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# Value Creation from the Impact of Business Analytics

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**Abstract.** Digital transformation is a key imperative across multiple industries globally. One of the main tenets of digital transformation is improving the intelligence quotient in an organization in order to enable accurate decision-making. Intelligence in the digital era is fueled by data and .by the ability to analyze data in a way that generates meaningful insights, thereby making an organization competitive. Literature shows that the benefits of being analytically competitive are widespread and impactful across many organization functions like strategy, finance, marketing and operations; but this can be accomplished only if an organization has the right level of capability for adopting and executing analytics initiatives. Data, leadership, people skills, culture and governance are capabilities that are essential for successful analytics endeavors in an organization. This study is focused on building an end-to-end perspective comprising input factors and outcomes of being analytically competitive.

**Keywords:** Big data, business analytics, culture, governance, strategy, technology, talent, business value, leadership.

## 1 Introduction

In coming years, the most intelligent organizations will need to blend technology-enabled insights with a sophisticated understanding of human judgment, reasoning, and choice. Those that do this successfully will have an advantage over their rivals (Schoemaker, P. J., & Tetlock, P. E. 2017). The Authors further state, a relatively new phenomenon, the Global intelligent enterprise is shaped by the growing power of computers and big data, which provide the foundation for operations research, forecasting models, and artificial intelligence (AI). An analogy to this, is Sam Palmisano, IBM CEO's, coining of the term "Globally Integrated Enterprise" (GIE) in his 2006 article where he terms it as this emerging business model that is built completely on the base of data and analytics. Prominent researchers within the field use the following definition of Business Analytics (BA): a combination of data, tools and technology, analysis and quantitative and qualitative methods used to build statistical, mathematical or computer-based models that can provide organizations with better insights to drive intelligent fact-based decisions (Davenport, 2005). Thomas Davenport introduces his latest publication Analytics 4.0 by stating that artificial intelligence (AI) is intrinsic to analytics; This statement emphasizes the significance of business analytics in an organization (Davenport, 2018) culminating to AI.

A review of the literature indicates that the value of BA is in its strategic competitive advantage (Sprongl,2013) and that business analytics is also a means for improved performance (Whitelock,2018). Various studies expand the value of BA to include the supply chain, research and development, pricing and human capital interventions (Davenport, 2005). Multiple articles also refer to the causal relationship between BA and organization performance, including an improvement in financial outcomes (Jamshi, 2017) (Rouhani, 2016). However, in order to realize the impact of BA, organizations need to have the right capabilities for gaining these benefits. The studies point towards analytics capabilities being adapted from the capability maturity model for software (Paulk, 2009). Research reveals that more than 150 versions are being studied in order to try and establish a BA maturity framework (Chuah & Wong, 2011).

### **1.1 Research objective**

The Capability Maturity Model (CMM) was first introduced by Watts Humphrey in 1988 at the Software Engineering Institute which then empowered organizations to gain an understanding of software process development and were able to improve their capabilities (Paulk et al., 2018). The CMM allowed organizations to measure their software process development and enable them to improve their capabilities. Since its introduction, there has been a steady growth of maturity models applicable to various domains. The objective of this paper is to build a preliminary understanding of a standardized global BA capability framework from existing literature that can create value for organizations. Thus, the Research questions (RQ) being addressed herein are:

RQ1: What are the significant variables contributing towards the BA framework?

RQ2: What are the potential outcomes from deploying a BA capabilities framework in an organization?

### **1.2 Scope of the Study**

Maturity models have been developed for both BA and BI separately (Ariyaratna, K., & Peter, S., 2019) An exhaustive study of maturity models brings out two distinct concepts, namely, Business Analytics and Business Intelligence maturity models. What distinguishes the two concepts is that BI builds analysis based on past data as support for decision-making, while analytics also have predictive capabilities that can analyze and suggest future changes ahead of time (Davenport, 2005). BI and BA have emerged as strategic differentiators for organizations globally. Cloud, AI and other advancements such as Internet of Things (IOT) are also quickly converging to the larger analytics canvas; however, this qualitative research is focused on studying business intelligence and business analytics capabilities and their impact on a firm.

## 2 Research Methodology

Research methodology helps to bridge the gap of understanding in a structured and systematic manner (Saunders et al., 2016). Research methodology is the science of studying techniques, based on which, the researcher can decide what study is to be conducted. Additionally, it includes logical, productive and planned steps that help lead to a better understanding of a phenomenon (Zikmund, 2009). The research methodology in this study details the existing core variables identified through an exhaustive literature survey.

