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Big Data exclusions and disparate impact: investigating the exclusionary dynamics of the Big Data phenomenon

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Dissertation submitted to the Department of Media and Communications, London School of Economics and Political Science, August 2014, in partial fulfilment of the requirements for the MSc in Media, Communication and Development. Supervised by Dr Ellen Helsper.

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Published by Media@LSE, London School of Economics and Political Science ('LSE'), Houghton Street, London WC2A 2AE. The LSE is a School of the University of London. It is a Charity and is incorporated in England as a company limited by guarantee under the Companies Act (Reg number 70527).

Big Data exclusions and disparate impact: investigating the exclusionary dynamics of the Big Data phenomenon

Charly Gordon

ABSTRACT

In the past few years, there have been seemingly endless hopes and claims made about the potential benefits of Big Data for society. The phenomenon has spurred the publication of countless media reports and fostered significant academic research in a variety of fields. However, despite this abundance of literature, the Big Data phenomenon suffers from considerable research gaps. Specifically, there has recently been a growing interest in the social consequences of Big Data with particular attention given to the phenomenon's potential to aggravate structural inequalities.

This study offers an inquiry into the phenomenon's impact in terms of social exclusion and its potential for harmful discrimination. By conducting semi-structured elite interviews, this paper seeks to assess the apparent contradiction between Big Data's dynamics of exclusion and the dominant conceptual projection of Big Data, which often portrays the phenomenon as inclusive and beneficial for society at large. To this effect, it seeks to investigate how those who hold a privileged position in the field of Big Data appraise the phenomenon's exclusionary dynamics as well as critically assess their recommendations on how to tackle Big Data's negative social externalities.

First, this study highlights the importance of conducting additional research on how digital exclusions may impact the phenomenon as the marketplace and the public sphere are increasingly remodelled by Big Data. Second, it underlines the urgency to tackle the glaring power asymmetries between those who create data trails and the organizations that have the ability to collect, store and analyze digital data. Policy initiatives should focus on creating an environment in which individuals can collectively regain bargaining power as well as on encouraging projects bent on insuring greater awareness and transparency in the data economy. In addition to Open Data initiatives, research in human-data interaction may offer a promising path to achieve greater individual control over data creation mechanisms and data portability.

INTRODUCTION

In the past decade there has been a growing fascination in industrialized countries for the potential benefits and pitfalls of Big Data. The phenomenon has given rise to much debate in a variety of fields of study (i.e. economics, computer science, journalism etc.) as well as in business, government and in the wider civil society. The ability to collect, store and analyze digital data in ways not possible just a few years ago has sparked intense discussions of what has now become a buzzword in the media and in the private sector. The phenomenon has been powered by the combined proliferation of digital devices and the surge in computing capacity that henceforth make it possible to process ever increasing amounts of data. Individuals spur this huge increase in data through the digital devices they operate and by an array of networked sensors embedded in physical devices. The latter, dubbed the 'Internet of things', is now complementing user-generated data with a growing number of devices that emit data independently.

'Big Data' is, in many ways, a vague term. Its definition varies depending on the context of inquiry and very often 'Big Data is less about data that is big than it is about a capacity to search, aggregate and cross-reference large data sets' (Boyd and Crawford, 2012: 663). It is often defined as 'high-volume, -velocity and -variety information assets that require cost-effective, innovative forms of information processing for enhanced insight and decision-making' (Gartner, 2014). This definition, first outlined in 2001 (Douglas Laney, 2001), has driven and structured many of the inquiries into Big Data to date. It considers two key aspects. First it highlights the underlying technological infrastructure that enables data analysis: 'Big Data is a term applied to data sets whose size is beyond the ability of commonly used software tools to capture, manage, and process the data within a tolerable elapsed time' (Manovich, 2011: 1). Second, the definition emphasizes the economic potential of these technologies 'designed to economically extract value from very large volumes of a wide variety of data' (Eastwood, Olofson and Villars, 2011: 3).

