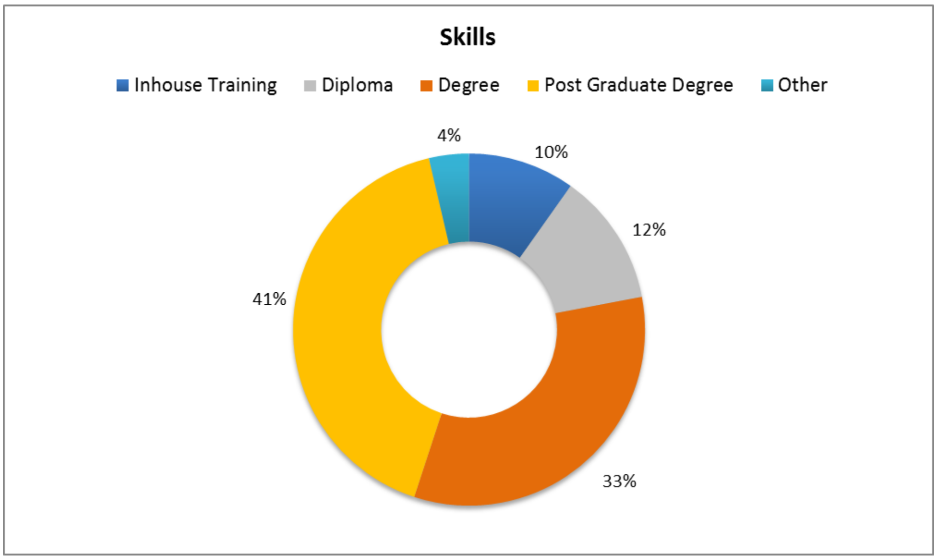
Figure 12: Industry Sector Demographics



4.3.3. SKILLS LEVEL

In this study, the skills level is determined by whether a person has a diploma, degree, post graduate degree, in-house training or some other form of qualification. Figure 13 below shows the distribution of skills level across the 75 respondents. 60% of the respondents have a post graduate qualification whilst 36% of the respondents have a university degree. The respondents with in-house training and a diploma are 10.7% and 13.3% respectively. Some respondents indicated that they had professional qualifications such as Microsoft Certified Solutions Associate (MCSA) and these were classified 'under other'.

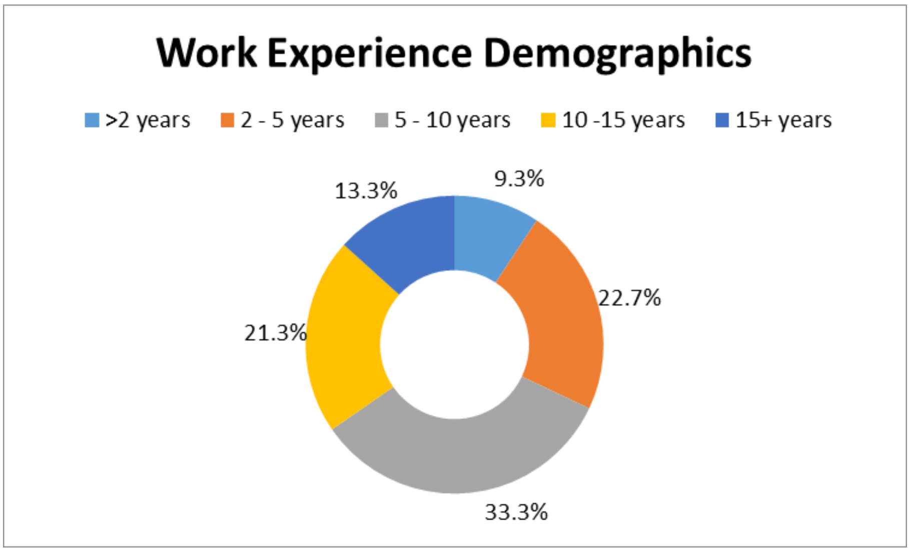
Figure 13: Skills Level Demographics



4.3.4. WORK EXPERIENCE

Figure 14 below shows that 33.3% of the respondents have been working for 5 to 10 years. The least experienced group has less than 2 years of experience and accounts for 9.3% of the respondents. Those with experience of 2 to 5 years make up 22.7% of the respondents. Respondents with the most experience are 21.3% for those with 10 to 15 years of experience and 13.3% for those with over 15 years of experience.

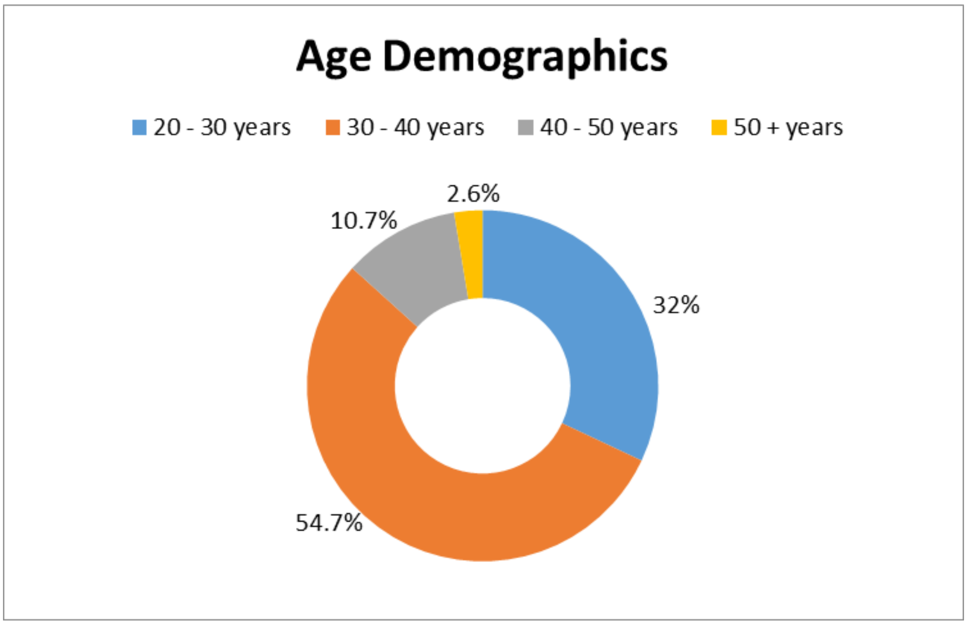
Figure 14: Work Experience Demographics



4.3.5. AGE

Figure 15 below shows the age demographics. The 30 to 40 years age group has the most respondents with a total of 54.7%. They are followed by the 20 to 30 years age group which accounts for 32% of the respondents. The 40 to 50 years age group makes up 10.7% of the respondents, whereas the over 50s make up 2.67% of the respondents.