Searching and reviewing of literature for BA and BI maturity models laid the foundation of this study. Over twenty related models or studies were found from Google Scholar, Emerald Insight, Research Gate and IEEE Xplore Digital Library and after an initial screening nine were selected for further assessment. Finally, variables were identified. The researchers do not claim this to be entirely exhaustive; however, the papers selected and reviewed considerably represent the wide-ranging body of the research work accomplished in this area. The review focuses on research institutes' papers and conference papers within the period of 2009- 2020.

## 3 Background

BA has been an evolving science and has manifested into a critical component in the world of business. There are multiple capability models that have been studied in the past that take their inspiration from the Capability Maturity Model for software (Paulk, 2009). The models from the literature have been segmented into four types, as represented below.

### **Real-World Models (Case-Study Based)**

Thomas Davenport and Harris (Davenport, 2005) recommended a framework for analytics maturity based on extensive real experiences of an organization in their journey of building analytics capabilities. They advocated the concept of analytics competitor, the highest level of utilising analytics within an organization to drive strategic value from business analytics investments. The framework emphasises five dimensions for analytics capability building: data and technology, enterprise, leadership, targets and techniques, Analysts (DELTA) based on various case studies. Although empirical evidence shows that BA systems bring benefits to organizations (Kohavi et al. 2002), few studies provide a sound theoretical basis for understanding how and why these benefits are achieved. The resource-based view theory discussed in the next section provides this theoretical base.

### **Theoretical Resource-Based Models**

Studies indicate multiple theoretical models that have been researched to build analytics capability within firms. One of the widely cited models is the Business Analytics Capability Framework (BACF) developed by Cosic (Cosic et al., 2015) that helps

organizations to evaluate their current Business Analytics initiatives. BACF arrived after an in-depth study of more than 50 publications. The framework refers to 16 variables that are clustered into four major capability areas, namely people, culture, technology & governance.

Another framework that builds an interesting perspective in BA capability is the Analytics Processes Maturity Model commonly referred to as APMM. (Grossmann, 2018). The APMM identifies analytics intervention within the firm processes into six key areas: Building analytic models, Deploying analytics models, Managing and operating analytics infrastructure, Protecting analytics assets through policies and procedures, Operating an analytics governance structure and Driving analytics strategy within the organization

Based upon the maturity of these processes, the APMM divides organizations into five maturity levels and the framework contributes very significantly in differentiating Analytics Maturity Level (AML) between organizations.

#### **Business-Intelligence Models**

BI has existed for a long time, and there have been multiple studies that have worked to establish the maturity factors for Business Intelligence. An exhaustive paper (Chuah & Wong, 2011) indicates that there are over 150 versions of BI models that have been studied in the past. From the vast number of models, the dominant variables that emerge are culture, strategy, business understanding and enablement along with data and skills.

#### **Consulting-Led Models**

Given the importance of BI and BA in the digital era, there have been significant studies done by Tier 1 consulting firms to understand the analytics maturity factors and the value of analytics initiatives for an organization. Studies by McKinsey (McKinsey, The Age of Analytics) (McKinsey, Building an Advanced Analytics Organization) point towards similar factors, as described earlier in the theoretical models, such as data, process management and culture as well as to more practical variables such as picking the right use cases that were not referred to in the previous frameworks. Additional interesting studies on analytics by AT Kearney (a study referred to as The Analytics Impact Index) and by Deloitte (a study referred to as The Analytics Advantage) point to organization structure (Analytics Centre of Excellence) as being a key component in driving analytics capability beyond the other factors described in the studies that were mentioned earlier. In summary, the emerging pattern of variables from various models is mentioned below:

1. DELTA model [11]: Data, Enterprise Leadership, Targets, Analysts, Technology, Techniques
2. BACF [7], APMM [16]: People, Process, Culture, Technology, Infrastructure, Governance
3. Gartner maturity model, TDWI maturity model, Hewlett Package business intelligence model [6]: People, Process, Technology, Culture, Strategy, Business enablement

4. McKinsey Model [2], AT Kearney Maturity Assessment framework [20], Deloitte Analytics Advantage [10]: Data, Process, Culture, Use Cases, Leadership, Strategy, Management, Information Technology, People, Governance

Observations from the literature review of multiple capability models highlight four recurrent independent variables that can drive the dependent variable ‘BA capabilities’ in an enterprise. These four variables are:

- Leadership (Management, vision and strategy)
- Information technology (data, tools and systems)
- Human capital (talent, skills and competency)
- Organization (structure, process, culture and governance).

