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IMPACT OF BIG DATA ON BUSINESS INTELLIGENCE AND DECISION SUPPORT SYSTEMS

Review Article / Original Research

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Abstract

Big Data is now poised to mutate decision-making systems. Indeed, the decision is no longer based solely on the structured information that was hitherto collected and stored by the organization, but also on all data not structured outside the corporate straitjacket. The cloud and the information it contains impacts decisions and the industry is witnessing the emergence of business intelligence 3.0. With the growth of the internet, social networks, connected objects and communication information are now more abundant than ever before, along with rapid and substantial growth in their production. In 2012, 2.5 exabytes of data (one exabyte representing a million gigabytes of data) came every day to swell the ranks of big data (McAfee et al., 2012), which should weigh more than 40 zettabytes from 2020 (Valduriez, 2014) for 30 billion connected devices (The Internet Of Nothings, 2014) and 50 billion sensors (Davenport & Soulard, 2014). One of the most critical aspects of all of this information flow is the impact these will have on the way decisions are made. Indeed, in the part of an environment in which data was scarce and difficult to obtain, it was logical to let decision-making be conditioned by the intuition of the experienced decision-maker (Klein, Phillips, Rall, & Peluso, 2007). However, since information and knowledge are now available to everyone, the role of experts and decision-makers is gradually changing. Big data, in particular, makes it possible for analytical and decision-making *systems to base their decision-making on global models. However, considering all the dimensions of the situations encountered, it was not until now that these systems were not within the reach of man, but were rationally limited (Simon & Newell, 1971). Big data and however, the processing of unstructured data requires modifying the architecture of decision support systems (DSS) of organizations. This paper is an inventory of developments undergone by aid systems decision-making, under the pressure of big data. Finally, it opens the debate on ethical questions raised by these new technologies, and it is observed that now, data analysis of personal data has become more debatable than in the past.*

INTRODUCTION

Business intelligence is a must theme in the domain of information management and communication systems. Several researchers from management sciences such as Simon, Kanheman or Klein have attempted to define the mechanisms leading to individual and collective decision making. The results of the various studies tend to the following conclusion: in extreme situations, the expert should rely on his intuition. It is indeed sometimes very complicated and risky to anticipate the reactions of a programmed machine (which follows fixed procedures) when a new situation occurs: the autopilot functions of airliners are deactivated for example, when faced with non-routine situations (Klein, 1999; Siegfried, 2014). The RPD (Klein's Recognition Primed Decision) provides a framework and direction for decision-making by the situation. It appears to be more suitable than decision-making systems that prove to be incompatible when used outside the scope of well-characterized problems whose evolution is known. However, the decision support system (DSS) is defined as follows: An interactive computerized system helping the decision-maker to manipulate data and models to solve ill-structured problems (Gorry & Morton, 1971). One is then faced with an inconsistency: the notion of "poorly structured problems" indeed induces inevitably the resolution of frequently complex difficulties. DSSs allow ideas to be shared and their main objective is to improve the quality of decisions made (Bätz & Siegfried, 2021). However, several limitations related to the adoption of these systems could be observed: it is indeed sometimes complicated for decision-makers not to rely on their experiences or to manage large amounts of information. The misunderstanding of theories built into the DSS may further lead to system rejection by users who in the case of Fmac, prefer to rely on the opinions of natural persons (Lebraty, 2006). The market is currently witnessing a revolution in the field of business intelligence, including the systems that are gradually equipped with Hadoop clusters opening the way to analysis and the use of big data (or big data). Jim Gray (Balazinska et al., 2007) suggests the following definition of big data: It is about "a large volume of information not structured and generated by a large number of new sources". Many analyses are undertaken around the interest that big data represents for business intelligence and DSSs (George, Hass & Pentland, 2014; Siegfried, 2015). The main parameter to be considered is not the dimension of big data but the quality and velocity of data (structured, semi-structured, unstructured) it contains, as well as the skills necessary for their operation: it is less a question of big data than of smart data. The decision-maker must find the data likely to generate value for the company and have the means to integrate it in decision-making: 30% of managers consider that the lack of a structure for data Big Data is the single most problematic (Davenport & Patil, 2012). The skills necessary for the analysis and processing of big data are still slowing down business (Siegfried, 2017). In this sense, big data currently only concerns a minority company, nine out of 10 of them felt in 2014 that they lacked the skills, technological or humans to embark on a big data strategy (Cointot & Eychenne, 2014). This communication is an inventory of developments in DSSs under pressure from the big data and therefore addresses the following issue: Are the current DSS adapted to big data environments? To provide some answers to this question, the first section is interested in the main models of decision, defining the DSS and their limits while explaining the interest that big data has for them. The second section presents the integration of current DSSs in a Big Data environment. Finally, the third section acts conclusion and opens the subject.