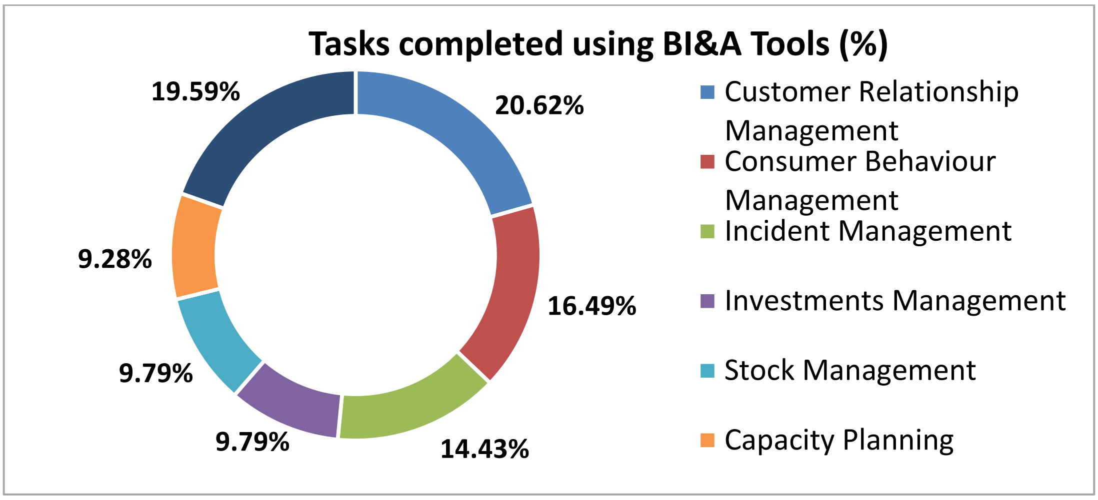
Figure 15: Age Demographics



4.3.6. TASKS COMPLETED USING BI&A TOOLS

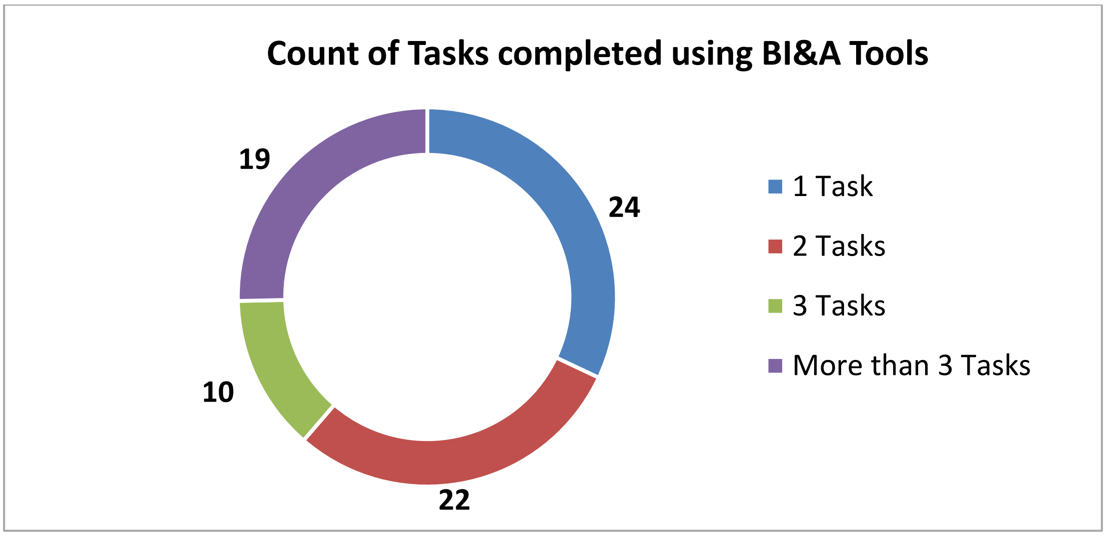
Figure 16 below shows that most respondents (20.62%) use BI&A for customer relationship management. Tasks such as fraud management, disease management and education analytics are classified under 'other' and account for 19.59% of the respondents. Other important uses of BI&A include consumer behaviour management (16.49%) and Incident management (14.43%).

Figure 16: Tasks completed using BI&A Tools



BI&A tools have multiple uses. Figure 17 shows that 24 (32%) respondents use BI&A only for one task, mainly consumer behaviour management. Customer relationship management and consumer behaviour management are common uses of BI&A tools from the 22 (29.33%) who use it for 2 tasks. All in all, 10 (13.33%) use BI&A for 3 tasks with most of them being part of the FSS and IT and Telecommunications; and 19 (25.33%) use it for more than 3 tasks.

Figure 17: Count of Tasks completed using BI&A Tools



4.3.7. BI&A TOOLS USED

Figure 18 shows the tools used. The largest group of respondents (40.56%) is the sum of respondents that did not meet the usage threshold of more than 5.5%. Many people in this group use in-house developed tools specific to their organisations. However, SQL Server Integration Services (SSIS) is widely used with 11.19% of the respondents indicating that they use it. Other widely used tools include QlikView (9.79%) and SAP/Business Objects with (9.09%).

Figure 18: Tools Used for BI&A

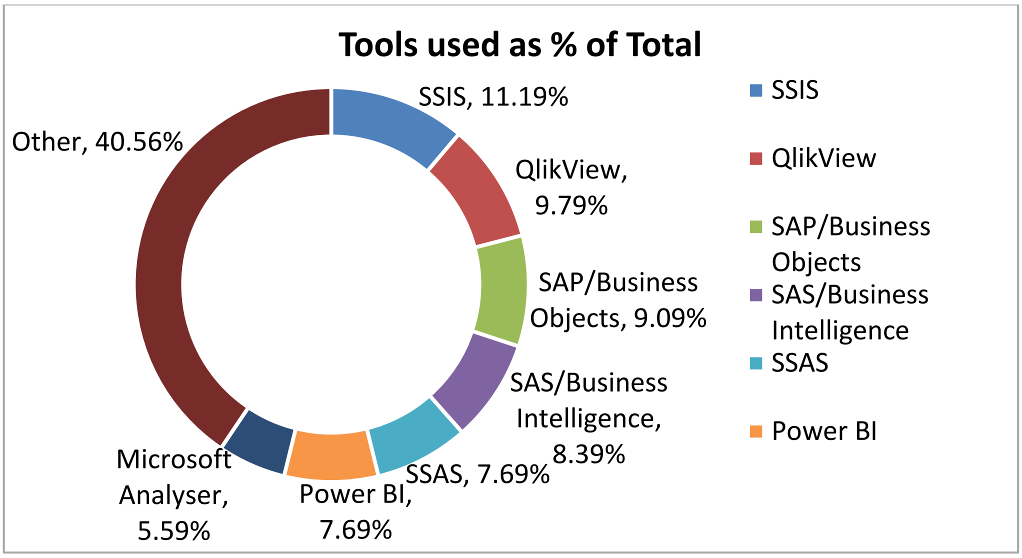
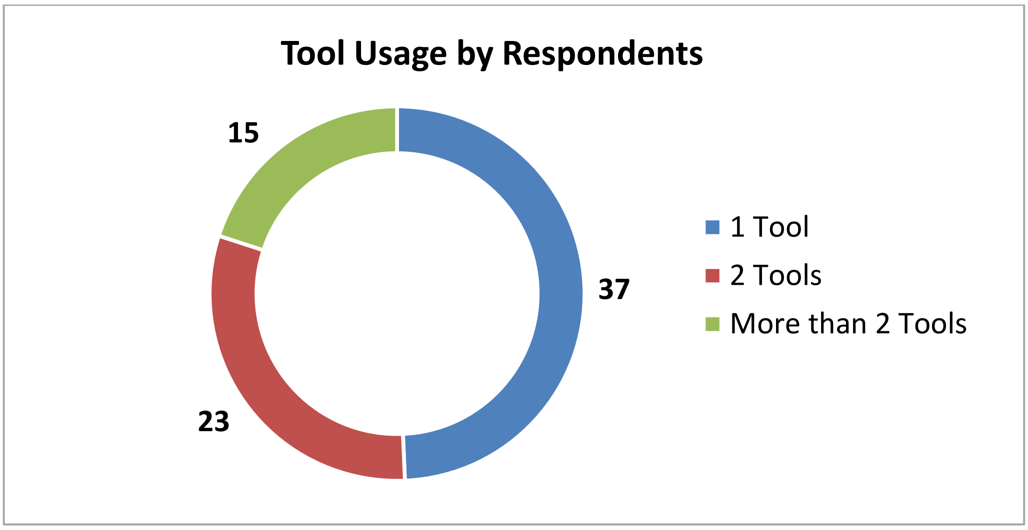


Figure 19 below shows that 37 respondents only use one tool, 23 Respondents use at least 2 BI&A tools and 15 respondents use more than 2 tools.