However, this technology-centred and value-driven definition offers a truncated image of the phenomenon. Indeed, the scope of this definition is too limited as it fails to encapsulate the social, ethical and cultural dimensions of the concept. Rather, the Big Data phenomenon rests 'on the interplay of:

(1) Technology: maximizing computation power and algorithmic accuracy to gather, analyse, link, and compare large data sets.
(2) Analysis: drawing on large data sets to identify patterns in order to make economic, social, technical, and legal claims.

(3) Mythology: the widespread belief that large data sets offer a higher form of intelligence and knowledge that can generate insights that were previously impossible, with the aura of truth, objectivity, and accuracy' (Boyd and Crawford, 2012: 663).

Like all technologies whose disruptive potential throws a shroud of mystery over their uses and outcomes, Big Data has given rise to social imaginaries that develop both utopian and dystopian rhetoric. It is often highlighted that tremendous benefits can stem from the insights of Big Data, like advances in medicine, transportation, education and improved product offerings among others. However, to consumers and citizens, the phenomenon is also often reminiscent of an Orwellian dystopia with the fears of privacy invasion, loss of liberty and increased corporate and state control. A survey conducted in twenty OECD and non-OECD countries found that for over 75 per cent of consumers in a majority of countries, the privacy of personal data is the most important issue (Dean, Kalapesi and Rose, 2013). It is no surprise then that the technical and legal corollaries of privacy and data security have been at the forefront of research when analyzing the negative externalities of Big Data.

Yet, there has recently been a growing interest in the social consequences of Big Data with particular attention given to the phenomenon's potential to aggravate structural inequalities. 'We must begin a national conversation on Big Data discrimination, and civil liberties' (Podesta, 2014: 64) states a report recently released by the Obama administration. The United States Federal Trade Commission has also launched a workshop to 'examine the potentially positive and negative effects of Big Data on low income and underserved populations' (Ramirez, 2014). Nevertheless, the study of the social consequences of Big Data has so far remained at the periphery of contemporary debates and much of the research on these topics has not yet gone beyond an exploratory phase.

This study offers a multidisciplinary inquiry into the exclusionary dynamics of Big Data. Specifically, the objective of this dissertation is two pronged. First, it attempts to structure and analyse the fragmentary literature on the social consequences of Big Data in terms of social exclusion and its potential for discriminatory outcomes. Second, by conducting semi-structured elite interviews, it looks to:

(1) Investigate how those who hold a privileged position in the field of Big Data appraise the phenomenon's social impact;
(2) Critically assess their recommendations on how to tackle Big Data's negative impact in terms of social exclusion and discriminatory outcomes.

LITERATURE REVIEW

> Our big data economy needs to be developed such that it promotes not only a sphere of privacy, but also the rules of civility that are essential for social cohesion and broad-based equality (Jerome, 2013).

The literature available on the empowering effects of Big Data seems endless. Many have called the phenomenon a 'game-changer' (Lund, *et al.*, 2013) and a 'revolution' (Kolb, 2013) that is 'sweeping, almost invisibly, through business, academia, government, healthcare, and everyday life' (Smolan and Erwitt, 2012: 3) and will ultimately 'transform how we live work and think' (Cukier and Mayer-Schonberger, 2013). Provided that industry and government allay privacy concerns, these 'Big Data evangelists' (Richards and King, 2013) are adamant about the phenomenon's ability to unleash a new era of prosperity for society at large. Though many of the techno-optimists' promises have yet to materialize, the ability to access and process large data sets in order to rationalize decision-making has already proven valuable for businesses and governments.

Governments are resorting to Big Data analysis to curb spending, improve service delivery, and detect fraud while increasingly opening their data to the public sphere. By leveraging their data, businesses have the ability to better predict market trends, optimize their supply chain and better segment their customer base, which can lead to a competitive advantage and greater sales (McKinsey Global Institute, 2011). However, the question of whether the Big Data phenomenon is inclusive or exclusive is one that has so far remained at the periphery of contemporary debates. Many proponents of Big Data fail to mention the phenomenon's negative social externalities in terms of social exclusion and its potential for harmful discrimination. This literature review is voluntarily wide in scope and builds on various fields of inquiry as it seeks to structure and analyze the fragmentary research conducted to date on these particular aspects of the Big Data phenomenon.

