Gordon Institute of Business Science
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# Big Data Analytical Capabilities: Does Entrepreneurial Orientation moderate their effect?

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**Abstract**

Organisations are looking increasingly to data and Big Data Analytical Capabilities (BDAC) to gain competitive advantage; however, few consider how the effect on performance is determined by their Entrepreneurial Orientation (EO). Applying the Resource Based View of the firm, this study pulls together two dynamic capabilities, BDAC and EO, to investigate their effect on Firm Performance (FPER). The study utilised moderated regression and results indicate positive and significant relationships between BDAC & FPER, BDAC & EO and EO & FPER, however, no moderating effect of EO on BDAC-FPER was found. The study uncovers a relationship between two capabilities, never before tested, and disproves the idea that dynamic capabilities can simply be layered to improve performance. Future research, introducing organisational ambidexterity and considering digital maturity, would add to the contributions made by this research.

**Keywords**

Strategy, Competitive Advantage, Dynamic Capabilities, Big Data Analytical Capabilities, Entrepreneurial Orientation

**Declaration**

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

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**Contents of document:**

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To whom it may concern,

**Identification of and motivation for target journal**

Article Title: **Big Data Analytical Capabilities: Does Entrepreneurial Orientation moderate their effect?**

**The Journal of Entrepreneurship** is a multidisciplinary forum for the publication of articles and research and discussion of issues that bear upon and enfold the field of entrepreneurship. Topics appropriate and related to entrepreneurship include intrapreneurship, managership, organisational behaviour, leadership, motivation, training and ethical/ moral notions guiding entrepreneurial behaviour.

This journal was chosen, as the research topic in question blends a focus on Entrepreneurial concepts (orientation) with the current and topical Big Data concept (Big Data Analytical Capabilities). This strategic view of entrepreneurship adds to the field of academia and provides practical implications. The research finds that while there is a positive relationship between the Entrepreneurial Orientation of organisations and Big Data Analytical Capabilities, there is no moderating effect of Entrepreneurial Orientation on the effect that Big Data Analytical Capabilities have on firm performance. These findings are new to their fields.

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Journal to be submitted:

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In terms of the sequence of authorship, the researcher (Luke Moerdyk) will be the first and corresponding author and the second author will be the researcher's supervisor (Manoj Chiba).

Should you have any concerns, please do not hesitate to contact either myself or my supervisor on the details provided below.

Yours sincerely,

**Luke Moerdyk**

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# Literature Review

## 1. Introduction

The growing interest in Information Technology (IT), and specifically big data, has lead to increased focus on the topic (Akter, Wamba, Gunasekaran, Dubey & Childe, 2016; Gupta & George, 2016) and its merits in the context of sustainable competitive advantage. Firstly, as many as 64% of organisations (Gupta & George, 2016) have increased investment into data driven initiatives or plan to, primarily due to the 5-6% improvement in performance observed with regards to profitability and productivity (McAfee, Brynjolfsson, Davenport, Patil & Barton 2012; Akter et al., 2016). Secondly, there has been significant and constant growth in the number of platforms that are able to generate and capture data; the internet, social media, mobile technologies, video & voice related, and transactional data, resulting in “organisations swimming in a vast sea of data” (Akter et al., 2016, p. 114). It has not yet been determined how the analysis of these big data are influenced by other capabilities, particularly the approach organisations take in response to new and uncertain opportunities, innovation and risk taking, all in a bid to become more competitive and ultimately improve the performance of the organisation.

According to Barney’s Resource Based View (RBV), competitiveness is built by accumulating valuable, rare, inimitable and non-substitutable resources, whether tangible or intangible in nature (Gupta & George 2016; Lin & Wu, 2013). Building on RBV, Teece, Pisano & Shuen (1997) developed the Dynamic Capabilities view, which deals with the pressing concept of competitive advantage in highly volatile and changing environments, by building, combining, reconfiguring and transferring capabilities in organisations. Inimitable sources of competitive advantage stem from concepts such as, “management of research and development, product and process development, technology transfer, intellectual property, manufacturing, human resources and organisational learning” (Teece, Pisano & Shuen, 1997, p. 510). According to Ambrosini & Bowman (2009) there are various types of dynamic capabilities, “Some are used to integrate resources, some to reconfigure resources; some are about creating new resources, while others are about shedding resources” (Ambrosini & Bowman, 2009, p. 9). This research focuses on two specific dynamic capabilities, namely Big Data Analytical Capabilities (BDAC) and Entrepreneurial Orientation (EO), and their relationship to competitive advantage, measured as firm performance (FPER).

How the relationship between BDAC and FPER is leveraged, is only recently and not extensively researched, few moderating variables have been tested, especially with regard to other dynamic capabilities. While the relationship between BDAC and FPER (Wamba et al., 2017; Akter et al., 2016), as well as EO and FPER (Lumpkin & Dess, 1996; Wiklund & Shepherd, 2003; Anderson, Kreiser, Donald, Kuratko, Hornsby & Eshima, 2014) have been measured and found to be meaningful, an outward looking perspective is lacking when considering the relationship between BDAC and FPER, that is the organisational capability to identify, seize and leverage opportunities presented by BDAC, encapsulated by the organisations outlook. The research builds on the growing (Gupta & George, 2016; Akter et al., 2016; Wamba et al., 2017; Garmaki et al., 2016) but limited knowledge base relating to BDAC, by understand the relationship between BDAC and FPER, and EO - which is introduced as a moderating variable. EO brings a critical element to the role that BDAC plays in organizations through the RBV mindset (Gupta & George 2016; Lin & Wu, 2013), compounding the BDAC advantage presented through FPER.

The research adds to the body of work relating to BDAC and adds a new and potentially critical construct (EO), which making it increasingly relevant and provides a fresh perspective in this data driven age of academia. In practice, the greatest value lies in the ability to compound dynamic capabilities on existing competencies and align them with organisational strategy for long term competitive advantage and superior performance.

While there is evidence that organisations that consider themselves data-driven achieve better financial and operations performance (McAfee et al., 2012), BDAC or EO on their own are not able to create competitive advantage, as competitive advantage is built by integrating and establishing several firm-level resources (Gupta & George, 2016) and widely regarded as a result of corporate strategy (Andrews, 1971; Porter; 1979). The literature that follows ties strategy formulations to the understanding of dynamic capabilities within organisations. The literature explores what is currently known about the constructs in question and follows a process of unpacking the important connection between two distinct dynamic capabilities. Linking BDAC, as well as the entrepreneurial mindset discussed as EO, to the performance of organisations (FPER), through the Resource Based View (RBV). The literature concludes by summarising the hypotheses tested and addresses the research model.

## 2. Strategy Formulation and the Source of Advantage

### 2.1 What is strategy

The definition of Corporate Strategy, according to the long standing work by Andrews (1971) is, “the pattern of decisions in a company that determine and reveal its objectives, purpose, or goals, produces the principal policies and plans for achieving those goals, and defines the range of businesses the company is to pursue, the kind of economic and human organisation it is or intends to be, and the nature of economic and non economic contribution it intends to make to its shareholders, employees, customers and communities” (Andrews, 1971, p. 52). Achieving sufficient or superior performance is therefore a result of strategic choices made (Child, 1972), in the pursuit of competitive advantage over rivals, and to create and maintain sustainability. It is them evident that BDAC and EO are both a result of a pattern of decisions, are implemented with an intended outcome and as part of a plan, aligning resources with the objective of the organisation in how they are implemented. They shape and are shaped by the strategic choices of an organisation. These strategic choices relate to the context in which the organisation operates and to the calibre of performance against which it measures itself and to the design of the structure of the organisation (Child, 1972).

Before a formulated strategy can be implemented, Andrews (1971) has proposed four components which should be met; (1) The identification of opportunity and associated risks, (2) Determination of the capabilities and resources available, (3) Personal values and aspirations of individuals in the organisation and (4) the acknowledgement of non economic responsibilities to society. To achieve high performance levels, Child (1972) suggests that it is not enough to only have goals and objective, largely determined by leadership teams within organisations. He suggests that organisations perform better when they align their strategy with the environment in which they operate, dealing with environmental complexity and variability. The more complex an environment, the more information the organisation requires to make informed decisions towards adapting to the changing conditions and remaining competitive (Child, 1972). This makes the first two of Andrew’s components particularly important and relevant to the use of data and organisational outlook, as they influence the approach taken to risk, evaluation of opportunities and resource arrangement.