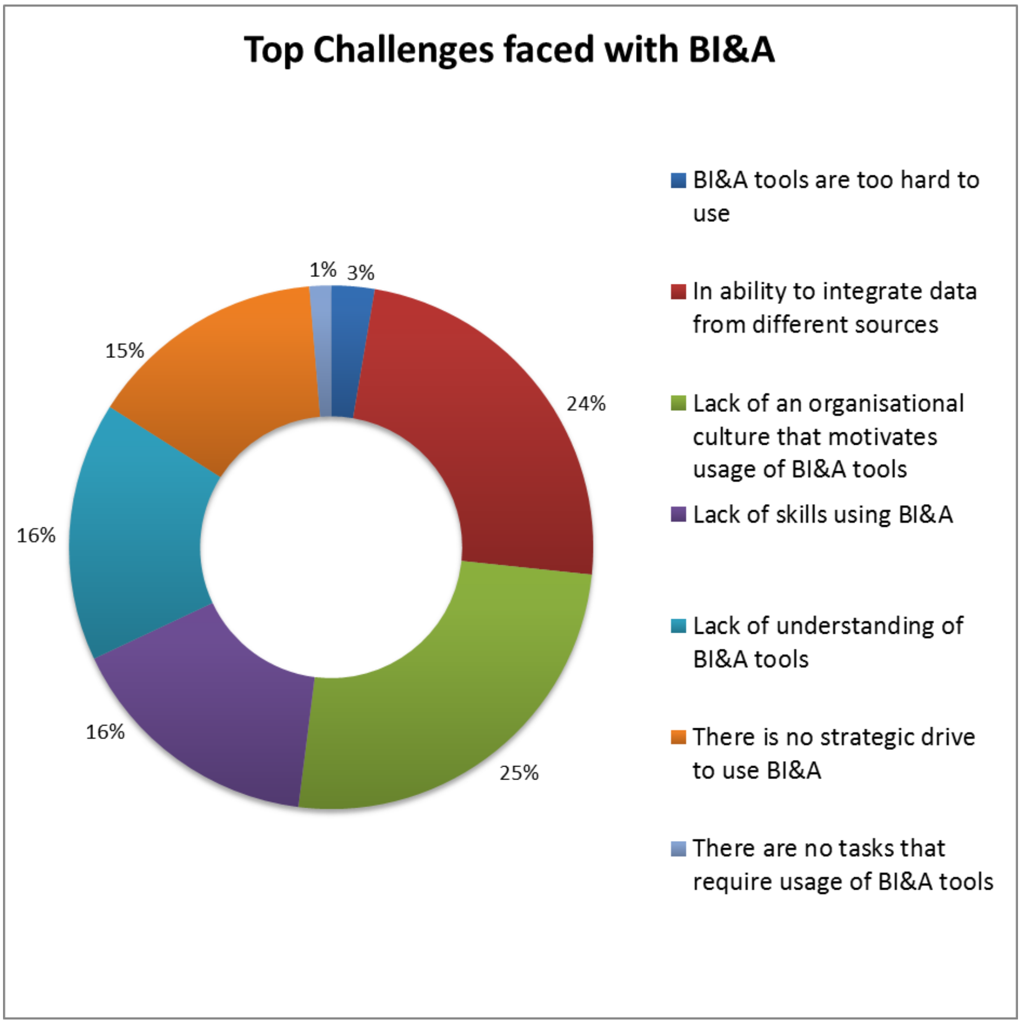
Figure 19: Tool Usage by Respondents



4.4. TOP CHALLENGES FACED IN USING BI&A

Figure 20 below shows the common challenges faced when using BI&A. The biggest challenge (25%) is the lack of an organisational culture that motivates usage of BI&A tools, seen in 31.57% of respondents from the FSS with roles like Data Scientist, Portfolio Manager and Quantitative Analyst. Integrating data from different sources is also a big challenge represented by 24% of the respondents. Only 1% of the respondents said that there are no tasks that require usage of BI&A tools in their organisation.

Figure 20: Top Challenges faced with using BI&A



4.5. K-MEANS CLUSTER ASSIGNMENT

Cluster analysis is a classification tool which is used by researchers as a way of representing the structure of data. According to Punj & Stewart (1983) data classification is concerned with identification of discrete categories, whereas structural representation is concerned with representation of relationships. By definition, cluster analysis is an exploratory data analysis method which sorts similar observations into sets or groups (Ketchen & Shook, 1996; Punj & Stewart, 1983). Cluster analysis is therefore known to provide rich descriptions of configurations that represent a way to meaningfully capture the complexity of organisational reality (Ketchen & Shook, 1996; Scott, 1974). However, there is no consensus in literature regarding the use of cluster analysis procedures (Ketchen & Shook, 1996; Punj & Stewart, 1983). It is recommended that data collected on different measurement scales goes through a standardisation process which enables different types of data collected on different scales to be comparable to one another (Merchant, 2000). In this study, data was collected on the same measurement scale, therefore no standardisation was required.

This study used the K-means cluster analysis method. In this method, observations of data with some notion of similarity are grouped together. This is achieved by partitioning data into K groups based on the descriptive features of the data (Ketchen & Shook, 1996). The observations are then iteratively assigned to one of the K groups. Punj & Stewart (1983) argue that there is no assurance of having arrived at a meaningful cluster. Therefore, to ensure the cluster solution is stable, an Analysis of Variance (ANOVA) test was conducted. In the study of configurations of international joint ventures, Merchant (2000), successfully used the ANOVA test to validate observed results. ANOVA is also adopted in this study as a statistical test for significance to validate the quality of the clustering solution.

Table 6 below shows the cluster solution and the ANOVA results. The F values range from 3.63 (lowest) to 40.90 (highest). The table also shows that all variables have a p value less than 0.05 ($p<0.05$). Therefore, it can be concluded that the averages between clusters are significantly different from one another and thus, the cluster solution is valid. Based on the conceptual model which consists of six variables, a total of six clusters were extracted. The figures in bold reflect patterns of interrelationships that emerge in each cluster as a result of significant relationships that form where respondents strongly agree, agree or somewhat agree.

Respondents were assigned to their clusters according to their mean score rating of the questionnaire items. As mentioned earlier, six distinct clusters were identified and each cluster was given a name based on the respondent work profiles. The names included key managers, investors, financial planners, general technologists, IT experts and IT strategists. The discussion that follows is the detailed analysis of each cluster.

Table 6: Cluster Analysis and ANOVA Table |1= Strongly Agree|2= Agree|3= Agree Somewhat|4= Neutral|5= Disagree Somewhat|6=Agree|7 =Strongly Disagree| ***The variable column in the table below represents a question item pertaining to that variable. Different questions can be asked about the same variable.***