The Big Data gap and data driven exclusions

Debates over the negative externalities of Big Data overwhelmingly focus on the privacy and the civil liberties of those who are included in the data sets. This approach based solely on inclusion is coming under increasing criticism and deemed insufficient by many. 'Big Data poses risks also to those persons who are not swallowed up by it—whose information is not regularly harvested, farmed, or mined' (Lerman, 2013: 56). Moreover, because digital exclusions create a signal problem in data sets, data contextualization and transparency is paramount to avert negative social outcomes when decision-making is informed by Big Data.

The pitfalls of data invisibility

Whether in the private or public sector, decisions are increasingly being informed by Big Data. This is raising concerns as the ‘digital production gap’ (Schradie, 2011) may exclude certain populations from an environment increasingly shaped by Big Data. A number of researchers have therefore warned about a Big Data gap, which may deepen existing exclusions and create new ones (Lerman, 2013; Schradie, 2013; Crawford, 2013). A recent project conducted by the city of Boston helps shed light on this issue. The initiative, called ‘Street Bump’, sought to use data generated by drivers’ smartphones to locate potholes in the town’s streets. Every time the cars drove over a pothole, a smartphone application would register the location and send the data to Town Hall so the pothole could be fixed. However, this technical solution to a collective problem is reliant on smartphone ownership and use. In effect, the project only received data from neighbourhoods with a high smartphone penetration rate and populations with a high propensity to use these types of applications. Therefore, ‘if you think about how this might be used to fix roads, we might see a future where the wealthy areas with young people get more attention and resources, unlike the areas with older citizens, who might get fewer resources [...] So if you're off the map, this could have some really material consequences for social inequity’ (Crawford, 2013).

The world shaped by Big Data is increasingly calibrated for what Jonas Lerman calls the ‘electronically harvestable’. ‘It could restructure societies so that the only people who matter--quite literally the only ones who count--are those who regularly contribute to the right data flows’ (Lerman, 2013). As the marketplace and the public sphere are remodelled by Big Data, consumers and citizens who are not swept up in the Big Data net could face significant economic harm and find themselves excluded from various aspects of political life.

Jonas Lerman’s approach to the problem in 'Big Data and its exclusions', though novel, fails to encompass the full scope of this Big Data gap. His article stresses the importance of access to technologies to produce data trails. His analysis, like much of the early literature on the digital divide, tends to focus on a spurious dichotomy between the ‘haves’ and the ‘have-nots’. This strictly binary, access-driven and technology-centred approach does not consider the more complex and multifaceted nature of digital exclusions. In addition to inequalities of access, digital exclusions encompass ‘inequalities of awareness and use’ (Katz, *et al.*, 2001: 416) that tend to overlap with other forms of social exclusion. A multitude of factors (education, age, gender and culture) should be taken into account in addition to ICT (information and communications technologies) penetration rates. Furthermore, even when ICTs are available, the terms of access and use are highly dependent on socioeconomic and cultural factors. To adequately assess digital exclusions, it is essential to analyze the complex relations between all these factors, which are often community-specific (Warschauer, 2002).

In this context, the concept of 'Big Social Data' is particularly pertinent as it emphasizes the social environment in which the 'digital human' creates data (Coté, 2013). Research shows that there exists a persistent inequity in online creation along the lines of socio-economic class and ethnicity (Hargittai, 2007; Correa, 2010; Boyd, 2011; Schradie, 2012). 'Specifically, people with lower levels of income and education are not accessing or creating online content nearly as much as people with a college degree and a comfortable middle-class lifestyle' (Schradie, 2013). The risk here is if policy-makers, researchers or even journalists focus extensively on Big Data analysis they will tend to overlook issues central to populations that are less vocal online or that produce smaller data trails.

Furthermore, because a variety of assumptions are built into the data creation mechanisms, the terms of participation often favour those who engage in what Alice Marwick calls self-branding or 'the strategic creation of identity to be promoted and sold to others' (Marwick, 2010: 15). This is particularly visible with social media platforms where individuals who 'inculcate a self-conscious persona which positions self-promotion, visibility, and comfort with idioms of advertising and commercialism as positive, high-status virtues' (Marwick, 2010: 15) and who aptly market themselves can shape their self-image in a proactive way and make themselves heard. By contrast, populations less inclined to self-branding carry the risk of being left on Big Data's periphery, unable to reap many of its benefits.