## 2.2 Competitive Advantage and Firm Performance

As has been established, strategy relates closely to the concept of choices, made by organisations, towards improved performance, prosperity or even survival (Augier & Teece, 2008). Choices in this regard include; product or service selection, where to offer them and how to attract customers, which operating model to implement, the structure of the organisation and the coordination of practices, as well as how to create competitive advantage, which competitors will struggle to imitate and that customers will be delighted by (Augier & Teece, 2008). Competitive advantage is, according to Ma (2000) achieved through two schools of thought, firstly the structural approach proposed by Porter (2008) and the Resource based view (RBV) proposed by Barney in 1986 and others, including Rumelt and Wernerfelt (Ma, 2000). It has been argued that competitive advantage gives organisations the necessary tools and skills to provide value to customers, and therefore provides superior firm performance (Ma, 2000). The RBV perspective of competitive advantage is more relevant to data analytics and entrepreneurial capabilities, as the theory suggest that internal resources such as capabilities, are more substantial determinants of competitive advantage than external resources (Graganza, Brooks, Nepelski, Ali & Moro, 2016). The four attributes, according to RBV, that create sustainable competitive advantage are Value, Rarity, Imitability and Non-substitutability (VRIN), the latter two, are said to provide the sustainable aspects. It has also been suggested that entrepreneurial vision as well as intuition are necessary to knowing which resources make competitive advantage sustainable (Graganza et al., 2016).

In addition to Porter's cost advantage and differentiation (1979), other sources of competitive advantage have been proposed, including; flexibility, speed and innovation, these are considered particularly important and technologically oriented and other emerging industries (Ma, 2000). There are, however four suggested situations which have been identified, in which competitive advantage is present without superior performance: "(1) a firm may have a discrete advantage that fails to develop into a compound advantage; (2) a firm may have a great competitive advantage over all rivals yet fail to fully tap into its potential; (3) a firm may have multiple competitive advantages over a rival but does not have the right combination or lacks competitive advantage in one critical area, which could turn the table; and (4) management intentionally sacrifices a competitive advantage” (Ma, 2000, p. 24). The discussed RBV suggests that the differentiation created and exploited by organisations is ‘anchored upstream’ (Augier & Teece, 2008). This implies that differentiation is rooted in the way the organisation does things, in other words, their capabilities, strategic decisions and routines, rather than by what they take to the market or their customers alone. (Augier & Teece, 2008). These concepts, along with the nature of this source of advantage being drawn from multiple schools of thought (entrepreneurship, decision making, innovation, behaviour and change management for example), lead to the emergence of dynamic capabilities.

## 3. Dynamic Capabilities

Competitive advantage requires both exploitation of internal and external capabilities, as well as the development of new capabilities. One key source of competitive advantage related to this, is the concept of dynamic capabilities. Dynamic refers to the changing nature of environments, requiring strategic responses, is related to the acceleration of change and need to innovate and adapt as well as understanding the essence and future of competition in markets which are tough to define and keep track of. Capabilities relate to the alignment, adaptation, integration and configuring of resources inside and outside organisations (Teece, 1994).

A core competency is considered to be the collective knowledge regarding an organization's coordination of resources and skills. These competencies therefore gives rise to true forms of competitive advantage, as an organization's ability to leverage competences will allow the organisation to adapt quickly and meaningfully respond to new opportunities. Core competencies do not diminish with use, or over time, but rather are built on and evolve if fostered (Prahalad & Hamel, 1990). Firm specific advantages (FSA) were proposed in the 1980’s, preceding the concept of core competencies (Prahalad & hamel, 1990) and RBV. FSA are developed through ‘know how’ or the development of capabilities, which competitors are not able to replicate, except over long periods of time and often at great expense (Rugman, Verbeke & Nguyen, 2011). The concept of exploiting these FSA’s internally, is known as Internalisation advantage, which involves the process of ‘creating, transferring and recombining’ the exploited FSA inside the organization, rather than utilising outsourced skill sets (Rugman et al., 2011). Lake and Ulrich suggest that at the most basic level, organisational capability is the management of individuals towards competitive advantage. (Ulrich & Lake, 1990).

Dynamic capabilities can then be defined as “higher level competences that determine the firm’s ability to integrate, build, and reconfigure internal and external resources/competences” as well as addressing and “possibly shaping, rapidly changing business environments” (Teece, 2012, p. 1395). Dynamic capabilities are different from ordinary competencies in their strategic nature, firms are able to sustain and foster competitive advantage by ‘layering’ dynamic capabilities on top of ordinary capabilities (which are ways of organising and getting things done). When aligned and integrated into a good corporate strategy, dynamic capabilities have the potential to improve positioning of products and services, increase the ability to target and and serve customer needs. Dynamic capabilities are therefore vital for enhancing entrepreneurial competences in creating markets and co-creation (Teece, 1994, 2012, 2014).

Three groups of activities have been identified relating to dynamic capabilities, these include sensing, seizing and transforming. It is therefore evident that capabilities are ever changing and not only built on the skills of individuals, but the collective learning as a result of collaboration. Sensing is defined as the “identification and assessment of an opportunity” (Teece, 2012, p. 1396), concepts including environmental scanning inside and outside of the organisation. Some of the activities related to sensing include investigating new markets and innovations, research and development practices and understanding technological transformation. Seizing is defined as, “mobilisation of resources to address an opportunity and to capture value doing so” (Teece, 2012, p. 1396), sensing involves selecting the right capabilities to align with the opportunities identified and chosen. Transforming is defined as, “continued renewal” (Teece, 2012, p. 1396), a concept also known as reconfiguring and is concerned with the capability to deal with change. (Teece, 2012, Arndt et al., 2017).

In order to determine and firms dynamic capabilities, three categories have been identified by Teece, Pisano and others (Teece & Pisano, 1994, Teece, Pisano & Shuen, 1997, Teece, 2012, Teece, 2013); managerial and organisational processes, present position and paths available. Process is defined as the ‘way things are done’ and typically refer to methods, patterns and current execution and learning. Position is related to establishment of technologies and intellectual property, customers being services and relations with partners. Paths refer to appeal and opportunities of the alternatives available to the firm (Teece & Pisano, 1994, Teece, Pisano & Shuen, 1997, Teece, 2012, Teece, 2013).

Managerial and organisational process include three vital concepts: Firstly, integration and coordination of internal as well as external activities and technologies is vital for the creation of competitive advantage. The patterns relating to integration are generally specific to each organisation and persist for long periods of time. The embedded nature of dynamic capabilities means that small and incremental changes to technologies, for example, can have monumental impacts on an organization's ability to remain competitive in changing marketplaces (Teece & Pisano, 1994, Teece, Pisano & Shuen, 1997, Teece, 2012, Teece, 2013). Second, learning is potentially more critical than even coordination, the process of experimentation and repetition enables organisations to become more adaptable, responsive and effective at identifying new opportunities or refining existing ones. Characteristics of learning help understand the concept in the context of dynamic capabilities. Learning is an individual and organisational skill, it involves social and collective behaviours and is enhanced by the quality and shared meaning of communication (Teece & Pisano, 1994, Teece, Pisano & Shuen, 1997, Teece, 2012, Teece, 2013). The knowledge developed through these activities is done so through existing patterns of behaviour, or routines within the organisation. Collaboration helps organisation identify problematic routines and avoid strategic missed opportunities (Teece & Pisano 1994). Lastly, reconfiguring and transforming is a learned skill within an organisation and takes considerable and deliberate effort. The ability to adapt to identified changes in the market, through scanning and evaluation of competition can result in highly flexible and dynamic organisations (Teece & Pisano, 1994, Teece, Pisano & Shuen, 1997, Teece, 2012, Teece, 2013).

