Leading Data Analytics Transformations

by

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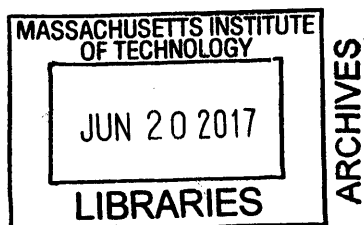John Van Maanen
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ABSTRACT

The phenomenal success of big technology companies founded with a strong emphasis on data, has epitomized the rise of the new "digital economy." Large traditional organizations, that were not long ago "on top of the world" are now at a crossroads. Their business models seem threatened by newcomers as they face pressure to "transform" and "modernize." Publicity has reinforced the perception that data can now be exploited and turned into a source of competitive advantage. In this context, data analytics presumably offers a vehicle to hasten this transformation.

Who are the individuals leading these transformation efforts? Where do they come from? What are their challenges and perspectives? This thesis attempted to answer these questions and by doing so, uncover the "faces behind the leadership titles." Interviews of 33 individuals leading data analytics in large traditional organizations and under different capacities, (i.e., at the C-Suite, at the senior leadership level and in middle management) had a few elements in common: They articulated the difficulty of change, and the significant challenges in balancing strategic design with political savviness and cultural awareness. At their core, these are true leadership stories.

Change management processes and the "Three Perspectives on Organizations" framework offer mechanisms to better understand the root causes for inhibitors of transformation and provide a path to guide data analytics initiatives. Whether data analytics proves to be a "passing fad" or not, by now, it has served as a catalyst for large traditional organizations to embark on transformation initiatives and re-examine ways to remain relevant. Leadership stories will most certainly abound as these organizations attempt to find ways to survive and prosper in what is now the "digital age."

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Introduction

Back in 2011, Andreessen penned a famous essay in the Wall Street Journal in which he claimed that software was eating the world. In a couple of memorable paragraphs, Andreessen reminded his readers that only 10 years before, one of the largest booksellers in the world (Borders) handed over its online business to Amazon. This commercial transaction came to symbolize the "passing of the torch" from the old economy to the new one. By 2011, several software-based companies came to disrupt a handful of traditional industries such as video rentals and music distribution. Moreover, Andreessen (2011) theorized that a more dramatic technological shift was imminent.

The most poignant description of what took place in the following five years can be seen in the lower portion of Figure 1 (Desjardins, 2016). Big technology companies rose to the top of the world displacing the once almighty energy companies, financial institutions, industrials and brick and mortar retailers.
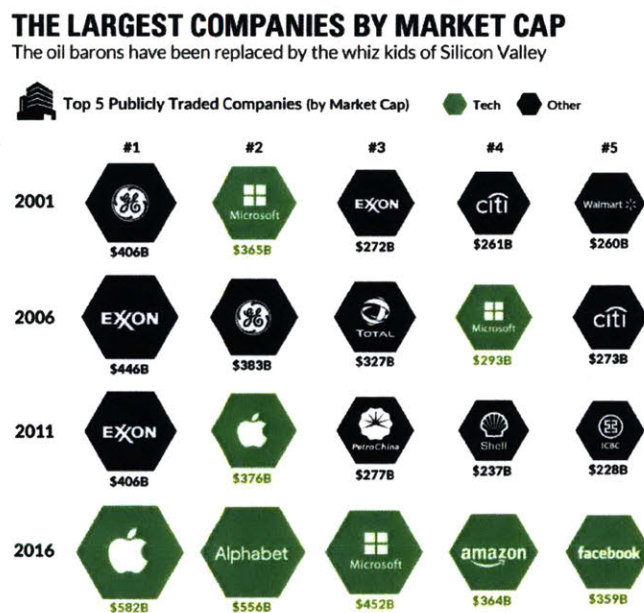
Figure 1. Largest companies by market capitalization, in Visual Capitalist, Retrieved March 9, 2017, from: http://www.visualcapitalist.com/chart-largest-companies-market-cap-15-years/

It is arguable that a single "silver bullet" was responsible for this dramatic shift in the economy. In fact, the decline in oil prices starting in 2014 partly contributed to oil and gas companies dropping down the charts in recent years. However, leaving changes in commodity prices aside, one pattern seems to emerge. Three out of the top five corporations in 2016 (i.e., Google, Amazon and Facebook) were companies started under the concept of data as a competitive asset. The other two (i.e., Apple and Microsoft); more traditional technology companies in comparison, have taken significant strides in adapting to the new wave of digital products, well beyond standard computer hardware and software products.

Has Andreessen's prophecy of "software eating the world" materialized? For starters, software has mutated and taken many different names. Cloud computing[1] and multisided platforms[2] have come to challenge and redefine what was only a few years ago called simply "software." More generically, "digital products" have made their way into a vast range of industries creating for them threats and opportunities. The success of highly publicized companies such as Uber has certainly reinforced the sense that digital disruption could occur in any sector of the economy. In that sense, it is possible that digital technologies are in fact "eating the world."

At the center of the new wave of digital technologies there are two key terms, "data" and "analytics." As: 1) the amount of data generated in all sectors of the economy grows to proportions unimaginable only a couple of decades ago, and 2) computational times and costs drop significantly following Moore's law, new possibilities for harvesting the value of data emerge. Terminology such as "big data," "data analytics,"

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[1] Cloud computing refers to the practice of using a network of remote servers hosted on the Internet to store, manage, and process data, rather than a local server or a personal computer.
[2] Multisided platforms are organizations which create value primarily by enabling direct interactions between two (or more) distinct types of affiliated customers. They often rely on digital products.

and "data-driven decision making" also have become popular through a myriad of publications gaining the interest from essentially all industries in recent years.

The definition of "data" varies greatly depending on the industry and the context in which it is used. A retailer for instance, would think of relevant "data" as aggregated figures of past and projected sales, or consumers' patterns and inventory levels. In contrast, a large oil exploration and production company, would interpret "data" as real-time information gathered from sensors in deep down underground reservoirs and at surface production facilities.

According to Ransbotham, Kiron, & Prentice (2015b); "Analytics can be described as the use of data and related business insights developed through applied analytical disciplines (for example, statistical, contextual, quantitative, predictive, cognitive and other models) to drive fact-based planning, decisions, execution, management, measurement and learning" (p. 11). Success stories around data analytics in the last few years include cases such as: 1) banks being able to more efficiently detect fraud and reduce transferred costs to customers, and 2) hospitals being able to better personalize care and reduce operating costs.

Interestingly, recent studies suggest that most companies which are effectively using analytics as a competitive advantage have been doing so since their creation (Ransbotham et al., 2015b). Fewer successful companies have migrated from a historical intuitive-based approach to data-driven decision making.

Different publications indicate that technology is no longer the roadblock to adoption of analytics at a large scale in organizations (Birtel, Pajtas, & Green, 2016; Davenport, 2007; Kiron, Prentice, & Ferguson, 2014; Lavalle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; MIT Sloan Management Review, 2016; Ransbotham, Kiron, & Prentice, 2015a; Ransbotham et al., 2015b; Ransbotham, Kiron, & Prentice, 2016). The biggest challenges are around organizational structures and culture. Ransbotham et al. (2016) rightly

illustrated the importance of company culture through a statement from Jim Sprigg, Director of Marketing and Analytics for InterContinental Hotels Group, who said: "Culture trumps data. I don't care how good your model is. If you don't understand the culture… you're not going succeed with analytics and deliver the success for the business."

Organizational challenges are often diverse and deep. Ransbotham et al. (2016) argue that in some instances, analytics capabilities are at odds with how established companies are managed and controlled. Ransbotham et al. (2015b) explain that data scientists – brought to organizations as a means of building up analytics capabilities – often do not understand the business and struggle to translate findings into insights and actions. Leaders, on the other hand, often lack the skills needed to apply output from data scientists. This gap has led in many cases to the inability to translate the results of analytics into strategy.

Kiron et al. (2014) emphasize the importance of fostering an "analytics culture" to marry business and technology towards a common goal. This is achieved through a set of behaviors, values, decision-making norms and outcomes. Kiron et al. (2014) further describe the difficulties of pursuing a shift in company culture from intuition-based to data-driven and conclude that companies with a top-down mandate for fact-driven decision making are far more effective in creating and capturing value from data analytics.

At the heart of a "data analytics transformation" there is a story of change management and leadership. Perhaps one of the most appropriate analogies corresponds to a previous transformational period, the electrification of factories that started in the mid-1880s. At the time, factories relied on line-shafting for power transmission and were designed vertically with several floors stacked on top of each other. [3] As the electrical dynamo made its way into industries, businesses realized that no significant value came from

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[3] A line shaft is a power driven rotating shaft for power transmission that was used extensively from the Industrial Revolution until the early 20th century. Prior to the widespread use of electric motors small enough to be connected directly to each piece of machinery, line shafting was used to distribute power from a large central power source to machinery throughout a workshop or an industrial complex. The central power source could be a water wheel, turbine, windmill, animal power or a steam engine. Power was distributed from the shaft to the machinery by a system of belts, pulleys and gears known as millwork ("Line Shaft," n.d.).

the mere action of replacing the steam engine with the dynamo. Business value only appeared when new factories were designed following a more horizontal design which emphasized the flow of materials in the production process (Figure 2).
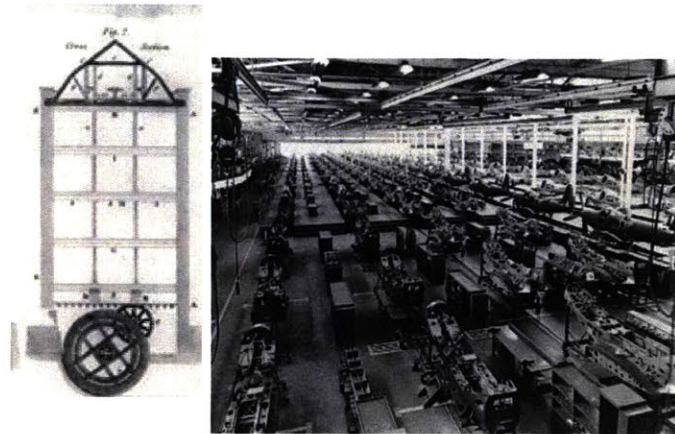
Figure 2. Line shafting factory layout (left), Boeing assembly line circa 1940s (right)

Interestingly, this same analogy was used by David (1990) to explain why the computer revolution of the 1980s would take time to translate into a big economic impact. Businesses and society in general lag behind technological progress. This time around the new "dynamo" is the data analytics technologies and the "factory layout" is the organizational structure and its cultural fabric.

A decade ago, MIT Professor Erik Brynjolfsson was quoted by Harford (2007) as saying: "Technology currently available is enough to fuel a couple of decades of organizational improvements. Even if technology stands still—it will not—there are already big changes stored up for us." Ten years later, the competitive pressure placed on traditional companies displaced by large (and sometimes small) technology firms is ever more real.

As these traditional firms recognize in data analytics a vehicle to "attempt a comeback", a new breed of leadership has emerged over the last decade. These leaders, whether they are called Chief Data Officers

(CDOs), Chief Analytics Officer (CAOs), VP of Data Analytics, or other related titles, face significant challenges as they attempt to infuse a data-driven culture in their organizations. Who are these leaders? Where do they come from? What are their challenges and perspectives? This thesis attempts to answer these questions.

Chapter 1
The Data Analytics Landscape

The world of data analytics is both old and new. Press (2013) reminds us that this seemingly new field is the result of the combination of the established discipline of statistics, with a relatively young one, computer science. Press stated: "Data science – which is often used interchangeably for data analytics – has emerged only recently to specifically designate a new profession that is expected to make sense of the vast stores of big data" (Press, 2013, para. 1). Data analytics has evolved quickly over the last decade introducing a myriad of technical terms, software products, services, organizational models and new occupations. The current landscape of data analytics might well be a transient one. For this reason, the sections here below are meant to provide context for the leadership themes further developed later in this thesis.

1.1   Data Analytics Concepts

The field of data analytics is characterized by special terminology. The terms "data analysis", "data analytics", "data science", and "big data" all have in principle different definitions. But it is not uncommon for academics and practitioners to use them interchangeably to represent the same concepts.

Currently, Wikipedia treats "data analysis" as equivalent to "data analytics" ("Data Analysis," n.d.) and defines it as "the process of inspecting, cleansing, transforming, and modeling data with the goal of discovering useful information, suggesting conclusions, and supporting decision-making." Other sources, e.g., Kte'pi, Bill, (2016) make a distinction between the two. Data analytics makes use of mathematical and statistical techniques, whereas "data analysis" relies on a broader set of tools (e.g., data visualization) to reach the same objectives. In this thesis both terms are used interchangeably following the earlier definition from Wikipedia ("Data Analysis," n.d.).

In data analytics projects, it is common for data scientists to create mathematical models which identify relationships among variables in a data set. In some instances, these models are also used for predicting future or hypothetical outcomes. These models are also often referred to as "algorithms." Even though this term carries a more formal definition in mathematics and computer science, in data analytics this term is often used to represent a broad range of models which possess descriptive and predictive capabilities.

"Big data" is a term popularized in recent years following the increasing computational power and incredible growth in data generated in all sectors of the economy. The magnitude of this "tsunami" of information is well epitomized by a couple of examples. Aiken & Gorman (2013) mention that: 1) Mobile traffic from AT&T increased by 8,000% between 2007 and 2010, and 2) every two days we create as much information as we created from the beginning of civilization until 2003.

Big data's actual definition refers to data sets which are so large or complex to be managed by standard software tools ("Big Data," n.d.). This definition is often seen as a moving target as the qualification of "large", "complex" and "standard software tools" constantly evolves. The term big data is also often used to refer to the field of data analytics. The basic premise - and often promise - of big data is that by analyzing large volumes of information from diverse sources, new insights might emerge. In spite of all these positives implications there is also a certain level of criticism ("Big Data," n.d.). One of the main arguments challenging big data come from Boyd & Crawford (2012). The authors argue that the use of large data sets does not necessarily mean a higher form of intelligence and knowledge. Big data still involves a certain degree of subjectivity. One of the best illustrations on this point comes from an application of big data by Google to predict outbreaks of flu. Google failed as it overstated the outbreak figures by a factor of two (Lazer, Kennedy, King, & Vespignani, 2014).

1.2   Types of Data Analytics

Data analytics techniques are varied and encompass a wide range of complexity and applicability. In general, there are two main types as follows:

1.2.1   Descriptive Analytics

As noted by Sivarajah, Kamal, Irani, & Weerakkody (2017), this is the simplest form of analytics. It often involves building summaries and visual displays – commonly called "dashboards" across different industries – of data sets. Descriptive analytics also make use of simple statistical concepts such as mean, median and standard deviation to facilitate basic interpretation of variables and patterns within the data. One important aspect of descriptive analytics is that it is often backward looking (Sivarajah et al., 2017). That is, it describes things which have already occurred. Watson (2014) indicates that this type of analytics has been used extensively for some time under the more established domain of "business intelligence."

1.2.2   Predictive Analytics

This type of analytics concentrates on forecasting using a wide range of statistical and data science methods falling under two main categories, "supervised" and "unsupervised" techniques. In supervised techniques, an algorithm is trained with known data before it is used for predictions. Unsupervised techniques explore underlying relationships between variables in data sets. Predictive analytics methods also have different levels of sophistication going from regression techniques – standard statistical technique introduced in the early 19th century – all the way to neural networks.[4]

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[4] A neural network is a computational model used in computer science and other research disciplines, that is based on a large collection of simple neural units (artificial neurons), loosely analogous to the observed behavior of a biological brain's axons ("Artifical Neural Network," n.d.).