Because the data encompassed by the Big Data phenomenon is diverse, multifaceted and context-specific, 'raw data is both an oxymoron and a bad idea; to the contrary, data should be cooked with care' (Bowker, 2005: 183-184). Yet, the ethos of the 'Petabyte Age' is taking Big Data analysis in the opposite direction.

The 'Petabyte Age' of data objectivity

A growing number of researchers are criticizing what they have dubbed 'data fundamentalism' and are underlining the importance of data contextualization and oversight. 'Internet sources are often unreliable, prone to outages and losses, and these errors and gaps are magnified when multiple data sets are used together' (Crawford, 2012). However, with the ‘Petabyte Age’ has come the myth of data objectivity: ‘with enough data, the numbers speak for themselves’ (Anderson, 2008). The Big Data phenomenon has given rise to ‘the widespread belief that large data sets offer a higher form of intelligence and knowledge that can generate insights that were previously impossible, with the aura of truth, objectivity, and accuracy’ (Crawford, 2012). This guarantee of certainty is often the trademark of technology industries and has very often driven the Big Data debate since its inception. Data is often portrayed as being natural, essential, neutral, and objective measures. This neo-positivist perspective, reminiscent of August Comte’s old adage of ‘savoir pour prévoir, afin de pouvoir’ (‘knowledge to predict, in order to act’), has led to what some have called ‘Big Data hubris’ (Lazer, *et al.*, 2014). The Google Flu Trends project offers an insightful illustration of this phenomenon. By aggregating the number of requests for certain search terms, Google Flu Trends seeks to provide ‘an estimate of current flu activity around the world in near real-time’. However, in February 2013, Nature assessed that the predictions of Google Flu Trends were significantly superior to those of the Center for Disease Control and Prevention, which bases its results on reports from US laboratories (Butler, 2013). Because the results offered by Google Flu Trends are in ‘near real-time’ (compared to those provided by US laboratories) there may be a temptation to act quickly on ‘estimates’ rather than on slower yet better tailored sources.

Extensive research is conducted using data from search queries or social media to examine social phenomena. For instance, because it is relatively accessible, Twitter has been very popular with a variety of actors, including scholars. Some have used it to analyze media event engagement (Shamma, *et al.*, 2010), others to study political engagement (Lotan, *et al.*, 2011), along with a flurry of other topics. Though many researchers highlight the limitations of their data, there is a risk that a lack of contextualization may lead to biased results. In this context, Grinberg *et al.*’s work on Hurricane Sandy is particularly revealing (Grinberg, *et al.*, 2013). In October 2012, over 25 million tweets about Hurricane Sandy were generated in as little as four days. However, a large majority of the tweets came from Manhattan, an area which did not bear the brunt of the storm. Very few tweets were posted from areas such as Breezy Point and the Rockaways, where the hurricane did the most damage. Therefore, ‘if we start using social media data sets to take the pulse of a nation, to understand what is happening in a serious crisis, or to actually allocate resources, we’re actually getting a skewed picture of what is happening’ (Crawford, 2013). This means that it is essential to properly contextualize the data in order to avert adverse social consequences when decisions are made based on partial findings from the data.

Yet the lack of transparency caused by data monopolization strategies often make it difficult to implement data oversight and adequately assess both the methodology and ethics of the research that is being conducted.

The adverse effects of data monopolization

Because access to data and the ability to draw meaningful inferences from it hold so much value, private actors have an economic incentive to create scarcity through monopolization strategies. Much of the data flows produced everyday are caught by a multitude of private sector organizations, making access to the data arduous or even impossible for outsiders. Policies regarding access to proprietary data vary from one company to another. Many organizations restrict access to their data completely while others may sell it, trade it or on some occasions offer small data sets for research purposes. Nevertheless this data insider-outsider dichotomy 'produces considerable unevenness in the system' (Boyd and Crawford, 2012). This may be problematic for three reasons. First, limited access to data may lead to a lack of methodological oversight, which is essential given the complexities and intricacies of data creation mechanisms. This lack of methodological oversight can have dire consequences when the sweeping claims made by what Kate Crawford calls the 'Big Data rich' are used to inform policy-makers. Second, the data insiders have the privilege of driving research agendas in a direction that suits their profit-seeking endeavours while making it difficult for outsiders to use the data for other purposes. This may harm certain research agendas (in particular critical research), causing a 'restricted culture of research findings' (Boyd and Crawford, 2012). Finally, recent events have shown how data monopolization may undermine much needed ethical oversight at a time when Big Data has greatly expanded the scope of human subject research (Booth, 2014).

