NEW HORIZONS FOR ORGANIZATIONAL DECISION SUPPORT MECHANISMS – PROMISES OF BIG DATA

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Abstract

The purpose of this paper is to analyze the tendencies relating to the use of Big Data for decision support in organizations. The term Big Data as used here refers to the very large and highly complex datasets that are posing a challenge to the tools traditionally used for data analysis. The discussion starts from the premise that organizations seek organizational intelligence by developing decision support methodologies, processes and systems to manage uncertainty and mitigate risk. The theoretical framework is based on Herbert Simon's concepts of bounded procedural rationality. Two key questions are posed: (1) Does Big Data enable decision makers to move toward substantive rationality? (2) Can the growing volume of data and increased computing capacity reduce the extent to which rationality is bounded and hence enhance prospective capacity? After a brief introduction to the main characteristics of Big Data, the paper reviews the cognitive elements of the decision-making process and the methodologies for developing decision support mechanisms. The attributes of analytical management are then outlined, the challenges of its implementation discussed, and its impact on productivity assessed. The conclusion is that even with access to a far larger universe of data and tools that enable Big Data to be analyzed, we are not approaching substantive rationality, owing above all to fundamental uncertainty. On the other hand, there is evidence of productivity gains by

organizations that base their decisions on the analysis of information. This impact relates mainly to risk management, specifically the establishment of processes capable of comparing heterogeneous alternatives using large volumes of data. One of the hypotheses discussed is that these organizations succeed in analyzing more effectively the factors that most influence their activities as a basis for more assertive decision making.

Key words: *Big Data, decision support, analytical management*

1. Introduction

The world is currently witnessing exponential growth in the volume of data generated and published on the internet. Mobile technologies, social media and location-based tools, among others, are generating and storing increasing amounts of information. According to the Fraunhofer Institute, 1.8 zettabytes (10^{21} bytes) of data were generated worldwide in 2012 and the volume will probably double every two years.

The concept of Big Data is widely used to refer to the recent growth in the capacity to analyze different types of data. In this paper the concept refers to the development of a range of techniques and technologies capable of analyzing large volumes of data of various different kinds. The possibilities that have been ascribed to Big Data include (1) faster processing of large volumes of data; (2) real-time analysis of different variables and indicators; and (3) enhanced models for predicting behavior. This ensemble of possibilities points to a new horizon for decision support mechanisms, given the additional capabilities of the analytical tools now available to minimize risk and identify valuable insights as a foundation for human decisions.

From the organizational standpoint, the search for more assertive decisions is a permanent issue. For decades, organizations have been pursuing ways to enhance strategic decision making. Increased capacity for rational analysis in the decision-making process has driven the development of different multi-criteria decision support methodologies. Recent advances in this field have led to the development of algorithms that can identify, measure and evaluate specific aspects of the proposed object of analysis, as well as multi-dimensional approaches capable of supporting decisions by taking into account their relationship with economic, social and environmental systems, among others.

Thus in connection with decision support mechanisms it is necessary first to identify the peculiarities that differentiate the possibilities of decision support based on Big Data compared with traditional data search and analysis methodologies. The elements that raise questions and differentiate the new methods from the old include (1) the possibility of analyzing data on a large scale in real time as a key input for a range of economic sectors; and (2) the fact that data is currently made available in non-structured form (geographic location, social connections, consumer preferences...), but with the potential for conversion into valuable information capable of adding value, managing uncertainty and, albeit incipiently, serving as a basis for more accurate analysis of individual behaviors.

In this direction, several case studies of organizations indicate that decisions made analytically on the basis of Big Data can positively influence corporate productivity, demonstrating that analytical capacity and its relationship to the decision-making process are a potential source of added value (Brynjolfsson et al., 2011).

