

Article

When big data meets dataveillance: The hidden side of analytics

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Abstract

Among the numerous implications of digitalization, the debate about ‘big data’ has gained momentum. The central idea capturing attention is that digital data represents the newest key asset organizations should use to gain a competitive edge. Data can be sold, matched with other data, mined, and used to make inferences about anything, from people’s behavior to weather conditions. Particularly, what is known as ‘big data analytics’—i.e. the modeling and analysis of big data—has become the capability which differentiates, from the rest of the market, the most successful companies. An entire business ecosystem has emerged around the digital data asset, and new types of companies, such as analytical competitors and analytical deputies, are proliferating as a result of the analysis of digital data. However, virtually absent from the big data debate is any mention of one of its constitutive mechanisms—that is, dataveillance. Dataveillance—which refers to *the systematic monitoring of people or groups, by means of personal data systems in order to regulate or govern their behavior*—sets the stage and reinforces the development of the data economy celebrated in the big data debate. This article aims to make visible the interdependence between dataveillance, big data and analytics by providing real examples of how companies collect, process, analyze and use data to achieve their business objectives.

Introduction

Over the past five years, the term ‘big data’ has captured the attention of business people, technologists and policy makers alike. ‘Big data’ is expected to offer unique opportunities for economic growth and innovation, and, thanks to ‘big data’, the public sector can become more efficient, and new business models, products and services can be created (Manyika et al. 2011). Talking about ‘big data’ means reflecting on the implications that the accumulation and analysis of an enormous amount of digital data have for organizations and for their information management strategies.

‘Big data’, in fact, indicates an array of business and information technology trends, whose existence was detected, more than 10 years ago, by Doug Laney, research Vice President for Gartner Research. In his article, Laney (2001) emphasized three key tendencies: (a) the remarkable volume of transactional data generated by e-commerce and the willingness of companies to retain this information; (b) the speed of data creation produced by the interaction between organizations and customers; and (c) the opportunity to integrate and manage a wider variety of information, with different formats and structures. These three trends became the three basic attributes of ‘big data’—i.e. volume, velocity and variety, which are known as the three basic v-attributes of big data. The official definition of ‘big data’ namely is: ‘high-volume, high-velocity and high-variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making’ (Gartner 2013a).

Thus, ‘big data’ as a concept serves to describe the management problems, IT needs and economic opportunities organizations face as a result of business process digitization, the expansion of the digital economy and the proliferation of internet-mediated human activities. The attribute ‘big’ serves to emphasize the need for deploying and relying on database management systems with very high processing capacity. From an information system perspective, we may say that ‘[b]ig data is when the size of the data becomes part of the problem’ (Magoulas and Lorica 2009: 11). In other words, the IT infrastructure necessary to handle data changes as a function of data size. This definition can also be considered appealing from a computer science perspective as ‘it scales’: the attribute ‘big’ indicates a different magnitude depending on the period of time we are considering. In the 1960s, big data was a couple of megabytes. Nowadays big data can be in the order of terabytes or petabytes. Probably in the near future ‘big’ will indicate yottabytes.

Besides volume, velocity and variety, some commentators have suggested adding other v-features to the definition of big data (BigData Startups 2013). Attributes such as *value* and *variability* would indicate two very relevant aspects of big data, which are respectively the creation of economic value and the presence of statistical variance in the data. *Big data analytics*, which indicates the application of data mining techniques to large databases, is the tool used to convert information into actions able to generate revenue, efficiency gains or market expansion.

The capacity of analyzing big data increasingly becomes a business differentiator: there are companies who outperform their peers thanks to their ability to apply analytics to their own data. These companies are known as *analytical competitors* (Davenport and Harris 2007). There are also companies that make profits by analyzing data for other organizations. Within this article, these companies are called *analytical deputies*. In fact, not all organizations have the IT resources or staff with the necessary mathematical skills to handle ‘big data’. They often need to buy, or to subcontract to other companies, data management and data mining services. Analytical competitors and deputies can be considered good examples of how *dataveillance* is used by private companies to succeed in the marketplace. *Dataveillance* can be considered a complex set of technologies and social practices that contributes to the production of socio-technical change (Bijker 1997).

Dataveillance, a concept originally forged by Roger Clarke (1988), refers to the systematic monitoring of people or groups, by means of personal data systems, in order to regulate or govern their behavior. In this article *dataveillance* specifically indicates the ability of reorienting, or nudging, individuals’ future behavior by means of four classes of actions: ‘recorded observation’; ‘identification and tracking’; ‘analytical intervention’; and ‘behavioral manipulation’. I particularly focus on the third category, i.e. analytical intervention. The multiplicity of goals achieved through analytical intervention will be presented as well as its relationship with other categories, particularly recorded observation, identification and tracking. In this way, I aim to unveil some of the complexity hidden in the ‘big data’ debate by describing the connection between data accumulation, knowledge generation and value creation, which is often obtained by producing a small change in people’s actions.

Dataveillance activities and their relationship with Big Data

‘Big data’, considered by some the new path to technological progress and economic welfare, presupposes the deployment and implementation of information systems enabling the creation and collection of digital data. These systems, which represent already mundane parts of everyone’s daily existence (Lyon 2001), make bureaucracies and organizations function, and let people participate in the life of modern societies (Lyon 1994). Among several distinctive attributes and functionalities embedded into the modern information systems that contribute to the achievement of these goals, surveillance is certainly the most ubiquitous, pervasive, and contested one.