### **3.1 Leadership (Management Vision and Strategy)**

The analytics maturity of an organization depends on the outlined strategy (Raber et al., 2012) as well as the level of executive leadership and support (Cosic et al., 2015). In his book *Competing on Analytics*, Thomas Davenport characterizes an analytics competitor as an organization that champions analytics from the top. The literature reveals the following critical success factors:

- Top-down support –the top-down leadership and executive support needed to drive an analytics agenda within an organization (Davenport, 2005).
- The type of industry and size of the firm –the nature of industry is a strong determinant in the BA capability of a firm. Digital natives such as Google and Amazon have a higher disposition towards analytics initiatives compared to the traditional firms (Sharon, M. S. D., & Aggarwal, V). Studies also indicate that within an industry, the larger a firm, higher is the analytics maturity level. Therefore, industry and size are important to be considered from a competitive perspective (Muller O. et al 2018).
- Analytics strategy – firms that have a clear and well-defined analytics strategy and road map have higher business analytics capability levels compared to organizations that have a tactical approach to the competency (AT Kearney)

### **3.2 IT (Data, Tools and Systems)**

The digital world throws up various types of unstructured data (beyond the well-known structured data component) such as image data, speech data and text data (Lemon, Verhoef, 2016) that needs to be managed well prior to analysis. There are multiple interesting views or categorization on the dynamic state of data; a common one is referred to as the seven ‘V’ by Vincent Whitelock (Whitelock 2018) and it classifies data under one of seven ‘V’ dimensions. In analytics terms, the key imperatives on the data front need to be: 1) Is the data relevant? 2) Do we have enough volume of data? 3) How

accessible is the data? 4) Does the data reflect all types of sources? 5) Can the data be trusted? Enabling technology is defined as an ecosystem that allows for the storage and processing of data inputs using multiple hardware and software processes, such as ETL and governance capabilities, either internally or through partner systems (Seddon et al., 2017). Tools are the functionality provided by the technology ecosystem that allow the organization to access, manage and analyze data effectively and efficiently (Seddon et al., 2017).

### **3.3 Human Capital (Talent, Skills and Competency)**

As data becomes more available, the ability to analyze and drive insights from data is becoming more critical (McAfee & Brynjolfsson, 2012). This requires human skills and expertise that are extremely dynamic and ever-increasing. Human skills in the business analytics domain include technological skills, business skills and management skills. These skills also emphasise the importance of being able to translate and communicate insights and values to the executives in an organization (Cotic et al. 2015). Davenport emphasises the need to not only recruit people with analytics skills but to also recruit people who have the ability to explain complex outcomes to decision makers in simple business terms (Davenport, 2005). A common term used to address the combined skill set is data sciences; according to a survey by McKinsey [13], data sciences is one of the most coveted professional jobs of the digital era. Being a data scientist entails having a broad perspective, from data to analysis to outcomes, which combines quantitative numbers analysis with qualitative insights and focuses on delivering business results within the organization.

### **3.4 Organization (Structure, Process, Culture and Governance)**

A well-reputed study by AT Kearney, a leading consulting firm, assigns the highest weights to the factor of organization that is composed of cross-functional data-driven decision-making, embedding analytics within the processes, tightly articulated roles and responsibilities and key constructs around building internally vs. outsource/partner (AT Kearney, The Value of Analytics, 2019). In a study of 25 business intelligence and analytics models (Foshay et al., 2015), 65% of the models emphasised the need for robust processes, 40% of the models reinforced the need for a formal organizational structure to enable business analytics, 60% of the models highlighted governance as a key aspect and 40% of the models valued the concept of cost-benefit analysis, thereby pointing towards the overall significance of the organization factor in business analytics capabilities. Another framework that focuses on the process aspect of BA capability is the Analytics Processes Maturity Model (APMM) (Grossmann, 2018). The APMM identifies analytics intervention within the firm processes into six key areas building analytic models, deploying analytics models, managing and operating analytics infrastructure, protecting analytics assets through policies and procedures, operating an analytics governance structure and driving analytics strategy within the organization.

### 3.5 Findings

The literature review thus validates that these four variables indeed enhance the impact on BA capabilities of an organization. It is now important to analyze these variables from the value creation standpoint.

## 4 Analysis

Big data and BA can lead to more informed insight, that in turn can result in better decisions and hence, greater performance gains (Sharma et al., 2014, A large proportion of empirical studies assume a direct relationship between big data and business analytics capabilities and performance outcomes, or through mediating organizational capabilities (Wamba et al., 2017). A combination of the four variables' (Leadership, IT, Human Capital and Organization) drives BA capabilities that creates value.