The exploratory study described in this paper set out to analyze the tendencies relating to the use of Big Data for decision support in organizations. The paper begins by discussing characteristic elements of the models that propose to analyze Big Data. Next it presents a brief review of the cognitive elements relating to the decision-making process and the methodologies used to develop decision support mechanisms. Third and last, it discusses the attributes and challenges of the establishment of analytical management and its impact on productivity.

The theoretical framework for this study began with the notion of bounded procedural rationality (Simon, 1965), and the key questions: Can the growing volume of data and increased computing capacity reduce the extent to which rationality is limited and hence enhance prospective capacity? Does Big Data enable agents to move toward substantive rationality?

The main point is an attempt to understand how Big Data technologies are actually assisting the decision-making process in organizations and how they relate to decision makers' cognitive and behavioral abilities.

2. What is Big Data?

Big Data is defined as very large and complex sets of digital data that are basically generated by the growth of the internet and are posing a challenge to traditional data storage, processing and analysis tools (Dobre & Xhafa, 2013; MGI, 2011; Syed et al., 2013)

The volume of data now being produced worldwide is indeed immense. In the past two years it is estimated to have reached some 2.5 quintillion bytes per day, or 90% of all the data created by mankind throughout history (Yiu, 2012). The difference is the type of data. Big Data consists mainly of two kinds, structured and unstructured. Structured data, the most common type, involves databases in which data is organized as a matrix divided into columns and rows. Structured data is understood by software and computers, and is organized so as to be understood by users as efficiently as possible. Relational databases and spreadsheets are examples of structured data. Some 10% of Big Data currently consists of structured data (Syed, Gillela & Venugopal, 2013). Unstructured data comes from various sources, such as sensors used to capture weather information, information posted to social networks, digital photos and videos, records of financial transactions, mobile telephone data etc. (Dobre & Xhafa, 2013). Unstructured data does not comply with a predefined model and does not relate efficiently to relational tables. Unstructured data currently accounts for 90% of Big Data.

For Einav & Levin (2013), the answer to the question "What is Big Data?" consists of four main elements: (1) availability of data in real time; (2) availability of data on a very large scale; (3) availability of data concerning novel types of variables; and (4) most data is of the unstructured type.

Precisely these characteristics of Big Data pose a challenge to computational tools, both hardware and software, in terms of storage, processing and analysis of all this data. Two aspects of the challenge are key: velocity and veracity.

Data velocity is "the speed at which data is created, accumulated, ingested, and processed" (Minelli et al., 2013, p. 10). Veracity has to do with the uncertainty that arises from a possible lack of data accuracy. In traditional models involving the storage of structured data, it is assumed that the data is precise and accurate. In contrast, unstructured data such as social media posts to Facebook, Twitter etc. may contain doubtful and uncertain components that have to be processed and analyzed considering their potential inaccuracy.

In light of these elements, some studies (IDC, 2011; Yiu, 2012) argue that the tools developed hitherto in the context of business intelligence[1] are challenged by, i.e. unable to cope with, the difficulties and challenges of managing Big Data. The existing analytical instruments are not capable of handling the volume and complexity of the data generated.

From the organizational standpoint, Minelli et al. (2013) note the demanding requirements place on organizations by the accelerating growth of Big Data. Private organizations are now seeking to enhance their analytical capabilities in order to access strategic information in real time, analyze it, and make decisions as quickly as possible.

In this context, it is relevant to note that new tools developed recently or now under development promise to enable prospective analysis of Big Data. Significant progress has been made in developing capabilities in predictive and prescriptive analysis. Predictive analysis focuses on the search for valuable insights regarding what will happen and serves as a basis for the development of alternative scenarios by means of the manipulation of variables, including "What if" questions".[2] Prescriptive analysis focuses on seeking to understand what might happen on the basis of different alternatives and scenarios, so that the best options can be chosen to optimize possibilities for future action[3] (Intel, 2013).