Surveillance—literally to watch over (Lyon 2007)—refers to the act of keeping a close watch over someone or something: a form of supervision performed through monitoring. The performance of this type of action, present across societies and eras, is often considered ‘a necessary evil’ that raises complex ethical paradoxes (Sewell and Barker 2001). Discerning the positive and negative aspects of surveillance is not only a conceptually challenging exercise, it may also produce limited results such as long lists of potential harms and benefits, rather than a deeper understanding of important sociological processes or mechanisms of contention (McAdam et al. 2008), such as escalation and demobilization of social movements groups’ identity formation or people’s resistance toward surveillance.

In order to reconcile the coercive and caring aspects of organizational surveillance (Sewell and Barker 2006), it would be useful to stop using surveillance as a blanket idea and to start unpacking those set of actions, and the relationships among them (Abbott 2007), forming the observation engine. If we believe that surveillance is all about the establishment of power relationships (Monahan 2011), and we are keen on understanding under what conditions being under surveillance produce a sense of alienation and domination (Fuchs 2011), we need to apply highly specific concepts and work on the articulation of their internal dimensions. For all these reasons, this article explores data surveillance, i.e. *dataveillance* (Clarke 1988), and its constitutive parts. The article also expands the original definition of the concept to comprehend the effects *dataveillance* may have on human behavior. The original definition of mass *dataveillance* referred only to *the systematic use of personal data systems in the investigation or monitoring of the actions or communications of groups of people* (Clarke 1988: 499). Here mass *dataveillance* indicates *the systematic monitoring of people or groups, by means of digital information management systems, in order to regulate or govern their behavior*. Finally, four categories of action define *dataveillance*. These are: 1. recorded observation; 2. identification and tracking; 3. analytical intervention; and 4. behavioral manipulation.

Recorded observation refers to the act of paying close attention—by watching, listening or sensing—to someone or something in order to gather and store this information in electronic format. Closed-circuit television (CCTV) systems are typical examples of technologies conceived to perform recorded observation. Sensors, such as motion or temperature sensors which detect vibrations or determine environmental temperature, are also examples of devices performing recorded observation. Recorded observation plays a key role in modern digital economies as it contributes significantly to increased data volume.

Identification alludes to the recognition of an object, or a person’s identity, through the analysis of an object, or a person’s unique features. *Tracking* refers to the possibility of tracing, or chasing, an object, or a subject, once each of them has been identified. Biometric technologies, such as iris recognition, or fingerprint scan, are typical examples of surveillance technologies developed to identify people. These technologies transform personal attributes, such as iris composition or fingerprint appearance, into unique digital codes. Radio-frequency identification (RFID) tags or bar codes are examples of technologies developed to identify and track objects. Passports or ID cards are traditional examples of means developed by national governments to identify people. Unique identifiers, which are numeric codes used to distinguish one record from another in a database, are another example of tools developed to identify and track either an object or a subject. From a big data perspective, identification may help tackling issues raised by data variety, as it enables the organization of different types of data through data matching, while tracking may contribute to data velocity, as it allows organizations to collect updated data about an object or a subject in real time.

Analytical intervention refers to the application of *analytics* to the transformation of the collected information into knowledge, usually as a result of the first two types of actions mentioned above. *Analytics* indicates the analysis of so-called ‘raw’ data in search of patterns, and the consequent transformation of these results into the kind of knowledge decision makers need to optimally orientate

their course of action, also known as ‘actionable’ knowledge (Gandy 2012). Thus, analytics is what connects ‘big data’, in logical and practical terms, with value creation. More specifically, ‘[a]nalytics is the process of developing actionable insights through problem definition and the application of statistical models and analysis against existing and/or simulated future data’ (Cooper 2012: 3).

It is worth noting that the term ‘actionable insights’ indicates a form of discernment generated to produce an action, rather than a theoretical description or comprehension of a phenomenon. Accordingly, the term ‘intervention’ gives emphasis not only to the active role played by analysts in creating the new knowledge, but also to the potential for change embedded in the knowledge created. It is important to remember that there is nothing ‘natural’ or ‘indisputable’ in the inferences made about the data analyzed. In fact, ‘everything about information is artificial’ (Lanier 2010: 140) and relying on mathematical models or statistical methods does not guarantee that the knowledge created is undeniable or truthful. Although the insights analysts derive from data are based on rigorous analytical procedures, they should not be considered neutral or objective realities. A complex mix of hidden intentions, systematic and random errors, partial information or biased visions of the problem, contributes to making this new knowledge as situated and partial as any other type of knowledge. The same algorithms developed to analyze data should be treated as contested, situated objects of inquiry (Barocas et al. 2013). Although analysts know the limits of the methods they apply and the limitations of the results they have produced, problems may emerge when the knowledge created is taken as absolute truth, squeezed into recommendations, and transformed into public policies or business decisions. When the knowledge produced through analytical intervention is translated into organizational strategies, procedures and practices, we are observing the last and most controversial category of action of dataveillance—i.e. behavioral manipulation.

Behavioral manipulation indicates the ability of influencing people’s actions intentionally. Organizations look for ways to translate the attribute ‘actionable’—mentioned above in ‘actionable insights’—into some sort of ‘doing’ (e.g. a policy, a procedure, or a technological artifact) able to nudge people’s behavior in a desired direction. The initiatives taken by organizations to orientate individuals’ actions are here defined *performative expectations*. More specifically, performative expectations indicate set of assumptions, or even theories, explaining the relationship between individuals’ prospective and desired behavior, and the sort of voluntary initiative undertaken by organizations to obtain that behavior. Of course not all effects produced by the initiatives undertaken on the basis of the knowledge generated through analytical intervention are intentional. A large array of unintended consequences, unexpected individuals’ reactions may also emerge from the implementation of performative expectations and may contribute to influencing people’s behavior in unforeseen ways.