The entrepreneurial function, especially in the organisational context, is embedded in dynamic capabilities. A new hybrid is proposed by Teece (2012), entrepreneurial managerial capitalism, which involves gauging opportunities and associated threats, coordinating resources according to a predetermined plan, and in some cases, re-designing organisational structures and systems to react to technological opportunities and competitive threats (Teece, 2012).

Dynamic capabilities in the context of the research proposed, are discussed from the perspective of BDAC and EO, both of which have the ability to contribute towards sustainable competitive advantage due to their intangible nature. BDAC and EO are largely non-substitutable and inimitable, despite not being specifically rare, they are undeniably valuable as the next sections discuss. It can therefore be argued that the formulation of strategy is a result of understanding and applying dynamic capabilities, towards opportunities identified and aligning resources to achieve the objectives set out. BDAC, enabled by Digital Data Streams (DSS), provide initial and continuous understanding (sensing) through analysis and insight generation. The insights gained are influenced by, and guide, the opportunities which organisations decide to act on (seizing), forming patterns of behaviours and strategic decisions (transformation). To create competitive advantage from such data capabilities, organisations need to focus on five important management functions, strengthening entanglement of data and strategy; leadership, talent management, technology, decision making and company culture (McAfee et al., 2012).

## 4. The Role and Rise of Data

The ability of organisations to create value, through new products, services or processes, is increasingly reliant and influenced by data. The rapid emergence and availability of data is changing the way decisions are being made and how operations and other organisational functions evolve to suit new customer needs and to remain competitive (Pigni, Piccoli & Watson, 2016). Organisations have both tactical and strategic opportunities if they make use of digital data streams. Tactically, real-time data can be used to make immediate decisions and react to a new or current needs and wants. Strategically, business models can be designed around insights gained. Digital data streams are created through a variety of platforms, including social media, digital corporate platforms, smartphones, internal information systems such as enterprise resource planning (ERP) software and many others. These streams capture the critical elements, which can largely explain questions relating to; who, what, when, where, why and how of events being tracked (Pigni et al., 2016).

The strategic implications of value creating through digital data streams can range from business model and strategy improvements, to full industrial transformation. Research (Pigni et al., 2016) has uncovered five processes for value creation, known as DSS Value Creation Archetypes. These archetypes can help strategy formulation with three major areas of risk; demand, efficiency and innovation. Generation and aggregation archetypes relate to pre-strategy, generating general capabilities. The service archetype relates to demand risk, efficiency archetype relates to organisational inefficiencies and the analytics archetype relates to innovation risk within organisations. The analytical archetype enhances the decision making process, by using the digital data streams and processing them to create or uncover insights. Value-creation opportunities are supported at a strategic level and innovation risk is reduced, making it the highest value impact archetype (Pigni et al., 2016). Pigni et al, (2016) suggest four dimensions around which capabilities consolidate; dataset, toolset, skillset and mindset.

Skill sets and mindsets are the most non-substitutable and intangible on the capabilities required to fully leverage the value of data streams. Strategic advantage as a result of using analytics and data revolve around the following aspects of organisations; leadership, talent management, technology, decision making and company culture (McAfee et al., 2012). Firstly, culture is particularly relevant in the context of EO and the mindset dimension of big data, influenced by the efficiency and analytical archetypes. Secondly, decision making is a result of having information available, with which to make informed, evidence based decisions towards strategic initiatives and patterns. Technology related to the infrastructure required for data collection, storage, analysis and related activities, encapsulated by Pigni et al, (2016) in their dataset and toolset dimensions. Management and talent, like culture are less tangible and therefore, according the the aforementioned RBV and dynamic capabilities, more likely to provide sustainability on their supplying of competitive advantage (Gupta & George, 2016).

## 4.1 Big Data Analytical Capabilities

McAfee et al, (2012) suggest that, “Companies that consider themselves as data-driven perform better on objective measures of financial and operational results. Creating new business and driving more sales” (McAfee et al., 2012, pp 6). Data driven strategy is often associated with the concept of big data analytics, which is defined as the all encompassing approach to organising, processing and interpreting the so called five V’s to create value for organisations by delivering sustainability enhancing plans, measuring performance and ultimately fostering competitive advantage (Akter et al., 2016).

The aforementioned V’s include; volume, variety, velocity, veracity and value, which are captured by the idea of big data. Big data focuses on the wide reaching scope of information, including but not limited to real-time data, forms of media beyond the traditional, social media and the data created by businesses through operations (Akter et al., 2016). Big data analytics are also considered a capability, defined as "the competence to provide business insights using data management infrastructure (technology) and talent (personnel) capability to transform business into a competitive force" (Akter et al., 2016, p. 114). Three fundamentals of big data analytics capabilities have been identified; Organisational (management capability), physical (infrastructure or technology) and human (analytical skill or talent) (McAfee et al., 2012).

Big Data Analytics Management Capabilities (BDAMAC) is closely linked to strategy formulation and decision making, this aspect of big data analytics capability has four components, Planning process, Investment decisions, Coordination and Controlling activities. This aspect of BDAC ensures sound decision making, weighs up cost-benefits, evaluates the organizational design and structures, as well as assessing and planning resource utilisation, budgets, human resources and strategic perspectives (Akter et al., 2016; Gupta & George, 2016).

Big Data Analytical Technology Capabilities (BDATEC) refer to the ability to provide a flexible setting for data scientists to develop, distribute and champion the data-oriented resources. This has three components, including; Connectivity, Compatibility and modularity (Akter et al., 2016). The technology aspect ensures that sources of data are aligned, connected, compatible and flow continuously, while having the ability to add and remove resources as required (Gupta & George, 2016).

Finally, Big Data Analytical Talent Capabilities (BDATLC) are related to the employee and their skillset in utilising the data, also termed 'know how'. This involves four distinct components or skill sets, Technical Knowledge, Technical Management Knowledge, Business Knowledge and Relational Knowledge. Activities such as database management, data visualisation and presentation, cross functional collaboration, knowledge of operating systems and software, programming languages are captured by the technical constructs. Business related constructs include understanding of the business environment and functions, communication and relationship building (Akter et al., 2016; Wamba et al., 2017; Gupta & George, 2016).

Literature provides evidence of BDAC contributing to increased FPER in organisations who are able to leverage their inherent inimitability and non-substitutable nature. Organisations have seen measurable results in price optimisation and profit maximisation, sales, profitability and market share and Return on Investment (ROI)

(Akter et al., 2016). All of the improvements mentioned relate to efficiencies, Pigni et al, (2016) discuss an efficiency archetype. While the link to strategy is clear in BDAC's ability to identify trends and opportunities in the marketplace, both small and large scale (Akter et al., 2016; Wamba et al., 2017), little focus has been placed on the ability of BDAC to improve innovativeness and proactivity by seizing these opportunities or even predicting them through the analytics archetype discussed. The outward and entrepreneurial perspective plays a pivotal role in understanding how BDAC can be leveraged further, to drive improved FPER and ultimately sustainable competitive advantage.

## 5. Entrepreneurial Orientation

Early literature of entrepreneurship related to what is considered 'the entrepreneurial problem' (Miles & Snow, 1978; Lumpkin & Dess, 1996), whereby going into business was the focus. Entrepreneurship process has since become the focus of strategic management, rather than the outcome of starting something new or introducing a groundbreaking innovation, the decision-making, methodological approaches and practices of being entrepreneurial and making the most of new and emerging opportunities. (Lumpkin & Dess, 1996; Covin & Wales, 2012). While 'new entry' is the central idea of entrepreneurial theory, it is not limited to a start-up as is common perception, but also includes 'internal venturing' (Lumpkin & Dess, 1996; Anderson et al., 2014). According to Lumpkin and Dess, "an entrepreneurial orientation then refers to the process, practices and decision-making activities that lead to new entry" (Covin & Wales, 2012, p. 679). This concept of 'new entry', as a central idea of entrepreneurial theory, includes external and internal venturing, entrepreneurship not only refers to individuals and their entry, growth and market entry, but corporates seeking growth through strategic expansion. The concept of entrepreneurship is also a firm-level one, with new entry in the context of corporates, referring to those actions and processes initiated to explore and or exploit new opportunities (Lumpkin & Dess, 1996; Anderson et al., 2014).