1.3 Data Analytics: Evolution and Current State

The formidable interest in data science and data analytics in recent years has distant origins. Press (2013) traces back their origin to John Tukey's publication: "The Future of Data Analysis" (Tukey, 1962). Tukey, a renowned mathematician and statistician, came to see data analysis as closer to science than actual mathematics, that is, intrinsically, an empirical science. The growing use of computers in the 1970s led to the creation of the International Association for Statistical Computing (IASC) in 1977. Its mission was to link statistics, computer technology and the knowledge of domain experts with the goal of converting data into knowledge (Press, 2013). The 1980s and 1990s saw growing digitization across a large spectrum of industries. Data generated in different sectors of the economy started to become attractive to many companies. A *Business Week* cover story introduced one of the main premises of big data and data analytics in marketing, companies are collecting vast information about customers are processing it in order to craft personalized marketing messages (Berry, 1994). Press (2013) comments that this period was marked by an early peak of enthusiasm followed by large disappointment. According to the author, "Many companies were too overwhelmed by the sheer quantity of data to do anything useful with the information" (Press, 2013, para. 6).

A decade later, a book titled *Competing on Analytics* by Davenport (2007) captured significant interest and is often identified as the catalyst for today's prominence of big data and data analytics. Davenport describes the emergence of a new form of competition based on the use of data, analytics and fact-based decision making. Later, in 2009, Hal Varian, Google's Chief Economist, was quoted as saying: "I keep saying the sexy job in the next ten years will be statisticians... the ability to take data – to be able to understand it, to process it, to extract value from it, to visualize it, to communicate it – that's going to be a hugely important skill in the next decades..." (Varian, 2009, para. 13). In the years following Varian's statement, there has been indeed an exponential growth in the demand for data scientists. Companies of all sizes

have started data analytics programs and invested in new IT infrastructure. Data analytics has risen in popularity, permeating corporate strategies.

While literature is full of examples detailing the potential of data analytics, one key questions lingers: Have large traditional companies succeeded at adopting data analytics at a large scale? Perhaps the most telling answer to that question comes from a recent publication by Ransbotham et al. (2016). The authors argue that managing with analytics is, at present, a mainstream idea but it is not a mainstream practice. At present, only a handful of large traditional organizations have taken the lead and invested significant resources in pursuing a "data analytics transformation." A couple of examples described by Ransbotham et al. include the Bank of England and General Electric (GE). In the case of GE, an ambitious program started in 2012 has brought focus to what is called the "industrial internet", a digital platform to aggregate and analyze data from industrial machines. The implementation of this program has required significant internal restructuring and is currently ongoing.

Other large organizations have pursued pilot implementations in data analytics (some successful and some not) and are experiencing the emergence of "data analytics pockets" which often lack central coordination. [5] As pointed out by Ransbotham et al. (2016), many companies struggle to figure out how to use analytics to take advantage of their data. Companies apparently underappreciate the organizational resolve necessary to achieve this goal.

1.4   Becoming a Data-Driven Organization

As indicated by Ransbotham et al. (2015b), companies classified as "analytical innovators", (i.e., leaders in the adoption of data analytics), appear to have a historic emphasis on data, that predate the interest in

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[5] Data analytics pockets refers to small organizational units which proactively engage in in small or medium-scale data analytics initiatives. In many cases, they gain recognition within their large organization.

data analytics. Certainly, technology giants such as Facebook, Amazon and Google epitomize the concept of data-driven organizations.

For large traditional organizations, the goal of becoming data-driven could prove an elusive target. A recent global survey of 720 companies revealed that 64% of organizations have invested or have plans to make investments in big data (Gupta & George, 2016). However, it is clear that investments on their own are not sufficient. Companies need to pursue ambitious plans covering technical, organizational and cultural aspects in order to effectively create business value. The difficulties are varied as described extensively in literature. Additionally, there is a lack of guidance to practitioners on who to address these challenges (Vidgen, Shaw, & Grant, 2017).

1.4.1   Elements of a Data Analytics Transformation

Henke, et al. (2016) propose a framework to guide data analytics transformation initiatives. This framework consists of a multistep process in which a company: 1) sets objectives, 2) organizes its data, 3) implements data analytics, 4) redesigns its procedures accordingly, and 5) introduces change management programs to increase adoption. In reality, large companies struggle to follow these steps in sequence. Multi-year programs often require early gains to maintain momentum.

Many companies struggle to figure out how to take advantage of their data and therefore an early definition of clear objectives is not always possible (Ransbotham et al., 2016). Accepting the fact that a credible and comprehensive framework for data analytics transformation does not exist in the literature, the five steps put forth by Henke et al. (2016) can be re-formulated to represent areas in which a company needs to focus. These areas are:

1.4.2   Vision and Strategy

It is hard to argue against the importance of setting a clear vision and strategy for data analytics at the company leadership level. This is, however, a very difficult task for most companies. In fact, Henke et al. (2016) reveal that setting up the right vision and strategy is the top-rated hurdle in a survey of C-suite executives and senior managers.[6] The lack of a large pool of reference cases for data analytics transformation also contributes to these difficulties. As a result, many companies often opt to launch short-duration pilot projects to gradually gain an understanding of the realistic possibilities of data analytics. The goal is that articulation of a broader vision and strategy will come after a period of experimentation.

1.4.3   Data Governance and Centralization

Henke et al. (2016) describe the need to create a central data repository drawing from internal and external sources. This data repository represents an "analytics sandbox" in the words of the authors. While the concept of centralizing data is conceptually simple to understand, it often proves to have complex ramifications into technical and organizational areas.[7]

Concentrating first on the technical areas, different levels of complexity can also be discerned (Sivarajah et al., 2017). These include: 1) data acquisition and warehousing, 2) data mining and cleansing, 3) data aggregation and integration, and 4) data interpretation. At a technical level, these areas require investment in IT infrastructure and creation of processes to ensure data quality and integrity are protected along the way. Technical challenges in this area can be significant (Sivarajah et al., 2017).

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[6] C-suite is a widely-used slang term used to collectively refer to a corporation's most important senior executives. C-Suite gets its name because top senior executives' titles tend to start with the letter C, for chief, as in chief executive officer, chief operating officer and chief information officer.

[7] Data centralization calls for integration of data generated in different departments or "silos" in an organization. The objective of data centralization is to gain a holistic understanding of a business.

At an organizational level, data quality and integrity are often under the realm of "data governance." This concept, central to data analytics, concentrates on control mechanisms to ensure that data entries (either by people or machines) meet precise standards. Without proper data governance, data analytics might well be meaningless. Jeanne Ross, Director of the MIT Sloan Center for Information Systems Research (CISR), emphasizes the need for leadership to dictate and pursue a "single source of truth" around data (Kiron & Ferguson, 2012). Data governance is fundamental to analytics but, in practice, it is not very visible and many times unpopular. Improvements in data governance are often invisible to large parts of the organization and take time to translate into a measurable impact onto the bottom line.

Centralizing data often implies "democratizing data." For instance, in a largely decentralized organization, all different departments and business units would need to adhere to protocols to share their data. These changes in organization and company culture are not easy to attain.

1.4.4   Modeling Insights

Henke et al. (2016) define "modeling Insights" as the application of data analytics techniques to uncover business insights. This is achieved through "data analytics projects", which are often non-linear and require several iterations of creation and testing of hypotheses. Data analytics projects also require integration of three distinct perspectives, namely: 1) statistics and analytics techniques, 2) computer programming, and 3) business knowledge. This requirement often implies the need for a multidisciplinary team.

1.4.5   Insights Implementation

While Henke et al. (2016) refers to this area as "Workflow Integration", a more generic description is "Insights Implementation." The outcome of data analytics models does not automatically translate into business value. On many occasions, the insights obtained suggest the modification of strategies, processes, decisions, etc. In some instances, these modifications can be performed automatically. One

example is a hedge fund which uses data analytics techniques to derive insights from the stock market. Once these insights are obtained, a second automated layer will take the appropriate actions, i.e., buy or sell a particular stock. In this case, there is no or little human intervention.

However, in most applications of data analytics - particularly in those relevant to large traditional organizations - human intervention is inexorably a feature. Insights from analytics often might suggest different ways of conducting a business. Whether it is uncovering operating inefficiencies or identifying alternative approaches for pricing products or carrying out marketing campaigns; analytics outcomes might be at odds with the existing "way of doing things" in an organization. In some other instances, data analytics insights might be difficult to implement as they may, for instance, require coordination of different areas of a siloed organization. Implementation of insights might also go against the existing managerial and general workforce incentives.

Insights implementation can be a major hurdle for large organizations, even those which have covered relatively well the three areas described above (i.e., vision and strategy, data governance and centralization, and modeling insights). In fact, Ransbotham et al. (2015a) and Henke et al. (2016) argue the number one barrier for adoption of analytics is by far translating its results into business actions.

The novelty aspect of data analytics often creates a situation in which data scientists brought to organizations do not understand the business sufficiently and managers are not able to understand the analytics results. Ransbotham et al. (2015a) highlight situations in which the organization's capacity to produce increasingly sophisticated analytics outpaces management's abilities to understand them. Others, such as, Henke et al. (2016) propose the creation of intermediary roles, (i.e., "business translators") to help bridge the gap between data science and business units and therefore facilitate implementation of analytics insights.

1.4.6 Organizational and Cultural Change

Henke et al. (2016) refer to this area as "Adoption" and describes it as proactively building management's capabilities and managing change throughout the organization. In practice, adoption encompasses a myriad of organizational and cultural challenges which can seem insurmountable to many companies.

To many, these challenges eclipse all other technical areas and represent the true roadblock to analytics (Lavalle et al., 2011; Ransbotham et al., 2016). Davenport (2007) quotes an executive who refers to the complexity of managing analytics transformation as "playing a fifteen-level chess game." An anonymous author at the *MIT Sloan Management Review* (2016) argues that a special combination of fortitude and persistence is required, particularly to do the unglamorous work at the foundation of analytics initiatives. The publication argues that this remains a big requirement for many companies and why so many of these initiatives have fallen short of expectations.

Arguably, organizational and cultural challenges stem from the fact that data analytics implies a different way of running a business and making decisions – particularly for companies with a strong legacy of intuition-based decision making. In many organizations data is seen a byproduct of business and often not looked at as an asset. Changing these paradigms takes time and significant effort.

Organizations pursuing data analytics transformation are exploring different routes to changing their cultures. One of these routes consists of talent development. Halper (2016) recently surveyed 370 companies revealing different ways in which companies are changing their talent make up. These include: 1) external recruiting of data scientists, 2) internal development of talent, e.g., business analysts are now required to become more sophisticated analytically, 3) creation of centers of excellence, and 4) appointment of chief data officers or chief analytics officers; to name a few.

1.5 Organizational Models for Data Analytics

A data analytics transformation implies a degree of organizational restructuring. Figure 2 reminds us that it took a redesign of the factory layout to materialize the business benefits of electrification. In a similar manner, data analytics - as a new and potentially disruptive technology - requires a rework of the "organizational floorplan."

The clear leaders of data analytics, e.g., Google, Amazon and Facebook, all have data analytics intrinsically embedded in all their business functions. This has been the premise of their business models and the indication is that, in time, data analytics will claim an even larger role in their strategy. For many large traditional companies attempting a transformation, their ultimate goal would be to similarly embed data analytics in all business functions. This is clearly a massive challenge which, even in the best-case scenario, would materialize only in the long term.

At present, many companies are pursuing the creation of Centers of Excellence (commonly abbreviated as "CoE") in order to provide leadership, raise awareness and disseminate best practices on data analytics. In the previously mentioned survey, one-third of the companies surveyed mentioned they had a data analytics CoE in place. An additional 26% were planning to deploy one in the next year (Halper, 2016).

Halper (2016) notes that the CoE can be structured in three basic ways. In a "centralized model", business units commission data analytics projects to a central CoE which serves the whole organization. In a "decentralized model", data scientists are embedded in different business units and rely on a central mechanism to ensure lessons learned and best practices are consolidated and enforced throughout the organization. Some other organizations use a "hybrid approach" which combines elements of both centralized and decentralized models.

1.6 New Leadership Roles in Data Analytics

As mentioned before, the job title of data scientist has seen phenomenal growth over the last decade. At present, there are indications that the large interest in data analytics is creating and will create additional positions. In fact, Henke et al. (2016) estimate that there could be a demand for 2 to 4 million business translators in the US over the next decade. They also argue that "while it is possible for organizations to outsource their analytics activities, business translator roles require proprietary knowledge and should be more deeply embedded in the organization" (Henke et al., 2016, p. 5).

The question that lingers in this current landscape is: What about data analytics leadership? As seen before, pursuing a data analytics transformation is strongly rooted in organizational and cultural aspects which arguably require a new breed of leaders.

Universities are beginning to address this question. Michelle Li, Director of the Business Analytics graduate academic program at MIT Sloan School of Management – interviewed for this thesis – offers some insights. Li mentions that the program she leads was started in 2016 with the key objective of "educating leaders in the executive suite in business analytics, this is, the future Chief Data Scientists." The program concentrates on young talent which will become future leaders of organizations. Li also mentions that interest in the program from both applicants and industry has been unprecedented. The first year, over 1,000 applications were received for only 16 seats. The second year, over 2,000 applications are expected for 50 seats. The expected growth of this program is predicted to outpace more traditional ones, such as MBA programs. Other universities, such as Stanford University and The Wharton School (University of Pennsylvania) are also planning to follow suit with similar offerings. Relatedly, companies across a large range of industries are appointing data analytics leaders. The job titles are varied and include: Chief Data Officer (CDO), Chief Analytics Officer (CAO), Head of Data Analytics, and Vice-President of Analytics.

1.6.1 The Chief Data Officer

The CDO is probably the most highly publicized leadership role in data analytics. Lee, et al. (2014) mention that the first known appointment of a CDO was made by Capital One back in 2003. Wikipedia instead argues that Visa appointed the first CDO in 2001 ("Chief Data Officer," n.d.).

In 2015, Gartner Inc. predicted that 50% of all companies in regulated industries would have a CDO by 2017 (McCall, 2015).[8] While at present it is not clear if this prediction will materialize, there are definite indications the CDO role has continued to grow at a fast pace. There are currently - as of the end of 2016 - 2,000 CDOs worldwide, compared to 400 back in 2014 ("Chief Data Officer," n.d.). The most recent forecast from Gartner Inc. (2016) predicts that by 2019, 90% of large organizations would have a CDO.

What is the driver behind this phenomenal growth in CDO appointments? Why is it that a large number of financial institutions, technology companies, industrials, insurance companies, and business professional services – to name a few – are creating these roles? One account is that the prominence that big data and data analytics have gained over the last decade has influenced the strategy of a large number of organizations. In the case of public companies, it is possible that the creation of a data-centric C-Suite role responds to shareholders' and markets' expectations around modernization and competitiveness in an increasingly digital landscape.