Despite the fact that the definition of *performative expectations* draws inspiration from Callon’s (1998, 2006) definition of performative discourses, the concept is meant to describe a specific reality where tools, such as economic incentives, graphical layouts, policies and procedures, are used to align actual behavior and expected behavior for the sake of the organization or person who is performing the alignment. This concept differs also from the role of expectations in the context of science and technological innovation described by the sociology of expectations (Brown and Michael 2003; Brown et al. 2003), for the latter focuses specifically on the ability of future promises to influence and steer present actions, especially innovation policy actions.

Although the explanation of behavioral manipulation provided explicitly focuses on people’s behavior, the chemical and physical behavior of objects, as well as the behavior of animals or other biological organisms, can also be included in the definition. As a matter of fact, there is an indiscriminate application of dataveillance along the entire supply chain: inanimate objects and animate subjects are treated as interchangeable parts of the same optimization function. The driver and the truck represent a typical example of how humans and machines have their behavior and their performance equally monitored and influenced by organizational procedures. Analytical intervention and behavioral manipulation can be

applied to improve any kind of organizational process: from indoor plants' growth or chickens' egg production, to call center workers' performance (e.g. Ball and Wilson 2000).

The rest of this article is devoted to explaining, through examples, how organizations use dataveillance to achieve their business objectives, focusing on the four sets of actions already presented. Each category of action complements and contributes to the success of other categories through a feedback loop (see figure 1). Surveillance devices proliferate as effective data gathering tools. They strongly contribute to data accumulation and to the 'big data' phenomenon. Once data are created and organized into databases, they can be analysed in search of patterns. The knowledge generated from data analysis informs the creation of policies and procedures, which quite often are intended to orientate people's behaviour. The end of each cycle represents the beginning of a new cycle: after some recommendation is implemented, new information is collected, analysed and transformed into new recommendations.

In order to understand each dataveillant category of action, the next section presents various examples of business practices ascribable to the dataveillant logic. Examples are reported in the same language used in official business reports. The positive or even emphatic tone sometimes adopted is not attributable to the author but to the original source of information, namely organizational websites or the business press.

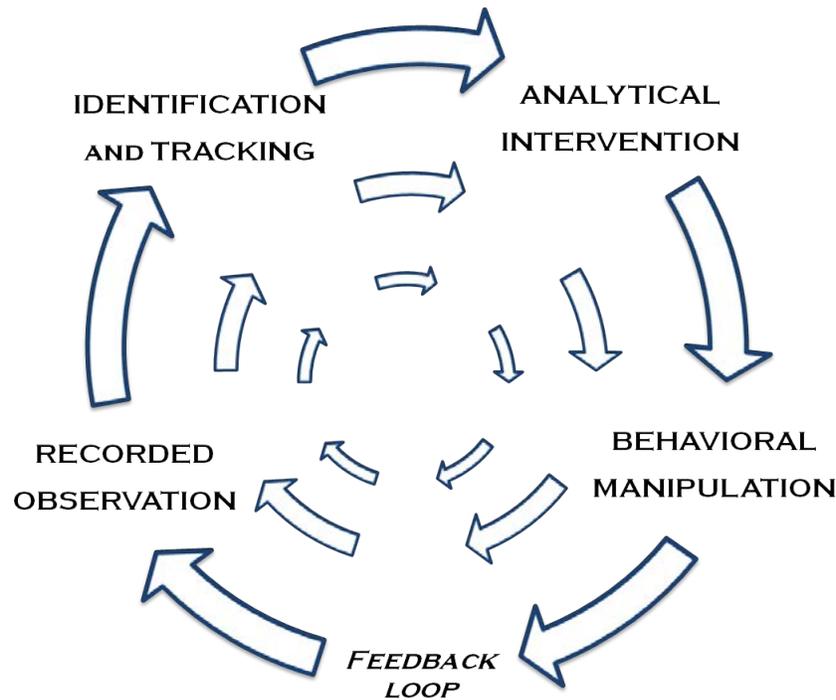


Figure 1. Relationship among the four categories of actions of dataveillance

Examples of dataveillance application and use

Corporate priorities deeply influence the way surveillance is enacted in modern societies (Ball and Snider 2013) and dataveillance is instrumental to organizations' achievement of highly relevant objectives. Workforce recruitment and retention, long-term customer loyalty, supply chain efficiency, security risk prevention, are just few examples of what can be achieved by means of dataveillance. In order to understand dataveillance and appreciate the multiple ways dataveillance serves corporate objectives, it is important to consider in more detail the four classes of activities described above.

Recorded Observation

Digitization (the conversion of an image, document, or sound to digital form) and the effects of Moore's law (Moore 1964) (particularly diminishing storage costs) have contributed to transforming dataveillance into a cheap, effective way to govern organizations. Nowadays any kind of information produced within an organization can be harvested to reconstruct people's activities in great detail. As the following examples demonstrate, data accumulation is often celebrated in business discourses as a promising path to economic success.

The American corporation *Caesars Entertainment*, whose brands include *Harrah's*, *Caesars Palace*, and *Paris Las Vegas*, collects data on almost any activity a customer can perform at their establishments, from gambling, to eating, drinking, attending a show, staying in a room, and so forth. Data are collected as a result of the company's *Total Rewards* loyalty card system, which collects data on over forty-four million clients, representing 80 per cent of their customer base (Gallaughier 2013).