The three main decision models: In the field of management sciences, several models have been defined to characterize the decision making:

• The analytical model: It makes it possible to deal with simple or complicated problems (from as long as they remain decomposable) of which the set of determinants is known. The objective of rational analysis is to define all the elements of a context, to list all the possible options and to make a choice about a weighting of elements of most importance to the decision-maker. Many tools (in the form of tables or maps) make it possible to carry out the steps preceding the decision making under this approach. The objective here is to optimize the decision to identify the best solution. The decision must also be the one that best meets the expectations of the decision-maker but may however be the result of a compromise between the elements to be considered (as long as there is no other better possibility). This model is the most suitable for the process of deciding certain environments (Kahneman, 2012).

• The model of bounded rationality (Simon, 1955): It concerns a novice individual in his field and is faced with a complex problem. The notion of rationality was the cornerstone of many of Simon's works, which highlights the limits of decision-makers in terms of cognitive abilities: physical limits and computational (relating to the individual's ability to efficiently schedule events). Simon argues that human rationality is in reality approximate, unlike that which should be demanded by certain situations (e.g., the anticipation of share prices). The intelligent design choice model (Simon & Newell, 1971) defines four phases of decision making. In this framework, the individual is faced with several potential solutions and selects the one that suits him best in terms of the context, his choice is therefore relatively rational.

• The Recognition Primed Decision model (Klein, 1999): Gary Klein built the RPD model compared to observations made during missions on the ground. This model is not interested in what individuals (experts) have to face a problem but in what they do when faced with it. Klein had noticed that experts such as firefighters are recovering intuitively to their experiences to make decisions about extreme situations. Through mental projection, experts show themselves capable of testing hypotheses and defining a course of action to anticipate the consequences of the decision they will make. They compare the problem they are facing now with others encountered in the past and use analogies to adapt what they know. This decision-making model allows experts in these fields not to have to compare the different possibilities available to them. The answer to a problem is indeed very often present in the "memory" of the expert who often does not have the time necessary to carry out a complete mapping element of the situation encountered. The decision here is directly dependent on the experience of the expert.

Each decision-making model is, therefore, more or less well suited to certain issues (simple, complicated, complex). The choice of model will also orient towards a certain type of DSS depending on the decision to be made. A firefighter's command cannot (in the context of operational missions) rely on the same decision support system as that used by a statistician to make medium or long-term projections. The big data is proving to be valuable for all of the models presented, but the information, however, will not be valued in the same way depending on the DSS and the decision-making model.

WHICH TYPE OF DSS FOR WHICH TYPE OF DECISION?