Although the tools are progressing in terms of data capture, storage and processing, this paper focuses on the analytical potential of Big Data and its capacity to yield competitive advantages, i.e. on Big Data Analytics: "the process of examining and interrogating Big Data assets to derive insights of value for decision making" (Yiu, 2012). Examples of organizations that are optimizing decisions and developing competitive advantages via their competencies in Big Data Analytics are Netflix and Amazon. Both use predictive algorithms to recommend products to customers,

[1] Business intelligence is understood here as the extraction, analysis and delivery of accurate information that is useful to decision makers. Traditional management information systems, such as ERP (Enterprise Resource Planning) or OLTP (Online Transaction Processing) process thousands of transactions as fast as possible in response to the organization's day-to-day operational and legal requirements. Thus BI can also be seen as a set of technologies and processes that use data to understand and analyze business performance (Davenport & Harris, 2007).

[2] Uses include forecasting, hypothesis testing, risk modeling, and propensity modeling.

[3] Uses include analysis and optimization of customer channels, business optimization, and risk management.

analyzing their previous purchasing history to select possible options. Another example is Google's search engine, which uses computational algorithms to rank web pages by relevance according to the user's browsing history.

According to IDC (2011), the potential of Big Data Analytics enables us to advance from an age in which models based on time series predominated to one in which the key paradigm will be the analysis of large volumes of data and (where appropriate) real-time processing to establish new types of predictive model, forecasts and optimization with a strong impact on the production capacity of organizations.

3. Rationality and uncertainty regarding the role of decision support mechanisms

The act of deciding depends on preceding steps that involve perceiving and evaluating the environmental conditions. This is a relevant field of study, both from the cognitive standpoint, i.e. "How are decisions made?", and from the standpoint of organizational management, i.e. "How to make the best decision?" The former relates to the processes that underlie decision making and the elements of which they are comprised. The latter involves the development of mechanisms capable of analyzing the context in which decisions are made with the aim of extracting insights, managing uncertainty, and expanding the rational capabilities of agents in order to enhance the assertiveness of decisions. This is a field positioned at the crossroads of organizational management, behavioral economics, computational mathematical programming and psychology.

From the standpoint of organizational management, Ferreira (2008) highlights the complexity of the analysis of decision making: The process of deciding requires a choice in the present that will have consequences in the future, but because these have not yet happened the decision-making process typically takes place in an environment of uncertainty, so that there will always be a risk spectrum, especially where decisions relating to scarce goods are concerned. In principle, therefore, decision support processes and mechanisms capable of managing uncertainty should have a positive influence on the productivity of organizations, enabling the risks relating to decisions to be more accurately analyzed and thus increasing the assertiveness of the decisions made.

Hence the significant influence of the work done by Simon (1965, 1978) in economics and organizational management, especially his research on decision making. In this research, the postulates of the neoclassical theory of perfect rationality, which in conjunction with the characteristics of the environment are said to produce adequate predictions of human behavior, are contrasted with behavioral theories that claim to indicate more modest and limited cognitive capabilities, albeit more realistic in individuals. His research concludes that the behavioral approach via empirical observation is a more fruitful method of analyzing the decision making process (Chart 1) and hence economic behavior.

Chart 1. Simon's model of the decision-making process

1. Intelligence or investigation stage: exploration of the environment, data processing, identification of problems and opportunities, evidence based on variables relating to the

problem.

2. Design or conception stage: creation, development and analysis of probable courses of action by the decision maker.

3. Choice stage: selection of an alternative or course of action.

4. Review stage: Analysis and reassessment of past decisions.

Source: Simon (1965).

Other research by Simon (1978) discusses the impossibility of dispensing with an analysis of the microscopic dimension of decision making in phenomena associated with political economy. Here he argues that the investigation of decision-making processes can also be a key input for the formulating of public policy or strategies in the private sector, proposing a number of different types of rationality that contextualize and support choice in the organizational context.