EyeSee Mannequin, produced by the Italian company *Almax*, uses facial recognition technology to "observe" who is attracted by [a company's store] windows and reveal important details about [a company's] customers: age range; gender; race; number of people and time spent' (Almax 2013). *Almax* is also testing voice recognition applications to listen to what shoppers say about mannequins (Roberts 2012). *Almax* Chief Executive Officer Max Catanese claims that retailers can use the dummies as long as they have a closed-circuit television license (Roberts 2012). Companies who bought or ordered the products (worth 4,000Euro or 5,130USD) want to remain anonymous, while companies who have not purchased the mannequins have rushed to deny any involvement.

The US telecom giant *Verizon* in 2011 filed a patent for a set-top box that uses 'a depth sensor, an image sensor, an audio sensor, and a thermal sensor' to detect whether a user is 'eating, exercising, laughing, reading, sleeping, talking, singing, humming, cleaning, playing a musical instrument, performing any other suitable action, and/or engaging in any other physical activity during the presentation of the media content' (RT 2012).

Organizations use recorded observation as a means to get to know their customers' habits better. Thanks to the information collected about people's actions and reactions (as part of *recorded observation*), organizations can send targeted advertising and personalized promotions (typical activities of the *behavioral manipulation* category) to customers whose profiles have been created by means of *analytical intervention* (Spangler 2003). This is not only an example of how dataveillance can be used to increase sales, but also reveals some of the complementarities among dataveillance categories and provides insight into the rationale behind data harvesting.

Identification and tracking

Swipe card entry systems are the typical example of an identification tool widely used by organizations. Their main purpose is to guarantee that only authorized staff is granted access to a company building. However, many organizations also use the information collected through swipe cards to monitor personnel working hours. Whether the technology is used only as an identification tool, or also as a tracking device, is an organizational decision and often employees have limited chances of voicing their concerns and can easily be captured into a web of ubiquitous monitoring devices. The example of the truck driver represents an exemplary case of constant tracking.

Cemex, of Monterrey, Mexico, was one of the first companies to equip its concrete-mixing trucks with computers and GPS locators in order to reduce cement delivery time to construction sites. In 2013, *UPS* redesigned its drivers' route structures through the ORION initiative (*On-Road Integrated Optimization and Navigation*). This massive operations project analyzed information such as truck speed, direction,

braking, and drive train performance collected through telemetric sensors installed on 46,000 UPS package cars (Davenport and Dyché 2013). *Schneider National*, a multi-national trucking company based in Wisconsin, USA, decided to go further and piloted a project to predict which drivers may be at greater risk of a safety incident. The idea was to produce a score by applying predictive analytics to its sensor and driver's data and initiate a pre-emptive conversation with the driver before the 'supposed' incident occurred (Davenport and Dyché 2013).

From an organizational perspective, people and objects are equally subject to the logic and rules of dataveillance. Loyalty cards, a typical example of a voluntary identification and tracking tool, function as customers' ID cards: they allow for the identification of customers by matching their purchasing history and promotion responses with their identities and characteristics. Customers who opt-in to loyalty programs are supposed to be informed about the way their data will be used. David Norton, former senior vice president of relationship marketing at *Harrah's Entertainment*, clarifies this point by saying that, in order to prevent a customer backlash, a company must be absolutely transparent and explain to the customer the value-proposition up front and set rules for what can be done with data (Davenport et al. 2007). The reality is that very often customers sign contracts they do not read and give their consent to data processing without being fully informed (Hoback 2013).

The underlying assumption is that people would accept to be monitored if they can gain something. The problem with dataveillance, as any form of surveillance, is that it represents an intrinsically asymmetrical relationship: one part, usually the company or the government deploys and controls the system, while the other part, either the employee or the customer, must accept terms and conditions imposed by dataveillance in order to participate in the transaction.

Analytical Intervention

Analytical intervention not only identifies specific tools and practices, but it also represents what we may call the hurricane eye of digitization. On the one side, recorded observation through the proliferation of digital devices and the multiplication of types of activities that can be performed through digital media—from dating to networking—is helping big data get bigger. On the other side, all this information would have virtually no value if there were no tool, or no analyst, able to make sense of all these data. The quality of the insights extracted from big data, and their implications for action, is what principally makes the big data debate so interesting nowadays.

If we want to understand how 'big data' can become '[t]he next frontier for innovation, competition, and productivity' (Manyika et al. 2011), we need to understand how the variability of big data can be transformed into economic value. The key to unlocking the true potential of big data is analytics. While big data will probably reach, in five or ten years, a peak of inflated expectations, tools such as predictive analytics are already paying off and demonstrating their market relevance through mainstream adoption (Gartner 2013b).

Analytical intervention can help organizations achieve many different objectives, from customer acquisition and retention to supply chain optimization; from scheduling or routing optimization to financial risk management; from product innovation to workforce recruitment and retention. Analytical intervention is a transformative force. By means of analytical intervention, subjects with similar profiles are clustered into groups, predictions about future trends are made, and the degree of association between events can be established.

Analytical intervention can be used by any functional area within organizations. From operation to personnel management, analytical intervention helps organizations become more efficient and more profitable. Analytical intervention is also applied by companies operating in very different sectors. Michael Lewis (2003), for example, tells the story of *Oakland Athletics'* General Manager Billy Beane,

who pioneered the use of baseball players' statistics—such as base runs, defensive runs saved, runs created, batting average on balls in play, etc.—to scout players often overlooked, or undervalued, in order to assemble a competitive baseball team. Using analytics to recruit workforce and manage employees' performance is becoming an established business practice. Personnel management is an area full of analytical applications: employees' behavior and their performance are constantly monitored and measured through many types of surveillance devices (i.e. CCTV, swipe cards, phone calls, ICT use, GPS tracking, etc.).