The disparate impacts of the Big Data phenomenon

In addition to exclusions associated with data production and access, the Big Data phenomenon can have disparate impacts and further entrench structural inequalities within society. The data of consumers and citizens who are swept up in the Big Data net is increasingly used to build 'digital dossiers' (Solove, 2006) in an attempt to profile and rank individuals. These profiles can be ascribed as characteristics applied to other individuals, which may perpetuate bias or usher new forms of discrimination (Berendt and Preibusch, 2014). Therefore, certain industry practices are causing alarm as they may circumvent legal frameworks and create new forms of voluntary or involuntary discrimination.

Claims of Big Data discrimination

Organizations are increasingly looking to collect and link data on individuals (location data, purchasing behaviours, social media data, search engine queries etc.) to determine patterns that can be used to make informed predictions. This can determine the costs and opportunities linked to certain populations and direct policy-makers on how to interact with these populations (Marwick, 2014). The predictive potential of Big Data can be highly beneficial. For instance, if properly implemented, predictive analytics can help emergency personnel optimize their response during natural disasters, inform governments on how to properly allocate resources during an epidemic, or enable cities to rationalize traffic flows on their streets. However, by making predictions about individuals' likely actions and risks, analytics 'have the potential to eclipse longstanding civil rights protections in how personal information is used in housing, credit, employment, health, education, and the marketplace' (Podesta, 2014: 1).

The troves of data available often 'allows for granular distinctions to be made between individual characteristics, preferences and activities' and whether these 'distinctions are made for the sake of personalization, research or public planning, they facilitate discrimination based on a wide spectrum of characteristics' (Tele and Polonetsky, 2013: 355). These practices based on differentiation are raising concern among a growing number of researchers on their potential risks for new forms of voluntary or involuntary discrimination. Some believe they will lead to 'serious, concrete and devastating harm' (Ohm, 2012). Others are backing a more nuanced approach and highlighting the complexities of Big Data discrimination.

One of the major difficulties here is to determine where 'value-added personalization and segmentation ends and where harmful discrimination begins' (Schrage, 2014). Such an endeavour requires unpacking the highly connoted and culturally malleable term of 'discrimination'. In *Judged by the Tin Man: Individual Rights in the Age of Big Data*, the authors underline the complexity in dealing with the term: 'Discrimination could be socially desired (e.g., treating minors as children and not as adults); generally acceptable (e.g., applying Amazon's Recommendation system to enhance consumers' shopping experience); or morally reprehensible (e.g., not hiring individuals of a certain age or race). It is difficult enough to decide which forms of discrimination are illegal, deciding whether discrimination that is not illegal is unethical or morally undesired may become daunting' (Tele and Polonetsky, 2013: 356-357). Determining where value-added personalization ends and harmful discrimination begins is an eminently ethical enterprise founded on culturally dependent considerations.

Yet, in a paper entitled 'Big Data's disparate impact', still in draft version and set to be published later this summer, Solon Barocas and Andrew Selbst attempt to formalize a typology of Big Data analytics' possible harmful discriminatory outcomes (Barocas and Selbst, forthcoming). First, harmful discriminations may emerge when the data and its analysis leads to erroneous inferences. Here, decisions taken on the basis of the inference can have an adverse effect on the person or population it targets. Eli Pariser calls this 'a bad theory of you' (Pariser, 2011). Though the impact is limited if its sole consequence is to inadequately target an ad, erroneous results can have dire consequences in peoples' lives when they are related to healthcare, employment, credit or law enforcement. For example, between 2004 and 2006, the failure of automated systems that manage the distribution of state benefits in Colorado led to the misallocation of Medicaid funds and food stamps (Citron, 2007). It is also easy to imagine spurious inferences scaring off employers or misleading law enforcement.