Variable	Analysis of Variance						Cluster 1 n=16	Cluster 2 n=19	Cluster 3 n=9	Cluster 4 n=15	Cluster 5 n=6	Cluster 6 n=10
	Between	df	Within	df	F	signif.	Mean					
self-efficacy	109.50	5	65.16	69	23.19	0.000	**3.06**	**1.79**	4.67	**1.33**	4.33	**1.40**
Training	104.71	5	141.29	69	10.23	0.000	3.81	**5.58**	4.11	3.20	2.67	**6.20**
Training	70.98	5	148.54	69	6.59	0.000	4.13	**2.79**	4.67	**1.80**	**3.17**	**2.40**
Ease of use	83.29	5	96.26	69	11.94	0.000	**3.00**	**2.00**	4.89	**1.73**	3.83	**1.80**
Ease of use	88.72	5	178.03	69	6.88	0.000	3.69	5.21	4.33	**3.00**	6.33	5.70
Ease of use	77.12	5	97.55	69	10.91	0.000	3.56	**3.11**	4.89	**2.00**	5.33	**2.80**
Ease of use	70.01	5	101.51	69	9.52	0.000	3.56	**2.68**	5.00	**2.13**	4.17	**2.10**
Nature of Task	131.49	5	61.18	69	29.66	0.000	**3.00**	**1.95**	5.33	**1.33**	**1.00**	**1.10**
Nature of Task	134.44	5	49.56	69	37.43	0.000	**3.00**	**1.42**	5.33	**1.60**	**1.33**	**1.00**
Nature of Task	129.35	5	43.64	69	40.90	0.000	**3.25**	**1.68**	5.33	**1.60**	**1.33**	**1.20**
Nature of Task	58.14	5	220.84	69	3.63	0.006	**3.38**	5.32	4.44	3.73	**3.33**	5.50
Organisational strategy	96.48	5	133.84	69	9.95	0.000	**2.13**	**3.00**	5.22	**1.93**	3.50	**1.30**
Organisational strategy	82.94	5	71.73	69	15.96	0.000	**1.94**	**2.53**	4.89	**1.53**	**2.67**	**1.30**
Organisational strategy	72.88	5	88.40	69	11.38	0.000	**3.06**	**2.42**	4.67	**1.73**	3.50	**1.40**
Efficiency	94.20	5	60.52	69	21.48	0.000	**2.75**	**2.58**	5.11	**1.40**	**2.00**	**1.40**
Efficiency	93.56	5	38.23	69	33.78	0.000	**2.63**	**2.37**	5.11	**1.53**	**1.67**	**1.30**
Efficiency	96.60	5	46.15	69	28.89	0.000	**2.69**	**1.89**	4.89	**1.27**	**1.50**	**1.20**
Efficiency	100.86	5	39.06	69	35.63	0.000	**2.44**	**1.89**	5.00	**1.40**	**1.17**	**1.10**
Strategic performance	92.18	5	51.50	69	24.70	0.000	**2.63**	**2.11**	4.89	**1.47**	**1.67**	**1.00**
Strategic performance	94.59	5	39.73	69	32.85	0.000	**2.50**	**2.42**	5.00	**1.60**	**1.50**	**1.00**
Strategic performance	89.40	5	43.26	69	28.52	0.000	**2.63**	**2.11**	4.89	**1.67**	**1.50**	**1.00**
Competitive Advantage	84.24	5	58.75	69	19.79	0.000	**2.50**	**2.74**	4.67	**1.47**	**1.67**	**1.00**
Competitive Advantage	66.20	5	48.15	69	18.97	0.000	**2.75**	**2.79**	4.56	**2.27**	**1.83**	**1.00**
Competitive Advantage	82.73	5	75.46	69	15.13	0.000	**2.75**	**3.11**	4.67	**2.07**	**1.17**	**1.10**
Competitive Advantage	98.30	5	56.36	69	24.07	0.000	**2.38**	**2.79**	4.89	**1.53**	**1.17**	**1.00**

4.6. INTERPRETING THE VARIABLES

To identify the unique qualities of each cluster, the mean score of each cluster was used in conjunction with the characteristics of each significant variable. The significant values are adopted from the ANOVA table and are put to four decimal places to show the extent of the significance.

4.6.1. PEOPLE

The people construct has self-efficacy and training as the category variables. Mean values with positive ratings are indicated in bold. Self-efficacy has the lowest mean scores of 1.33 and 1.4 in cluster 4 and cluster 6 respectively. These mean scores for self-efficacy are close to 1, which indicates a rating of strongly agree; whereas cluster 3 has a mean score of 4.67, indicating that the respondents somewhat disagree that they have the confidence and ability of using BI&A tools. The cluster table for the people construct is shown in Table 7 below.

Table 7: People Construct Cluster Analysis Table

Variable	Cluster (* Mean values with positive ratings are in bold)						
	1	2	3	4	5	6	signif.
	n=16	n=19	n=9	n=15	n=6	n=10	
	Mean						
Self-efficacy	**3.06**	**1.79**	4.67	**1.33**	4.33	**1.40**	0.00
Training	3.81	5.58	4.11	**3.20**	**2.67**	6.20	0.00
Training	4.13	2.79	4.67	**1.80**	**3.17**	**2.40**	0.00

4.6.2. TECHNOLOGY

Table 8 below shows that the respondents in clusters 1, 2 and 6 agree-somewhat that BI&A tools are easy to use, whereas, respondents in cluster 4 agree that BI&A tools are easy to use, mostly in the way they interact with the tools. In contrast, the respondents from clusters 3 and 5 disagree-somewhat that BI&A tools are easy to use, especially with regards to the mental effort required in using the tools.

Table 8: Technology Construct Cluster Analysis Table

Variable	Cluster (* Mean values with positive ratings are in bold)						
	1	2	3	4	5	6	signif.
	n=16	n=19	n=9	n=15	n=6	n=10	
	Mean						
Ease of Use	**3.00**	**2.00**	4.89	**1.73**	3.83	**1.80**	0.00
Ease of Use	3.69	5.21	4.33	**3.00**	6.33	5.70	0.00
Ease of Use	3.56	**3.11**	4.89	**2.00**	5.33	**2.80**	0.00
Ease of Use	3.56	**2.68**	5.00	**2.13**	4.17	**2.10**	0.00

4.6.3. TASKS

The tasks construct is represented by the usefulness variable. Table 9 below shows that clusters 2, 4, 5 and 6 generally agree on the usefulness of BI&A tools, especially because they use information provided from different systems or because they work with large volumes of data. Respondents from cluster 1 and 3 on the other hand, show that they do not feel the full usefulness of BI&A tools. This may be attributed to the already existing gap created by misalignment of task requirements and what BI&A solutions offer. The ideal situation for these clusters is to close this gap and ensure that BI&A fits the task it is supporting. However, the respondents in question do not work with business problems that require BI&A tools, hence they do not see its usefulness.

Table 9: Tasks Cluster Analysis Table

Variable	Cluster (* Mean values with positive ratings are in bold)						
	1	2	3	4	5	6	signif.
	n=16	n=19	n=9	n=15	n=6	n=10	
	Mean						
Usefulness	**3.00**	**1.95**	5.33	**1.33**	**1.00**	**1.10**	0.00
Usefulness	**3.00**	**1.42**	5.33	**1.60**	**1.33**	**1.00**	0.00
Usefulness	**3.25**	**1.68**	5.33	**1.60**	**1.33**	**1.20**	0.00
Usefulness	**3.38**	5.32	4.44	3.73	**3.33**	5.50	0.01

4.6.4. STRUCTURES

The structures construct is represented by the organisational strategy variable (see Table 10 below). The respondents in cluster 6 strongly agree, whereas those in clusters 2 and 5 agree to a lesser extent that top management is interested in BI&A tools and aware of their benefits so much that they encourage their usage thereof. This is contrary to cluster 3 where the respondents disagree-somewhat.

Table 10: Structures Cluster Analysis Table

Variable	Cluster (* Mean values with positive ratings are in bold)						
	1	2	3	4	5	6	signif.
	n=16	n=19	n=9	n=15	n=6	n=10	
	Mean						
Top Management Support	**2.13**	**3.00**	5.22	**1.93**	3.50	**1.30**	0.00
Top Management Support	**1.94**	**2.53**	4.89	**1.53**	**2.67**	**1.30**	0.00
Top Management Support	**3.06**	**2.42**	4.67	**1.73**	3.50	**1.40**	0.00

4.6.5. BUSINESS VALUE

Efficiency and strategic performance make up the variables for the business value construct Results in Table 11 below show that cluster 4 and cluster 6 strongly agree on the value provided by BI&A tools. However, respondents in cluster 3 somewhat disagree that BI&A has any value especially when it comes to increasing their productivity.

Table 11: Business Value Cluster Analysis Table

Variable	Cluster (* Mean values with positive ratings are in bold)						
	1	2	3	4	5	6	signif.
	n=16	n=19	n=9	n=15	n=6	n=10	
	Mean						
Efficiency	**2.75**	**2.58**	5.11	**1.40**	**2.00**	**1.40**	0.00
Efficiency	**2.63**	**2.37**	5.11	**1.53**	**1.67**	**1.30**	0.00
Efficiency	**2.69**	**1.89**	4.89	**1.27**	**1.50**	**1.20**	0.00
Efficiency	**2.44**	**1.89**	5.00	**1.40**	**1.17**	**1.10**	0.00
Strategic Performance	**2.63**	**2.11**	4.89	**1.47**	**1.67**	**1.00**	0.00

Strategic Performance	**2.50**	**2.42**	5.00	**1.60**	**1.50**	**1.00**	0.00
Strategic Performance	**2.63**	**2.11**	4.89	**1.67**	**1.50**	**1.00**	0.00

4.6.6. ORGANISATIONAL SUCCESS

Table 12 below shows clusters 5 and 6 strongly agree that BI&A contributes positively towards gaining competitive advantage. On average, clusters 1 and 2 agree-somewhat that there are competitive benefits resulting from the use of BI&A. The results from these clusters indicate that BI&A tools help the organisation become much more profitable therefore they are much more useful. In contrast, cluster 3 respondents disagree-somewhat that BI&A has value, especially in helping their organisations perform better.