However, the area where analytical intervention is most widely used is certainly marketing. Analytical intervention can be used, for example, to identify a product's optimal price, which is the profit-maximizing price or, in most of the cases, the highest price a customer is willing to pay—a practice known by economists as first-degree price discrimination (Acquisti 2008). A typical example of second-degree price discrimination is the possibility of choosing first class on a train or a plane. Finally, 'in third-degree price discrimination, merchants assign differential prices to different consumer segments based on some observable group characteristics' (Acquisti 2008: 21). Consumers may find such practices unfair and may oppose this practice (Englmaier et al. 2012). Quite often consumers are not aware they can be charged different prices and it is usually unpleasant to discover it. This event is clearly described in this blog post:

Amazon is quoting me a higher price than it's quoting my friend, on the same product. I knew this was theoretically possible, of course, but I didn't realize online stores engaged in these practices much these days. After all, is it really worth annoying customers when they find out? After a bit of experimentation, it seems to me that what's going on here is that those with a Prime membership are being quoted a higher price. Ouch. So the thanks I get for paying for the Prime membership and shopping at Amazon a lot is higher prices. No thank you.

(Hargittai 2008)

The way people react is highly dependent on the degree of transparency of the price at which the goods or services are sold and on the presence of alternative purchasing channels. In the case of revenue management, a form of price discrimination typical of hotels and airlines, customers often know they are playing a sort of price roulette, but they also feel they cannot escape the 'bargaining with the machine' reality (Pallitto 2013). The more third-degree price discrimination practices become an industry standard, the more customers are invited or forced to play by its rules.

Marriott International Inc., a leading hospitality company headquartered in Maryland, USA, with more than 3,800 properties and 19 hotel brands like the *Ritz-Carlton Hotel*, determines the optimal price for guest, conference facilities and catering. The company applies a revenue opportunity model that computes actual revenues as a percentage of the optimal rates that could have been charged (Davenport 2006). Although the system offers recommendations about the price that should be charged, local revenue managers can override the system's recommendations when certain local factors impossible to predict, such as bad weather conditions like a hurricane, occur.

As the example of the bottle of water in the desert demonstrates, demand, more than cost, is what determines price. Marketing professor Katherine N. Lemon notes how 'analytics enable firms to understand how poorly they can treat individual or group customers before those people stop doing business with them' and claims marketing should investigate and pay more attention to the 'unintended and un contemplated use' of customers' information (Davenport et al. 2007: 44).

Price discrimination strategies can exclude consumers from transactions, by targeting only certain categories of customers while excluding others—a practice known as redlining (Danna and Gandy 2002).

Yet, as long as companies can gain a profit, the possibility of assessing customers' future prospects can also allow companies to offer services to segments of the market previously excluded. In the case of insurance companies, high-risk customers can be charged a higher price, while low-risk customer could get a discount.

The North American auto insurance firm *Progressive*, for example, manages to profitably insure customers in traditionally high-risk categories like young motorcycle riders. Customers are divided into narrow groups, or cells, such as motorcycle riders ages 30 and above with a college education, credit score over a certain level, and no accidents. Then, analysts perform regression analyses to identify factors that most closely correlate with the losses each group engenders (Davenport 2006) and apply simulation software to test the financial implications of these hypotheses. *Progressive* then sets the price for the cells in such a way as to enable the company to earn a profit across a portfolio of customers groups, which may imply that a customer in a high-risk cell may pay a premium price that compensates the lower price paid by a customer in a low-risk cell. These assessments are often performed by matching information gathered by external providers, such as credit score or past traffic incidents, with information owned by the company.

As further explained in the section on 'analytical intervention champions,' analytics can be used in a large variety of ways within organizations to transform data into recommendations for action and, then, profit. Analytical intervention can even be used to create products and services. For example, *Google* uses smart phones as sensors to determine traffic conditions. In this application *Google* reads the speed and position of millions of cars to construct the traffic pattern and select the best routes for those asking for driving directions (Economist 2010).

Analytical intervention champions: analytical competitors and analytical deputies

Analytical competitors and analytical deputies have the resources and willingness to hire that critical mass of analysts needed to leverage data. The main difference between these two types of companies is that analytical competitors analyze their own data, while analytical deputies analyze data on behalf of other companies. In both cases analytics become a key competitive capability, and internal IT and human resources are devoted to create an analytical culture within the organization. In fact, the use made of data by companies depends on firm employees' skills and management data-driven attitude (Manyika et al. 2011).

The American firm *Procter & Gamble* has a centrally managed so-called 'überanalytics' group, which consists of more than 100 analysts from such functions as operations, supply chain, sales, consumer research, and marketing (Davenport 2006), which represents a typical example of how analytical competitors put analytics to work. Sometimes companies have too much data and need to create partnerships with external analytical deputies to better understand their data. In 2011 the American multinational retail corporation *Wal-Mart* decided to share consumer sales data with *AC Nielsen*—a global marketing research firm—despite the risk of making this information also available to competitors, hoping to gain a better understanding of their customers' need for both the retailer and its suppliers (Troy 2011).

Analytical Competitors

Companies who outperform competition by relying on 'analysis, data and systematic reasoning to make decisions' are referred to as analytical competitors (Davenport et al. 2010: 4). This type of enterprise is characterized by an integrated IT infrastructure enabling employees and analysts to get access and analyze different types of data, coming from different sources, in real time. Resources are devoted to ensure that data are clean, accurate, secure and relevant. In fact, 'good data is the prerequisite for everything analytical' (Davenport et al. 2010: 19).