Simon considers two kinds of rationality,[4] substantive rationality and procedural rationality. Substantive rationality corresponds to the basic behavior in the rational decision-making process that predominates in neoclassical economics. Thus it enables the agent, if the universe considered does not change, to make the decisions that are closest to optimizing behavior. Procedural rationality relates to the process of deliberation in decision making and the influence of the context, and is closer to the common-sense view of reason than substantive rationality in so far as it acknowledges that rationality is bounded. Based on this premise, the number of possibilities the agent has to cover in order to establish an optimal solution to a problem exceeds the individual's computational cognitive capacity, and this inevitably prevents the agent from making best decision.

Given the goal of analyzing the challenges and prospects for the development of decision support systems in the context of the new technological tendencies known as Big Data, the starting-point proposed for this discussion is the concept of bounded rationality advanced by Simon. Chart 2 summarizes the four basic types of procedural rationality, while Chart 3 outlines the types of uncertainty to be analyzed in decision making.

Chart 2. Typology of procedural rationality

Objective rationality: decisions based on facts and measurable data or data prescribed as effective.

Subjective rationality: decisions based on real information and knowledge filtered by personal values and experience.

Conscious rationality: adjustment of means to ends is a conscious process.

Deliberate rationality: adjustment of means to ends is deliberately sought.

Organizational rationality: aimed at the organization's goals.

[4] In this paper, rationality means the decision-making process that should logically lead to the optimal result, given a precise assessment of the decision that takes into account the values and preferences of the decision maker.

Personal rationality: aimed at the individual's goals.

Source: Simon (1965).

On the subject of uncertainty, several authors have contributed to the development of typologies that can be used in analyzing the context for decision making. Among these contributions, one of the most important is the distinction proposed by Dosi & Egidi (1991) between substantive uncertainty, where not all the information needed for a decision relating to a specific outcome is available, and procedural uncertainty, where uncertainty derives from limitations to computational and cognitive capacity that prevent an unequivocal decision based on the available information. Dequech (1997) distinguishes between strong and weak uncertainty, characterized mainly by the absence of a reliable probabilistic distribution of possibilities. This distinction relates directly to substantive uncertainty as formulated by Dosi & Egidi (1991).

The third typology (Dequech, 2000) distinguishes between two types of strong and substantive uncertainty: ambiguous uncertainty and fundamental uncertainty. Ambiguous uncertainty also relates to the impossibility of probabilistic distribution, but in this case the decision maker usually knows all possible outcomes of the decision. Fundamental uncertainty, in contrast, is characterized by the possibility of creativity and non-predetermined structural change.

Chart 3. Typology of uncertainty

<table>
<tr><td rowspan="3">Substantive uncertainty: lack of all the information needed for a decision to be made relating to a specific outcome.</td><td rowspan="2">Strong substantive uncertainty: impossibility of probabilistic distribution</td><td>Ambiguous uncertainty: also relates to the impossibility of probabilistic distribution, but in this case the decision maker usually knows all possible outcomes of the decision</td></tr>
<tr><td>Fundamental uncertainty: in contrast, characterized by the possibility of creativity and non-predetermined structural change</td></tr>
<tr><td>Weak substantive uncertainty: possibility of probabilistic distribution</td><td></td></tr>
<tr><td>Procedural uncertainty: derives from limitations to computational and cognitive capacity that prevent an unequivocal decision based on the available information</td><td colspan="2"></td></tr>
</table>

Source: Based on Dequech (2000) and Dosi & Egidi (1991).

The argument sustained here is that decision support systems allied with Big Data technologies and the establishment of a decision-making culture based on analytical management have had a positive impact on the management of uncertainty, especially of the procedural type, extending the bounds of objective, conscious and organizational rationality. The next section discusses the contextual organizational elements that characterize the development of decision support systems, starting from the premise that organizations seek the means to expand their business intelligence.