Second, the inferences are correct but entail that certain people or populations are subject to adverse determination. This can be particularly problematic in the marketplace. Because individuals are considered higher risk or higher cost they may be subject to lower standards of customer service, be subject to unfavourable price discrimination schemes, have higher insurance premiums or be denied loans regardless of stringent industry regulation. Based on the inferences, marketers can tailor campaigns and promotions to build relationships with more profitable customers. 'Conversely, an immediate way to cut costs and preserve resources might be to discourage the least profitable and most costly shoppers' (Schrage, 2014) by increasing prices or reducing the level of service to create barriers. For instance, in *Paying the Wealthy for Being Wealthy: The Hidden Costs of Behavioral Targeting*, Laura Moy and Amanda Conley show how 'the costs to consumers of highly targeted marketing are likely borne disproportionately by those with the least disposable income' (Groman, 2013). Furthermore the use of alternative scoring techniques in regulated industries can undermine legal mechanisms that ensure fairness: 'The growing use of so- called 'e-scores' —a form of invisible (to the consumer) online ratings — can help determine our credit worthiness, 'lifetime value,' or even the prices we pay. These e- scores can be used to blacklist or engage in discriminatory practices against individuals or even groups of consumers' (Mierzwinski, 2014: 1).

Finally, ‘there are attempts to formally classify people along the line of protected classes’ (Barocas, 2014). The distinction here defines an individual or group along the lines of ethnicity, religion, gender, sexual orientation etc. Because explicitly tailoring products or services to the aforementioned considerations is often in blatant violation of antidiscrimination laws, industry practices use more subtle denominations that nonetheless have a possible disparate impact. An FTC inquiry into the practices of Data Brokers identified ‘marketing segments that focus on ethnicity, financial status, and health conditions. Examples of segments with apparent ethnic dimensions include ‘Metro Parents’ (single parents who are ‘primarily high school or vocationally educated’ and are handling the ‘stresses of urban life on a small budget’) and ‘Timeless Traditions’ (immigrants who ‘speak some English, but generally prefer Spanish’) (Brill, 2014). The FTC noted that although these practices do not infringe upon US antidiscrimination laws, it is clear that the categories can be used to treat consumers in a discriminatory way thereby entrenching structural inequalities.

Privacy monetization’s unequal outcomes

Because industry practices have desperate impacts, it is increasingly clear that today’s privacy policies are insufficient to tackle some of Big Data’s adverse social outcomes. A recent report from the European Network and Information Security Agency shows how a large majority of consumers prefer carrying out transactions with privacy-invasive agents provided that prices are lower (Jentzsch, *et al.*, 2012). However, like all commodities, consumers value privacy differently. Vulnerable socio-economic groups have more to lose from privacy invasion (see 'Claims of Big Data discrimination'), yet they are the ones that are the most inclined to dabble in the data trade for its short-term benefits (e.g. free online services, immediate promotions on entering loyalty programmes etc.). On the contrary, ‘the wealthy, better educated are in a better position to become the type of sophisticated consumer that can take advantage of Big Data. They possess the excellent credit and ideal consumer profile to ensure that any invasion of their privacy will be to their benefit; thus, they have much less to hide and no reason to fear the intentions of data collectors’ (Jerome, 2013). Furthermore, should wealthy consumers want to protect their data, they have the economic and cultural capital to adequately value their privacy, use data-privacy tools or pay for the premiums of privacy-friendly alternatives. Here too, ‘even assuming they can be informed about the value of their privacy, the poor are not in a position to pay for their privacy or to value it over a pricing discount, even if this places them into an ill-favoured category’ (Jerome, 2013). Therefore, it is essential for regulators to acknowledge the unequal outcomes of privacy monetization and the urgency of addressing power asymmetries and social inequalities in the data economy.