### 4.1 Leadership

In an issue on leadership development, Harvard Business Review (Ashkenas & Manville, 2018) aptly describes leadership as uniting people around an exciting, aspirational vision and as building a strategy for achieving the vision by attracting and developing the best possible talent to implement the strategy and relentlessly focusing on results in the context of the strategy. Studies indicate that the importance of leadership for BA is the same as any other function (Grossman, 2018). Successful analytics endeavours depend on multiple factors, including strategy and leadership. Successful companies have built a role around Data and analytics commonly referred to as the Chief Data Officer or Chief Analytics Officer thereby placing critical importance on the strategic leadership aspect for the competency. Another research study on five diverse reputed global brands, Ebay, Cancer LinQ, Walmart, Deutsche Bank and UPS (Grover et al., 2018), demonstrated that, with strong leadership as a moderating/driving factor, these organizations achieved:

- Functional benefits – financial performance, growth, revenue, cost reduction and customer retention
- Strategic benefits – reputation, satisfaction and market leadership

### 4.2 IT

Business analytics or Big Data Analytics (BDA) is often referred to as a 'new paradigm of knowledge assets' (Hagstrom, 2012, p. 2), or 'the next frontier for innovation, competition, and productivity' (Manyika et al., 2011, p.1). This is possible due to the adoption and use of data, tools, technologies, infrastructure and platforms for a firm's operations to achieve and sustain competitive advantage.



Another key component of the IT solution is to have a clear information agenda that can enable BA initiatives to drive the necessary outcomes. A well-acknowledged and comprehensive study by MIT Sloan (Lavelle, S et al., 2011) on big data and analytics charted information agendas as visions and road maps that can align IT with analytics and business needs. The IT agenda spans information governance policies and tools and data architecture, including structured and unstructured data, data relevance and currency, master data management and analytics tool kits that support reporting and visualization in advanced analytics.

### **4.3 Human Capital**

Talent is a critical driver in building a competitive advantage and helping organizations innovate with analytics (Ransbotham et al., 2015). Talent capability refers to the competence to deliver BA in a big data environment. Talent capability for BA is a combination of technical skills, technology understanding, business knowledge and domain. An interesting quantitative study of service analytics which is categorized as a dynamic capability shows how talent capability mediates the relationship between technology, information and firm performance (Akter et al., 2019). Another study's findings indicate that the outcomes of BA are significantly driven by talent capability, which can be achieved by maintaining a balance of hiring external people with sound analytical skills and of upskilling the existing team through customized training programs (Ransbotham, et al, 2015).

### **4.4 Organization**

In a study entitled 'Building an Analytics Organization', McKinsey describes an analytics organization (department) as an ecosystem that is enabled by deep functional expertise and that provides access to data, tools and technology and fosters talent development to deliver business outcomes. It has the responsibility to govern and encourage an analytics culture across the company. Similarly, a study (Krishnamoorthi, S., & Mathew, S. K. 2018) using a case study methodology proved that Organization variables contribute positively to BA capabilities that in turn deliver positive business performance.

Another study (Espinosa, J. A., & Armour, F, 2016) provides a valuable framework that serves as an ecosystem for capturing the essential elements of an organization that enable big data/business analytics outcomes.

### **4.5 Results**

The effective outcome of BA capability driven by the four variables impacts four key areas:

- Financials, which includes profitability, cash flow management and risk mitigation.

- Operations/shared services, which includes optimization, human-resource effectiveness, improving IT effectiveness and mitigating cyber-security challenges.
- Sales marketing and customer management focused on acquiring and retaining customers, improving customer experience, marketing Return on Investment optimisation and product-portfolio management.
- Strategic imperatives around increasing market share, market growth and competitive advantage.

## **5 Conclusions**

Globally, firms are investing in business intelligence and business analytics with the objective of gaining a competitive advantage in an intensifying market. However, to gain this advantage, firms need to focus on building the right maturity levels and stay invested in the journey of analytics. Higher the maturity of the capabilities, better is the quality of analytics and broader are the impacts for the organization.

### **5.1 Discussions**

This research paper is based on qualitative research from relevant papers and is validated using secondary data. A conceptual framework identifying relevant factors contributing towards BA capability within an organization has been outlined and the study also provides a preliminary view on the value creation by implementing the framework. This research contributes to the global BA and BI practice and helps organizations in their path of becoming Globally Integrated Enterprises

### **5.2 Recommended Contribution of Theory (Integrated Model)**

Previous papers have successfully drawn out the contribution of BA to individual theories - TOE framework (Nam, D. et al, 2019)) and the TAM framework (Brock, V. F., & Khan, H. U. 2017). However, given the wholistic nature of the analytics function there is a potential opportunity to validate the framework towards an integrated model (Wilber. K, 1997) The Integral model emphasises that in the new world, the sum total of multiple theories is successfully applied to achieve a superior outcome.

### **5.3 Limitations and Scope for Future Research**

BA is an extremely dynamic subject, and it covers a wide variety of competencies under its span. In addition, analytics maturity is a concept that is derived from the capability model, and there is no standard industry level framework to assess maturity. Given this background, the interpretation of BA factors and related variables on maturity may tend to be subjective, depending on the user approach. The preliminary impact of BA is

clearly tangible and needs to be further studied by industry, geography and functions using primary data in order to harness the optimal value from the competency.

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