- **The Case for the CDO**

CDO appointments also respond in many cases to a well-thought-out strategy which recognizes that top-down transformation is essential. The literature in the area presents arguments supporting the appointment of a CDO. Aiken & Gorman (2013), for instance, build a case for the CDO around the argument that the more traditional C-Suite roles, such as the CIO (Chief Information Officer) are unfit to

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[8] Gartner Inc. is an American research and advisory firm providing information technology related insight for IT and other business leaders located across the world.

drive a data analytics transformation. Aiken & Gorman (2013) explain that even though current CIOs have achieved enormous success over the last two decades, their broad scope on technology management prevents them from focusing resources on data issues. In addition, the authors claim - from combined experience and research sources - that 90% of CIOs are not data knowledgeable. This is, CIOs traditionally come from computer science and IT (Information Technology) backgrounds in which data management is not an integral part of the educational curricula. Aiken & Gorman claim that students in both fields explicitly learn that data management is not part of what IT leaders do. Moreover, data analytics implies an often-cited and deeply important principle: "Data is an Asset." Aiken & Gorman argue data is in fact an organization's sole non-depletable, non-degrading, and durable strategic asset. This rather simple principle has proven to be very hard to embrace in large traditional organizations which see data as a by-product of business. For many companies, treating data as an asset implies a significant shift in operational, organizational and cultural structures which requires dedicated leadership. Also, if data is truly treated as an asset, successful data governance is not sufficient to drive value. At a high level, data must support strategy. At a more granular level, connecting data to value involves a delicate coordination of processes, people and technology. Aiken & Gorman use the analogy of "Data Leveraging" to articulate these ideas (see Figure 3).
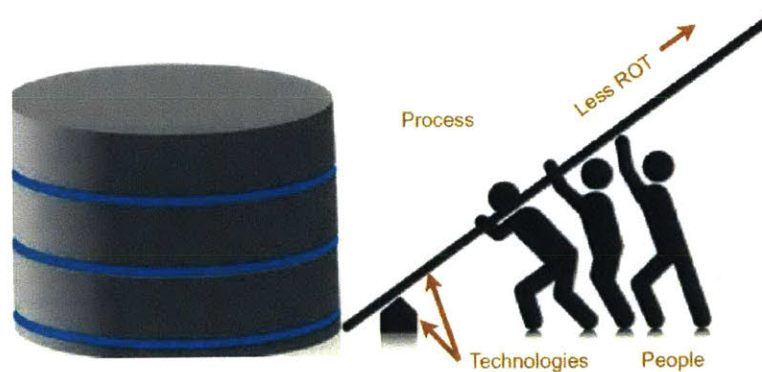
Figure 3. Data leverage concept as presented by (Aiken & Gorman, 2013), Note: ROT stands for Redundant, Obsolete and Trivial Data, its reduction increases data leverage

In discussing the emergence of the CDO, Lee et al. (2014) argue that seemingly tedious data problems often are business problems requiring executive intervention. In many organizations, this realization has been gradual and has followed a three-phase sequence.

In **Phase 1**, groups from IT departments assigned to sort out data problems discover that their root causes cannot be addressed by the IT group alone. In **Phase 2**, companies appoint data middle-managers with a variety of titles, e.g., data quality managers, data stewards; and start data governance mechanisms, committees and counsels. In many instances the success of these initiatives is limited. Lee et al. (2014) illustrate the difficulties faced by data middle-managers through a couple of stories drawn from interviews conducted in 12 companies. In one of those stories, a data quality manager from a US healthcare institution attempts to re-examine the processes for collection and storage of customer data. An executive complained by saying: "You are digging in my backyard – Get out of my backyard!"

Phase 3 is marked by the realization that middle management is not in a position to dictate business process changes to higher ranking executives and to influence at an enterprise level. For these reasons, several organizations have opted to appoint CDOs at an executive rank.

Aiken & Gorman (2013) argue that the CDO should report out of the IT domain and should be given the same importance as other C-Suite functions such as the CFO (Chief Financial Officer). The authors argue that such a structure would help impose a much-needed bias towards data-centric development practices.

- **The multiple dimensions of the CDO**

The CDO role encompasses technical, leadership and change management areas, including: 1) progressing the data governance agenda at all levels of the organization, 2) identifying new business opportunities pertaining to data, and 3) defining technical specifications for data architecture and leading their implementation.

Sentance (2015) claims that the CDO role demands individuals who are bilingual, speaking the language of the C-Suite and engaging in meaningful technical discussions. Moreover, a CDO must operate across organizational silos to be effective. The scope of the role involves extensive cooperation and interaction with IT, business units and technology departments. The CDO role is clearly multi-dimensional.

Lee et al. (2014) propose a "cubic framework" in an attempt to help organizations assess and strategize the CDO role. The three dimensions of this framework are: 1) collaboration, i.e., inwards vs. outwards, 2) data space, i.e., traditional vs. big data, and 3) value impact, i.e., service vs. strategy. Different locations in this three-dimensional space give rise to 8 defined CDO roles (see Figure 4).

The cubic framework recognizes the fact that companies are different. Therefore, specific needs and priorities require distinct CDO profiles. Moreover, as needs and priorities change with time, the CDO role must evolve accordingly. It can be argued that in most transformation programs – data analytics being one of them – evolution and a refocusing of priorities are some of the few certainties.
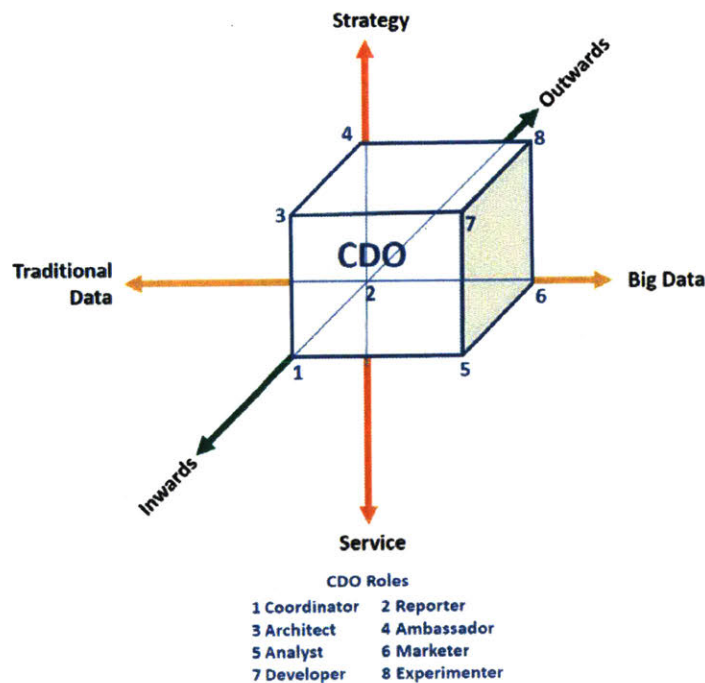
Figure 4. CDO's cubic framework proposed by Lee et al. (2014)

1.6.2   Other Data Analytics Leadership Roles

Even though literature concentrates largely on the CDO as the leader of data analytics, other less-common leadership roles do exist. In the C-Suite, the CAO (Chief Analytics Officer) has gained prominence in the last few years. ("Chief Analytics Officer," n.d.) indicates that while the CDO focuses on data processing and maintenance, the CAO focuses on providing input into operational decisions based on the analysis. Hypothetically, as companies undergo data analytics transformation, the CDO role transitions into the CAO. In early stages of a transformation program, the CDO focuses on articulating the philosophy of "data as an asset" and concentrates its efforts in pushing a data governance agenda. As these efforts succeed, the organization moves into a second phase in which data analytics is used to derive actionable insights in pursuit of positive business impact. For some companies, this second area is in principle the scope of the CAO.

Other companies opt to pursue a data analytics transformation program through existing C-Suite roles, such as the CIO, CTO (Chief Technology Officer), and the CDiO (Chief Digital Officer). In practice the scope of these roles vary greatly from company to company and quite often overlap.

Interestingly, in a large number of traditional companies, the highest data analytics authority is placed at a senior leadership level below the C-Suite. These "de-facto CDOs or CAOs" often have the title of "VP of Analytics" and their scope and accountability are often similar to those of formally-appointed CDOs and CAOs. In a few cases, Chief Data Scientists – which are often strongly technical roles limited to management of a group of data scientists – can be classified as de-facto CDOs or CAOs.

Leadership in data analytics also exists - and often thrives - in middle management. In many companies, as mentioned, data analytics sometimes appears in "pockets" of the organization. Kiron et al. (2014) indicate that these groups often find ways to innovate with analytics, yet those abilities are not extending across the organizations. Data analytics champions in these leading business units often see themselves

facing unique opportunities and difficulties. On one hand, their proximity to business needs allows them to target very focused data analytics initiatives with the aim of demonstrating business value. On the other hand, their distance from senior management hinders their visibility and support for their initiatives.

1.7 Unanswered Questions in the Literature

Data analytics is clearly a fast-paced, evolving area. Many large traditional organizations are either at early stages or in the midst of a transformation process. They seek a special breed of leadership with a few hints from industry and academia. The transient nature of data analytics leadership roles also adds to that complexity and criticality. In a revealing analogy, Aiken & Gorman (2013) remind us that the title Chief Electrification Officer is not in as widespread use today as it was when organizations were scrambling to learn how they could use electricity to support their business objectives...

The normative literature offers important guidelines for leadership around data analytics transformation. However, in many instances, the large list of attributes required of a data analytics leader seems elusive and perhaps even distant from "actual people." The cubic framework for the CDO proposed by Lee et al. (2014) is arguably the most sophisticated analysis of leadership in data analytics. While this framework can be helpful in realizing the complexities of the CDO role – and all data analytics leadership roles – it also raises fundamental questions about "the real people behind the leadership title." These include:

- What educational and professional background must a data analytics leader have to simultaneously cover technical areas (data dimension), business areas (value impact dimension), and organizational areas (collaboration dimension)?
- What are the skills a data analytics leader needs to evolve through very dissimilar roles - e.g., from a coordinator to an experimenter, or from an analyst to an ambassador as shown in Figure 4?

- How can large traditional companies develop internal resources and/or attract external talent to fill data analytics leadership roles? Are individuals with these qualities even attracted to large traditional companies?

- Given these constraints, what can be realistically expected from data analytics leaders?

- Who are these leaders? Where did they come from? What are their challenges and perspectives?

Chapter Two of this thesis explores these questions through interviews with leaders of data analytics transformations.

Chapter 2
The Leaders Behind the Titles

As large traditional organizations are either displaced by "Big Tech" or fear disruption of their business models, they seek transformation through new technologies such as data analytics. Leaders of this transformation come into the picture with high expectations. They are presumably required to possess a broad range of technical and leadership skills but often lack a clear roadmap. Their story is in fact a leadership story.

How does one understand the roles of people leading data analytics transformations? Beyond academic literature and frameworks, one word comes to mind: "Conversation." Chapter Two of this thesis explores this very aspect. Through my interviews with data analytics leaders I attempt not only to "put a face to the role" but also to validate certain guidelines from the normative literature covered in Chapter One, and to identify uncovered challenges and perspectives.

2.1   Interview Methodology

Interviews with 33 data analytics leaders were conducted between November 2016 and March 2017. Interviews were structured as open discussions in which interviewees were encouraged to freely describe the perspectives and challenges of their role while adding elements of their professional background and personal stories whenever appropriate.

A total of 85% of the interviews were carried out via telephone / video-conference conversations mainly due to geographical limitations and 15% of the interviews consisted of face-to-face meetings. Interviews typically ranged between 30 to 60 minutes and were initiated by open-ended questions such as: "How did you become a CDO?", or, "What are the main challenges you face while championing data analytics in

your organization?" From that point on, the interviewer followed a loose ethnographic framework in which follow-up questions were devised from "surprising facts" and the use of "unfamiliar terms."

An example of a surprising fact is:

Interviewee: "I have never come across a data scientist who is not interested in learning about the business context" – which led the Interviewer to ask: "Do you then think data scientists can transition over time to business roles?"

An example of an unfamiliar term which led to multiple follow-up questions is:

Interviewee: "A lot of companies are overpaying for dashboarding thinking this is data analytics" – which led to the interviewer to ask: "What is dashboarding?", "How is it different from data analytics", "Why do you think companies are overpaying for it?"

Information from conversations was captured in notes and audio recordings. A comprehensive transcript of each conversation was prepared. Follow-up discussions were also conducted in cases requiring further clarification. Subsequent phases of the analysis included: 1) synthesis of each interview listing important insights in different categories, e.g., leadership themes, technological themes, etc., and 2) a global synthesis of all interviews by themes, highlighting areas of agreement and contrasting views.

2.2 Interview Sample

Table 1 shows basic demographics for the 33 interviewees. While the breakdown of industries represented in each one of the leadership roles (pie charts on the right-hand side of Table 1) is simply an indication of the pool of individuals interviewed for this thesis, one general observation can be made: The roles of CDO and CAO are either non-existent or very rare in the oil and gas industry. This observation was confirmed by verifying professional databases and in discussion with several senior leaders in the industry. In terms of geographical location, only four out of the 33 interviewees were located outside of the US,

three of them in Europe and in Latin America. Six out of the 33 interviewees are women. Interviewees represent 25 organizations, out of which, three are public sector agencies and five are private companies. The remaining 17 are all public for-profit companies.

Table 1 Interviewee demographics

Number of Interviewees

By Industry

14 **Oil & Gas**
5 **Industrials & Utilities**
5 **Business Consulting & Services**
3 **Public Sector**
3 **Financial Services & Banking**
2 **Software and IT Services**
1 **Pharmaceutical**

By Organizational Hierarchy

C-Suite
4 **Role with Partial Data Analytics Responsibilities**
10 **CDO or CAO**

Senior Leadership
13 **De-facto CDO or CDO**

Middle Management
6 **Data Analytics Champion**

Figure 5 to Figure 7 present the interviewees' company demographics (excluding public sector agencies) in an effort to articulate what constitutes "large" and "traditional" firms, the focus of this thesis. First, company size is represented by three key variables: 1) number of employees, 2) yearly revenue, and 3) market capitalization. The companies range between 4,500 to 340,000 employees, $6 billion to $234 billion in yearly revenue, and $19 billion to $ 504 billion in market capitalization. All correspond to "large" corporations. Data analytics leaders (Google, Facebook and Amazon) are included in Figure 5 to Figure 7 as a reference only. This thesis concentrates on traditional organizations pursuing a transformation and not on companies founded relatively recently with a strong data-driven culture. In an effort to define what constitutes a "traditional" company, Figure 7 shows the foundation year of each company against yearly revenue and market capitalization.

