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BEYOND TECHNOLOGY: MANAGEMENT CHALLENGES IN THE BIG DATA ERA

EDUARDO DE REZENDE FRANCISCO[1]
eduardo.francisco@fgv.br
ORCID: 0000-0001-8895-2089

JOSÉ LUIZ KUGLER[1]
jose.kugler@fgv.br
ORCID: 0000-0003-1625-7807

SOONG MOON KANG[2]
smkang@ucl.ac.uk
ORCID: 0000-0003-1605-601X

RICARDO SILVA[3]
ricardo.silva@ucl.ac.uk
ORCID: 0000-0002-6502-9563

PETER ALEXANDER WHIGHAM[4]
peter.whigham@otago.ac.nz
ORCID: 0000-0002-8221-6248

[1]Fundação Getulio Vargas, Escola de Administração de Empresas de São Paulo, São Paulo, SP, Brazil

[2]University College London, School of Management, London, United Kingdom

[3]University College London, Department of Statistical Science, London, United Kingdom

[4]University of Otago, Department of Information Science, Dunedin, Otago, New Zealand

INTRODUCTION

The ability of organizations to produce, collect, manage, analyze, and transform data has increased rapidly over the past decade (Delen & Zolbanin, 2018). This has resulted in significant new challenges regarding how data can be leveraged for improving business decisions and how this new scenario changes business processes and operations (Vidgen, Shaw, & Grant, 2017). The widespread adoption of advanced analytical methods (e.g., machine learning) has attracted significant interest (Gupta, Deokar, Iyer, Sharda, & Schrader, 2018; Vassakis, Petrakis, & Kopanakis, 2018) particularly because the required data storage and methods can be accessed remotely through web-based interfaces such as cloud services. This has resulted in an increased belief that businesses must actively engage with this technology to remain competitive. However, this Red Queen scenario comes at a cost as collecting, curating, and managing large datasets requires expertise and dedicated staff, often consuming resources that do not contribute to core business activities. Consider the fact that there is an increasing role for data scientists and data engineers, among others, within organizations (Davenport & Patil, 2012). Roles such as Chief Data Officer (CDO) and Chief Analytics Officer (CAO) are now commonplace within most organizations.

There is also the issue regarding data preparation. The mantra that 80% of the effort is in the management of data is still largely correct. In addition, the appropriate use and interpretation of predictive models requires expertise that involves both a deep understanding of the underlying business and the assumptions and limitations of each model. Finding suitable people that have skills from both a business and technology perspective can be difficult. The cost-benefit trade-off for businesses in relation to Big Data is often difficult to assess and may lead to failures in how the proposed solution is developed and linked to the business model (Loebbecke & Picot, 2015). There are many examples of organizations, especially government and publicly funded organizations, in which scarce resources may be wasted on failed analytical projects because of a misunderstanding about how the data is meant to be used, the types of data that are collected, and the questions the model intends to address. There are also relevant issues with slow development lifecycles in the analytical arena. Since technology is evolving at a rapid rate, a project that takes a significant amount of time may result in a solution that is expensive compared with a solution using the latest technology. Knowing when to develop, and when to wait, is also a key challenge to the current mechanisms of analytical governance.

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There is a need to understand how organizations should transform their business models when confronted with this increasingly rich world of data, and how they can ensure compliance with correct practices not only from the perspective of technology but also from the managerial, ethical, and societal viewpoints. Early discussions on the theme of Big Data were often framed around the V's perspective (volume, velocity, variety, value, veracity, variability, visualization) (Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015), and although these concepts still remain relevant today there is increasing acknowledgement that data is not a disconnected concept. This has led to the notion of managing data from an ecosystem perspective (Demchenko, de Laat, & Membrey, 2014). Broadly, a natural ecosystem operates at a range of spatial and temporal scales from the individual within a species, to the species community, to food webs and the environment, all within the context of both exogenous drivers (such as climate and competition) and endogenous factors (such as nutrient requirements). Data can also be seen within this broader framework (Gupta et al., 2018) and should therefore be used and modelled as part of a larger, dynamic system, rather than as a separate, disconnected concept. This includes the origin from which data is collected, other digital devices and sensors, technology providers and broader communities involved in data creation, policy making, and so on.