DSS can be data or model-oriented (Alter, 1977). They allow sharing of ideas and aim to improve decision-makers decisions. Data-driven DSSs are suitable for "intuitive" decisions in so far as they do not require a choice between different options. Neural networks and systems using artificial intelligence belong to this type of DSS. The article "Human problem solving" (Simon & Newell, 1971) was a pioneer in the field of artificial intelligence. This article describes the development of programs capable of emulating humans for performing tasks such as chess or puzzles. Neural networks are built, concerning this research, based on emulation (Lebraty, 2006). They make it possible to link the conception of the DSS and the cognition of the decision-maker. The objective is to know how the average individual processes and uses the information he has to disposition. The concept of cognitive style had hitherto been a subject of contention between groups of researchers, some denouncing the immaturity of the concept to be used as the basis of a DSS system, the others asserting that a DSS adapted to the decision-maker could not but be more effective. The cognitive approach has, however, highlighted the importance of the Human Machine Interface (HMI) and the need to create tools that adapt to the decision maker's mental model. The advent of big data is very promising for DSSs since the analysis and exploitation of these data will make it possible to consider the cognitive style of the decision-maker, as well as the context of the situation encountered, by the RPD model (Klein, 1999). Model-oriented DSSs (this is the case with expert systems) offer choices between several options for decision-makers. The main limitation of these systems is related to their rationality limited to a few specific points (depending on the models they contain), which does not allow the development of a global vision (Klein, 1999). Request processing times are also particularly important and de facto block the generation of results is continuous (Brasseur, 2013). Researchers are therefore faced with machines equipped with algorithms capable of providing rational results that are much more relevant than those resulting from human reasoning (Meehl, 1959), but incapable of realizing associations between all the different elements of a situation (notably temporality) and acting according to the context. It is found that each of these DSSs has its weaknesses. The big data could nevertheless soon level these and make analytics the cornerstone of future takes decision-making. They will allow machines to free themselves from the obligation to focus on one or a few elements of situations, thus resulting in an era where artificial intelligence will be based on models considering all the attributes of the context. Moreover, the computational capacities of the machine are not limited (unlike those of humans) or at least evolving according to technological advances. The system Watson (designed by IBM) combines algorithmic artificial intelligence with a behaviour modelled on human deduction capacities (Cointot, Eychenne, 2014). This system is not based solely on calculations (unlike the analytical system having defeated Garry Kasparov at chess in 1996) but can go "read" for example various text content on Wikipedia or social networks, etc. These analyses lead it to make deductions without limiting oneself to simple algorithmic reasoning. Watson is now capable of generating cancer diagnoses equivalent to those of a specialist. It is also kept informed of the latest news and discoveries in good real-time, which a man cannot do. Unlike Watson and the developed DSSs around big data, most current DSSs (whether they are data or model-oriented) was not built to fetch information outside of their databases.

Several models relating to the implementation of big data can be chosen by an organization (Cointot, Eychenne, 2014): The disruptive model: big data is in this case the central element of the decision and everything is built around its architecture. Companies such as Yahoo or Google rely on this model. The scalable model: big data is integrated to enrich the IT model already present in the business. It is here simply a potential source of data. The hybrid model: The data warehouse is in this case linked to the big data system. The two systems are well integrated and each deals with specific data. This model makes it possible to strongly impact the decision-making model of companies. The solutions offered by Oracle or Teradata are of this type. The majority of companies wishing to integrate big data into their processes decision-makers already has an architecture dedicated to business intelligence. Almost none, therefore, chooses to set up a disruptive model for fear of having to redefine in its entire decision-making “framework”. Most companies, however, do not need total big data solutions but specialized solutions to deal with a specific problem (VanRijmenam, 2014), the choice of an evolutionary or hybrid model is therefore valid. Organizations, however, often face challenges when seeking to address large amounts of data while keeping their existing ones (Schmarzo, 2014):

- None of their basic tools have been designed to process information passing through social networks or unstructured content. They are dedicated to the analysis of classic and structured data (in rows and columns).
- Data warehouses (data warehouses based on the Online Analytical Processing: OLAP) have been put in place in the past to help decision-makers in organizations. The objective of these warehouses is to make data very heterogeneous accessible to all users. However, OLAP systems do not support has some formats (for example video formats) and therefore cannot analyse and process certain big data (Brasseur, 2013).
- Old systems do not allow predictive recommendations to be made (Lebraty, 2006). Tools dedicated to artificial intelligence also require the use of a natural person to carry out requests. The new tools of prediction create models that will be continuously transformed by the analysis of historical data, they thus gain in performance over time. The Knowledge Graph of Google works according to this model and will ultimately allow from the search engine to the knowledge engine. It will thus be possible to directly question Google who will make associations concerning the history comprehensive research carried out worldwide, but also about data personal data of users (Van Rijmenam, 2014).
- It is difficult for decision support systems to query several databases data (Lebraty, 2006). However, a big data strategy requires considering the cloud computing databases (which is the only element offering the capabilities of storage compatible with big data) alongside corporate data several big data cloud services exist (e.g., Cloudburst, Oracle Cloud service, etc.).
- Taking into account the temporal dimension is problematic for the classic DSSs (Cointot & Eychenne, 2014). It requires the use of processing analyzing and correlating data and information from thousands or even millions of continuous sources (e.g., MapReduce). A few million messages may need to be scanned per second. This analysis makes it possible to no longer define trends a posteriori (classic systems) but in real-time: this is a revolution. This analysis uses GPS data, various technical information, etc. and allows to advise users according to events (example: modification of the behaviour following the occurrence of an engine failure). The data comes from sensors, smartphones, or social networks. The dimension temporal will be more fully studied in the next part of this communication and a tool to take it into account will be presented.