Sources: Revenue. Market Capitalization and Employee from Google Finance (2016). Average Fortune 100 Company figures calculated from Fortune 500: http://beta.fortune.com/fortune500/. Note: Facebook, Amazon and Google are considered the world leading firms in Data Analytics and are shown only for reference, i.e., not interviewed for this thesis.
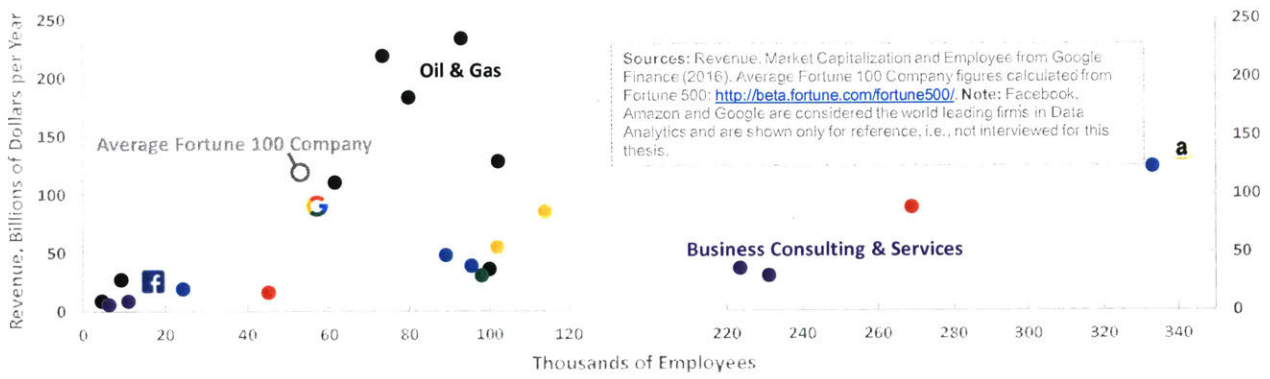
Figure 5. Interviewees' company demographics (Part A)
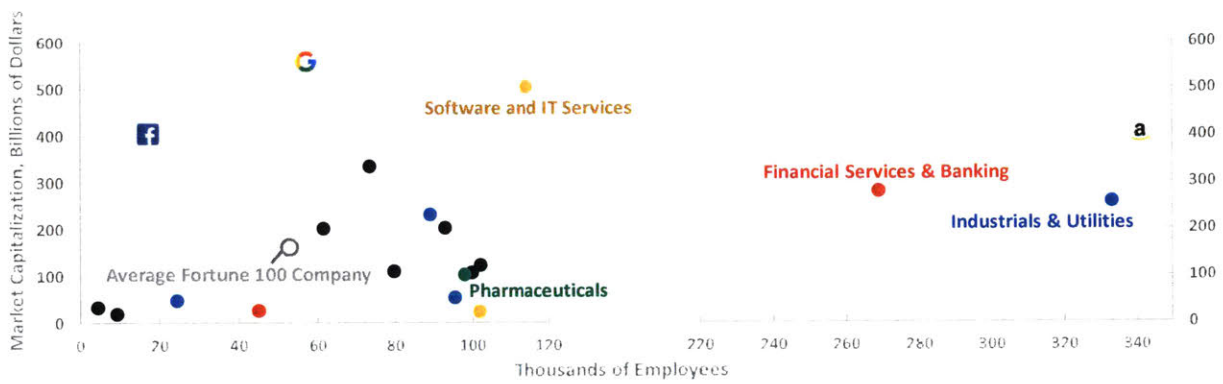
Figure 6. Interviewees' company demographics (Part B)
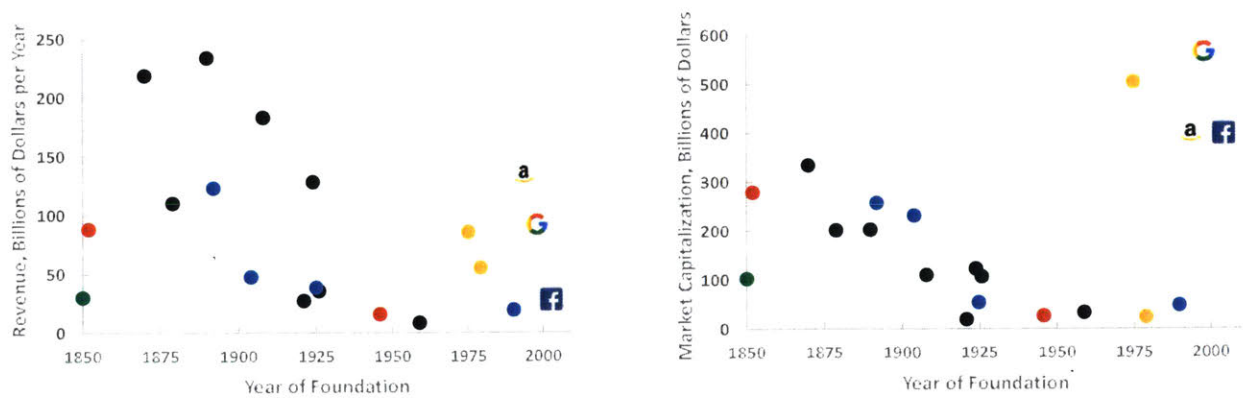
Figure 7. Interviewees' company demographics (Part C)

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As can be seen, a large number of individuals interviewed were from companies founded prior to 1950. Only four companies were founded between 1959 and 1990. All these are considered traditional organizations in this thesis. Finally, the right-hand side corner of Figure 7 shows the stark difference between traditional corporations and the young, and highly appraised Google, Facebook and Amazon.

2.3 How Do Data Analytics Leaders Emerge?

For most companies, leadership requirements are presumably dictated by the competitive environment in which they operate. The creation of data analytics leadership roles responds to both external and internal factors. Additionally, there is a clear scarcity of senior leadership in data analytics given the novelty of the field. University programs with offerings in data science leadership are recent. Leadership roles such as CDO, CAO and VP of Analytics were practically non-existent a decade ago. As companies face this small pool of candidates, they often groom leaders internally and/or seek external talent. This section explores the rationale the individuals interviewed said these companies followed to create leadership roles in data analytics and the background of the people they chose to fill these positions.

2.3.1 The Emergence of Data Analytics Leader

Creation of data analytics leadership roles responds in to a conscious effort to pursue transformation. Interviews highlight different reasons for companies to embark on data analytics programs and selecting leaders to lead such efforts. The reasons include:

- **A sense of "lagging behind":** As the concepts of data-driven decision making and use of data as a strategic asset are highly publicized, many of those interviewed feel as if the companies they are in should be acting faster. In fact, 64% of interviewees openly mentioned that they felt their organizations are lagging. To the question of "Who are the leading companies?", many interviewees mentioned large technology companies such as Amazon, Google and occasionally General Electric.

About 50% of interviewees in organizations without data analytics roles in the C-Suite mention that the appointment of a CDO or a CAO would not be surprising. It would, they said, constitute a step in the right direction. The other 50% expressed doubts over the effectiveness of new C-Suite roles.

- **Shifting competitive forces**: Several interviewees point to the changes in their organizations' competitive environment which have resulted in data analytics taking over a more prominent role at the corporate board level. Changes in competitive forces are also influenced by micro and macroeconomic factors. For instance, oil and gas companies have seen drastic cuts in their revenues following the drop in oil prices between 2014 and 2016. While data analytics roles at the C-Suite are not - for the moment - common in this industry, this drop in revenue is said to have led to data analytics appointments at a senior leadership level according to respondents from the industry.

- **Scaling-up from "data analytics pockets"**: Several interviewees from large organizations – particularly those with highly decentralized organizational structures[9] – refer to pockets of data analytics appearing in different departments or business units. In many situations, positive outcomes of these initiatives have led top management to appoint a central leader (in the C-Suite or at Senior Leadership levels) with the aim of coordinating efforts and further developing capabilities.

- **Additional incentives in highly-regulated industries**: Those interviewed said that in highly-regulated industries which deal with significant amounts of data, (e.g., financial institutions), the motivations for creating data analytics leadership roles often comes from regulatory and risk management concerns which carry urgency. In those cases, the leadership roles start being in a "defensive mode" with the expectation that over time they will transition gradually to an "offensive mode" (e.g., engage in revenue seeking activities).

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[9] Several interviewees use the term "federated organization" to refer to companies which have grown from acquisitions and are composed of independent business units divided by business function and/or geography.

- **Culture shift at the C-Suite**: Some interviewees, particularly those in business consulting organizations with contacts in a large number of companies, point out that in several cases, newly appointed CEOs with "something to prove" embark on top-down cultural shift programs resulting in the creation of new data analytics leadership positions.

2.3.2   Background of the Data Analytics Leader

One revealing finding is the fact that while data analytics is perceived as a highly-specialized field, only a relatively small percentage (13%) of the leaders interviewed come from a career in statistics and data science. A large percentage (87%) come from varied backgrounds, such as IT, engineering, accounting, finance, etc. Despite this diversity, they appear to have one thing in common: They are said to possess a strong business acumen. This is, they have been in different roles in their companies and are often seen as "trusted leaders" before being appointed to lead data analytics. One interviewee who works for a large business services company which advices organizations in data analytics transformation, alluded to an internal study his company had conducted of 1,500 organizations, and then said: "There has been a mixed record for CDO and CAO roles... If I could generalize, I would say that the root cause for these roles not being effective is when companies opt for very technically competent people in these positions but who lack business acumen. In fact, these roles require a much higher degree of stakeholder management, trust building and relationship with executives."

Figure 8 shows a schematic of the background of data analytics leaders. The extreme left in the horizontal line represents a highly technical background in data science and statistics. The extreme right represents a strong business acumen. Three interviewees are located along this spectrum of backgrounds, their stories follow.

Background in data science / statistics	"Business acumen" background	
13% of leaders interviewed	**87%** of leaders interviewed	
De-Facto CDO - 1	CDO - 1	CDO - 2
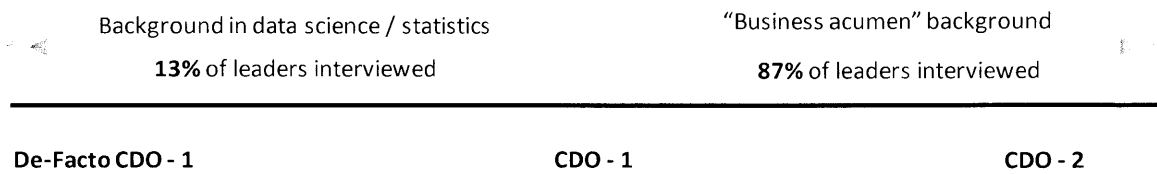
Figure 8. Data analytics leader background (schematic)

De-Facto CDO-1 began his career by starting a highly-successful data analytics consulting company in the early 1990s. This company was acquired by a major business consulting firm in 2016 which turned it into its main data analytics division. Reflecting on his career and path to data analytics leadership, the interviewee mentioned:

> *"When I was in high school I was one of the top mathematicians in the country. I didn't want to be one sided so I ended up going to a liberal arts college, to study literature and philosophy. I didn't do any math until I had to do a project as an undergrad and was discovered by a professor who put me under his wing. He got me into MIT and I pursued a PhD... When I was ready to graduate, I couldn't find a company which was interesting, so I got back to the companies that sponsored me and started a company which provided heavy analytics services... While at MIT, I noticed that the brightest kid could achieve in 10 minutes the same as the rest of the class would take the complete history of time. There was an advantage to speed. I set up to provide the speed and the technical competency, to leverage the data companies had. I led a very successful consulting company in that area over the last 20 years."*

CDO-1 describes himself as "an accomplished analyst and executive leader of data who combines significant IT skills and in-depth business acumen." Over the last decade, he was sequentially the CDO of three large financial institutions in the US. Reflecting on his early career and first role as a CDO, he said:

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"When I graduated from school I didn't know exactly what I wanted to do... I graduated with a degree from financial services. I started working underwriting credit card applications. This was my first exposure at understanding credit, the statistics and all the data surrounding that. I have an affinity for that... I like data. Every decision I have made at an entry level, as an analyst, every question I got, I gravitated towards data... I was working leading a project in a bank in 2008 when the role of CDO started to get on people's radar. They asked me: why don't you try to do that? At the time, there were not a lot of books written... I was trying to figure it out, you couldn't Google it... It was trial and error... By the time I left in 2013 we have built the first data office, we have established a core set of responsibilities and we have put the organization on a good path to leverage data as a strategic advantage."

CDO-2 is a seasoned executive with a 28-year career in one of the top global business services firms. Over the years he has held several leadership roles in areas such as IT risk management and electronic commerce and was recently appointed as a CDO. An accountant by education, CDO-2 reflects on his new role:

"My background is not highly technical, although I manage technical practices... I wouldn't consider myself as a technician but I probably understand it better than the average guy... I was not asked to do this for my technical skills, I have lots of technical folks I can leverage. I'm helping the firm by protecting and getting value from the massive amounts of data we have..."

The strong emphasis on business acumen coming from the interviews also seem to reinforce a paradox in data analytics. While this is in large part a technical field, its implications are deeply organizational. This would seem to explain why most organizations seem to coalesce around the idea of a "business person" leading data analytics. For many in organizations that are in a transformational stage, this profile seems more appropriate than a strong background in data science.

Another aspect of analytics transformation is that it comprises several stages. It usually starts with data governance, trying to influence different levels in the organization. These are all pre-requisites to the implementation of predictive analytics. However, data analytics leaders in companies that are in early steps require a significant and sustained effort to gradually instill data governance principles. Technology appears as secondary in importance.

The adjective that most interviewees consider as essential for the job is: "diplomacy." One CDO said: "The 'D' stands for Diplomacy and not for Data." Several interviewees also mention technical skills are important but secondary to diplomacy. As one interviewee mentioned: "The reason why they picked me is because I know the organization very well... I can talk to people about potential roadblocks... the most important thing is to get trust from senior leaders..."

Having emphasized the criticality of business acumen, most interviewees also mention that a solid technical background - particularly in quantitative fields, engineering and sciences – can also be important in order to: 1) develop an appreciation for data sciences, and 2) have credibility when managing and interfacing with highly-technical teams. In fact, it can be argued that as organizations progress in their transformation, data analytics leaders will be required to have a stronger technical background.

2.4   Data Analytics Leadership Through Three Lenses

The "Three Perspectives on Organizations" framework (Ancona, Kochan, Van Maanen, & Westney, 2004) provides a useful vehicle to decompose the complexity of the role of the data analytics leader. This framework emphasizes the co-existence of strategic, political and cultural perspectives at the heart of all organizations. Awareness of these three perspectives is a fundamental element for effective leadership.

According to Ancona et al., "the strategic lens sees organizations as fundamentally rational." By aligning the organization structure with its strategy, managers can make their organizations successful. The

authors also emphasize that strategic views seek both "efficiency" and "effectiveness." Efficiency looks at achieving strategic goals at the minimum possible cost and effectiveness looks at ensuring goals are achieved at an acceptable standard. Ancona et al., also mention that leaders operating under this perspective often use metaphors of the organization being a machine or a system. Terms such as "re-engineering" the organization are common to strategic views.

It can be argued that organizational structures in large traditional organizations are potentially unfit to favor a data analytics transformation. Similar to the period of electrification of factories, it is possible that realizing the full potential of data analytics requires an overhaul of existing organizational structures. In this context, strategic design becomes particularly relevant.

Ancona et al., highlight the fact that organizations are not exclusively strategic designs, but they are also political systems. The key elements of power and politics involve: interests – i.e., what people want, what's at stake for them -, conflict, competition, coalition-building and negotiation. The authors argue that the political perspective is the least discussed of the three lenses, but it is perhaps the most important one. The relevance of the political lens in the context of data analytics transformation programs is also significant. Not by coincidence a CDO interviewed mentions "The D in my title is actually for Diplomacy..."

The third perspective or lens is culture. According to the authors, the cultural perspective encompasses the norms and behaviors people must follow to become fully functioning and accepted by others in the organization. An organization's culture is rooted in the past and thus, it can be difficult to uncover and articulate. Culture becomes the fabric of an organization to the point that employees take it for granted and natural. The subject of data analytics shows sharp contrasts in organizational culture. To many, technology companies such as Google, Amazon and Facebook operate under strong data-driven cultures very different than those of large traditional organizations. Culture is a recurrent theme in practically all interviews. It is sometimes used in frustration, e.g., "We need to change our culture, otherwise we'll

perish...", or, "Our senior management comes from a time where data was not important. They need to change their culture..."

Figure 9 shows examples of statements from different interviewees which help illustrate the three perspectives on organizations.

Leading Data Analytics
Three Perspectives on Organizations - Ⓢ Strategic Ⓟ Political Ⓒ Cultural

Leading from the Middle Ranks

"Culturally, anyone who owns data know they're the sole owners of it... If you don't have to go to Joe to run a financial analysis for you, this is like handing his keys... especially if these people [data scientists] are smarter than him... he's cooked! So Joe is not going to voluntarily relinquish the keys to that kingdom..."

"Data analytics teams have started to spread like mushrooms... Every pocket thinks they're the ones doing meaningful analytics and start competing... We need central coordination..."