The myth of algorithmic neutrality

Finally, the risks developed previously may be further entrenched by the myth of algorithmic neutrality. With the Big Data phenomenon, many businesses and public actors 'foster an illusion that classification is (or should be) an area of absolute algorithmic rule—that decisions are neutral, organic, and even automatically rendered without human intervention—reality is a far messier mix of technical and human curating' (Dwork and Mulligan, 2013: 35). Algorithms are not neutral. The 'promise of algorithmic objectivity' (Gillespie, forthcoming) fails to consider the many assumptions built into the technology that may replicate biases with machine-generated results reflecting or amplifying different ideological claims. Astrid Mager, for example, argues that 'the 'new spirit of capitalism' gets inscribed in the fabric of search algorithms by way of social practices' (Mager, 2012).

Attempts to classify and predict behaviours are not neutral; they reflect the designers' purposes as well as their implicit values. This may be most visible in what some have called the 'search engine filter bubble' (Pariser, 2011). By making assumptions on past data, individually tailored search results can reinforce structural inequalities. This leads Solon Barocas to ask if these practices may result 'in a self-reinforcing and self-perpetuating system, where individuals are forever burdened by a history that they are encouraged to repeat and from which they are unable to escape' (Barocas, *et al.*, 2013). In a recent paper entitled 'Discrimination in online ad delivery', Latanya Sweeney has shown how ads with the word 'arrest' are displayed on Google's search results with greater frequency with black identifying first names than with white identifying first names. This raises the 'questions as to whether Google's advertising technology exposes racial bias in society' (Sweeney, 2013). This example clearly highlights how algorithms are first and foremost socio-technical constructions. When analyzing scoring algorithms, Danielle Citron and Frank Pasquale stress that 'the biases and values of system developers and software programmers are embedded into each and every step of development' (Citron and Pasquale, 2014: 14). However, few developers see algorithms as 'artefacts embodying moral and aesthetic choices' or recognize their role in modelling 'people's identities, aspirations, and dignity' (Bowker and Leigh Star, 2000: 4).

METHODOLOGY AND RESEARCH DESIGN

In order to acquire the most pertinent empirical data for my research, I chose to conduct semi-structured elite interviews. In this section, I will justify the methodological framework I used and clarify the interview process from its inception to the analysis of the data.

Rationale for method used

Why opt for qualitative semi-structured interviews?

The purpose of this study is exploratory in nature. It seeks to shed light on how specific aspects of a phenomenon, that have yet to be fully researched, are assessed by those who hold a privileged position in the field of Big Data. Therefore, my study is inherently qualitative and due to its exploratory nature, a semi-structured interview method was deemed appropriate. One of the strengths of this method is that it gives time and leeway to explore a variety of issues thoroughly. After specific topics in line with my research questions were evoked and discussed, loose, open-ended questions let the interviewees formulate answers with more freedom. This allowed them to drive the discussion towards issues they felt were important while enabling me to discover and tackle new issues (Bauer and Gaskell, 2000). Conducting highly structured interviews would have left less room for serendipity and would therefore have been detrimental to this research project. Furthermore, a face-to-face semi-structured interview methodology seemed particularly fitting given the potentially sensitive nature of the questions asked (Fielding and Thomas, 2008).

Defining 'elite'

To further structure my methodological approach I chose to analyse the Big Data phenomenon through the lens of Pierre Bourdieu's field theory. Although the phenomenon is diverse and multifaceted, Big Data can increasingly be seen as an independent sociological field where agents compete for power. Pierre Bourdieu identifies the field as 'a field of forces, whose necessity is imposed on agents who are engaged in it, and a field of struggles within which agents confront each other, with differentiated means and ends according to their position in the structure of the field of forces, thus contributing to conserving or transforming its structure' (Reed-Danahay, 2005: 32). By using Bourdieu's concept as a framework to understand power relations in the Big Data phenomenon it becomes possible to determine which actors have the legitimacy to speak and be heard. In other words, it can help determine which actors and whose discourse is predominantly driving the phenomenon and influencing the way Big Data is perceived. As a microcosm that is relatively autonomous from the wider social space, actors within a field value different types of capital. Acquiring this capital (whether economic, social or cultural) and mastering the specific rules of the field enable certain actors to gain a dominant position. It is precisely these 'elite' agents I am interested in for this paper. Due to their position within the field, they have extensive symbolic power or the 'ability to make people see and believe, to confirm or transform the vision of a phenomenon' (Bourdieu, 1991: 170). It is because these 'elite' agents have the ability to construct the reality of the Big Data phenomenon that they are central to this paper.