Table 12: Organisational Success Cluster Analysis Table

Variable	**Cluster (* Mean values with positive ratings are in bold)**						
	1	2	3	4	5	6	signif.
	n=16	n=19	n=9	n=15	n=6	n=10	
	Mean						
Competitive Advantage	**2.50**	**2.74**	4.67	**1.47**	**1.67**	**1.00**	0.00
Competitive Advantage	**2.75**	**2.79**	4.56	**2.27**	**1.83**	**1.00**	0.00
Competitive Advantage	**2.75**	**3.11**	4.67	**2.07**	**1.17**	**1.10**	0.00
Competitive Advantage	**2.38**	**2.79**	4.89	**1.53**	**1.17**	**1.00**	0.00

4.7. CLUSTER ASSIGNMENT

The observations are assigned into relevant clusters. The clusters are given names based on the dominant work profiles of the respondents in that cluster.

4.7.1. CLUSTER 1

cluster 1 is labelled 'key managers'. It comprises of 21.33% (16 observations) of the sample, of which, 50% of this figure are key managers and 31.25% are technologists. Educationists, investors and financial planners each account for 6.25%. In this cluster, there is a high configuration between tasks and structures with top management support being a key factor. The respondents agreed that top management are interested in using BI&A tools and are aware of the benefits. However, not all were convinced that management encourage usage of BI&A tools. The respondents did not agree that training was being adequately provided. This could have impacted their self-efficacy as they suggested that they did not entirely agree that they have confidence in their ability to use BI&A tools. This is amplified further by 50% (8 respondents) of respondents in this cluster who say that their biggest challenge is their lack of skills and understanding of BI&A tools. A smaller group of people in this cluster (3 respondents) believe that there is a lack of organisational culture that motivates usage of BI&A. The same number of respondents also believes that there is no strategic drive to use BI&A.

4.7.2. CLUSTER 2

This cluster is labelled 'financial planners' and is comprised of 19 observations. In this cluster, 12 (63.15%) are from the financial services sector with careers spanning from quantitative analysts, risk analysts, and portfolio managers. There is some indication that BI&A is adding value as the best performing construct is the organisational value construct which has an average mean score of 2.20. This value is obtained from a low configuration between tasks, people, technology and structures. The low levels of alignment can be attributed to the fact that the people in this cluster use information from different systems introducing data challenges. It is interesting to note that the respondents indicated that their top challenge is integrating data from different systems. Another challenge facing this group is that even though they have been given information on how to use BI&A tools, some mental effort is still required on their part. Furthermore, according to this group, there is no strategic drive to use BI&A.

4.7.3. CLUSTER 3

Cluster 3 is labelled 'general technologists' and is comprised of 9 observations. The majority of members of this group (8 respondents) have been termed general technologists who operate in the IT and telecommunications, financial services, health and retail industries. This cluster is the worst performing, with scores ranging between 4.11 (neutral) and 5.33 (somewhat disagree,) indicating that the respondents do not use BI&A technology. Overall, these mean scores show that there is no alignment. The respondents have no interest in using BI&A and they do not find any value in it. Furthermore, there is lack of management drive. Most individuals in this cluster highlighted that their biggest challenge is their lack of knowledge of using BI&A tools, which can be linked to lack of proper training. Findings from this cluster show that alignment is essential in ensuring the success of BI&A.

4.7.4. CLUSTER 4

Cluster 4 is the third best performing cluster and is labelled 'IT strategists'. It is aligned with TTPS showing a configuration that has more significance in driving BI&A. This cluster consists of 15 observations mainly made up of IT executives and general technologists. A total of 66.67% of the respondents have working experience of over 5 years. They use BI&A mainly for customer relationship management, incident management and stock management. The results from this cluster report that there is strong agreement that BI&A adds value to their decision-making. However, 46.67% (7 respondents) of this cluster indicated that their biggest challenge is integrating data from different sources. It is evident that many organisations are facing data related challenges, especially managing large amounts of data.

4.7.5. CLUSTER 5

This cluster is made up of 5 observations, mainly consisting of IT experts, all in the 30-40 age group. The main tools used by this cluster include Microsoft Analyser, Oracle Data Mining and SAP Business objects. Unlike the general technologists in cluster 3, cluster 5 is the second best performing cluster, even though there is only partial alignment between people and tasks. The usefulness of BI&A in completing tasks is the most influential factor in driving organisational performance. The respondents stated that they work with large volumes of data needed for decision-making. The value of using BI&A is therefore generated by reducing uncertainty and improving operational effectiveness. This value then feeds through sales growth and improved organisational performance. This cluster believes that lack of an organisational culture that motivates usage of BI&A tools impedes the success of the organisation. Furthermore, the gap in alignment of technology and structures highlight areas of improvement. According to Zheng, Yang & McLean (2010), an organisational environment that supports its people in using BI&A is critical to establishing appropriate technology infrastructure and to assimilating BI systems for organisational benefit. Furthermore, in such an environment, top management plays a significant role in effective deployment of BI systems.

4.7.6. CLUSTER 6

Cluster 6 is the best performing cluster. This cluster validates the value and positive impact created by BI&A when there is alignment. This cluster is made up of 10 observations, mainly consisting of a mix of IT experts and financial planners, most of them in the 30-40 age groups. 60 % (6 respondents) of the respondents in this cluster have a post graduate qualification with 5 respondents working in the financial services sector. Cluster 6 was the best performing, illuminating the relationships between TTPS. The uniqueness of the configuration that forms between the factors presents the combinations and relationships that are currently working well, resulting in high organisational performance. It is evident that top management is influential in creating a positive environment that is appealing for taking advantage of BI&A usage. Furthermore, people are receiving adequate training which is working in boosting their self-efficacy in using BI&A. An interaction therefore emerges from structures encouraging cohesiveness in people using BI&A technology to complete their daily tasks, resulting in high organisational performance; more so because the technology adequately fits the tasks they are being used for. However, 70% (7) of respondents in this cluster highlight a lack of understanding of BI&A tools and lack of skills in using BI&A as a major challenge among BI&A users, just as in Cluster 1.

4.8. ALIGNMENT OF TTPS

The primary objective of this study was to identify ways to leverage BI&A by examining the configuration of TTPS and the nature of this alignment. Results from Table 12 have shown that TTPS works in intersection to formulate configurations that yield different levels of alignment. The nature of the configurations and status of alignment is based on the number pattern that arises from the significant cluster solution values indicated in bold. The patterns which form show that respondents either strongly agree, agree or somewhat agree. Table 13 below illustrates the different configurations in which TTPS can either have low levels, average levels, good levels or high levels of alignment. Partial alignment and misalignment are also evident in some clusters. Partial alignment is when there is alignment between two or three factors (see cluster 1 and 5), whereas misalignment (see cluster 3) shows lack of alignment between all the factors. Furthermore, these levels of alignment reflect different levels of business performance. These configurations help to predict combinations that work well together and allow for BI&A value generation. The configurations that emerge also show gaps that need to be addressed.