The earliest definition of EO is from a strategic viewpoint, "In the entrepreneurial mode, strategy-making is dominated by the active search for new opportunities" as well as "dramatic leaps forward in the face of uncertainty" (Covin & Wales, 2012, p. 679). The recently accepted fundamental of EO state that an organisation exhibiting EO should show evidence of three behaviours, innovativeness, proactiveness and risk-taking (Anderson et al., 2014), two additional behaviours are discussed in the original work, autonomy and competitive aggressiveness. Entrepreneurial orientation is therefore how new entry is approached and is characterised by five dimensions; innovativeness, risk-taking, proactiveness, autonomy and competitive aggressiveness (Lumpkin & Dess, 1996; Kreiser, Marino & Weaver, 2002; Anderson et al., 2014; Kim, 2018).

Innovativeness has been closely linked to entrepreneurship, the economic process of ‘creative destruction’ was proposed, a concept of wealth creation through disruption, as resources shift from existing firms to new ones (Lumpkin & Dess, 1996). The concept of innovativeness mirrors an organisations propensity to engage in and foster new ideas, experiment, change and adapt, thereby creating something new, be it a product, service or process (Lumpkin & Dess, 1996; Kreiser et al, 2002). Technological innovativeness and product-market innovativeness are difficult to separate but are equally critical in understanding the role of innovativeness in the entrepreneurial orientation or organisations. Technological innovativeness is fundamentally product and process generation, and includes concepts and practices such as research, industry knowledge and technical proficiency. The emphasis shifts then from technologies and methods to development of improved processes (Lumpkin & Dess, 1996; Kreiser et al., 2002; Teece et al., 1997).

Risk-taking and entrepreneurship have been entwined as far back as 1734, when Cantillon claimed that the defining difference between employees and entrepreneurs was uncertainty and risk-taking. In a strategic context, Baird and Thomas uncovered three types of risk; venturing into the unknown, committing a relatively large portion of assets, and borrowing heavily (Lumpkin & Dess, 1996). In holds true that almost all decisions involve a degree of risk and therefore no decisions are completely safe or risk-free, rather risk ranges depending on context and situation.

Proactiveness is essentially the concept of having a forward-looking perspective, preempting changes and anticipating future needs and plans. This includes seeking and identifying new opportunities, which may or may not be related to current offerings or products, in a bid to gain an advantage. The suggested conceptual opposite of proactiveness is not reactiveness, but rather passiveness, an indifference or inability to grasp new opportunities (Lumpkin & Dess, 1996; Kreiser et al., 2002).

Both Autonomy and competitive aggressiveness are not included in the measurement instrument chosen to measure EO in this study. They have recently been excluded, most notably because they have been considered reflective measures while the EO construct is considered formative. Since only the highest-order construct was reported on, only formative sub-constructs are included to maintain the pure model status (Covin & Wales, 2012). Autonomy refers to independence and the independent actions taken by individuals or groups of people in taking an idea or concept through to a state of realisation. Competitive Aggressiveness differs from proactiveness, in its focus on rivalry in terms of trends and needs that exist in the market, rather than opportunities presented by new entry into markets. Therefore, competitive aggressiveness alludes to an organisations ability to outperform rivals in a marketplace, through intense and direct competition.

There is a large body of work confirming the positive relationship between EO and FPER, including a meta-analysis, based on 51 studies, indicating that even under various contexts, the relationship is robust (Kim, 2018). Despite this, many questions continue being raised relating to the balancing act between exploitation and exploration of new opportunities (Augier & Teece, 2008), opening the door to further understand efficiency and analytical data archetypes (Pigni et al., 2016), specifically those that facilitate and improve opportunity sensing and decision making, and their relationship with EO.

## 6. Conclusion

Strategy provides a clear link to BDAC and EO through dynamic capabilities, especially when considering the sustainability, they provide to competitive advantage from the RBV perspective. Both BDAC and EO can and should be considered, when established within an organisation, to be difficult to imitate and even more difficult, if not impossible to substitute. Dynamic capabilities, especially those which enable or leverage an organisation's ability to scan its environment, identify trends and opportunities, enable organisations to better adjust and coordinate efforts and resources towards changes in the environment, providing weight to Child’s (1972) argument for the need of information in complex and dynamic markets, towards organisations aligning their strategy to their environment. “The fundamental question for management is to figure out how best to employ the firm’s existing assets, and how to reconfigure and augment those assets and tie them together in a viable business model to help augment the value proposition being brought to the customer” (Augier &

Teece, 2008, p. 1197). The sustainability elements of the proposed VRIN theory (inimitability and non-substitutability) can and have been argued to be associated with dynamic capabilities (Teece, 1997; Teece, 2012) in the pursuit of superior firm performance, with known benefits seen by layering dynamic capabilities on top of known competencies (Teece, Pisano & Shuen, 1997). Capabilities relating to big data, especially managerial, infrastructure and talent driven ones are such capabilities (Wamba et al., 2017; Akter, 2016, McAfee et al., 2012). Leveraging the data streams created by organisations is best suited to innovative objectives when analytics is involved (Pigni et al., 2016).

The role of management, with regards to risk taking and proactiveness is fundamental to both the managerial activities included in the BDAC sense (BDAMAC), including planning, investment, coordination and control (Akter et al., 2016; Wamba et al., 2017). It can also be argued that the technology and talent possessed by an organisation will enable its levels of EO, particularly with relation to innovation and proactiveness. The linkage between proactiveness and risk taking with regards to seizing opportunities is clear, while innovation and sensing provide an interesting conduit, as does the link between EO and the pattern of decision making in strategy formulation.

Wiklund and Shepherd (2003) conclude with a finding that EO moderates the relationship between knowledge-based resources and firm performance. These knowledge-based resources include procedural, market, and technology knowledge, but fall short of specifying analytics (BDAC) in their discussion of how technology aids in opportunity discovery and exploitation (Wiklund & Shepherd, 2003). Together, EO and BDAC provide a potentially pattern altering approach to tactical and strategic choices, made on the basis of evidence gathered, towards the ultimate goals of firm performance and sustainable competitive advantage.

## 7. Hypotheses and Research Model

**As BDAC increases, the performance of the organisation increases.**
Literature provides evidence of positive relationship between BDAC and FPER, specifically related to pricing, profitability, return on investment and sales through superior insight being gained and utilised in the aforementioned decision-making process (Akter et al., 2016). With existing literature on this vital relationship, it is key to

establish a positive and significant relationship, against which to benchmark a moderated relationship with the introduction of another dynamic capability, EO.
**H1:** *BDAC has a significant, positive effect on FPER*

**The relationship between BDAC and EO, is strong and positive.**
The mindset perspective, with regards to EO and BDAC, aligns with the fundamentals of dynamic capabilities from the sensing (availability and insight from information as a result of data analysed), seizing (proactiveness and risk-taking) and transforming (innovation) perspective. Confirming a clear link between them is therefore key establish a positive relationship between these two dynamic capabilities, resulting in the second hypothesis.
**H2:** *BDAC and EO have a significant positive relationship*

**An organisations performance increases, as its EO increases.**
Existing literature on the relationship between EO and FPER supports a positive parallel, from authorities on the topic, such as Covin, Lumpkin and Wiklund (Gupta & Bantra, 2016). Firms who focus their efforts and attention towards opportunities in their markets are likely to have high measured of innovativeness, risk-taking and proactiveness, the three key dimensions measureable for EO of firms (Wiklund & Shephard, 2003). Measuring this final construct against FPER, closes the proverbial 'loop' before testing for moderation.
**H3:** *EO has a positive & significant effect on FPER*

**The effect of BDAC on FPER will increase as EO increases.**
"Knowledge has the greatest ability of all resources to serve as a source of sustainable differentiation" (Wiklund & Shephard, 2003, p. 1308). Under the notion that dynamic capabilities create advantage by means of identification, seizing and transforming opportunities, by 'layering' capabilities, supports the idea that multiple dynamic capabilities should increase each others effect on FPER. The final hypothesis tests the moderating effect that EO has on BDAC and FPER's relationship, with the idea that the relationship should become stronger.
**H4:** *EO has a significant positive moderating effect on BDAC enabling FPER*