3.1. The search for business intelligence in organizations: the role of multi-criteria decision support mechanisms

According to March (1994), "Organizations pursue intelligence. That is, they can be described as seeking to adopt courses of action that lead them over the long run to outcomes that they find satisfactory, taking into account any modifications of hopes, beliefs, preferences and interpretations that occur over time", as well as the conflicts over these elements that naturally take place within organizations. In the view of academic theorists, organizational intelligence entails "trying to understand a complex and changing system of causal factors on the basis of incomplete, ambiguous and contested information" (March, 1994). This involves "anticipating and shaping an environment that consists of other actors who are similarly and simultaneously anticipating and shaping their environments."

For March (2006), the pursuit of intelligence in organizations developed around concepts and functions such as strategic management, planning, economic analysis, and analysis of decision making, "buttressed by the development of elaborate tools for guiding organizations toward favorable outcomes". He terms these tools "technologies of rationality" (March, 2006). Their contribution takes the form of interpreting the context for decision making and developing a set of procedures to ensure that action is "the product of mind and choice". Technologies of rationality involve three components:

1) Models of situations that identify sets of variables, their causal structures, and sets of action alternatives.
2) Collections of data capturing histories of the organization and the world in which it acts.
3) Decision rules that consider alternatives in terms of their expected consequences and select the alternative with the best expected consequences from the point of view of the organization's values, desires, and time perspectives (March, 2006).

In the world of business organizations, this is the context for decision support mechanisms. From a historical perspective, the development of decision support methodologies and systems intensified after the second world war. A number of methods for evaluating complex situations and preparing decisions gave rise to a broad research field known as "Operational Research". In the 1970s theoretical and methodological advances led to widespread application of multi-criteria methods of evaluation and decision analysis, known for short as multi-criteria decision making (MCDM).

According to Roy & Bouyssou (1993), it is difficult to separate the concept of decision from the concept of "decision-making process", as a number of situations that occur successively during the decision-making process have a significant influence on the act of deciding. They define decision support as "the activity of the person who, through the use of explicit but not necessarily completely formalized models, helps obtain elements of responses to the questions posed by a stakeholder in a decision process. These elements tend to clarify the decision, and usually to prescribe or simply to encourage behavior that will increase the coherence between the evolution of the process and the objectives and values supported by the actors who intervene in the process" (Roy & Bouyssou, 1993).

These methods seek to apprehend the multiplicity of factors involved in the pursuit of goals, and to enhance the coherence of individual or collective appreciation, all with the ultimate aim of better evaluating and decision making in greater proximity to the real world (Flament, 1993). Generally speaking, MCDM can be thought of as a framework with four levels: (1) definition of the object of evaluation and decision, and of the spirit of the analysis to be performed; (2) analysis of consequences and of the process of developing criteria; (3) modeling of preferences and operational approaches to aggregation of the outcomes of these preferences; (4) decision-making procedures (Roy & Bouyssou, 1993).

Once the object of analysis has been defined and the characteristics of each attribute and goal have been measured, it is possible to compare alternatives, without seeking an optimal solution. According to Martinez (1998), MCDM methods aim to: select the best alternatives; accept alternatives that seem good and reject those that seem bad; and rank the alternatives in descending order. The same source describes four main methods for this type of choice: linear weighting; multi-attribute utility; hierarchical analysis; and outranking methods.

Hierarchical analysis (the best-known method is analytic hierarchy process, AHP) decomposes a complex unstructured situation into its component parts, hierarchizes them, and ranks each component in terms of relative importance, while also enabling sensitivity analysis, and is probably the most used approach worldwide (Martinez, 1991).[5] Among the methods of outranking are those of the French school, consolidated in ELECTRE (ELimination Et Choix Traduisant la REalité, which means "Elimination & Choice Translating Reality") and PROMÉTHÉE (Preference Ranking Organization Method for Enrichment of Evaluation).