C-level executives have a strategic vision of the use of—and resources devoted to—analytics across the enterprise. These IT-‘savvy’ CEOs (Haggerty 2012) are keen on making fact-based decisions. As reported by Haggerty (2012), exemplary IT-savvy CEOs are: Lorenzo Zambrano of *Cemex* in Mexico; Robert ‘Bob’ McDonald, retired *Proctor & Gamble* Chairman of the Board; or Toshifumi Suzuki, CEO and President of *7-Eleven* Japan. The typical attitude of this type of CEO is well explained by the words of Rollin Ford, executive vice president and chief administrative officer for *Wal-Mart* Stores: ‘[e]very day I wake up and ask, “how can I manage data better, analyze data better?”’ (Economist 2010).

Analytical competitors also hire people with the necessary mathematical and statistical skills to analyze data. Analytical professionals, who ‘create advanced analytical applications by developing statistical models and algorithms to be used by others in the organization’ (Davenport et al. 2010: 93), are also called *data scientists*. The head of the unit is usually known as *Chief Scientific/Science Officer*. These people typically have an advanced education in computer science, computational physics or biology, which granted them very good programming capabilities (Davenport et al. 2012). Yet analytical competitors also employ analytical semiprofessionals, who ‘apply the models and algorithms developed by professionals on behalf of the rest of the business’ (Davenport et al. 2010: 94).

Finally, analytics support a distinctive capability within the organization. The focus usually is on one or a maximum of two functions. Analytics can be equally applied to achieve different purposes: from an increase in sales to improved operational efficiency, from financial risk management to personnel screening, from information security to suppliers selection. There are seven main functional areas analytics can serve (see figure 2). These are: (1) pricing; (2) customer selection, customer loyalty, and customer service; (3) product and service quality; (4) research and development (R&D); (5) supply chain optimization; (6) management of human capital; (7) financial performance management.

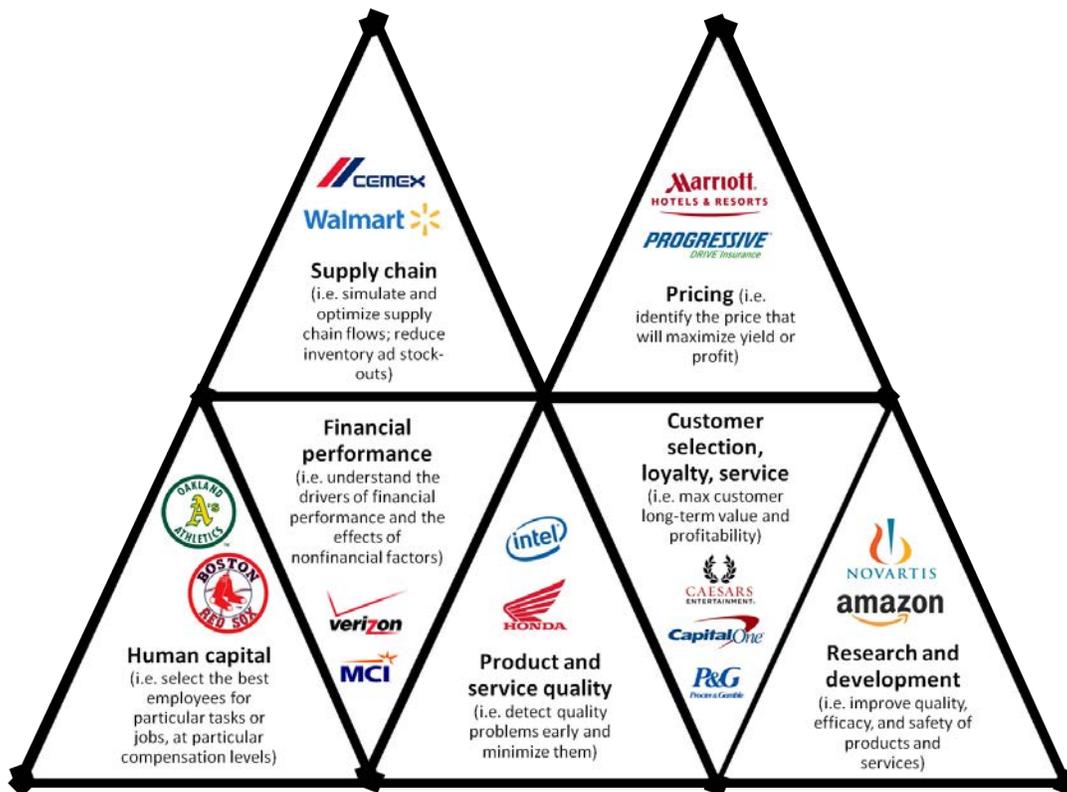


Figure 2. Examples of analytical competitors' analytical capabilities. Source: author's elaboration of Davenport and Harris (2007).

Analytical Deputies

Analytical deputies are what the business press calls ‘data crunchers’. If a company has the data, but not enough analytical resources, it can benefit from the services and products offered by businesses specialized in analytical solutions, such as *Retention Science*, based in California, USA, which produces customer retention and marketing automation software. As explained by *Retention Science* co-founder Jerry Jao:

Big data simply means business intelligence at a larger scale. [...] We’re building Retention Science to help businesses make sense of data more easily and turn data into actionable campaign recommendations. [...] Retention Science focuses on the data points that will positively increase the accuracy of our recommendations to our clients. [...] Whenever we engage a new client, we set experimental and control groups so we can clearly measure our benefits and focus on improving our results. We leverage machine learning technology to continuously improve our algorithms so we can make more accurate campaign predictions to help our clients maximize customer retention.

(Bloomberg 2013a: 1)

The business jargon used by Jao can be decoded as follows: Retention Science will identify those relevant aspects (‘data points’) of a company’s product or service which influence a customer’s willingness to keep buying those products or services (‘customer retention’), and will transform this knowledge into a plan for action for their clients (‘actionable campaign recommendations’). The plan for action will contain not only individually-tailored offers and promotions, by using the program ‘Intelligent Pricing’ for example, but also predictions—based on a ‘Customer Profiling Engine’—about future purchases (Bloomberg 2013a).