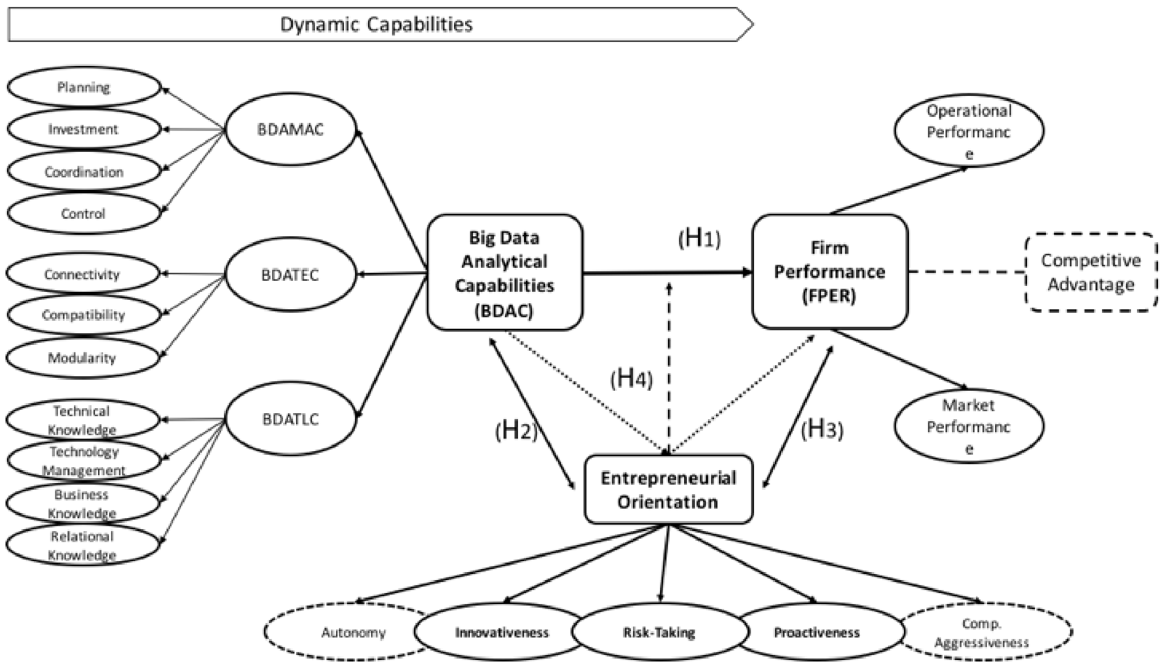


**Figure 1.** Conceptual Research Model - The relationships between BDAC, EO and FPER

Source: Author's Own.

# Methodology

## 1. Introduction

This section covers a number of topics, relating to the aim of the research in general and how it went about testing the four hypotheses in question. The hypotheses being tested were;

**H1:** *BDAC has a significant, positive effect on FPER*

**H2:** *BDAC and EO have a significant positive relationship*

**H3:** *EO has a positive & significant effect on FPER*

**H4:** *EO has a significant positive moderating effect on BDAC enabling FPER*

The research made use of a number of statistical analysis techniques to test the direction, strength and significance of relationships. The methodology employed includes the following sub-sections:

- Research Approach
- Research Design
- Research Instrument
- Data Analysis
- Limitation of Research

## 2. Research Approach

The assumptions made by the research philosophy, advised the research strategy and therefore the methodology, data gathered and analysis conducted (Saunders & Lewis, 2012). The purpose of this philosophy is to underpin the choices and decisions made in supporting a research position, that research position guides what, how and why the research was carried out (Carson, Gilmore, Perry & Gronhaug, 2001).

The research conducted sought to empirically confirm relationships between BDAC, EO and FPER, as well as assess whether the BDAC - FPER relationship was moderated by EO, by use of statistical methods. The relationships between BDAC, EO and FPER were hypothesised in a bid to explain relationships (Carson, Gilmore, Perry & Gronhaug, 2001) and were summarised into four hypotheses. Therefore, the research conducted was based on a positivism philosophy, allowing for factual and replicable philosophy, with an outcome of explained relationships observed (Wamba, Gunasekaran, Akter, Ren, Dubey & Childe, 2017; Saunder & Lewis, 2012). The nature of the study lent itself to structured questioning and statistical quantification of relationships between the aforementioned variables, BDAC, EO and FPER. The use of statistical analysis to formulate results allowed for independence on the part of the researcher, which resulted in objective findings, explaining the 'cause and effect' relationship between variables measured (Wamba et al, 2017).

The research was designed to explain and confirm the relationships between BDAC, FPER and EO, as well as the moderating effect of EO by making objective, deductive generalisations (Morgan, 2014). Quantitative constructs existed for BDAC, EO and PFER, these were used to empirically test the existing theory and new hypotheses by measuring responses gathered from structured surveys in the form of scales. The resulting findings are limited by the scales used and the quantitative approach limited the breadth and depth with which respondents may have responded, by standardising and structuring a formal questionnaire. This deductive approach was designed to confirm or challenge the existing theory and provide generalised findings with regards to the relationships tested (Morgan, 2014; Saunders & Lewis, 2012). The questionnaire designed and used to collecting data was typical of a descriptive study, which sought explain and describe the characteristics of the sample population, validating the theory used as a basis for hypotheses, it therefore suits the purpose of the design (Saunders & Lewis, 2012) and is able to "describe systematically and accurately the facts and characteristics of a given population or area of interest" (Dulock, 1993, p. 153).

The replicable, statistical and descriptive nature of the survey based, quantitative research design allowed for quantification of hypotheses tested (Wamba et al., 2017). The data was collected once for each respondent, by means of an structured online questionnaire (Survey Monkey), allowing for rapid collection of responses, at a relatively low cost, affording respondents anonymity and fast access to results for the researcher (Zikmund & Babin, 2010). The results represent a point in time, indicative of a cross-sectional time horizon (Saunders & Lewis, 2012).

# 3. Research Design

## 3.1 Population

Salkind defines a research population as, “the entire collection of entities one seeks to understand or, more formally, about which one seeks to draw an inference” (2010, p. 1052). The population of Big Data organisations is not known nor was it possible to clearly measure for census or statistical sample design. With this unknown population, the research aimed to provide insights into organisations in general, with a focus on those using big data to make decisions, or able to use data to inform strategic decisions, similar to the work done by Akter et al., (2016) focusing on ‘business analysts’ and ‘IT professionals’. This broad population is narrowed somewhat by refining the applicability of findings to include organisations with dedicated insights, data science, analytics or other data relevant positions. The population includes organisations from numerous industries and of varying sizes, due to the non-specific application of data and insights drawn from it. No qualifying criteria was placed on the amount of data stored, nor the amount of data produced by the organisation. Limiting the population by means of defining data creation, storage and usage parameters would limit the insights drawn for the research, as the volume of data being produced and processed globally continues to expand and makes such parameters become outdated quickly, reducing the effective lifespan of the findings.

## 3.2 Unit of Analysis

The unit of analysis relates to the subject of the study, which may be generalised through analysis (Lewis-Beck, Bryman & Futing Liao, 2004). The research questionnaire was sent to individuals, employed at various levels within their respective organisations, but results and findings are generalised across the sample, representing the relevant findings and their impact on the performance of firms (FPER). The results are not specific to the organisations, geographies or industries of the individuals who responded, but represent organisations as a whole.

## 3.3 Sampling Technique

Non-probability surveys made use of purposive sampling, due to the short term nature of the research and the undefined population in question (Greener, 2008). The population of organisations with BDAC or EO and data specific roles and expertise is not known, neither is the population of those business people who use analytics or big data on a frequent basis, making probability sample impossible and irrelevant to the study’s objective. The size of the sample is ambiguous without using quota sampling (Saunders, Lewis & Thornhill, 2009) and Greener (2008) suggests that the size of the sample for purposive or snowball methodologies is determined largely by the objectives of the research and the hypotheses.