Table 13: Alignment of TTPS

Cluster	Level of Alignment	Source of Alignment	Level of Business Performance	Main Challenge
Cluster 1	Partially aligned because of poor training and low self-efficacy which impacts usability of BI&A	Tasks, Structures	Low business performance	Lack of skills and understanding of BI&A tools
Cluster 2	Low level of alignment because users find it difficult to get BI to do what they want it to do	TTPS	Average business performance	Integrating data from different sources
Cluster 3	Misaligned	None	Very poor business performance	Lack of knowledge of using BI&A
Cluster 4	Good levels of alignment with many areas of improvement in how the imperatives interplay	TTPS	Good organisational performance	Integrating data from different sources
Cluster 5	Partially aligned even though users do not have the confidence in using BI&A tools	Tasks and People	Good organisational performance	Lack of organisational culture that motivates usage of BI&A tools

Cluster 6	High level of alignment The users have the necessary BI&A skills. Top management support is also available and they find BI&A very useful in improving organisational performance	Tasks, People, Technology and Structures	High organisational performance	Lack of understanding of BI&A tools

4.9. SUMMARY OF RESULTS

Chapter 4 covered the analysis of results. The survey attracted a response rate of 62.5%, with the FSS (41.10%) having the highest number of responses, followed by IT and Telecommunications (26.03%). Most of the respondents are in the 30-40 years age group and 60% have a post graduate qualification. After conducting a Cronbach Alpha test, all the data was deemed reliable and no anomalies were observed, therefore all the responses were used for further data analysis. Cluster analysis was the main data analysis method supported by the ANOVA test which showed that the p values are uniformly distributed and significant at $p<0.05$.

There is agreement in Clusters 1, 2, 4, 5 and 6 that BI&A is valuable in influencing business value in improving decision-making and organisational success. In contrast, cluster 3 shows that there is no value being obtained from BI&A as the mean values range between 4.11 and 5.33. The mean values show that Cluster 6 is the best performing, representing a high level of alignment with structures being the construct with the greatest influence while cluster 3 is the worst performing.

There is a strong indication that TTPS interplay to formulate configurations that yield in different levels of alignment (low levels, average levels, good levels or high levels of alignment, partial alignment and misalignment). The following chapter further discusses these findings in relation to the study objectives and research questions, and recommends what organisations need to do in order to ensure that they get maximum value from BI&A.

CHAPTER 5: DISCUSSION AND RECOMMENDATION

Scholars like Riabacke et al. (2014) suggest that BI&A can leverage business value in terms of improving strategic business processes. This study answers the research question and proves that BI&A can be leveraged to add organisational value. It can be confirmed TTPS are interrelated and work together to formulate synergies that result in different levels of alignment. As shown in Table 14 above, patterns of configuration exist between TTPS to varying degrees and, where there is a higher level of alignment, organisational value of BI&A is also high.

This confirms the proposition that the stronger the level of alignment between TTPS, the more positive the value created by BI&A. Indications by Ammeenwerth et al. (2006), point out that technology is developed in response to a specific task requirement. Technology therefore affects the work that is being done and how it is done. The results of this study have shown that the nature of tasks to be completed requires BI&A tools, for instance, people work with large volumes of data and currently, this data deluge is driving organisations to use more sophisticated tools that deal with data (Chaudhuri et al., 2011).

As people use BI&A tools to complete their tasks, they only feel the benefit if they have adequate self-efficacy and training. A high level of self-efficacy is seen to come from training and as a result, users clearly know how to use BI&A tools. According to Compeau & Higgins (1995, p. 189) *"self-efficacy represents an important individual trait, which moderates organisational influences"* for example, encouragement and support. Self-efficacy and training are reinforced by some form of mental effort which is required when using BI&A tools. This maybe because the nature of tasks is complex, thus presenting a challenge when dealing with large volumes of data provided from different systems. Challenges facing organisations in relation to complexity around the nature of tasks include aggregating data from different sources (Dobbs, Stone & Abbott, 2002). Interestingly, there is no indication of any challenges in integrating data from different sources, even though they use large volumes of data from different sources.

According to Boyton et al. (2015), the greatest challenge in having successful BI&A remains with organisational and management buy-in. Most literature on alignment focuses on aligning organisational structures with strategy. To answer the question of how strategy implementation and execution can be improved to achieve alignment, a top down approach is more valuable in making BI&A part of the organisational culture. Strategic alignment is identified as a fundamental pre-condition in making BI&A successful. Top management support has also been highlighted as an important factor in information systems (Lin, 2014).

This study affirms the role of top management as identified by Lin (2014), who suggested that when top management are supportive, they encourage usage of technology. Results have shown that support from top management is a key factor in determining organisational success. Top management strive to meet strategic goals and consider the process of economics in terms of efficiency, demand and value provided by technology solutions (Lin, 2014). Also, because today's organisations have become knowledge intensive, they prefer to compete in the market by deriving strategic value from technology (Chaudhuri, 2011). BI&A is seen to help develop products, services and competences that help an organisation to gain advantage over competitors (Ucakturk and Villard, 2013). This therefore clarifies the positive relationship that forms between usage of BI&A and organisation success. Leveraging BI&A by alignment is thus an important factor in ensuring competitiveness and success in organisations.

Most of the respondents agree that they have the confidence required to use BI&A. Even though there are no instructions on using the tools, they are getting some form of training. However they still find BI&A difficult to use. Top management are strongly involved in the usage of technologies such as IBM Cognos, SAS Business Intelligence, SAP/Business Objects, QlikView and QlikSense. These have the advantage of improving organisational efficiency and competitive advantage which clarifies the positive performance effects of using BI&A. However, lack of organisational culture that motivates usage of BI&A tools is an issue for many of the respondents. This hinders strategy implementation and execution to achieve organisational success.

Implications of this study therefore point towards BI&A implementation. The study delineated how TTPS need to be aligned for BI&A to provide competitive advantage. These factors are all encompassing though, the contextual contingencies are not always clear cut. Ramakrishnan et al. (2012), note that organisations are driven by various reasons in their technology implementation. They also say that because of all these reasons, organisations are pressured to implement BI without fully understanding its value. The model for aligning TTPS can be valuable if adopted by organisations as it identifies configurations that can assist organisations to leverage the value obtained from BI&A, which in turn improves decision-making and organisational success.

CHAPTER 6: CONCLUSION

This study investigated ways to leverage BI&A through the alignment between tasks, technology, people and structures, and highlighting the levels of this alignment. This was achieved by using the gestalt/configurational approach. The analysis of results shows useful insights on six patterns of configurations. The patterns identified show four partially aligned clusters, one misaligned cluster and one fully aligned cluster. This study therefore concludes that the Gestalt approach is useful in identifying the level of alignment by identifying coherence amongst a set of theoretical attributes. The configurations identified indicate complexities in their interaction, thus, no single competitive strategy can create superior value.

This study proves that high organisational success is reached when there is an adequate level of alignment between TTPS. In practice, organisations can identify what is working well together and what is not. This will help organisations achieve their competitive advantage by ensuring information systems provide direction and flexibility to react to opportunities. However, there is concern about the clusters where misalignment is reported. There is a need to provide organisational guidelines and awareness on how to achieve alignment between TTPS. There is support for the notion that BI&A is useful in supporting the nature of tasks. It has also been established that training is a key factor and can be influenced by top management support. It is imperative that organisations include all stakeholders and have policies and procedures in place to ensure success.

Even though there is support that best configuration is where TTPS are completely aligned, tightly coupled configurations may arise and this could have negative outcomes, especially when there are changes in the organisational environment. Most models of alignment assume that organisations are built on mechanistic principles and that management uses structured, planning-oriented approaches to business objectives. In such firms alignment may work, but not in others. Nonetheless, TTPS are not perishable; they remain in a constant symbiotic relationship. Whilst all the variables are equally important, top management support and the nature of task show themselves as dominant imperatives in ensuring alignment. This result offers organisations useful insight on how top management is essential in driving organisational goals with regards to technology implementation. Top management also drive technology management practices by their leadership and commitment.