However, analytical deputies do not help other organizations just with their marketing data. Large organizations with many employees have to efficiently manage information about workforce schedule and performance. *Journyx Inc.*, based in Texas, USA, automates payroll, billing, and cost accounting activities for government contracting, energy, pharmaceuticals, and business services markets worldwide. It offers a Web-based time-tracking solution for employee time tracking called ‘Journyx Timesheet’ and modules for resource scheduling that tracks resource usage across projects called ‘ProjectXecute’ (Bloomberg 2013b).

Yet not all companies have the resources and human capital to use analytics. Despite this fact, these companies are taking advantage of big data as well, as explained in the following section.

The profitable un-analytical market for data

Finally, companies who own data but have neither the intention nor the ability to develop their analytical skills can increase their revenue by simply selling data. Any company managing business-to-customer transactions can easily become a huge repository of customer data. A manager interviewed by Davenport and colleagues expressed very clearly how valuable customers’ data can be for retailers: ‘we make more money selling data to retail data syndication firms than we do selling meat’ (Davenport et al. 2010: 8). The market for data, as we may call it, which originates from digitization of business activities, helps to financially support and complement several traditional business models, from grocery retailers to novel e-commerce activities. For example, information about *Party Pieces* website’s clients is usually sold to other businesses interested in sending female-related promotions to affluent women with young children (Schlesinger 2010). *Party Pieces* is a British company owned by the family of Kate Middleton, Prince William’s wife.

The market for personal data often relies on customers’ lack of awareness of its functioning to keep working. Customers seem to accept the reality of the market for data as long as it produces only direct marketing campaigns. Yet the issue becomes much more controversial when ‘a shopper’s grocery purchases ... directly influence the availability or price of her life insurance products—and not necessarily

in a good way' (Davenport et al. 2007: 44). The negative and discriminatory effects of these practices on people's lives are certainly not new to surveillance scholars (e.g. Gandy 2009), but they are not given much attention by many people working in the business industry.

Behavioral manipulation

The last, most ethically contested part of the dataveillance engine is certainly behavioral manipulation. This is the phase when the 'actionable insights' gathered as part of analytical intervention are transformed into initiatives or artifacts conceived to modify people's behavior. The term 'manipulation' is used intentionally to indicate a change of behavior caused, partially or entirely, by external factors that may or may not be recognized by the persons whose behavior is targeted. The term 'manipulation' does not say anything about whether or not behavioral manipulation is influencing people's lives positively or negatively. Analytical intervention and behavioral manipulation can be used equally for public policy reasons or for marketing and business reasons. Whether they are used to increase public health, by for example discouraging smoking cigarettes, or to increase sales, by, for instance, encouraging the consumption of a certain alcoholic beverage, the term 'manipulation' only indicates that people may be not completely aware that they are part of an experiment, and the implications may be not fully understood by the organization who is performing the experiment. As a matter of fact, technological devices may alter human behavior in many ways.

When I work with experimental digital gadgets, like new variations of virtual reality, in a lab environment, I am always reminded of how small changes in the details of a digital design can have profound unforeseen effects on the experiences of the humans who are playing with it. The slightest change in something as seemingly trivial as the ease of use of a button can sometimes completely alter behavior patterns.

(Lanier 2010: 13)

However, as mentioned in the first section on analytical intervention, organizations, especially business organizations, are more interested in reaching their targets than in fostering scientific discovery. Garry Lyons, chief innovation officer at *MasterCard*, New York, USA, explains the company's 'digitally agnostic' attitude toward product innovation, saying that,

[A]ny device is potentially a device of commerce, enabling the user to buy what they want from within the content without having to leave the content. There is no reason why *ShopThis!* couldn't be rolled out when watching a movie or video. You see an actor who has a nice shirt on, you activate *ShopThis!*. This is an example of incubation where we move quietly, test, learn, iterate.

(Stout 2013: 2).

MasterCard's ShopThis! lets shoppers buy items directly from digital magazines. Condé Nast's *WIRED* was the first publication to offer the *ShopThis!* with MasterPass technology to its readers on October 15, 2013, with the November iOS tablet edition (MasterCard 2013). *Ebay* and *Amazon* have initiated similar services and *Google Shopping Express* is currently available for California residents. In-content purchasing is meant to satisfy a customer's immediate desire to buy something. Whether this practice leads to instant gratification or contributes to the development of compulsive behaviors, such as shopping disorders, are emerging empirical and ethical questions. The effects of in-content purchasing on media and film production have not been foreseen yet. Whether people want consumerism to be embedded in any digital device is not just an open question, but also a question about the future we are imagining and bringing into being.

Therefore, behavioral manipulation becomes, probably, one of the most challenging and interesting aspects of dataveillance. Certainly it is the most relevant aspect from an organizational perspective: the

actual value of big data and analytics can be found in the effectiveness of the recommendations given at the behavioral manipulation stage. These recommendations may sound innocuous—‘does your company want to sell more? Send these personalized promotions, change the layout of your website, change the slogan of your ads,’ and so forth—or they may sound frightening depending on the objective pursued and on the vision of the problem offered.

Incentive and reward systems employed within organizations to increase performance can be seen as forms of behavioral manipulation schemes. Employees not only accept being constantly monitored, they also adapt their behavior to fit organizational expectations in order to have the chance to gain wage increases or to be promoted. Dataveillance and its categories of action are not only ways to achieve strategic organizational goals, but also tools for managing and governing organizations internally.