The De-Facto Data Analytics Leader

"I get pinged all the time for CDO jobs in companies stuck in the 80s... The problem is not where to go, but how to bring the organization with you... That's risky, you can alienate the organization against you very quickly... "

"Cultural challenges are substantial... My CFO [large financial institution] referred to linear regression [one of the most common data science techniques] as 'voodoo'! "

Leading Data Analytics at the C-Suite

"I believe the 'D' in CDO stands for diplomacy"

"It's amazing to see how many organizations we've worked with, have spent tens of millions of dollars in analytics without being clear enough... Are we improving effectiveness or efficiency of the current strategy? Are we transforming the strategy? That sounds obvious but it's very hard to do..."

Figure 9. Examples of strategic, political and cultural perspectives from data analytics leaders

2.4.1 Strategic Challenges

The two examples of strategic challenges shown in Figure 9 help illustrate some of the structural challenges data analytics poses to organizations. The key questions are: 1) Why is it that an incremental technology such as data analytics requires an organization "re-engineering"? 2) Haven't large organizations adapted relatively well to previous waves of information technologies, (e.g., internet)? and 3) Why is it different this time around? A partial answer to these questions is that data analytics is perhaps

not an incremental technology and the demand for matching organizational models is potentially greater now than in previous transformational eras. This section explores these hypotheses through a strategic lens.

- **Challenging existing organizational structures**

Most interviewees described their organizations as "highly siloed." Large organizations often are comprised of specialized, independent units. This structures are the result of previous re-engineering efforts focused on efficiency and efficacy, and, in many cases, the result of growth through mergers and acquisitions. While there is an argument for organizational silos, most interviewees refer to these structures as inappropriate for fostering data analytics. The premise of "big data" and analytics, calls for the integration of different sources of data to drive value creation. In organizational terms, this means either moving away from organizational silos or making connections between silos.

A company like General Electric has embarked on a highly-publicized transformation program, which looks at creating new organizational structures more appropriate to the new digital age (Lohr, 2016).[10] Other organizations are starting to look at making connections between silos and are finding out that their incentives system needs to be reformulated.   In the words of a data analytics champion from a large financial institution:

> *"In our bank, most incentives are driven by 'uptime metrics' [i.e., web applications available and accessible to customers]. The data analytics teams are asked to do something very different, and they struggle to get appropriate cooperation from different organizational silos when uptime is the only incentive... We need to device new KPIs [Key Performance Indicators] which fosters the behaviors we need..."*

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[10] GE is cited by many interviewees, particularly those in industrial and oil and gas sectors as a leading firm in digital transformation.

Other areas of data analytics hint at the need for significant shifts into how organizations operate. The implication of these changes also leads to "re-engineering" of organizational structures. A De-Facto CDO of a large business consulting firm provides an example of this point:

"One of the real values of analytics that people don't talk about is that, in general, companies make very big decisions (1 or 2 per year) which require intensive analysis. With the advent of analytics, it allows you to make millions of decisions slightly better, which gives you as much benefit as one big decision but it means setting up an entire system so the companies which allow themselves to make millions of decisions would do a lot better."

Other organizations also anticipate data analytics and other new digital technologies, e.g. Artificial Intelligence (AI) [11] could naturally disrupt their own organizational structures. The CAO of a large business services company mentions:

"Analytics can put pressure on things, even in the context of our business where we have 230,000 people in professional services organizations whose business model has been there for 100 years. Their model was around monetization of consulting hours. We hired smart people, we trained them in the services and we sell their hours to clients... This is going to change by technology, AI, analytics. The stress this puts on the business model is enormous..."

- **New organizational models for Data Analytics**

While most interviewees mention that data science should be ultimately embedded in all business units, this is seen as a far-away goal. No individual interviewed could associate a time horizon to this ideal model. Discussions on organizational models concentrated on more immediate options, such as the ones

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[11] AI stands for Artificial Intelligence. Colloquially, the term "artificial intelligence" is applied when a machine mimics "cognitive" functions that humans associate with other human minds, such as "learning" and "problem solving" ("Artificial Intelligence," n.d.).

described in Section 1.5, i.e., centralized, decentralized and hybrid models. Interviewees had contrasting views on this subject. No model emerged as a clear favorite. Figure 10 shows a summary of the interviewees' opinions on the subject.

16	*Interviewees mention **all models** are equally valid an depend on the organization*
8	*Highly favor **hybrid** models*
5	*Highly favor **centralized** models*
3	*Argue **against decentralized** models with no clear preference for another one*
1	*Argues **against centralized** models with no clear preference for another one*

Figure 10. Interviewees' views on organizational models for data analytics

Not only there are different preferences for organizational models, but companies are also having fluid internal conversations on which model is more appropriate. On different occasions interviewees asked which models were more prevalent in other organizations and industries.

As shown on Figure 10, eight interviewees listed the hybrid model as their top choice. This model is also referred to as "hub and spoke." The Chief Digital Officer of a large industrial company explains:

> *"At the hub you have hard core data scientists; 'the big guns', creating intellectual property, looking at advanced analytics, setting standards. In the spokes, you have people who are talented but who are not hardcore in data science."*

A very similar view comes from the De-Facto CDO of a large oil and gas company who states:

> *"The optimum is a hybrid model... you need to have a group of hardcore data scientists, who understand process, capabilities, emerging technologies and applications. You want to take a percentage of those, embed them in the business, to provide these skills to the business but also to provide business-context back to the data scientists. And you create a rotation system. Their*

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careers are managed as data scientists. There's a '2% rule' which is that on occasion data scientists stay in the business. This structure is key not only in terms of making sure the discipline works but also in terms of fostering an analytics culture."

A contrasting view comes from an executive in another large oil and gas company, who favors a more centralized approach. The head of analytics of this company states:

"We have a centralized model, strong in data science and IT. We call it 'IT-ish data science.' Whenever there is a business problem, they get partnered with business people. We don't have a model to embed people in the business. I'm not sure how this is going to change in the future but I don't think it will triple in size. This is serving us well; we are by far the leading [oil and gas] operator in data science at the moment... We had over one-billion-dollar value creation from data science. As that increases, people will listen more..."

Limitations in resources and scarcity of data analytics talent are also important drivers which favor centralized models. In fact, these two factors were highlighted by representatives of all four government agencies interviewed for this thesis.

Interviewees who argue against decentralized model point out to the idea that "like minds want to work together." If data analytics resources are dispersed they cannot share their ideas. The head of analytics of a medium-size oil and gas company reflects on his experience with a decentralized approach:

"We have tried that [decentralized approach] with three data scientists. They were very isolated, didn't have any collaboration, any growth. That was not effective. Now all data scientists report to me. As we build that collaboration or skill set we might be rotating people into different business areas."

One interviewee (head of analytics in a large business consulting firm) who argues against a highly centralized model, recalls two first-hand experiences with large technology corporations:

"The problem I saw was that these two companies had a hard time treating them [data scientists] as cost centers. They wanted those people to start becoming profitable on their own, which caused the business people to become more successful than the mathematical people. In one of these companies, the centralized team had 20 people and if they were very good working in businesses, they got hired away by them, so the central team ended up with the ones who were not the best. The central team was the survival of the least fit. The best talent was in the individual companies and not on the central team. I've seen that more than once... You must be careful if you have a central team to keep it solid..."

Beyond basic organizational models, some companies interviewed also refer to the creation of "data citizens." This concept seems more common in organizations dominated by a workforce with a scientific or engineering background. In a hybrid model, data citizens would be people who can familiarize themselves with data science and serve as a gap between the hub and the business people in the spokes.

- **Strategic challenges of data centralization**

One of the greatest technical difficulties of data analytics initiatives is often around data governance and data centralization as described in Section 1.4.1. Failure to properly address these aspects greatly hinders the chances for a company to harvest value from predictive analytics. Interviews highlight different strategic challenges organizations face when attempting to build the "data governance and centralization pillars." While most – if not all – large traditional organizations do not have a shortage of data, the processes to capture it, control its quality and centralize it often are distant to what is required in a data analytics transformation. In some cases, the right data is nowhere to be found. The Chief Transformation Officer from a large National Oil Company in Latin America explains:

"We spend a lot of time just looking for data. The night before a big presentation we look for data until 8 pm, thus we spend little time in analysis... When the new CEO arrived, he used to say: I don't have any information! We came up with a piece of paper for executive briefings with oil price, production from all fields, data from refining, etc. All that was done manually. We're not in big data yet."

In some other cases, vast amount of data also hinders the potential to drive value from it. The CDO of a large business services company reflects:

"For us and for many, we spend a disproportionate of the time managing, extracting and loading data... We call it 'data janitoring'... I work closely with data scientists, but we have a very significant challenge just managing the data... It is often like finding a needle in a haystack..."

Pursuing a data governance and centralization agenda is a daunting task for many organizations. Data is generated by processes and applications controlled by individual parts of the organization or "silos." Aggregating this data in a central repository involves a significant effort. A CDO from an industrial consulting organization mentions that in complex industrial companies - e.g., aerospace - the number of software applications generating data could be between 10,000 and 100,000. The task of even understanding the interaction of all these applications, let alone centralizing the data they generate is enormous. At the heart of this challenging agenda, there seems to be a shift in strategy highlighted by different interviewees. This is, "software applications do not last, even business processes do not last, but data tends to last..." However, even as data takes a more central role in the strategy of organizations, the challenges of governance and centralization remain current.

- **Insights implementation**

Companies which have been able to push their data governance and centralization sufficiently to pursue predictive analytics have also faced challenges in the implementation of the insights gained. To go from a

central data repository – technically referred to as data lake - to actionable insights, is a significant challenge. The implementation of predictive analytics and transforming insights into actionable tasks is seen as the ultimate goal but difficult to achieve. The CAO of a large business services company, also advising several companies on data analytics transformation, reflects:

> *"Even after you have very interesting powerful insights this is still half the equation. In many cases, you have a person who must do something different as a result of the analytics. The process must change, this could be an operations person, a marketing person... Many companies hit a wall here. We talk about business process design, change management, the individual skillsets of the end users and the incentives they're under... Companies which have been more successful have a better appreciation of these things..."*

- **Strategic evolution of the data analytics leader**

Several interviewees also reflect on the fact that their leadership roles are quite dynamic and need to evolve based on the progress of the data analytics transformation agenda. In early stages, there is heavy emphasis on data governance, later as these governance initiatives gain momentum, more emphasis is placed on business-centric activities looking at deriving value from data. The CDO of a large financial institution reflects on this evolution in his previous role as CDO of a bank:

> *"Because of the incredible focus on risk management [in the bank], we were spending 80% of our time in governance in areas related to risk management aspects. The other 20% was focused more on establishing frameworks for business-enabling activities. By the time I left, we flipped that and we were 50/50 with the goal in 5 years to be 20% in areas of compliance and 80% using data as a strategic asset to generate revenue. You don't have unlimited funding or unlimited resources. You sometimes must prioritize based on the current state of the organization..."*

Several interviewees agree with literature arguing for the role of the CDO evolving with time into the CAO. This is, reflecting a change in priorities from governance agendas for business goals. This opinion is not, however, unanimous as a few interviewees also claim the CDO should always be business-centric. Data governance without a solid business focus is flawed in their view.

Strategic challenges of data analytics transformation can be summarized as follows:

- Data analytics poses pressure on existing organizational structures. There seems to be a lack of consensus over the best organizational model for embedding data analytics into an organization.

- Data centralization can be a daunting task from a technical standpoint. Traditional organizations which have historically generated large amount of data, struggle to centralize it. Data governance and data quality are major issues.

- Taking insights of data analytics into action is a major challenge. Often, the output of data analytics implies the need for changing the way an organization operates.

- In an ideal scenario, an organization would first go through a phase of adoption of data governance principles and policies and later would pursue implementation of data analytics. Leaders of these transformation initiatives are also expected to evolve and adapt to the current requirements of the organization.

2.4.2 Political Challenges

Political aspects of data analytics leadership roles can be subtle, private, and, therefore potentially difficult to uncover within a short-duration interview. However, this does not mean they are not significant. In fact, it can be argued that all the challenges of a transformation carry a strong political component. This section touches on a few political aspects which became apparent in the interviews.

- **The role of a diplomat**

The importance of the political lens in the context of leading data analytics can be illustrated through an interview extract of the CDO of a federal agency:

> Interviewer: "A CDO mentioned to me the "D" in his title stands for diplomacy, do you agree?" -
> Interviewee: "Here there is no absolute incentive for people to work with the CDO to create new work. It increases their risk, the benefits will be small for people individually, for the organization the potential gains are big. It is not motivating enough for them to say we want a CDO. You have to lay down the roadmap, show the value quickly... Even though they are convinced, they are skeptical... A Diplomat is a way to describe it..."

The same interviewee also mentions that he was chosen for the CDO position because he knows all parts of the organization well, he can talk to people about potential roadblocks, and, most importantly, he is trusted by senior leaders. In fact, handing over control of data to a central entity is a contentious subject and "trust" in the data analytics leader becomes paramount.

Pursuing a data analytics transformation also makes the leader susceptible to alienating its own organization. A statement originally included in Figure 9 and shown again in Figure 11 illustrates this point.

The De-Facto Data Analytics Leader

"I get pinged all the time for CDO jobs in companies stuck in the 80s... The problem is not where to go, but how to bring the organization with you... That's risky, you can alienate the organization against you very quickly... "

Figure 11. Statement from interviewee on political challenges of data analytics

Interestingly, this interviewee points out at the convergence of strategic, cultural and political views in one single statement. While the strategic design (i.e., where to take the organization) seems clear, the cultural component (i.e., organizations stuck in the 80s) creates a major risk, in the view of the interviewee. The political component (i.e., how to bring the organization with you) becomes the most important challenge of the job. Political savvy has presumably a prominent role.

Additionally, interviews highlight the fact that the data analytics leader must constantly move across organization silos, building relationships and trust, articulating the value of data analytics in business terms. The most seasoned data analytics leaders mentioned that they have "learned their lessons along the way." This is, over time they have crafted their message and made it "business centric" instead of "technical centric."

- **Balancing act between "pockets in the organization" and "top down mandates"**

Essentially all those interviewed refer to data analytics initiatives and expertise as appearing in different parts of the organization. In some instances, so-called "data analytics pockets" appear "naturally" as business units are compelled to embark on analytics initiatives. For instance, one of the data analytics champion interviewed, described a data analytics initiative she led in a supply chain unit of a major industrial corporation:

> *"We are the first division to develop a fully mature data analytics capability... We spent four years working on projects to drive business performance improvements. We got to the root cause of what generated bad data. We're changing behaviors of people who executed these transactions [in allusion to how bad data was generated]. Now data is better and we're getting a truer picture of our division."*

In other cases, seeding different pockets in the organization might correspond to a directive from the top of the organization, such as running experiments on technology, changing the organizational model, and evaluating which is more effective.

Most interviewees recognize that leadership at the top of the organization and in pockets below is essential. However, this also creates tension between middle and top management. In fact, three interviewees championing data analytics from middle management expressed highly critical views of the top data analytics leadership in their organization. Most of the criticism corresponded to senior management being too far removed from actual business needs.

- **Unspoken interests**

Under the political lens, interests refer to "what people want" and "what is at stake for them" (Ancona et al., 2004). Interests remain largely unspoken in interviews, potentially due to the format of short-duration conversations which often does not allow the articulation of complex relationships inside organizations. However, there are different indications of the relevance of interests at the center of data analytics transformation programs. Some revealing views come from interviewees who candidly spoke about their experience in a prior organization. A data analytics champion from a large financial institution talked about his experience in a previous employer:

> *"Data analytics teams have started to spread like mushrooms... Every pocket thinks they're the ones doing meaningful analytics and start competing... This was a very dysfunctional company to take decisions."*

The interest of one business unit championing analytics might in fact conflict with those from another unit in the organization. For many organizations in early stages of adoption, there is a potential sense that the first unit which demonstrates value will be awarded a "big prize." These data analytics champions would

understandably seek promotions and gaining visibility on their efforts. One might argue that in a healthy organization a limited degree of conflict is also necessary.