6.1. LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

The goal of this study was to explore ways in which BI&A can be leveraged by limiting the scope of the study to investigate interplay between tasks, technology, people and structures. This study was also limited to a South African context and mainly focused on large corporates with most of the respondents being in the 30 to 40 years age group. Consequently, findings from this research should be generalised conservatively as they may not apply outside the South African context or to an older age group. The other limitation is the selection bias among the respondents who were targeted through purposive sampling. For future research, it may be valuable to focus on Small, Medium and Micro-sized Enterprises (SMMEs) to close the gap created by focusing on large corporates. Furthermore, the business landscape is not fixed. It is necessary to conduct this study over a substantial period of time to assess stability of the clusters due to transformations that come along with continued changes to task, technology, people and structures. TTPS form a baseline of key elements which must be aligned but they are not all encompassing. It is therefore imperative for organisations to include external links, for example regulatory requirements, so as to come up with a better comprehensive list of influencing factors. The research model needs to be expanded to include more variables. These variables can be extracted from normative and regulative elements in organisations and the industry sector as whole.

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APPENDIX A – SURVEY COVER LETTER

University of Cape Town

Department of Information Systems

Leslie Commerce Building

Upper Campus

16 December 2016

Dear Sir/Madam,

I am currently working towards a Masters degree in Information Systems at UCT. As part of the fulfilment of my studies I have developed a survey to assist in understanding of how organisations can leverage Predictive Analytics tools to facilitate decision-making tasks which will in turn result in improved organisational success. This research has been approved by the Commerce Faculty Ethics in Research Committee. I would really like to include your organisation in my research and would appreciate it if you could please answer this survey.

Completion of this survey is voluntary and anonymous and will take approximately 15 minutes. This survey can be answered by people in decision-making positions within organisations that use Predictive Analytics tools to facilitate decision-making. Please share this survey with anyone who fits this group and forms part of a South African organisation, to increase the chance of people answering this questionnaire and to add value to the research in a South African Context. You are welcome to email me if you would like more information.

Due date: Please complete this survey at your soonest convenience, no later than Tuesday 31 January 2017.

Kind regards,

Rutendo Mushore (Researcher)

mushore.rm@gmail.com / mshmor005@myuct.ac.za

Prof. Maichael Kyobe (Research Supervisor)

michael.kyobe@uct.ac.za

APPENDIX B - QUESTIONNAIRE

University of Cape Town
Department of Information Systems

Leslie Commerce Building

Upper Campus

Private Bag X3 - Rondebosch - 7701

Tel: +27 (0) 21 650 2261 Fax: +27 (0) 21650 2280

BUSINESS INTELLIGENCE & ANALYTICS SURVEY

Business Intelligence & Analytics (BI&A) has emerged as an important area of study for both practitioners and researchers, reflecting the magnitude and impact of data-related problems to be solved in contemporary business organisations. BI&A is about the development of technologies, systems, practices, and applications to analyse critical business data so as to gain new insights which help in decision-making (Lim et al., 2013).

This is a confidential questionnaire. Therefore, no one will have access to it and the information you have given. It is also anonymous, so please avoid putting your name on it and no one will know you answered it.

Answering this questionnaire is completely voluntary and you may, at any time, decide to exit. This will take 15 minutes of your time. Please mark with an X in the relevant box provided.

A. General Information - Demographics

1. Industry Sector					
2. Department					
3. Job Title					
4. Skills level	In house	Diploma	University	Post Graduate	Other

	training		Degree		
5. Working Experience	>2 yrs.	2-5 yrs.	5-10 yrs.	10-15 yrs.	15+ yrs.
6. Age	20-30 yrs.	30-40 yrs.	40-50 yrs.	50+ yrs.	

Which of the following tools do you use in your day to day decision-making Tasks?						
SAP/Business Objects		*SAS/Business Intelligence*		*Web Trends*	*IBM/Cognos*	
Clementine Data Mining		*SAS Text Miner*		*Oracle Data Mining*	*IBM/SPSS Statistics*	
Microsoft Analyser		*SAS Webhound*		*Oracle Hyperion*	*Inxight Text Mining*	
QlikView		*QlikSense*		*SSAS*	*SSIS*	
Tableau		*Power BI*		*SPLUNK*		
Other Specify						

I use BI&A tools to complete the following decision-making tasks							
Incident Management							
Stock Management							
Investments Management							
Analysing Stock Markets							
Education Analytics							
Fraud Management							
Crime Management							
Customer Relationship Management							

Consumer Behaviour Management							
Capacity Planning							
Disease Management							
Pharmaceutical Drugs Management							
Other							

B							
Rate how far you agree with the below statements regarding your BI&A tools skills:							
	Strongly Agree < -------------------------------------- > Strongly Disagree						
	1	**2**	**3**	**4**	**5**	**6**	**7**
PE1. I have confidence in my ability to use BI&A tools to facilitate my decision-making tasks							
PE2. There are no instructions on how to use BI&A tools to facilitate my decision-making tasks							
PE3. I am getting adequate training on how to use BI&A to facilitate my decision-making tasks							
Indicate how usable BI&A technology is							
TE1. My interaction with BI&A tools is clear and understandable							
TE2. Interacting with BI&A tools does not require my mental effort							
TE3. I find BI&A tools easy to use							
TE4. I find it easy to get BI&A tools to accomplish what I want them to do							

Indicate your need for BI&A in decision-making Tasks							
TA1. I work with large volumes of data needed for decision-making							
TA2. I use information provided from different systems for my decision-making tasks							
TA3. I work with business problems that require BI&A tools							
TA4. For my decision-making tasks, I cannot aggregate data from different systems for analysis							
Rate the role and influence of managerial structures in BI&A							
ST1. Top management is interested in using BI&A tools							
ST2. Top management is aware the benefits of using BI&A tools							
ST3. Top management encourage the usage of BI&A tools							
Rate how far you agree with the organisational success attained from using BI&A tools							
VA1. I am satisfied with the efficiency that BI&A tools bring in facilitating my decision-making tasks							
VA2. I am satisfied with my increased productivity in completing decision-making tasks when I use BI&A tools							
VA3. I feel that using BI&A aids in effective decision-making							
VA4. I feel that using BI&A reduces uncertainty and improves operational effectiveness							
VA5. I feel that using BI&A tools results in reduced operational costs because of better decision-making							

VA6. I feel that using BI&A enables me to rapidly react to business events and perform proactively in business planning.							
VA7. Using BI&A helps me improve my performance in decision-making tasks							
Rate how far you agree with the organisational success attained from using BI&A tools							
SU1. BI&A tools help the organisation become much more profitable							
SU2. Decision-making using BI&A tools helps the organisation gain market share							
SU3. Decision-making using BI&A tools helps improve sales growth							
SU4. The organisation performs much better with the use of BI&A tools							

Indicate your top challenge with Business Intelligence and Analytics						
Lack of skills using BI&A	Lack of understandin g of BI&A tools	In ability to integrate data from different sources	BI&A tools are too hard to use	Lack of an organisatio nal culture that motivates usage of BI&A tools	There is no strategic drive to use BI&A	There are no tasks that require usage of BI&A tools

APPENDIX C – CONSTRUCT, SUMMARY OF VARIABLES & SOURCES

Construct	Variable	Source
People	Self-efficacy	(Hester, 2014)
	Training	(Hester, 2014)
	Training	(Hester, 2014)
Technology	Ease of use	(Giboney et al., 2015)
	Ease of use	(Giboney et al., 2015)
	Ease of use	(Giboney et al., 2015)
	Ease of use	(Giboney et al., 2015)
Tasks	Nature of tasks	(Giboney et al., 2015)
	Nature of tasks	(Giboney et al., 2015)
	Nature of tasks	(Giboney et al., 2015)
	Nature of tasks	(Giboney et al., 2015)
Structures	Top Management Support	(Lin, 2014)
	Top Management Support	(Lin, 2014)
	Top Management Support	(Lin, 2014)

Construct	Variable	Source
Business Value	Efficiency	(Elbashir et al., 2008)
	Efficiency	(Elbashir et al., 2008)
	Efficiency	(Elbashir et al., 2008)
	Efficiency	(Elbashir et al., 2008)
	Strategic performance	(Elbashir et al., 2008)
	Strategic performance	(Elbashir et al., 2008)
	Individual Performance	(Elbashir et al., 2008)
Organisational Success	Competitive Advantage	(Peters et al., 2016)
	Competitive Advantage	(Peters et al., 2016)
	Competitive Advantage	(Peters et al., 2016)
	Competitive Advantage	(Peters et al., 2016)

APPENDIX D – ETHICS APPROVAL FORM

UNIVERSITY OF CAPE TOWN

FACULTY OF COMMERCE

Igniting Knowledge and Opportunity

Commerce Faculty Ethics in Research Application Form

Any person planning to undertake research in the Faculty of Commerce at the University of Cape Town is required to complete this form **before collecting or analysing data**. If any of the questions below have been answered YES, and the applicant is NOT an Honours student, the form it should be submitted to the supervisor (where applicable) and from there for approval by the Faculty EIR committee: Ms Samantha Alexander (**samantha.alexander@uct.ac.za).**

It is assumed that the researcher has read the UCT Code for Research involving Human Subjects (Available at http://web.uct.ac.za/depts/educate/download/uctcodeforresearchinvolvinghumansubjects.pdf) in order to be able to answer the questions in this form.