In 2013, companies spent nearly $ 31 billion to integrate big data technologies into their structures (Van Rijmenam, 2014). When a company integrates big data into its decision-making strategies, it goes from a vision-oriented towards the past to one oriented towards the future (use of real-time data to define trends, etc.). IT has been observed that, several relating limitations are taken into account by the big data environment by DSS of companies. It should be noted that the big data environment also strongly impacts visualization tools. Processing a large amount of data requires defining representations capable of leading to an understanding of the results. Relationships must also be put forward (curves, tables, etc) and can henceforth call upon very complex multidimensional models (cubes, stars, etc). This complexity imposes to put forward continuums (which the human eye, unlike the machine easily). It becomes very easy to generate stories from raw data. The system can thus make mental projections about the information it contains and automatically transcribes it in the form of stories. The objective is to make accessible to decision-makers the course of action he proposes (Davenport & Soulard, 2014), Narrative Sciences a par example set up a function of this type to help users within the framework of the writing articles.

The interface must also be particularly suitable, given the influence that it can have on the decision-maker (Schmarzo, 2014). Complexity should also be avoided to allow the user to take ownership of the system. He just wants to know what's going on and what to do (based on good practices that have worked in the past).

RESEARCH METHODOLOGY

This paper focuses on the Impact of big data on business intelligence and decision support systems. To conceptualize the impact of big data on business intelligence and specifically decision support systems qualitative research is carried out in this paper to conclude. Several research articles on the topic of big data and DSS were studied. Most of the literature reviewed is from the previous decade. DSS is a core component of BI to some extent the two terms can be used synonymously. Some research that tries to quantify the impact that big data has made on DSS is also included to get a better understanding of the topic.

RESULTS AND DISCUSSION

Big Data is about to mutate the current decision-making processes and concerns all operational information systems (stocks, CRM, etc.) (Van Rijmenam, 2014). The integration and use of unstructured big data in support systems decision-making are done through the use of different tools. In this environment, Hadoop does benchmark open-source software offices for leveraging big data. At the same time systems such as a big table, H base(apache), etc. are widely deployed in cloud infrastructures (private and public) (Liebowitz, 2015). These systems allow the analysis and processing of petabytes of data and thousands of continuous requests. The notion of expiry of the data takes on its full importance in the context of these real-time analyses and it is necessary to define the time intervals within which the analysed data is valid. Management scalable data appears to be a priority for future DSSs. The emergence of a database management system translates this desire to mutate both the applications to exploit data and the DSS guiding decision-making. At the level of the decision-making process of the DSS, the impact of the big data will be felt from the problem identification phase until the proposal of a different course of action by the system. The decision-maker will retain the choice of implementing the proposals or not.

It can be judged based on the decision-making process or the outcome (Lebraty, 2006). When in connection with the decision-making process, rationality (of the process) is a criterion to consider. On this subject, there is the explanation provided previously that, the advantage of the systems decision support based on big data tools resided in their ability to consider global models and to guide towards more rational decisions than those resulting from human reasoning. The realization of a formal argument makes it possible to improve the rationality of a decision. Therefore, the DSS interface must make the information accessible by avoiding highlighting complex mathematical calculations: argument cards can be used for semi-automated reasoning. Argumentation makes it possible to raise awareness of the context, to give legitimacy to the decision. It also strengthens evaluating individuals about the information available to them. When performance is evaluated based on the outcome, return on investment (ROI) appears as a key indicator of this measure. Many companies believe that setting up a big data strategy represents a significant cost with no guarantee of results. They estimate that the ROI of the planned project will be low or even zero. These projects are revealed however paying for most companies and only 2% of them find themselves facing a total failure (Sweeney research, 2014). The main cost relating to the establishment of these strategies is linked to human resources: data scientists are indeed very expensive (Davenport & Patil, 2012) and increasingly in demand (Wixom et al., 2011). The gains that big data should allow will be very significant for organizations shortly, but the sectors will not be impacted in the same way. The use of big data technologies can enable a 60% increase in margins in retail and a 50% reduction in assembly and development costs in the manufacture (Manyika et al., 2011). Big data projects make it possible to reduce the time allocated to the realization of a task or a process, they are therefore a source of profitability for organizations (Brasseur, 2013).