4. Big Data, analytical management and organizational productivity

The term analytical intelligence has been used to refer to the extensive use of data, quantitative and statistical analysis, explanatory and predictive models, and fact-based management to guide organizations' decisions and actions (Davenport & Harris, 2007). According to these authors, analytical intelligence can be considered a subsystem of business intelligence, and is easily confused with analytical information technology. The main difference lies in the human and organizational factors that add value via analytical leadership by organizations. Analytical leaders are organizations that select one or more distinctive competencies as a foundation for their strategies and comprehensive data analysis, quantitative and statistical analysis, and fact-based decision making.

[5] Software for AHP includes Expert Choice. For an introduction to MCDM applications, see Barba-Romero (1997).

As discussed in Section 1, technological progress now enables enormous volumes of data to be collected and stored. However, although organizations have this huge volume of data available to them, the management of Big Data and above all the capacity to extract valuable information from it has not expanded at the same pace. The main challenge is how to align the new possibilities for data analysis with business strategy. From the operational standpoint the challenges relate to managing: (1) the possibility of conflicting data sources; (2) integration of applications, since data collection and analysis cross organizational boundaries; and (3) enabling analytical intelligence as a distinctive competency (Davenport & Harris, 2007). To address these challenges, organizations must answer the following questions: (1) What data is necessary to compete with analytical intelligence? (2) Where can this data be obtained? (3) How much data is required? (4) How can data be made more precious and valuable for analysis? (5) What rules and processes are needed to manage data from creation to deletion?

With regard to the development of analytical management and access to Big Data, the first step can be taken in two directions, internal and external. For internal data, corporate systems are a natural starting-point. An organization that wishes to optimize its supply chain can start with a demand planning application. Corporate systems – applications that automate, relate and manage the flow of information for business processing, such as order processing, for example – often help firms make progress toward analytical leadership. They provide consistent, accurate and up-to-date data for tasks such as financial reporting and supply chain optimization.

As for external data, managers have the option of contracting with firms to supply financial, credit and customer information, as well as market research. Another important source is government, which is one of the largest suppliers of economic, industry-based and demographic data, among other types. Other less structured and more socially diffuse sources range from emails and social networks to location-based or GPS data, images, videos, and biometric data. In addition, physical-world data is increasingly disseminated via sensors and radio frequency identification devices (RFID).

In this context software developers are increasingly building analytical resources into corporate systems. The challenge here is to take into account the new possibilities for analytical management based on Big Data and decision support methodologies. This entails using computer systems to analyze large volumes of data swiftly and efficiently in order to deliver information of relevance to the decision-making process, and establishing methodologies capable of both aggregating the perceptions of different agents regarding specific objects of evaluation and analysis, and comparing, ranking and selecting the best alternatives for action in accordance with specific strategic goals.

From the cognitive standpoint the challenge is expanding the capacity to process and analyze the growing volume of data and variables that relate to the organization's and decision maker's context. This competency requires the implementation of analytical management and the development of mathematical algorithms and specific systems that above all influence procedural, weak substantive and ambiguous uncertainty. Furthermore, an organizational culture based on analytical management relates to the development of objective rationality, where the decision maker uses facts and data that are measurable or prescribed as effective.

4.1. Organizational productivity enhancement through Big Data

In different cases and sectors the literature shows that firms that adopt technologies and practices for data analysis and apply them as decision support mechanisms obtain productivity gains. According to research by IDC (2011), projects that implement an analytical software package generate an average return on investment of 140%, while customized development using analytical tools generates 104%. The rest of this subsection presents a review of the literature on the advantages obtained by using data for decision support.

Analyzing the period 1987-1994, when personal computers became more widely used, firms changed their routines and new information systems enabled rapid and efficient data retrieval and organization, Brynjolfsson & Hitt (2003) calculate productivity gains from this technology ranging from 0.25% to 5% for a universe of 600 firms. This shows that simply adopting more advanced computer technology does not translate directly or automatically into gains. A number of complementary assets must be deployed if the overall process is to succeed in terms of establishing methods and procedures capable of leveraging the analysis of growing volumes of data as an important decision support mechanism.