Political challenges of data analytics transformation can be summarized as follows:

- Diplomacy is a key attribute of the leader of data analytics. The ability to gain trust at different levels of the organization is paramount to pursuing highly challenging agendas, such as data governance.

- Pursuing a data analytics transformation agenda also has added risks, such as "alienating an organization" against the transformation program, or even, against the leader. Political savvy is essential to prevent these outcomes.

- Data analytics demands a balancing act between pursuing initiatives in "pockets" of the organization and enforcing "top down mandates."

- Interests of individuals and/or parts of the organization can undermine or data analytics transformation efforts.

2.4.3 Cultural Challenges

Cultural challenges around data analytics can be diverse. This section highlights a subset of three areas which became apparent in many of the interviews.

- **Democratizing data is an unpopular deed**

As described in Section 1.4.3, data centralization initiatives often imply "democratization of data." This is, for centralization efforts to succeed, members of the organization must be willing to publish their data for others to access and use. Centralizing and democratizing data throughout a large organization makes logical sense, but why is it so challenging? While the technical scope of these initiatives is certainly complex, interviews reveal that subtle cultural factors can be important inhibitors of data governance

initiatives. The statement from one interviewee (originally included in Figure 9 and shown again in Figure 12) helps illustrate this point.
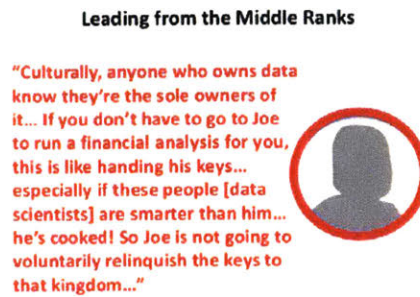

Leading from the Middle Ranks

"Culturally, anyone who owns data know they're the sole owners of it... If you don't have to go to Joe to run a financial analysis for you, this is like handing his keys... especially if these people [data scientists] are smarter than him... he's cooked! So Joe is not going to voluntarily relinquish the keys to that kingdom..."

Figure 12. Statement from interviewee on cultural challenges of data democratization

These types of statements are prevalent across my interviews. Leaders behind data analytics transformation programs across the spectrum of industries approached for this thesis, talk about cultural challenges at length. Stories of business owners who guard their data jealously sometimes veer into genuine concerns over appropriate use of information once centralized and, in some occasions, convey a sense of threat to their job security. The vision of a company which uses data transparently and efficiently is enticing at an organizational level, but at an individual – business owner – level, it does not seem to resonate to the extend required to build momentum.

Cultural aspects can be even more subtle. Often, incumbent leaders in organizations have risen to their present positions before the current boom in big data and analytics. In many cases, prior successes in their careers have presumably pre-conditioned them to replicate a proven managerial style. New trends such as analytics are often received with a degree of skepticism. Of course, such skepticism can be healthy under the right circumstances. While broad generalizations are inappropriate, many interviewees recognize that cultural considerations need to be addressed either through education initiatives and/or through generational changes in leadership.

Initiatives around, for example, data democratization are very unpopular. When an IT department or a CDO approaches business units to progress this agenda, they find out it is incredibly hard to sell. At their core, data democratization initiatives imply a change in people's behaviors with respect to data. In most cases, it is difficult to set up incentives to change these behaviors. As pointed out by different interviewees, data democratization does not bring an immediate impact on the bottom line of the company. In the words of a newly appointed CDO in a government agency:

"I'm new on my role as a CDO... If I start by pursuing Data Governance, I might as well spend two years arguing with people"

The VP of analytics of a large oil and gas multinational, reflecting on the difficulties of a multi-year data governance initiative, summarizes his views as follows:

"If a traditional organization is planning to start their data analytics journey with an ambitious data governance program, I wish them well..."

Further analysis of interview statements displays a common line of resistance shared by functional leaders reluctant to collaborate with data democratization and centralization agendas. This is shown in Figure 13.

Data democratization makes sense for the organization,

however...

- I've been successful so far, why change?, why now?
- What's in it for me? Publishing my data is not aligned with my incentives...
- My data might be used improperly / out of context
- Handing over my data might make me vulnerable...
  - I might lose power...
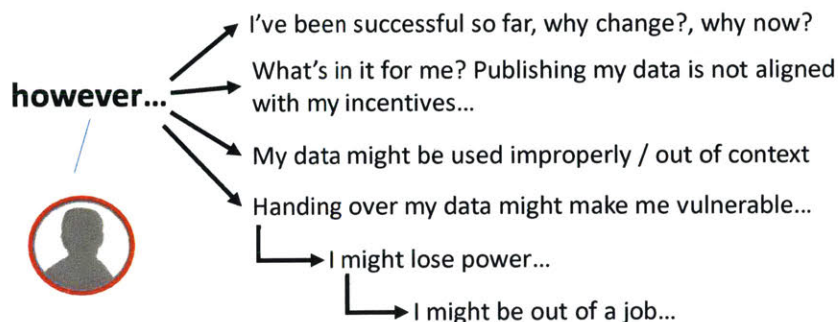   - I might be out of a job...

Figure 13. Potential line of thought in business owners unwilling to support data democratization initiatives

A further look at interviews reveals another set of cultural challenges. In organizations where IT has been historically seen merely as a support function, there seems to be a natural tension between these departments and the business units. Data democratization initiatives led by IT face significant resistance from business units which adopt an attitude of "we know better than IT." The VP of IT of a large oil and gas multinational argues:

> *"If you are seeking funding to put a big database to mine it [data democratization initiative] you get a lot of resistance. Business owners argue: We don't need to spend money on that, we know what to sell, we know our customer, we know how to grow, things like that..."*

The historical lack of appreciation for the IT function is potentially a big cultural challenge in many organizations. While the data gathered in interviews is not sufficient to make a general statement in this regard, different interviewees mention anecdotes reinforcing this point. The VP of analytics of a large oil and gas multinational recalls one illustrative episode:

> *"In a meeting between the CIO and the CEO of my company, a large part of the conversation centered around the CEO's laptop problems..."*

Data democratization agendas clearly require strong collaboration between IT, business units and technology departments. Some interviewees see that cultures in which there is a tighter integration between these functions are more effective in making progress in data governance matters.

- **Incumbents and Newcomers: The Tension Between Business Acumen and Data Science**

Data scientists face a paradox when communicating to senior business managers, this is: *"if you give them analysis in a 'black box' they don't trust it, if you give them a ton of data, they don't know what it means..."*

This paradox helps illustrate a much more fundamental cultural tension at the heart of data analytics transformation programs. Data analytics is a highly technical area but leaders in this field often do not

come from a background in data science (see Section 1.3.2). At the leadership level, business acumen is often preferred than a strong technical knowledge in analytics.

But what about at lower levels in the organization? Interviews explored this very aspect. Specifically, interviewees were asked if it was more effective for an organization trying to build analytics capabilities to train business people in data science or to train data scientists about the business.

Surprisingly to me, a large majority mentioned the first option (training business oriented people in data science) was far more effective. In the words of one of the most experienced CDOs interviewed:

> *"I believe that the business acumen is a critical component. I've done it before. I've taken a brilliant PhD, mathematician or statistician, highly skilled, put them in a business unit to develop insights into a business unit, and yes, they were successful... but I've also taken someone who's familiar with the business processes and practices, upskilled them with better tools, and knowledge in the data science space and they have been exponentially more effective. I believe that from my experience. I've done it both ways."*

A head of Analytics from a financial institution, with an even more radical opinion, comments:

> *"It is better to take someone who understands the business definitely and teach them some data science... PhDs don't want to do business, they don't have the personal and communication skills, I can't get these people trained enough to talk to CEOs... People with the business context, I can train them to run a team and get results."*

Why the disdain for highly specialized data scientists in some organizations? There seems to be three reasons highlighted in interviews. These are: 1) data scientists are often thought to lack a minimum business acumen and required communication skills to interface with business leaders, 2) data scientists

are thought to lack the proper motivation for business-facing activities, and 3) data scientists are thought to rely too heavily on an academic approach which is not well received in businesses.

Communication skills are certainly at the center of this tension. Academic programs in data science are starting to emphasize communication in their curricula. On the positive side, it can be expected that data scientists which develop communication skills would be quite successful and impactful. A CDO interviewed, who started in highly technical roles and grew into leadership, reflects on his early struggles around communication and possible ways forward:

> *"I struggled earlier in my career with that. I'm a quantitative thinker, I'm comfortable with data, when I talked to business partners, I got frustrated with my inability to get my point across. I was conveying the message wrong. I was using technical words, speaking to them as if they were analysts. Within the data science space, we spend a lot of time in communication processes, how to give a compelling case and business centric manner. That is a difficult skill for some people to excel at. I have found a lot of people who grasp that and become effective, but some of them [data scientists] are honestly not business facing. They're incredibly talented. They can get insights which can transform a business but someone else needs to carry them forward."*

The world of data analytics shows signs of a breach between academia and industry as mentioned in point 3) above. The Chief Digital Officer of a large industrial company mentions:

> *"You have to be able to have people who are not academic, people who know how to operationalize models into business applications."*

The head of Analytics of a large financial institution agrees:

> *"Some companies wanting to start data science often want to get people from Harvard, MIT, Caltech. So they get academic types. They bring them in... However, in academia it is fatal to go*

forward before you try everything that fails, these people tend to fail. If they're lucky, you have someone in the business who understand what they are after, runs away with it and gets something... They don't usually get to that conclusion until they fail..."

These comments; highly stereotypical of the data scientist profession need validation. I interviewed leaders with, mostly a business acumen. But, it is somewhat surprising to hear these comments from senior leaders who have dealt with many teams and have years of experience. A follow-up study could explore the views of highly technical data scientists with respect to business leaders.

In trying to compensate for this breach between data scientists and business units, some companies create multi-disciplinary teams. While this is in principle a strategic approach, it also has a cultural component to it. Such units are introduced to take dissimilar functions and create a modified culture around data. Several interviewees highlight the need for: 1) data science, 2) business acumen, and 3) communication and storytelling to be at the core of multi-disciplinary teams. As data science matures, these functions might presumably become more tightly integrated.

Other companies also refer to education initiatives that are intended to bridge the cultural divide. These include: 1) formal courses and social activities promoted by a Center of Excellence in Data Analytics, and 2) nomination of transitional roles, such as data citizens and data science translators to facilitate interactions between highly technical data scientists and non-data-savvy business leaders.

- **Incumbents and Newcomers: The Tension Between Engineering and Data Science**

Interviews revealed a latent tension at the heart of engineering-dominated organizations. 20 out of the 33 people interviewed belong to this type of organizations, including oil and gas, utilities, industrials and one federal agency. Data analytics implementations in engineering-dominated organizations have some key particularities. First, in these organizations, data has historically played a significant role. The orientation of the workforce (including senior leadership) typically emphasizes data-driven decisions.

These organizations also generate massive amounts of data from hardware and from software applications. Data, historically has been a byproduct of the business and therefore data governance mechanisms have not been pursued to the extend they should. For these organizations, data analytics is an enticing proposition as it promises to reveal opportunities for increasing efficiency, minimizing operational risks and increasing profits.

Many of these organizations have started data analytics initiatives, recruiting data scientists – although still in relatively modest numbers – with high expectations. The challenges these organizations face trying to merge engineering disciplines with data science can be significant. Specifically, engineering and data science are based on different principles. Engineering emphasizes the search for understanding of underlying mechanisms behind natural phenomena through the scientific method. It is often common to refer to "first principle models" as the predictive models engineers use to forecast future conditions and to evaluate decision-making. Data science, on the contrary, is based on the use of statistics and numerical techniques to find underlying correlations in a dataset. Data science is often uninterested in the actual mechanisms which explain a certain pattern in data. This is, "correlation" is favored over "causation." The contrast of these different approaches, reinforced by education and professional experience, is at the heart of the tension between engineering and data science.

In this context, the engineer is the incumbent. Whether we look at oil and gas, industrials or utilities, the engineer knows the specific ways of producing value. Large companies have long established standards and procedures which regulate the application of engineering to business processes. The data scientist as a newcomer, enters this environment with an obvious disadvantage.

Over the past few years, industry publications and organizations have promoted the role of data sciences in engineering-based industries. Arguably, the average engineer in an industrial company has an awareness of data analytics, but remains unfamiliar with its specific applications, techniques and the

overall potential and limitation of the field. Data science has entered the curriculum of engineering programs only recently, thus, it is fair to assume that most incumbent engineers have no formal education in data science. The novel nature of data science arguably leaves incumbent engineers in two camps: 1) those who consider that algorithms and data science in general might hinder engineering judgement, and 2) those who see opportunities to either "augment" the capabilities of engineering disciplines with data science or to create career growth opportunities.

At present, the concept of "augmented engineering" seems to be gaining traction in several engineering-based organizations. Five interviewees referred to the idea of retaining current engineering methods but "augmenting" their predictive power with the introduction of analytics. The same interviewees described current initiatives in their organizations looking at the creation of new "hybrid models" combining first principle and data science approaches. These hybrid models would be used in principle by multi-disciplinary teams composed of engineers and data scientists or by engineers proficient in data science. But, this concept is far from being a standard practice as data science and engineering remain segregated in most organizations.

Several engineering schools are also ramping up the data analytics and data science content in their curriculums. In principle, the newer generations of engineers will be more data savvy. However, worries persist. For example, the head of Analytics in a large industrial firm (who also holds a BSc and 2 MSc degrees in engineering) stated:

"Engineering must become an analytics-based field, if it is going to survive. There are so many things engineers can benefit from it. My fear is that engineering degrees might become obsolete."

Out of all engineering-dominated firms interviewed, GE is perceived as leading the way in embedding data science in the heart of their businesses. The head of Human Resources at GE Oil & Gas mentions some cultural challenges encountered in this transformation process. To wit, as GE tries to

attract data scientists, the company looks to adopt some of the work practices of big technology firms. Also, traditional engineering-dominated companies, typically have stringent education requirements for job candidates in technical positions. The head of Human Resources at GE Oil & Gas mentions that these requirements might need to be reconsidered and downplayed with the introduction of data scientists. In fact, the interviewee recounts an anecdote in which a job candidate scored at an impressive level on a technical test leading to a job opportunity in computer programming and data science. But, this candidate had no formal technical education. He, nonetheless, joined the company and performed well above expectations.

While we are still at early stages in the introduction of data analytics in large engineering-dominated organizations, there are clear indications of the transformative nature of this trend. The cultural challenges of data analytics transformation explored in this section can be summarized as follows:

- Data centralization and democratization are very unpopular agendas. While these initiatives are clear and agreeable at an organizational level, they are often seen as a threatening by many individuals. In handing over data, individuals often see they are "relinquishing the keys to their kingdom."

- Introduction of data science in many organizations dominated by "business acumen" cultures has created tension. Interactions between these two groups has also raised challenges leading to the introduction of intermediate roles and education programs.

- Organizations dominated by engineering functions also experience tension derived from the introduction of data sciences. While these organizations already rely heavily on data, they operate under engineering principles such as the scientific method. Data science is different in that regard. The emphasis in "correlation" instead of "causation" is foreign to many incumbent engineers.

Chapter 3
A Path to Data Analytics Transformations

Chapter Two of this thesis explored the complexities and challenges data analytics transformation programs face in today's organizations. At a first glance, data analytics appears to be mostly about technical complexities. However, interviews reveal large underlying organizational and cultural difficulties. Not surprisingly, many interviewees emphatically mentioned that 'technology is the easy part; the organizational and cultural aspects are the really hard ones.'