Students must include a copy of the completed form with the dissertation/thesis when it is submitted for examination.

1. PROJECT DETAILS	
Project title:	

Principal Researcher/s:	**Email address(es):**	**Rutendo Mushore** **Mushore.rm@gmail.com**
Research Supervisor:	**Email address(es):**	Michael Kyobe Michael.kyobe@uct.ac.za
Co-researcher(s):	**Email address(es):**	**N/A**
Department:		

Brief description of the project:

The research project presents a conceptual model proposing that four key organisational imperatives interplay and form configurations and patterns of complexity. Therefore, for an organisation to be successful these imperatives need to be aligned. A questionnaire has been developed to ask questions that intend to accurately portray the relationships/configurations/patterns between task, technology, people and structures and extend understanding on how organisations can leverage predictive analytics tools for organisational success.

Data collection: (please select)

☐Interviews ☒Questionnaire ☐Experiment ☐Secondary data ☐Observation

☐ Other (please specify): ______

Have you attached a research proposal OR a literature review with research methodology? (please select) ☒Yes ☐No

2. PARTICIPANTS

2.1 Does the research discriminate against participation by individuals, or differentiate between participants, on the grounds of gender, race or ethnic group, age range, religion, income, handicap, illness or any similar classification?	YES	NO X
2.2 Does the research require the participation of socially or physically vulnerable people (children, aged, disabled, etc.) or legally restricted groups?	YES	NO X
2.3 Will you be able to secure the informed consent of all participants in the research? (In the case of children, will you be able to obtain the consent of their guardians or parents?)	YES X	NO
2.4 Will any confidential data be collected or will identifiable records of individuals be kept?	YES X	NO
2.5 In reporting on this research is there any possibility that you will not be able to keep the identities of the individuals involved anonymous?	YES	NO X
2.6 Are there any foreseeable risks of physical, psychological or social harm to	YES	NO

participants that might occur in the course of the research?		X
2.7 Does the research include making payments or giving gifts to any participants?	YES	NO X

If you have answered **YES to any of these questions**, please describe how you plan to address these issues (append to form):

Affiliations of participants: (please select)

☒Company employees ☐Hospital employees ☐General public ☐Military staff ☐Farm workers ☐Students

☐ Other (please specify): ______

Race / Ethnicity:

Are you asking a question about race/ethnicity in your questionnaire?

☐ Yes ☒No

Which race categories have been used?

Have you included the option: "Prefer not to answer" as part of your race/ethnicity question?

3. Provision of Services

Does your research involve the participation of or provision of services to communities?

If your answer is YES, please complete below:

3.1 Is the community expected to make decisions for, during or based on the research?	YES	NO X
3.2 At the end of the research will any economic or social process be terminated or left unsupported, or equipment or facilities used in the research be recovered from the participants or community?	YES	NO X
3.3 Will any service be provided at a level below the generally accepted standards?	YES	NO X

If you answered YES to any of these questions, please describe below how you plan to address these issues.

3. ORGANISATIONAL PERMISSION

If your research is being conducted within a specific organisation, please state how organisational permission has been/will be obtained:

Prior to distributing the questionnaire, a permission will requested

Have you attached the letter from the organisation granting permission? (please select)

☐ Yes ☒ No, but this **will be** obtained before commencing the research ☐ Not applicable

Are you making use of **UCT students** as respondents for your research? (please select) ☐ Yes ☒ No

If yes, have you contacted Executive Director: Student Affairs for permission? (please select) ☐ Yes ☐ No

Was approval granted? (please select) ☐ Yes ☐ No ☐
Awaiting a response

Are you making use of **UCT staff** as respondents for your research? (please select) ☐ Yes
☒ No

If yes, have you contacted Executive Director: Human Resources for permission? (please select) ☐ Yes
☐ No

Was approval granted? (please select) ☐ Yes ☐ No ☐
Awaiting a response

Contact Emails: Executive Director: Human Resources (**Miriam.Hoosain@uct.ac.za)**

Executive Director: Student Affairs (**Moonira.Khan@uct.ac.za)**

4. INFORMED CONSENT

What type of consent will be obtained from study participants?

☐ Oral Consent

☐ Written Consent

☑ Anonymous survey questionnaire (covering letter required , no consent forms needed)

☐ Other (Please Specify)

How and where will consent/permission be recorded?

Have you attached an informed consent form to your application? ☒ Yes ☐ No

5. SponsorShip of Research

If your research is sponsored, is there any potential for conflicts of interest?

If your answer is YES, please complete below

4.1 Is there any existing or potential conflict of interest between a research sponsor, academic supervisor, other researchers or participants?	YES	NO
4.2 Will information that reveals the identity of participants be supplied to a research sponsor, other than with the permission of the individuals?	YES	NO
4.3 Does the proposed research potentially conflict with the research of any other individual or group within the University?	YES	NO

If you have answered **YES** to any of these questions, please describe how you plan to address these issues (append to form)

6. RISK TO PARTICIPANTS
Does the proposed research pose any physical, psychological, social, legal, economic, or other risks to study participants you can foresee, both immediate and long range? (please select) ☐ Yes ☒ No **If yes, answer the following questions:**
1.
2.
3.

I certify that I have read the the Commerce Faculty Ethics in Research policy ☐
(http://www.commerce.uct.ac.za/Pages/ComFac-Downloads**)**

I hereby undertake to carry out my research in such a way that

- there is no apparent legal objection to the nature or the method of research; and
- the research will not compromise staff or students or the other responsibilities of the University;
- the stated objective will be achieved, and the findings will have a high degree of validity;
- limitations and alternative interpretations will be considered;
- the findings could be subject to peer review and publicly available; and
- I will comply with the conventions of copyright and avoid any practice that would constitute plagiarism.

Signed by:

	Full name and signature	Date
Principal Researcher/Student: Rutendo Mushore	Signed	19/11/2016

This application is approved by:

Supervisor		
HOD (or delegated nominee – for all Honours Projects):	Signed	
Chair: Faculty EIR Committee (only for postgraduate research at Master and PhD level)		

CHECKLIST	SELECT
A full copy of a research proposal or a literature review with methodology is attached in a separate file	☒
Interview schedules / cover letters / questionnaires / forms and other materials used in the study are attached in separate files	☒
Organisational consent letter / UCT student or staff approval letter	☐
On your cover letter to your questionnaire have you included the following? 1. The following UCT Logo 2. A sentence explaining the aim of the research 3. Sentences of a similar nature to below must be included in the cover letter or consent form: This research has been approved by the Commerce Faculty Ethics in Research Committee. Your participation in this research is voluntary. You can choose to withdraw from the research at any time. The questionnaire will take approximately X minutes to complete	NA ☐ ☒ ☒ ☐

You will not be requested to supply any identifiable information, ensuring anonymity of your responses.	☐
Due to the nature of the study you will need to provide the researchers with some form of identifiable information however, all responses will be confidential and used for the purposes of this research only.	☒
Should you have any questions regarding the research please feel free to contact the researcher (insert contact details).	☒
	OR
4. Have you scanned in your signature for the last section of the form?	☐
	☐
	☒