Purposive sampling allowed for targeting of appropriate respondents, based on their positions within organisations, their proximity to data related decision making, understanding of competitive advantage, strategy and entrepreneurial concepts as selection criteria to form part of the sample. As the research hypotheses and theme is largely concerned with strategic elements, including competitive advantage, a purposive sample was considered typical case, presenting a degree of non-statistical representativeness (Saunders, Lewis & Thornhill, 2009).

A sample of 200 respondents was targeted and introduced an element of snowball sampling to the methodology. These respondents were directly contacted via email, LinkedIn and via phone call. Snowballing enabled respondents to pass the questionnaire on to other persons, fitting the criteria in their or other organisations. While respondents were likely to pass the questionnaire on to others, with similar traits to themselves, a fairly large number of initial contacts was used, avoiding homogeneity in the sample, a common bias for snowball sampling (Lewis-Beck, Bryman & Futing Liao, 2004; Saunders & lewis, 2012).

## 4. Research Instrument

### 4.1 Questionnaire Design

The measurement device used for the research, was a self administered online questionnaire, using a 7-point Likert scale. Likert scales are rating scales used to measure attitudes, perceptions and opinions of respondents, through questionnaires (Boslaugh, 2008). The scales used will be measured on a 1-7 point Likert scale, as per the existing scales used in the formulation of the questionnaire (Akter et al., 2016; Wamba et al., 2017; Covin & Wales, 2012).

Categorical questions were used to gather demographic information (Krosnick, 2009), in order to understand the variety of respondents, trends in terms of the individuals who respond and any role, education or industry specific information in terms of responses for future research. The questionnaire was designed on the basis that it would address the research hypotheses, while meeting all ethical requirements (Saunders & Lewis, 2012). Respondents received an explanation of what the research was about and why their responses were important. Anonymity was ensured and Non-disclosure agreements were offered if respondents desired. The research questionnaire is presented at Exhibit 1 in the appendix of this section.

Dependent Variable:

The items used in the questionnaire were developed prior to this research. Firm performance (FPER) was measured using a second order formative construct, which contains two first-order reflective constructs, namely operational and market performance (Wang, Liang, Zhong, Xue & Xiao, 2012). Each first-order construct was measured from the adapted Ravichandran and Lertwongsatien scale, which included four items, pertaining to the firm's relative performance over a three-year period. The three-year view is intended to reduce the short term and availability bias (Wang et al., 2012).

Independent Variable:

Entrepreneurial Orientation (EO) was measured using the, nine item, Miller/Covin and Slevin scale from 1989 (Covin & Wales, 2012), includes three first order constructs; Innovativeness, Risk-taking and Proactiveness. While this second-order construct measured three first order dimensions, EO was treated as a single 'composite weighting' view of entrepreneurship, as per Miller (1983) (Kim, 2018), for this reason, EO is never broken down to its three first-order parts.

Independent Variable:

Big Data Analytical Capabilities (BDAC) was measured using the constructs and scales proposed by Akter et al., (2016) and Wamba et a, (2017). This scale made use of eleven first order constructs and three second order constructs (Management, Technology & Talent), totalling 44 items (Akter et al., 2016; Wamba et al., 2017). Both the second order constructs and the highest order, BDAC construct were measured. This was done so as to further unpack hypothesis two (BDAC and EO have a significant positive relationship). According to Akter et al., the first order dimensions of

BDAC are considered reflective of the higher order dimensions, stating that the "direction of causality is from construct to item" (Akter et al., 2016, pp 121).

### 4.2 Data Collection

Using self-administered, online questionnaires not only allowed for standardisation of questions to multiple respondents, but offered cost and time efficiencies. Standardisation allows for scale of respondents, increasing the robustness of the sample while the digital nature made it easy to administer and sped up data collection and organising. Questionnaires are easy to administer and relatively easy to analyse (Dubois, 2016), Survey Monkey® was used to administer the questionnaire, as a low cost, reliable and easily accessible platform. Potential drawbacks on Survey Monkey® included the lack of interviewer to ensure quality, consistency and accuracy of responses, and respondents either not starting (resulting in a non-response) or not completing the questionnaire (incomplete response). Incomplete responses made the questionnaire in question unsuitable for use, if less than 80% of the questionnaire was completed. This cut-off was chosen by the researcher to ensure maximum accuracy, while including the largest possible sample in the event that some questions were not understood or not answered because of respondent error.

The questionnaire was screened by the researcher and supervisor to ensure thoroughness, flow, spelling and ease of understanding questions included. The questionnaire went through Ethical clearance, to ensure no ethical violations. A pre-test (pilot survey) was done, whereby the questionnaire was sent to respondents matching the sample criteria. The pilot was intended to uncover any operational faults or difficulties the questionnaire may have had, as well as identify any obvious trends or outliers in the data collected. The nine responses from the pilot confirmed no errors, ambiguity or general concerns and full functionality, these responses were not used for analysis.

## 5. Data Analysis

### 5.1 Reliability

Reliability of the items and related constructs used for BDAC, EO and FPER have previously been tested using Cronbach's Alpha (Wamba et al., 2017; Covin & Wales, 2012; Wang et al., 2012). Cronbach's Alpha tests for internal reliability, assessing the consistency of responses in a questionnaire comprised of multiple items for each construct (Lewis-Beck et al, 2004; Wegner, 2016). Wang et al (2012) and Wamba et al, (2017) suggested the Cronbach's Alpha should measure over 0.70 for first order constructs. All first order constructs measure above the prescribed 0.70 for BDAC, EO and FPER (Wamba et al., 2017; Covin & Wales, 2012; Wang et al., 2012). Reliability was tested again after data was collected was the research in question, also using Cronbach's Alpha returning Cronbach's Alpha values above 0.80 for EO and FPER, while the three BDAC sub constructs returned value over 0.90 (all others were above the required 0.70). The total BDAC construct was also tested for reliability, using the three aforementioned sub-constructs, returning a value of 0.949, proving its reliability.

### 5.2 Principal Component Analysis

To establishing validity of the constructs and items used, exploratory factor analysis (EFA) was conducted, as it verifies convergent and discriminatory validity of the sub-constructs used (Akter et al., 2016). Confirmatory Factor analysis was not considered after taking into account the sample size (101) implications for the 12-16 items per second order BDAC constructs, "If the factors have 10 to 12 items that load moderately (0.40 or higher), then a sample size of 150 or more is needed to be confident in the results" (Beavers, Lounsbury, Richards, Huck, Skolits & Esquivel, 2013, p. 3). EFA was conducted on the following constructs, using a Principal Component Analysis (PCA) and varimax rotation method; FPER, EO and the three second-order BDAC constructs, BDAMAC, BDATEC and BDATLC. Component Analysis (PCA) was used to summarise the many variables, while maintaining the dimensions of the data, using orthogonal rotations (Varimax), as it is widely used and considered as best practice (Beavers et al., 2013).

Kaiser-Meyer-Olkin (KMO) is a measure of the "shared variance in the items" (Beavers et al., 2013, pp 4) with the accepted minimum or middling KMO score is 0.70 according to Vogt (2005) and Beaver et al, (2013). Analysis of each construct returned KMO scored of above 0.70 and for BDAC constructs, scores of above 0.90 are observed.