In this regard, the field of **"Change Management"** seems highly relevant. Change Management relates to the approaches and methods for achieving significant restructuring in an organization. In 1996 John P. Kotter wrote the best seller "Leading Change" (Kotter, 1996) in which he proposed a practical eight-step process for change management. This framework seems appropriate for guiding data analytics transformations.

Chapter Two of this thesis revealed the coexistence of strategic, political and cultural challenges in the agendas of data analytics leaders. The **"Three Perspectives on Organizations"** framework offers a practical way of decomposing the many dimensions of leadership roles within the context of data analytics.

My work in this thesis has led me to believe that the most feasible path to data analytics transformation in large traditional organizations comes from the combination of **"Change Management"** and **"Three Perspectives on Organizations"** principles. This results in a "loose framework" intended to: 1) provide a general navigation guide to the transformation process, 2) serve as a tool to raise awareness over potential roadblocks and inhibitors to transformation, and 3) reinforce the importance of strategic, political and cultural views at every step in the process.

3.1 Transformation Framework

Figure 14 shows - from bottom to top - the eight sequential steps at the basis of Kotter's leading change model. A full description of each step – along with recommended actions and common pitfalls – can be found in (Kotter, 1996). Additionally, every step in the transformation ladder uncovers strategic, political and cultural challenges as articulated in the interviews presented in Chapter Two. Transformation leaders are therefore required to effectively and continuously engage the organization in these three dimensions.
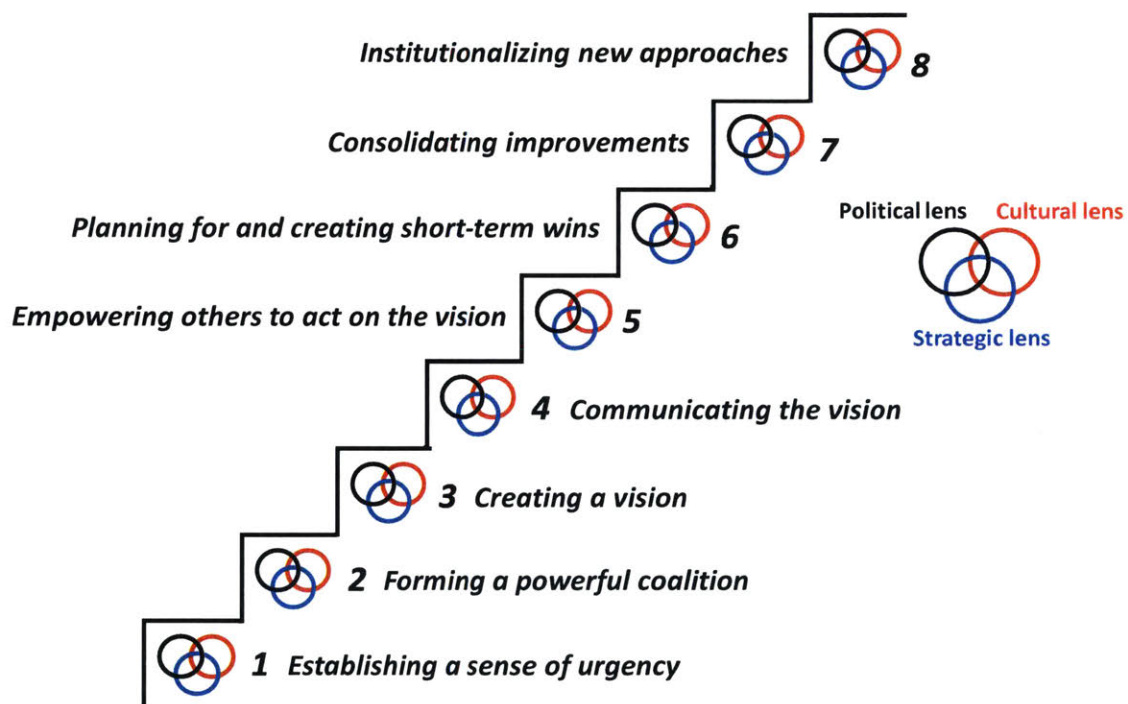

Institutionalizing new approaches — 8

Consolidating improvements — 7

Planning for and creating short-term wins — 6

Empowering others to act on the vision — 5

4 Communicating the vision

3 Creating a vision

2 Forming a powerful coalition

1 Establishing a sense of urgency

Political lens   Cultural lens

Strategic lens

Figure 14. Proposed framework for guiding data analytics transformation efforts

Advancing from Step 1 to 8 takes, in most cases, several years and skipping steps or taking shortcuts are both counterproductive to the change effort. Kotter argues that many change initiatives fail as managers do not recognize that transformation is a process and not an event. Some additional considerations from the Change Management framework particularly relevant to data analytics transformations include:

- Large traditional organizations are presumably in the early stages of data analytics transformation journeys. For starters, the "Sense of Urgency" (Step 1) seems to have permeated most traditional companies started prior to the relatively recent appearance of the technology giants such as Amazon, Google and Facebook. All interviewees recognized that their organizations are aware of the changes in market and competitive realities and the increasing emphasis on the digital economy and technologies such as data analytics. Several interviewees openly recognized their organizations' inability to transform might well leave them irrelevant in today's economy, and even in danger of disappearing altogether.

- Two observations can be made with respect to "Forming a Powerful Coalition" (Step 2) in the context of data analytics transformations. The first one is related to the obvious, but often forgotten principle that 'transformation is not the result of a single individual's effort, but rather, the outcome of building an effective coalition.' No single individual can be realistically expected to effect change in an organization, let alone to simultaneously entertain strategic, cultural and political perspectives. One interviewee illustrates this point through an experience in which a technically-competent data analytics leader failed in his transformation effort, presumably because of his lack of political savvy and cultural awareness. In this story, it is apparent that no coalition was established. The second observation on Step 2 is that many traditional organizations have taken or are in the process of taking concrete steps into forming "transformation coalitions." Actions here include: 1) creation of company-wide transformation units, and 2) appointment of new data analytics leadership roles at high levels in the organization. The attention and interest data analytics has gained over the last few years, all the way to the C-suite, can in fact result in the formation of forceful coalitions inside organizations.

- "Creating a Vision" (step 3) is arguably the current bottleneck in data analytics transformation programs. No interviewee could articulate a clear vision for their organizations around data analytics. In most cases, interviewees acknowledged such vision did not exist. According to Kotter: "If you

cannot communicate the vision to someone in five minutes or less and get a reaction that signifies both understanding and interest, you are not done with this phase of the transformation process" (Kotter, 1996, p. 9).

- The few interviewees who referred to an existing vision, often emphasized the concepts of data governance and data centralization. A sample vision statement in that area would be: "Once we are able to centralize and organize all our data, our organization can become more efficient and competitive." While this statement is certainly clear and agreeable at an organizational level, it lacks inspiration and motivation at the individual level. It is also arguable that data centralization constitutes a goal in itself. Employees understandably would be left to wonder: "Where do I fit in the picture?", and "What does it mean for me and my job?" This vision is therefore incomplete and often threatening to some people.

- An ultimate vision for data analytics transformation – this is, after data governance and centralization are achieved – seems to also lack clarity. This lack of clarity is pronounced around two issues: 1) for most organizations, it is not completely clear the benefits data analytics can bring to them. This presumably explains why different companies are in an experimentation phase aiming to better understand its benefits; and 2) there is a latent perception that data analytics and the more sophisticated technologies, such as artificial intelligence, might mean a loss of jobs. While many companies acknowledge this possibility, no interviewee mentioned any structured plans in their organizations to protect the workforce. Figure 15 summarizes limitations of current vision statements.

- It is worth pointing out that all interviewees referred to ongoing proof-of-concept studies, pilot projects or other data analytics initiatives in their organizations. In principle, these activities can be understood as part of "Planning for and Creating Short Term Wins" (Step 6 in Kotter's model). However, the lack of a clear vision might well mean this is part of the experimentation phase which

may lead organizations to discover the potential of data analytics. Companies that reach this point would arguably be in a better position to craft a clear and focused vision which would enable them to progress through the change management process more efficiently.
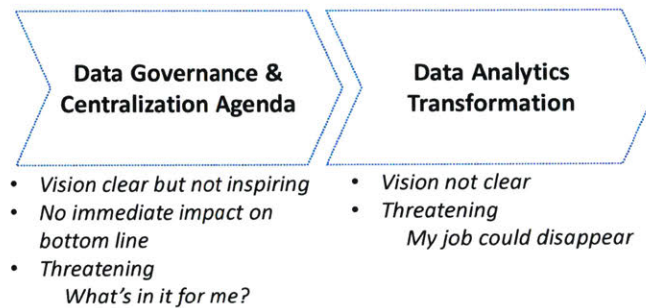

Figure 15. Analysis of data analytics vision statements

3.2   Practical Implementation of Three Perspectives in Organizations

The field of "Design Thinking", popularized by the company IDEO, provides an example of a practical implementation of the "Three Perspectives on Organizations" seemingly relevant to data analytics transformations.[12] At the core of the Design Thinking approach there is a large emphasis on people. After all, it is individuals and teams which ultimately fuel change in an organization. Data analytics transformation initiatives are not different. Interviews presented in this thesis uncovered the complexity of change agent roles that go far beyond technical considerations.

In a book titled *The Ten Faces of Innovation,* Littman (2005) described the need for a "coalition" as a guiding force in transformation programs. This coalition is composed by individuals with complementary

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[12] Design Thinking is a method for practical, creative resolution of problems and creation of solutions. IDEO is considered a leading consulting firm in Design Thinking applied to design of products, services, environments and digital experiences. More recently, Design Thinking has been used in the context of management consulting and organizational design.

roles, covering strategic, political and cultural perspectives. These roles are grouped under three categories, namely:

Learning roles concentrate on developing and testing prototypes of ideas, exploring fundamental aspects of the organization culture and bringing external ideas from other cultures and industries – a process often referred to as "cross-pollination." In data analytics transformation programs, these critical roles are responsible for uncovering and testing potential applications for data analytics. This process involves gaining a fundamental understanding of latent needs which can only be gained through active observation and interaction with the potential end-users of analytics applications. As an example of this, one interviewee from a large bank referred to a data analytics initiative in her organization which emphasized a deep understanding of its employees' interactions with data – through ethnographic studies - as a precursor to the design of analytics solutions (Birtel et al., 2016).

Experimentation is also a key aspect of learning roles. As data analytics is unfamiliar to many organizations, implementations must go over "bumps along the road." Experiences gained in trials of prototypes often uncover subtle requirements not initially anticipated. Learning roles are fundamental in the evaluation of the outcome of these prototypes. In some cases, outcomes might indicate the need to modify technical solutions to better adapt to the organization needs. In other cases, they might imply the need for changes in the organization structure and culture to better harvest the value of technology.

Organizing roles are played by individuals who are savvy about the counterintuitive process of how an organization moves ideas forward. According to Littman: "In IDEO we used to believe that the ideas should speak for themselves. Now we understand that organizing roles have known all along that even the best ideas must continuously compete for time, attention and resources" (Littman, 2005, p. 9). The importance of managing political aspects of data analytics transformation programs cannot be understated. The scope of organizing roles includes: 1) recognizing potential organizational roadblocks for analytics initiatives –

often leading unpopular agendas, such as, data governance – and designing strategies to get around them, and 2) arranging multi-disciplinary teams and directing their efforts to business-centric goals which can help win over skeptical leaders.

Building roles focus on creating an architecture of data analytics solutions tightly integrated to business objectives. The scope of these roles can be highly technical, typically encompassing analytics, IT and business domain knowledge. For building roles to be effective, it is critical they apply insights uncovered from learning roles and channel the empowerment from organizing roles.

In IDEO's framework, it is not necessary to design three-people leadership teams covering the different perspectives. In many situations, this may be costly, inefficient and simply impractical. Moreover, Littman states that effective leaders need to adopt different roles at times, depending on the particularities of the situation.

The left-hand side of Figure 15 shows the correspondence between Design Thinking roles and the Three-Perspectives on Organizations framework. The right-hand side of Figure 15 shows the most common orientation of data analytics leadership roles under the three lenses.[13] Starting from the cultural lens, Data Analytics Champions – often in middle management positions – commonly lead pilot projects aimed at simultaneously solving a business problem and proving the value of analytics. The outcome of pilot projects is usually uncertain. Unsuccessful projects cannot be discounted simply as failures. Most organizations recognize that unsuccessful attempts are valuable as they provide important learnings for future efforts. In that sense, Data Analytics Champions are often aligned with learning roles and to the cultural lens. In contrast, CDOs are often strongly aligned with political perspectives in the organization. The scope of the CDO commonly focuses on pursuing a data governance agenda, which can be very

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[13] Note that this orientation is only indicative and is proposed based on the output of the interviews I conducted and the literature sources presented in Chapter One. The true orientation of data analytics leaders greatly depends on the organization and the background of the individual filling the role.

contentious and often associated with trust and management of interests as discussed in this thesis. CDOs are largely organizing personas. CAOs appear as more strategic in nature than CDOs. In fact, several interviewees mentioned that once a CDO succeeds in data governance initiatives, this role changes focus and transitions over to strategic objectives. In some companies, there is a formal change in title from CDO to CAO at that point in time. But, it is fair to assume that this change in focus occurs gradually, and therefore this role is in principle located at the intersection of political and strategic lenses. Finally, VPs of Analytics are generally highly strategic roles. They often focus on management of data analytics resources and the creation and maintenance of systems and processes to ensure the output of data analytics projects is tied to business objectives.
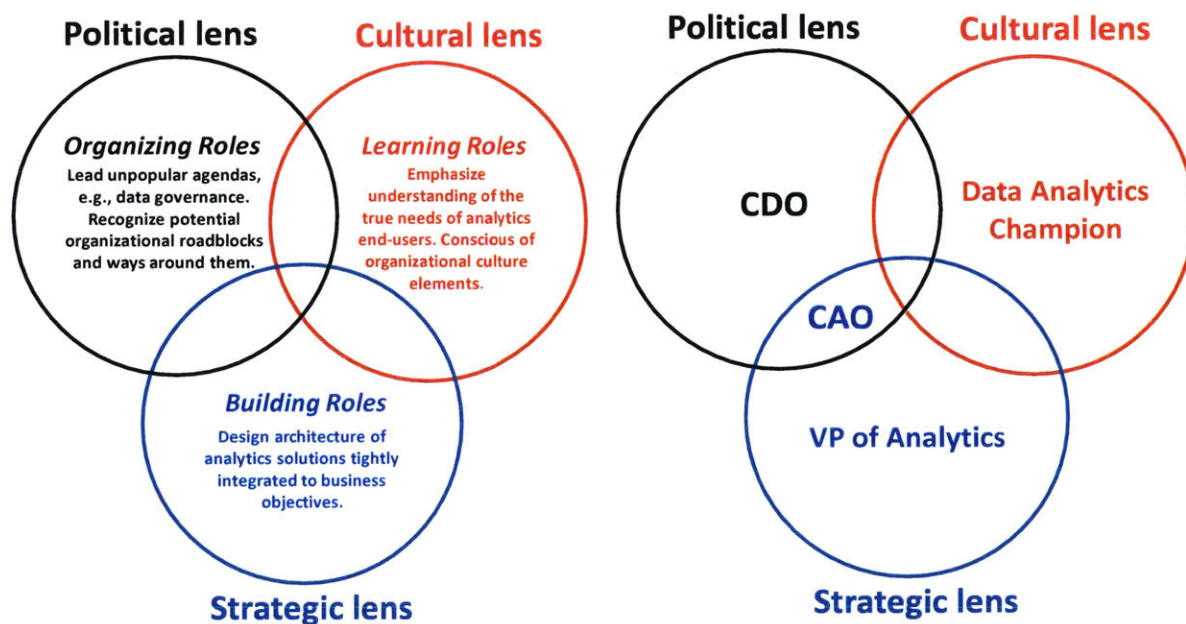

Figure 16. Design thinking roles in the three-perspectives on organizations framework (left), data analytics leadership roles relative to the three-perspective on organizations framework (right)

For organizations pursuing transformation around data analytics it is important to be mindful of the need for a coalition which covers the three different perspectives. This does not necessarily mean that an

organization needs simultaneously, Data Analytics Champions, a CDO, a CAO and a VP of Analytics. In fact, there might be different coalition arrangements which can be equally successful. A couple of illustrative examples include:

- **Coalition 1**: A VP of Analytics starts in a learning role, working closely with selected business units running pilot projects aimed at get better understanding of the true potential of analytics. With time, he/she transitions over to a more strategic role. In parallel, a CDO pursues a data governance agenda preparing the ground for analytics implementations at a larger scale in the organization.
- **Coalition 2**: A CEO who has fully embraced data analytics transformation as a top priority can be an effective champion of highly-political data governance and data democratization agendas. In parallel, a VP of Analytics can support Data Analytics Champions in different business units, consolidate learnings with time and gradually move to larger implementations.