More recent research by Tambe, Hitt & Brynjolfsson (2012), based on a 2001 survey of 250 firms, correlates the capacity to monitor the external environment via investment in information technology (IT) with productivity gains. The survey included questions on decentralization of activities, practices for acquisition of external information, benchmarking methods and frequency, whether the involvement of partners and suppliers in new projects was encouraged, and the extent to which the firms sought to recruit new employees or researchers.

The findings suggest that "extroverted", or externally focused, firms that invest more in IT develop and bring new products to market faster. In other words, they are more effective and agile in research, development and innovation. The main point made by these authors is the importance of pursuing external data sources and of converting external data into relevant information for decision support. This is an indication of risk mitigation, since data can be captured and treated in real time to provide a rapid understanding of the behavior of consumers and competing firms so as to make decisions more assertively.

The Deciding Factor: Big Data & Decision Making (Capgemini, 2012) portrays the growing tendency to extract valuable information from data and base decision making on the evidence derived from the universe analyzed. The survey of more than 600 senior executives reveals a belief that in the next three years data-driven decision making will gain ground compared with decision making based on the experience of CEOs and boards, with growth of at least 20% in the near term. This perspective shows the growing capacity of analytical management to become a significant compass for the development of competitive advantages and value creation.

5. Final considerations: prospects and challenges for Big Data in the development of decision support systems

This study set out to analyze trends in the use of Big Data for decision support in organizations. The questions that motivated the analysis include: (1) Does Big Data lead decision makers to move toward substantive rationality? (2) Can large volumes of data and expanding computational capacity reduce the degree to which rationality is bounded and hence increase prospective capacity?

The answer to the first question is negative. Even with access to a far larger data universe and tools that enable analysis of Big Data, albeit incipiently, we are not approaching substantive rationality, defined as a process in which decision makers possess full knowledge of all the variables involved as well as their impacts. This is mainly because we will never be able to be aware of and control all variables and all possible causal relationships. Research, development and innovation (RD&I) activities are an example. One type of uncertainty, fundamental uncertainty, is persistent in these activities, associated mainly with the introduction of innovations that constantly disrupt established standards. Hence the very characteristics of RD&I, especially the imponderability and multidimensionality of their impacts, are the main source of uncertainty in this case.

However, there is evidence that firms are succeeding in adding value by means of analytical management based on Big Data. This increase in productivity may be associated with better management of uncertainty, especially procedural uncertainty, and with improvements in the computational capacity to analyze data. Moreover, the new trends in Big Data also appear to be influencing the ability to make decisions rationally, by enabling organizations to analyze more variables and larger volumes of data for decision support purposes. These possibilities appear to give competitive advantages to different sectors of organizations and in specific processes, particularly the optimization of internal organizational processes, the analysis of consumer behavior, marketing decisions, risk analysis, and investment decisions.

The answer to the second question therefore relates mainly to risk management. One of the hypotheses raised to explain the productivity gains achieved by organizations that make decisions analytically is that they succeed in analyzing more effectively the factors that most influence their activities. This hypothesis is strengthened by the significant progress made in the development of predictive and prescriptive systems based on Big Data. From the theoretical standpoint, in light of the framework proposed by Herbert Simon, the main impacts of decision support systems based on Big Data are associated with the objective, conscious and organizational types of rationality.

The principal challenge to the advancement of decision support systems is therefore the need to achieve greater proximity between existing decision support methodologies and the new trends in Big Data (analysis of large-scale highly diversified data, expanding data processing capacity, and real-time decision support), in conjunction with consciousness raising among managers and the collection of information on the environment in which the organization operates.

From the organizational standpoint, analytical management based on Big Data is set to intensify and become an important driver of value creation and competitive advantage.

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