**Table 1.** Reliability and Validity results

| 2nd Order Construct | 1st Order Construct | Item Label | Component Matrix Load Factor | KMO | % of Variance | Cronbach's Alpha | Cronbach's Alpha (Total BDAC) |
|---|---|---|---|---|---|---|---|
| FPER | Operational Perfromance | OPPER1* | NA | 0.767 | 76.88% | 0.848 | |
| | | OPPER2 | 0.712 | | | | |
| | | OPPER3 | 0.793 | | | | |
| | | OPPER4 | 0.725 | | | | |
| | Market Perfromance | MARPER1 | 0.72 | | | | |
| | | MARPER2 | 0.751 | | | | |
| | | MARPER3 | 0.834 | | | | |
| | | MARPER4* | NA | | | | |
| Big Data Analytical Manageme nt Capabilities (BDAMAC) | Planning | BDAMACPL1 | 0.847 | 0.910 | 78.01% | 0.971 | 0.950 |
| | | BDAMACPL2 | 0.885 | | | | |
| | | BDAMACPL3 | 0.880 | | | | |
| | | BDAMACPL4 | 0.894 | | | | |
| | Investment | BDAMACIN1 | 0.866 | | | | |
| | | BDAMACIN2 | 0.853 | | | | |
| | | BDAMACIN3 | 0.859 | | | | |
| | | BDAMACIN4 | 0.801 | | | | |
| | Coordination | BDAMACCO1 | 0.750 | | | | |
| | | BDAMACCO2 | 0.736 | | | | |
| | | BDAMACCO3 | 0.787 | | | | |
| | | BDAMACCO4 | 0.735 | | | | |
| | Control | BDAMACCT1 | 0.849 | | | | |
| | | BDAMACCT2 | 0.870 | | | | |
| | | BDAMACCT3 | 0.894 | | | | |
| | | BDAMACCT4 | 0.828 | | | | |
| Big Data Analytical Technology Capabilities (BDATEC) | Connectivity | BDATECCN1 | 0.856 | 0.915 | 70.66% | 0.962 | |
| | | BDATECCN2 | 0.786 | | | | |
| | | BDATECCN3 | 0.861 | | | | |
| | | BDATECCN4 | 0.818 | | | | |
| | Compatibility | BDATECCM1 | 0.831 | | | | |
| | | BDATECCM2 | 0.804 | | | | |
| | | BDATECCM3 | 0.877 | | | | |
| | | BDATECCM4 | 0.853 | | | | |
| | Modularity | BDATECMO1 | 0.827 | | | | |
| | | BDATECMO2 | 0.816 | | | | |
| | | BDATECMO3 | 0.880 | | | | |
| | | BDATECMO4 | 0.873 | | | | |
| Big Data Analytical Talent Capabilities (BDATLC) | Technical Knowledge | BDATLCTK1 | 0.808 | 0.951 | 82.62% | 0.978 | |
| | | BDATLCTK2 | 0.896 | | | | |
| | | BDATLCTK3 | 0.874 | | | | |
| | | BDATLCTK4 | 0.900 | | | | |
| | Technology Management | BDATLCTM1 | 0.866 | | | | |
| | | BDATLCTM2 | 0.874 | | | | |
| | | BDATLCTM3 | 0.897 | | | | |
| | | BDATLCTM4 | 0.921 | | | | |
| | Business Knowledge | BDATLCBK1 | 0.878 | | | | |
| | | BDATLCBK2 | 0.875 | | | | |
| | | BDATLCBK3 | 0.861 | | | | |
| | | BDATLCBK4 | 0.849 | | | | |
| | Relational Knowledge | BDATLCRK1 | 0.910 | | | | |
| | | BDATLCRK2 | 0.885 | | | | |
| | | BDATLCRK3 | 0.853 | | | | |
| | | BDATLCRK4 | 0.765 | | | | |
| Entreprene urial Orientation | Innovation | EOINN1 | 0.759 | 0.860 | 65.65% | 0.885 | |
| | | EOINN2 | 0.637 | | | | |
| | | EOINN3 | 0.793 | | | | |
| | Risk-Taking | EORIT1 | 0.815 | | | | |
| | | EORIT2 | 0.707 | | | | |
| | | EORIT3 | 0.734 | | | | |
| | Proactiveness | EOPRO1 | 0.749 | | | | |
| | | EOPRO2 | 0.710 | | | | |
| | | EOPRO3 | 0.599 | | | | |

Source: Author's Own.

Bartlett's Test of Sphericity, indicated significance of all constructs tested, with p-values less than 0.05. Each of the three main constructs (BDAC, EO and FPER) were tested, as well the the three second-order constructs for BDAC, with their Eigenvalues and Sum of squares loadings analysed. For the FPER construct, two components returned Eigenvalues larger than one, with the full set of eight items, explaining 69.602% of cumulative variance. The rotated component matrix (Varimax) produced, showed than item one and eight were loading onto the wrong component, and it was decided that they would be removed from the construct to improve accuracy of results and best represent the data. Upon running the factor analysis again, without these two items, the cumulative variance improved to 76.822%, with a KMO of 0.767.

### 5.3 Statistical tests conducted

Demographic data collected was quantitative in nature, categorical and ordinal (ranked) (Akter et al., 2016, Covin & Wales, 2012, Saunders & Lewis, 2012). These demographic variables were included, to control for any bias anticipated due to demographics (Akter et al., 2016) with the intent of being used as control variables in linear regression, both moderated and not. The online nature Survey Monkey®, enabled digital data collection, storage and analysis with the use of SPSS. The 7-point Likert scale used for the scales selected will provide data for analysis of variables with regards to BDAC, EO and FPER. These items were coded into the survey on a 7-point sliding scale, ensuring less response coding after data collection. The demographic questions were coded to calculate frequencies and proportions.

Descriptive analysis was used as a first step, providing the initial examination of the data set. Descriptive statistics provided initial understanding of responses collected, enabling calculation of frequency, percentage and means, medians and modes (central tendency) to be measured (Tustin, Ligthelm, Martins & Van Wyk, 2010). Descriptive analysis on the constructs (first order BDAC, and FPER and second-order for EO) provided dispersion or variability (standard deviation) and variance (Saunders & Lewis, 2012; Tustin et al., 2010).

The relationship between variables was statistically measured using Pearson's correlations analysis. The Pearson's correlation measured the strength of the relationship (linear) between variables, BDAC and EO in relation to FPER (Boslaugh, 2008). Correlation coefficients range between -1 and +1, with a coefficient of 0 indicating perfect independence of variables. The research hypotheses seek to prove positive relationships, coefficients greater than 0.70 are considered strong (Saunders, Lewis & Thornhill, 2009). The SPSS output for Pearson's correlation produces a test for significance of each relationship (a p-value), these test for significance at both 99% ($p < 0.01$) and 95% ($p < 0.05$). The correlation coefficients and significance between variables tested aid in answered Hypotheses 1 and 3, while they prove the null hypothesis H2.

Moderated regression analysis was carried out, addressing hypothesis 4 (H4: EO has a significant positive moderating effect on BDAC enabling FPER), to understand the “comparison of alternative models” (Kim, 2018, p. 196). Linear regression aided in answering the other hypotheses.

In the case of the moderating effect that EO has on BDAC and FPER, the moderating effect can be measured in one of two ways, interaction effects or path analysis (Allen, 2017). Interaction effects are measured using a moderated regression analysis to test hypotheses (Kim, 2018), allowing for the comparison of models (with and without moderating variables), this suits the objective of the study, which aims to test a moderating effect between existing and established constructs.

Lowry and Gaskin suggest that linear regression models are well suited to simple models with few independent variables, even when testing moderating effects (2014). Path analysis, by means of Covariance Based - structural equation modelling (CB-SEM), or Partial Least Squares - structural equation modelling (PLS-SEM), was not considered options for a number of reasons. Most importantly, the universally accepted heuristic with regards to choosing a methodology to test moderation, is sample size. Much like the consideration and argument for choosing EFA over CFA, the sample size for this study did not provide sufficient responses for the number of items or structural paths (Lowry & Gaskin, 2014). The guideline is that the sample size should have, at least, a sample size ten times that of the number of “structural paths directed at a particular construct” (Lowry & Gaskin, 2014, pp 132) which for the BDAC, even at second-order level (sub constructs) requires 120 responses for the technology related sub-construct, the remaining two sub-constructs require 160 respondents.

Interaction effect will be measured, by means of moderated multiple regression analysis between BDAC and FPER, by introducing EO. The resulting statistical output provided a beta (B) score pre and post interaction term, the direction (negative or positive sign) of the beta score indicated the direction of moderating effect and the beta score indicated the strength (Allen, 2017). Finally, the significance of the interaction is observed, being considered significant when $p < 0.05$.