What are the current trends in Big Data analytics? There are two main directions worth mentioning in relation to business decision making: Integrated data infrastructures (IDIs) and the internet of things (IoT) (Ahmed et al., 2017). The main concept of IDIs is that linking or associating data together may provide additional opportunities for examining the structure and relationships between all of these datasets. Many government organizations have collected data through separate organizations, such as justice, health, education, income, social services, community, and population statistics (e.g., regular census collections). However, until recently, most of these data could not be linked in a useful way and it was difficult to obtain a common format or gain access to these types of data. IDIs allow these types of data to be used together, allowing an ecosystem view of society to emerge by presenting person-centric microdata that can be related to aggregated data. Understanding how individuals interact, how decisions are made by individuals, and how these are reflected in societal outcomes (Newell & Marabelli, 2015) allows a greater understanding of why people behave under different circumstances. This means that businesses must understand the way in which social structures, from the individual to the societal perspective, are operating, and therefore the business opportunities that can be leveraged from the individual perspective. IDIs allow questions to be addressed in areas as diverse as agricultural production, mental health, education development, the labor market, immigration, tourism, wage disparities, gender inequality, and so on. However, there are complications with using an IDI; security issues mean that access is often limited or highly controlled, and access for business purposes may be limited unless there is a direct association with a research organization such as a university. However, the current trend in developing IDIs means that businesses will ultimately benefit from these linked data sources, whether it be for their own purposes or as a provider of tools and methods for integrating and using such data sources.

The Internet of Things (IOTs) (Ahmed et al., 2017) continues to be driven by consumer demand with the promise of improved personalization of services and control over many individual decision-making processes. The eventual rollout of fast 5G wireless networks and the increase in connectivity among all devices (remember when the smart-phone was introduced, but now it is just a phone) will lead to business opportunities in terms of how these connections are used, what they represent from an individual perspective, and which new products and services can be created around this ecosystem. Access to this data will also allow new approaches to understanding individual behavior, how consumer demand is created (Erevelles, Fukawa, & Swayne, 2016), and methods for optimizing how individuals interact with systems. Smart electronic devices also allow local processing to be performed; the notion of edge computing and the pre-processing of data to filter and reduce how information is used will become a fundamental aspect of IOT development. Business opportunities exist from both the hardware and software perspective, from what types of devices will be used to how they will interact as a system. The world of sensors and how this will change our perspective in terms of business opportunities has only just begun.

This huge, unprecedented influx of data offers a plethora of opportunities. However, to leverage such opportunities we need to develop meaningful models; to make sense of the complexity that characterizes our economic, political, and social challenges we need to develop sensible, well-articulated models that attempt to reveal how causal processes overlap and interact (Page, 2018).

From a management perspective, the mission is how to recognize which business processes can benefit from what kind of models, how the data can be organized and used, and how analytical results can be incorporated into the decision-making framework.

ACCEPTED ARTICLES

In this special issue, we focus mainly on the most basic of these challenges, namely, the decision to implement Big Data technologies. In "Factors affecting the adoption of big data analytics in companies," Cabrera-Sánchez and Villarejo Ramos (2019) examine the barriers to implement Big Data techniques based on online survey of managers in different areas such as marketing, finance, and human resources. They found that companies with little or no experience with Big Data are more prone to social influence, exhibit higher expectations about the new technology and have higher resistance to adopt the new technology, whereas companies with more experience are more interested in easy access and necessary support for the technology and show lower expectations about its performance.

With special attention to experiences in Brazil, in their paper "Intention to adopt Big Data in supply chain management: A Brazilian perspective," Queiroz and Farias (2019) use a similar framework as that employed by Cabrera-Sánchez and Villarejo Ramos (2019), namely the unified theory of acceptance and use of technology (UTAUT), to analyze specifically the intention to adopt Big Data techniques among Brazilian supply chain management professionals who had some experience with the technology. For these professionals, the main factor to adopt the Big Data technology depends on IT infrastructure such as access to high-speed internet and integration with other systems.

In their paper, "Information management capability and Big Data strategy implementation," Maçada, Brinkhues, and Freitas Junior (2019) investigate how an organization's expectations about benefits and costs of Big Data are influenced by its ability to access data and information from its environment, to process them, and to meet the market needs based on them, or "Information Management Capability" (IMC). They demonstrate that IMC is positively related to value expectations and negatively related to cost expectations, which in turn negatively affect the intent to purchase resources and capabilities to implement Big Data.

Finally, as an application of Big Data, Insardi and Lorenzo (2019) in "Measuring accessibility: A Big Data perspective on Uber service waiting times", used some basic Big Data techniques to study mobility access in a large urban setting using estimated waiting times of all Uber products in the city of Sao Paulo. Their major finding is that the estimated waiting times are highly related to socio-economic variables of the neighborhoods (districts). For example, the authors found a strong relationship between the waiting times and the proportion of non-white population.

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