To concretely illustrate the gains induced by big data projects, taking into example the chain of stores Macy's. This company has chosen to set up an application to optimize the price of its goods (depending on the weather, supply, etc). The prices of the 73 million items can now be optimized in one hour compared to 27 hours before the implementation of the application. Macy's saves thus 70% on the cost of the material. The freed-up time can finally be used to respond more quickly to unforeseen events (Davenport & Soulard, 2014). Overall, the ROI of big data projects is very high. The police department of a large city in North America has, for example, launched a predictive analysis project (merger of the local database with a national crime database). The results of the project were a net decrease in crime and an ROI of 863% (Nucleus Research, 2012). Nucleus Research concludes its study by the fact that the ROI of a big data project is on average higher 241% than a classic business intelligence project. One euro invested in a big data project brings in around nine euros. The repayment term is also much lower than for classic business intelligence projects (six months versus 27 months).

CONCLUSIONS

The purpose of this communication is to respond to the following problem: The current DSSs are they suitable for big data environments? Several elements such as the need to be able to process unstructured content and consider the temporality of the data indicate that traditional decision support systems are poorly suited to big data environments. Business intelligence architectures must therefore be redefined to get the most out of big data strategies. The TADSS is an example of a tool that can be integrated into classic DSS to consider big data, without requiring a complete replacement of existing systems. Tools of this type should attract the companies without a problem that remain cautious about doing big data the central element of decision-making (disruptive model) (Milea V et. Al., 2013). This mistrust has its foundation in the costs imposed by the renewal of their decision-making systems. It has been, however, observed that the return on investment of big data projects is very high and that reimbursement times are low. The association of people and big data in the context of decision-making could forma magnificent partnership (Brasseur, 2013). This requires inventing new structures organizational making it possible to take advantage of the machine's strengths to overcome the weak humans (McAfee et. Al., 2012). Crime and corruption cost the world two trillion dollars per year while traffic jams weigh seven to eight billion dollars in the UK's only budget (Helbing, 2014b). Faced with all these losses, an algorithm able to bring an improvement of just 1% of decisions would bring a profit immense for companies. However, the promise of big data goes well beyond this single point of percentage (Helbing, 2014a). The development of connected objects should itself strongly influence DSSs, strengthening their ability to offer share prices temporal: 30 billion connected devices (The Internet of Nothings, 2014) and 50 billion sensors (New Vantage Partners & Davenport, 2014) will be scattered across the world in 2020. Big data including the use of data it contains, however, raises many ethical questions. At a time when Metrics, a start-up established in Michigan, attempts to develop a tool to collect and monitor personal data users in almost all aspects of their lives (health, mood, budget, fitness physical, online activity, etc), it is increasingly a question of defining a framework for use of big data (Davenport & Soulard, 2014). Governments until then did not have the data needed to control all parts of companies, but this is changing. Each new sensor integrated into digital devices is one more step towards the ultimate knowledge behaviour of individuals. They are the relays of an individual's interests, passions, etc. computers now perform 70% of financial transactions while the first hotlines fully computerized are operational (e.g., IBM Watson Hotline).

LIMITATIONS AND STUDY FORWARD

Researchers should not be afraid of major upheavals (major innovations have always been vectors of fears, like for example television) but try to accompany them and adapt to them. IT and big data are the third industrial revolution and this will increase for several more decades (McAfee et. al., 2012). Computers are currently making inroads into new worlds and humankind is witnessing a real game of chess, with a man on one side and technology on the other (Levy & Murnane, 2013). One must remain in constant alert vis-à-vis the interference that can cause the machine screw concerning personal intuitions (Klein, 2004). Finally, it is necessary to require programmers to develop information technology for support rather than domination. During this study, it was found that there is a lack of quantitative research on the impact of big data on BI and DSS of specific industries. Further exploration can be done in specific industries to fill gaps.

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