The constructs being tested were mean-centred, which involved subtracting the mean of each variable, from the variable itself. The new variables were named FPERcentered, BDACcentered and EOcentered. To run the moderated regression analysis, interaction terms were created, these terms, BDACEOinteraction and FPEREOinteraction were introduced by multiplying mean centered variables by each other (namely the mean-centered variables BDAC*EO and FPER*EO) to test for moderation of BDAC and FPER relationship's direction, strength and significance. The coefficient of determination or model fit, was determined for both models, with and without moderating variable, by means of the R Square and the change in R Square between models. The coefficient indicates whether or not the introduction of a moderating variable improves fit and the amount of variance in FPER (dependent variable) can be explained by the independent variables (BDAC and EO) (Saunders, Lewis & Thornhill, 2009). Autocorrelation was tested using the Durbin-Watson (DW) score observed, a score of around 2 is considered to be a result showing no autocorrelation (Lewis-Beck, Bryman & Liao, 2004). Variance inflation factors (VIF), is a measure for collinearity in multiple regression analysis (Vogt, 2005). An acceptable score of should be lower than ten, above which would indicate multicollinearity being problematic (Mills, Durepos & Wiebe, 2010).

## 6. Limitations

The research was carried out, largely in the South African context, potentially limiting or contextualising the depth of understanding that will be the studies outcome, this could limit the generalizability of the results. The study represents a point in time, or cross-sectional analysis of the relationship between BDAC, EO and FPER (as well as the moderating effect of EO), this limits the insights drawn and gives rise to potential future research of a more longitudinal nature. The researcher predicted that the moderating effect of EO is likely to change over time, while within the BDAC construct, technology is predicted to become less influential than management and talent. The instrument used for BDAC is relatively new and likely to be improved on as the literary base and volume on research on the topic grows as predicted by the researcher. The 7-point scale used is said to potentially introduce acquiescence bias, and might benefit from 9-point scales in the future (Akter et al., 2016).

**Summary of Methodology**

This research addressed four hypotheses, using a positivism approach, to confirm causal relationships relating to BDAC, EO and FPER variables. Pearson's correlation and regression analysis was used to test these hypotheses, by statistical techniques applied to data collected via digital surveys. Data collection made use of existing items and scales, adapted from current and long-standing research in the fields of EO and BDAC, with scales found to be reliable and valid. The total useable non-probability sample of 101 respondents were used to understand strategic relationships at an aggregated level.

**Table 2.** Summary of hypotheses, tests and variables and constructs

| Hypothesis | Construct | Variables | Tests |
|---|---|---|---|
| H1: BDAC has a significant, positive effect on FPER | BDAC | Independent | Regression |
| | FPER | Dependent | |
| | | Independent | Correlation |
| H2: BDAC and EO have a significant positive relationship | BDAC | Independent | Correlation |
| | EO | Independent | |
| H3: EO has a positive & significant effect on FPER | EO | Independent | Regression |
| | | Dependent | |
| | FPER | Independent | Correlation |
| H4: EO has a significant positive moderating effect on BDAC enabling FPER. | FPER | Dependent | Regression |
| | BDAC | Independent | |
| | EO | Moderator | |

## Appendices:

### **Exhibit 1.** Research Questionnaire

| | | Questions |
|---|---|---|
| Demographic | 1 | What is your gender? |
| | 2 | What is your age? |
| | 3 | What is the highest level of education you have completed? |
| | 4 | Do you have a specialised qualification in any of fields below? |
| | 5 | Which of the following best describes the principal industry of your organization? |
| | 6 | What is your position at your organisation? |
| | 7 | Does your organisation have any department or departments related to data collection, management and analytics? |
| Firm Performanc | 8 | Our productivity has exceeded that of our competitors. |
| | 9 | Our profit rate has exceeded that of our competitors. |
| | 10 | Our ROI (Return on Investment) has exceeded that of our competitors. |
| | 11 | Our sales revenue has exceeded that of our competitors. |
| | 12 | We have entered new markets more quickly than our competitors. |
| | 13 | We have introduced new products or services to the market faster than our competitors. |
| | 14 | Our success rate of new products or services has been higher than our competitors. |
| | 15 | Our market share has exceeded that of our competitors. |
| BDAC - Manageme | 16 | We continuously examine the innovative opportunities for the strategic use of big data analytics. |
| | 17 | We enforce adequate plans for the introduction and utilization of big data analytics. |
| | 18 | We perform big data analytics planning processes in systematic and formalized ways. |
| | 19 | We frequently adjust big data analytics plans to better adapt to changing conditions. |
| | 20 | When we make big data analytics investment decisions, we think about and estimate the effect they will have on the productivity employees' work. |
| | 21 | When we make big data analytics investment decisions, we consider and project about how much these options will help end-us quicker decisions. |
| | 22 | When we make big data analytics investment decisions, we think about and estimate the cost of training that end-users will need |
| | 23 | When we make big data analytics investment decisions, we consider and estimate the time managers will need to spend overse change. |
| | 24 | In our organization, business analysts and line people meet frequently to discuss important issues both formally and informally. |
| | 25 | In our organization, business analysts and line people from various departments frequently attend cross-functional meetings. |
| | 26 | In our organization, business analysts and line people coordinate their efforts harmoniously. |
| | 27 | In our organization, information is widely shared between business analysts and line people so that those who make decisions c jobs have access to all available know-how. |
| | 28 | In our organization, the responsibility for big data analytics development is clear. |
| | 29 | We are confident that big data analytics project proposals are properly appraised. |
| | 30 | We constantly monitor the performance of the big data analytics function. |
| | 31 | Our analytics department is clear about its performance criteria. |
| BDAC - Technolo | 32 | Compared to rivals within our industry, our organization has the foremost available analytics systems. |
| | 33 | All remote, branch, and mobile offices are connected to the central office for analytics. |
| | 34 | Our organization utilizes open systems network mechanisms to boost analytics connectivity. |
| | 35 | There are no identifiable communications bottlenecks within our organization when sharing analytics insights. |
| | 36 | Software applications can be easily transported and used across multiple analytics platforms. |
| | 37 | Our user interfaces provide transparent access to all platforms and applications. |
| | 38 | Analytics-driven information is shared seamlessly across our organization, regardless of the location. |
| | 39 | Our organization provides multiple analytics interfaces or entry points for external end-users. |
| | 40 | Reusable software modules are widely used in new analytics model development. |
| | 41 | End-users utilize object-oriented tools to create their own analytics applications. |
| | 42 | Object-oriented technologies are utilized to minimize the development time for new analytics applications. |
| | 43 | Applications can be adapted to meet a variety of needs during analytics tasks. |
| BDAC - Tale | 44 | Our analytics personnel are very capable in terms of programming skills. |
| | 45 | Our analytics personnel are very capable in terms of managing project life cycles. |
| | 46 | Our analytics personnel are very capable in the areas of data and network management and maintenance. |
| | 47 | Our analytics personnel create very capable decision support systems driven by analytics. |
| | 48 | Our analytics personnel show superior understanding of technological trends. |
| | 49 | Our analytics personnel show superior ability to learn new technologies. |
| | 50 | Our analytics personnel are very knowledgeable about the critical factors for the success of our organization. |
| | 51 | Our analytics personnel are very knowledgeable about the role of big data analytics as a means, not an end. |
| | 52 | Our analytics personnel understand our organization's policies and plans at a very high level. |
| | 53 | Our analytics personnel are very capable in interpreting business problems and developing appropriate technical solutions. |
| | 54 | Our analytics personnel are very knowledgeable about business functions. |
| | 55 | Our analytics personnel are very knowledgeable about the business environment. |
| | 56 | Our analytics personnel are very capable in terms of planning, organizing, and leading projects. |
| | 57 | Our analytics personnel are very capable in terms of planning and executing work in a collective environment. |
| | 58 | Our analytics personnel are very capable in terms of teaching others. |
| | 59 | Our analytics personnel work closely with customers and maintain productive user/client relationships. |
| Entrepreneurial Orientatic | 60 | In general, the top managers of my firm favour… |
| | 61 | How many new lines of products or services has your firm marketed in the past five years (or since its establishment)? |
| | 62 | Changes in product or service lines have been… |
| | 63 | In general, the top managers of my firm have… |
| | 64 | In general, the top managers of my firm believe that… |
| | 65 | When confronted with decision-making situations involving uncertainty, my firm… |
| | 66 | In dealing with its competitors, my firm… |
| | 67 | In dealing with its competitors, my firm… |
| | 68 | In dealing with its competitors, my firm... |

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