In summary, the transformation framework I present in this chapter is intended to provide a general path to guide data analytics initiatives. The key leadership component in this process is the creation of a versatile guiding coalition which is required to operate in strategic, political and cultural dimensions depending on the particularities of the organization and the transformation effort.

Chapter 4
Summary and Conclusions

The phenomenal success of big technology companies, such as Google, Facebook and Amazon, all founded with a strong emphasis on data, has epitomized the rise of the new "digital economy." Large traditional organizations, that were not long ago "on top of the world" are now at a crossroads. Their business models seem threatened by newcomers as they face pressure to "transform" and "modernize." Publicity has reinforced the perception that data – historically seen by many traditional organizations as a byproduct of doing business – can now be exploited and turned into a source of competitive advantage. In this context, data analytics presumably offers a vehicle to hasten this transformation.

I started my work in this thesis by exploring relevant managerial frameworks in the data analytics literature which could help guide transformation initiatives in large traditional firms. I found out that a large part of the literature focuses on illustrating the potential value of data analytics and providing formulaic approaches for its implementation. Subsequently, I decided to concentrate on literature sources which offered a richer articulation of the complexities of the transformation process. Publications which illustrated the challenges faced by actual companies were particularly insightful. Throughout this exercise, I became increasingly intrigued by the people leading these transformation efforts. Literature describes new leadership roles including: CDOs, CAOs and VPs of Analytics. Recommendations for individuals in these roles abound in the normative literature. However, the list of attributes required from these leaders often seems elusive and even distant from "actual people." Subsequently, the main questions unanswered in my review of the literature were: Who are the people leading data analytics transformations? Where do they come from? What are their challenges and perspectives?

In an effort to find answers to these questions, I interviewed a total of 33 data analytics leaders from large traditional organizations including: oil and gas companies, industrial corporations, financial institutions,

business consulting firms, software / IT companies, pharmaceuticals and a few government agencies. My interviews with these leaders followed a "loose ethnographic framework" in which I encouraged interviewees to freely describe the perspectives and challenges of their roles, while adding elements of their professional background and personal stories whenever appropriate. Interviews revealed recurring themes, areas of agreement and contrasting views. Further analysis also revealed tension between: 1) academia and industry, 2) employees and leaders with a strong "business acumen" and those who favor "data-centric" approaches, and 3) engineers and data scientists.

Once I developed a fuller appreciation for the complexity of leadership roles and the challenges of data analytics initiatives in different organizations, I came to realize the paramount importance of two reference frameworks. First, **Change Management** theory offers a practical guide to transformation efforts, highly relevant in data analytics initiatives. Change Management facilitates identification of common pitfalls and development of strategies aimed at gaining momentum and consolidating gains. Second, the **"Three Perspectives on Organizations"** framework offers a means to decompose the organizational complexities derived from data analytics initiatives into strategic, political and cultural perspectives. The interviews I conducted, revealed that while data analytics appears to be predominantly a technical subject dominated by strategic perspectives, it is in fact strongly influenced by political and cultural perspectives. The recognition that an effective data analytics leader needs to operate in these three dimensions made me realize that this leader cannot be one single individual. Data analytics transformation needs to be led by a "coalition."

My recommendations for organizations embarking on data analytics transformation initiatives are:

- **Favor general guiding principles over highly-formulaic approaches** – I personally advocate for the use of a rather loose framework which emphasizes general concepts of "Change Management" and the "Three Perspectives on Organizations" to guide data analytics transformation programs. I consider

that overly complex frameworks tend to overemphasize the role of strategic views in detriment of political and cultural perspectives, which I consider as extremely important in data analytics initiatives.

- **Establish a versatile leadership coalition** – While many organizations debate between recruiting a highly technical leader for analytics or appointing an internal leader with strong knowledge of the business, I consider a more appropriate approach consists on establishing a coalition of individuals closely aligned with the strategic, political and cultural challenges within the organization. This coalition also needs to adapt to different stages in the transformation process. For instance, an organization pursuing an ambitious data governance agenda, might initially require leadership with a strong political leverage. As the objectives of this agenda are achieved, and the organization moves into using analytics to obtain a competitive advantage, leadership would need to adapt to reflect a more strategic focus.

- **Craft an inspiring vision for data analytics** – My work in this thesis made me realize that an inspiring vision for data analytics transformation is deeply needed in many organizations. Many interviewees recognized that a clear vision for analytics did not exist in their companies. Others, offered vision statements which emphasized the concepts of "data democratization and centralization." While these concepts are largely acceptable at managerial levels, I do not believe they are sufficiently inspiring for individual employees. In some instances, individuals see these initiatives as threatening their job security. I consider the lack of a clear and enticing vision is currently the main inhibitor of data analytics transformations. For many organizations, it is understandable that developing a clear vision on analytics is a tall order. After all, most traditional companies are still trying to figure out what analytics can do for them. I believe it is acceptable for organizations in this situation to embark on experimentation initiatives (e.g., pilot projects), acknowledging that a proper vision is yet to be developed. In this case, management of expectations during the experimentation phase is critical to the credibility of the transformation process.

- **Embrace design thinking principles** – I consider that design thinking principles, and particularly, people-centric tools popularized by the company IDEO provide a practical application of the "Three Perspectives on Organizations" framework relevant to data analytics transformations. I believe many data analytics initiatives overemphasize the role of technology and often underestimate the actual needs of people using analytics and the organizational and cultural contexts in which they operate. In my opinion this bias can be prevented by involving learning, organizing and building roles in data analytics initiatives as advocated in design thinking methodologies.

- **Recognize that tension between incumbents and newcomers can constitute a driving force for change** – While it is unavoidable to have tension and even conflict in most transformation processes, I consider this can be a positive force if channeled appropriately. As data scientists are making their way into traditional organizations and work closely with incumbents, this creates opportunities for mutual influence and creation of a new cultural fabric. In my opinion, this would help 1) focusing data analytics efforts into practical, business-centric goals, and 2) re-evaluating historical subjective decision-making processes in favor of more objective data-centric approaches.

Finally, whether data analytics proves to be a "passing fad" or not, by now, it has served as a catalyst for large traditional organizations to embark on transformation initiatives and re-examine ways to remain relevant. Leadership stories will most certainly abound as these organizations attempt to find ways to survive and prosper in what is now the "digital age."

References

Aiken, P., & Gorman, M. (2013). Understanding the Current C-level is not Data-Knowledgeable. *The Case for the Chief Data Officer*, 5–17. https://doi.org/10.1016/B978-0-12-411463-0.00002-4

Ancona, D., Kochan, T., Van Maanen, J., & Westney, E. (2004). *Three Perspectives on Organizations. Managing for the Future: Organizational Processes and Behavior.*

Andreessen, M. (2011, August 20). "Why Software Is Eating The World." *Wall Street Journal*, pp. 1–5. Retrieved from http://online.wsj.com/article/SB10001424053111903480904576512250915629460.html

Artifical Neural Network. (n.d.). Retrieved April 28, 2017, from https://en.wikipedia.org/wiki/Artificial_neural_network

Artificial Intelligence. (n.d.). Retrieved April 28, 2017, from https://en.wikipedia.org/wiki/Artificial_intelligence

Berry, J. (1994). Database Marketing. https://doi.org/10.1007/978-0-387-72579-6

Big Data. (n.d.). Retrieved March 16, 2017, from https://en.wikipedia.org/wiki/Big_data

Birtel, C., Pajtas, J., & Green, M. (2016). Unleashing the power of an analytics organization: why a large financial institution used ethnography to transform analytics. Retrieved March 13, 2017, from https://www.epicpeople.org/unleashing-the-power-of-an-analytics-organization-why-a-large-financial-institution-used-ethnography-to-transform-analytics/

Boyd, D., & Crawford, K. (2012). Critical Questions for Big Data Provocations for a Cultural, Technological, and Scholarly Phenomenon. *Information, Communication & Society*, *15*(5), 662–679. Retrieved from doi: 10.1080/1369118X.2012.678878.

Chief Analytics Officer. (n.d.). Retrieved March 26, 2017, from https://en.wikipedia.org/wiki/Chief_analytics_officer

Chief Data Officer. (n.d.). Retrieved March 25, 2017, from https://en.wikipedia.org/wiki/Chief_data_officer

Data Analysis. (n.d.). Retrieved March 15, 2017, from https://en.wikipedia.org/wiki/Data_analysis

Davenport, T. H. (2007). *Competing on analytics: The new science of winning. Total Quality Management & Business Excellence.* Boston, MA: Harvard Business School Press. https://doi.org/10.1080/14783360902925454

David, P. A. (1990). The dynamo and the computer: an historical perspective on the modern productivity paradox. *The American Economic Review.* https://doi.org/10.2307/2006600

Desjardins, J. (2016). Chart: The Largest Companies by Market Cap Over 15 Years. Retrieved March 9, 2017, from http://www.visualcapitalist.com/chart-largest-companies-market-cap-15-years/

Gartner. (2016). Gartner Estimates That 90 Percent of Large Organizations Will Have a Chief Data Officer by 2019. Retrieved from http://www.gartner.com/newsroom/id/3190117

Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. *Information*

and Management, 53(8), 1049–1064. https://doi.org/10.1016/j.im.2016.07.004

Halper, F. (2016). *Best Practices Report*. Renton, WA.

Harford, T. (2007). The shock of the new. Retrieved March 13, 2017, from
http://www.slate.com/articles/arts/the_undercover_economist/2007/06/the_shock_of_the_new.html

Henke, N., Bughin, J., Manyika, J., Wiseman, B., & Sethupathy, G. (2016). *The Age of Analytics: Competing in a Data-Driven World*.

Kiron, D., & Ferguson, R. B. (2012). Do You Need a Data Dictator? *MIT Sloan Management Review, 54*(1), 1–4. Retrieved from
http://proxy.lib.strath.ac.uk/login??url=http://search.proquest.com/docview/1115278043?accountid=14116%5Cnhttp://ensor.lib.strath.ac.uk/sfxlcl41?url_ver=Z39.88-2004&rft_val_fmt=info:ofi/fmt:kev:mtx:journal&genre=unknown&sid=ProQ:ProQ:abiglobal&atitle=Do+Y

Kiron, D., Prentice, P. K., & Ferguson, R. B. (2014). The Analytics Mandate. *MIT Sloan Management Review, 55*(4), 1.

Kotter, J. P. (1996). *Leading change.* Boston, Mass. : Harvard Business School Press, c1996. Retrieved from
https://search.ebscohost.com/login.aspx?direct=true&db=cat00916a&AN=mit.000845149&site=eds-live&scope=site

Kte'pi, Bill, M. (2016). Data Analytics (DA). In *Salem Press Encyclopedia of Science*.

Lavalle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). Big Data, Analytics and the Path From Insights to Value. *MIT Sloan Management Review, 52*(2), 21–32.

Lazer, D., Kennedy, R., King, G., & Vespignani, A. (2014). The Parable of Google Flu: Traps in Big Data Analysis. *Science.* https://doi.org/10.1126/science.1248506

Lee, Y., Madnick, S., Wang, R., Wang, F., & Zhang, H. (2014). A Cubic Framework for the Chief Data Officer: Succeeding in a World of Big Data. *MIS Quarterly Executive*.

Line Shaft. (n.d.). Retrieved April 28, 2017, from https://en.wikipedia.org/wiki/Line_shaft

Littman, T. K. with J. (2005). *The Ten Faces of Innovation*.

Lohr, S. (2016, August 27). G.E., the 124-year-old software start-up. *The New York Times*. Retrieved from
https://www.nytimes.com/2016/08/28/technology/ge-the-124-year-old-software-start-up.html?_r=0

McCall, T. (2015). Understanding the Chief Data Officer. Retrieved from
http://ib3.bislr.net/m?s=svds&m=s_570ff54c-6ce1-47fc-b394-ea41d22c3e93&u=http://www.gartner.com/smarterwithgartner/understanding-the-chief-data-officer-role/&r2=d1u78w1u5wqqexvq5ttqct3k5thpyv9fexr2urvfdtu6avkm5xuq0v3fc5j76btj60rkabth64qnavk4cnt76x31dtj6jv

MIT Sloan Management Review. (2016). Lessons from Becoming a Data-Driven Organization. *MIT Sloan Management Review*, (58215), 17. https://doi.org/10.1126/science.1203356

Press, G. (2013). A Very Short History of Data Science. Retrieved March 14, 2017, from https://www.forbes.com/sites/gilpress/2013/05/28/a-very-short-history-of-data-science/#547b2da55cfc

Ransbotham, S., Kiron, D., & Prentice, P. K. (2015a). Minding the Analytics Gap. *MIT Sloan Management Review*, *56*(Spring), 63–68.

Ransbotham, S., Kiron, D., & Prentice, P. K. (2015b). *The Talent Dividend. MIT Sloan Management Review* (Vol. 56). Retrieved from http://sloanreview.mit.edu/projects/analytics-talent-dividend/

Ransbotham, S., Kiron, D., & Prentice, P. K. (2016). Beyond the Hype: The Hard Work Behind Analytics Success. *MIT Sloan Management Review*, *57*(3), n/a. https://doi.org/10.1016/j.aqpro.2013.07.003

Sentance, B. (2015). If You Don ' t Have a Chief Data Officer , Get One Fast. *Money Management Executive*.

Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. *Journal of Business Research*, *70*, 263–286. https://doi.org/10.1016/j.jbusres.2016.08.001

Tukey, J. W. (1962). The Future of Data Analysis. *The Annals of Mathematical Statistics*, *33*(1), 1–67. https://doi.org/10.1214/aoms/1177704711

Varian, H. (2009). Hal Varian on how the Web challenges managers. *McKinsey Quarterly*, (January 2009), 1–6. Retrieved from http://www.mckinseyquarterly.com/Hal_Varian_on_how_the_Web_challenges_managers_2286

Vidgen, R., Shaw, S., & Grant, D. B. (2017). Management challenges in creating value from business analytics. *European Journal of Operational Research*. https://doi.org/10.1016/j.ejor.2017.02.023

Watson, H. J. (2014). Tutorial : Big Data Analytics : Concepts , Technologies , and Applications Tutorial : Big Data Analytics : Concepts , Technologies , and Applications, *34*.