The future of big data and dataveillance

Dataveillance, with its emphasis on data accumulation and analysis through recorded observation and analytical intervention, is actively contributing to the demand for the automation of standardized tasks. Automation brings advantages to both consumers (Nawrocki 2013) and organizations (Hale 2012). Artificial Intelligence (AI) systems are widely applied to authorize financial transactions, to schedule manufacturing operations, to configure software, or even to diagnose medical problems (Waltz 1996). Data mining agents, for instance, are computer programs designed to identify patterns in specific sets of data and to trigger alarms when required (Janssen 2013; wiseGEEK 2013). They have the ability to automate repetitive tasks and work autonomously and continuously in an established software environment. Article 15 of the European Union Data Protection Directive (EC 1995) protects citizens from being subject to decisions ‘based solely on automated processing of data intended to evaluate certain personal aspects.’ Nonetheless, people must know they have been subject to an automated decision process in order to complain.

As some commentators have already envisioned, all the information gathered through recorded observation will ultimately feed into ‘intelligent’ machines which will, sooner or later, answer questions like a super-human being. IBM has already demonstrated that machines can play certain games better than humans. In 1997 ‘Deep Blue’ defeated Garry Kasparov, the world chess champion, while in 2010, ‘Watson’ won *Jeopardy!*—an American television game—by answering clues with its machine-synthesized voice and thanks to millions of documents, including dictionaries and encyclopedias, that consumed four terabytes of disk storage (Jackson 2011). Currently, there are plans to employ Watson to help health care providers in deciding how to treat patients (Upbin 2013). Gartner Inc. expects 10 per cent of computers to be learning machines by 2017 and revenues earned by IBM for Watson to account for 10 per cent by the end of 2018 (Thibodeau 2013).

Software and algorithms are socially constructed, which implies that humans enjoy absolute freedom in deciding how to design and change them. Of course, this is true as long as people manage to be imaginative and avoid ‘lock-in’ processes.

SOFTWARE EXPRESSES IDEAS about everything from the nature of a musical note to the nature of personhood. Software is also subject to an exceptionally rigid process of ‘lock-in’. Therefore, ideas (in the present era, when human affairs are increasingly software driven) have become more subject to lock-in than in previous eras.

(Lanier 2010: 12)

The degree to which persons, and particularly data analysts, are constrained by the software they use or the algorithms they develop are open empirical questions. So are questions about the implications of behavioral manipulation and analytical intervention for people and societies. My aim in examining the

phenomenon of ‘big data’ through the lens of dataveillance has been to reconstruct the business logic of data accumulation, helping people reformulate these problems and think about alternative ways to address them.

Conclusions

The ‘big data’ debate is mainly characterized by marketing talk: vendors of IT solutions explain to their business clients how to build and profit from the creation of a ‘big data’ environment, while providers of analytics solutions offer examples of how the algorithms they develop have helped their clients in many ways, from improving customer retention to increasing supply chain efficiency. Yet, the ‘big data’ debate is also populated of advocates who come from the public and non-profit sectors. ‘Big data’ is then presented as the new panacea to most human problems. It may help scientific discovery, offer early warning of disease contagion, help prevent illegal activities, and foster the understanding of societies and humans in completely novel ways. Projects such as *The Human Face of Big Data* (Smolan and Erwitte 2012) try to give a visual understanding of how ‘big data’ applications can help tackle several societal problems. Besides the many proclaimed advantages, ‘big data’ implies the deployment of new surveillance-based data gathering technologies, and the wide use of algorithms and profiling procedures that have unexplored social implications.

The present article has been an attempt to shed light on the relationship between three different yet related ideas: big data, dataveillance, and analytics. From workforce monitoring to customer profiling, the number of applications and inventions that incorporate embedded surveillance functionalities is not only growing, but spreading throughout both the private and the public sector. The optimization logic is applied indiscriminately to both humans and machines. Increasingly, algorithms and machine learning applications become the only viable way to make sense of this huge amount of data. However, we should not make the mistake of considering data accumulation a simple technology-driven affair. A relevant portion of big data comes from the growing reliance on dataveillance to achieve organizational goals.

Despite the relevance of the topic, any serious discussion about where the data come from, why and by what means this information is collected, and what kind of implications *big data* may have for the future of our societies, is still very limited. In particular, the mechanisms through which data are collected, and the ultimate purpose and rationale behind continuous data gathering and observation, are made invisible and are not part of the debate. This lack of clarity prevents us from understanding whether big data should be considered as simply a fad (Abrahamson 1991) and what quality of innovation big data is creating. It also reinforces the persistent tendency to consider technology in neutral terms. From an agnostic standpoint, a technology is an equal-opportunity enabler (Schmidt and Cohen 2013): it can be used to achieve good as well as bad ends, depending on the intentions of the people who are using it. If we look at ‘big data’ and analytics through the lens of dataveillance, though, we look beyond a narrow view of technologies as having positive or negative effects and see them as part of socio-technical systems: situated objects, embedded into social and economic relationships, informed by thoughts, interests and beliefs.

Dataveillance, as presented in this article, traces the connection between seemingly unrelated facts: the accumulation of data, the proliferation of sensors, and the unnoticed modification of individual habits. The articulation of this concept helps us identify potential technological lock-ins, future trends, and alternative scenarios. Thus, this article also represents a call for further research, especially with regard to three specific questions that need to be asked when assessing a technological artifact contributing to the dataveillant engine: How does a specific surveillance technology end up being the standard? What are the implicit assumptions about personhood and human nature embedded in this technology? And how is this technology changing people’s identities and their mutual relationships?

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