Particularities of elite interviewing

Before analyzing my sampling and my recruitment method it is important to look at some of the particularities of elite interviewing. Though elite interviews are more prevalent in journalism than in academia, many scholars have written about the intricacies of elite interviewing as a method of research in social sciences (Dexter, 1970; Merton, Fiske and Kendall, 1990; Ostrander, 1995; Odendahl and Shaw, 2002). In this research project, two aspects were particularly apparent during the course of the interviews. First, the interviewer must understand and master a number of codes specific to elite interviewing as such (e.g. rules of on and off the record) as well as those specific to the field of inquiry (e.g. industry jargon, codes of conduct, values and dispositions of the different actors etc.). Although I had to familiarize myself with codes specific to elite interviewing, I had already acquired a set of codes specific to the field of inquiry during previous professional experience. Second, there exists an issue regarding the power relations between the interviewer and the interviewee. By the very nature of elite interviewing, 'an interviewee, concerned with presenting his/her viewpoint may want to control and dominate the interview. If so, the interviewer may not be able to control the format, or direction of the interview' (Richards, 1996: 201). Therefore, it rapidly became apparent that a key skill in elite interviewing is the ability to redirect the discussion in accordance with the topic guide while maintaining a certain degree of flexibility. A number of other very concrete aspects of elite interviewing are mentioned in the following paragraphs, which focus on my research design.

Research design

Sampling and recruitment

To identify elite actors in the field of Big Data, I chose to contact professionals who had participated in Big Data related conferences in the past year. For convenience and because I have a preference for face-to-face interviews in the context of this research project, I contacted participants from Paris. These include professionals from both the private and the public sector. Nevertheless, I found that private sector actors were often disproportionately represented during these conferences. My sample tries to reflect this trend. I also tried to include individuals from large organizations as well as professionals from smaller start-ups. Therefore, I settled on a selection of participants that accounts for an appropriately diverse scope of perspectives (Bauer and Gaskell, 2000). I contacted over 30 professionals by email in June and conducted 13 interviews between 9 July and 29 July. The interviews lasted from forty-five minutes to one hour and fifteen minutes. The profiles of the participants are outlined in Table 1 below:

TABLE 1. Interviewee profiles

Interviewee	Organisation	Public/Private	Organisation activity	Interview Method
D. C. - Chief Market Manager Software Platform Development	Microsoft France	Private	Computer Software - Computer Hardware	Face-to-Face
L. H. - Category Marketing Leader Big Data & Analytics	IBM France	Private	Computer Software - Computer Hardware - IT Services	Face-to-Face
L. T. - Associate Director Big Data & Analytics	CSC France	Private	IT Services - IT Consulting	Face-to-Face
D. B. - Founder and director	Tinyclues	Private	Data Analytics - Predictive CRM	Face-to-Face
M. L. - Analyst - Big Data & Analytics	Octo Technology	Private	IT Consulting - Data Analytics	Telephone
M. N. - Associate Director Business Development	Synomia	Private	IT Consulting - Data Analytics	Face-to-Face
A. D. - Director	Nugg.ad	Private	Data Analytics - Predictive Behavioral Targeting	Face-to-Face
J. C. - Director Big Data Analytics	Quantmetry	Private	IT Consulting - Data Analytics	Telephone
H. P. - Principal Analyst, Serving Enterprise Architect Professionals	Forrester Research France	Private	Market Research	Telephone
P. N. - Founder and director	Decideo	Private	French Online Community of Data Scientists	Skype
T. C. - Marketing Innovation Manager	APEC	Not-for-profit Partnership	Business Partnership that offers executive HR consulting and services to its members	Face-to-Face
H. V. – Director of Etalab and France's newly appointed Chief Data Officer	Etalab	Public	Etalab is the Open Data Project of the French Government under the authority of the Prime Minister	Face-to-Face
F. M. - Expert in Digital Trust	French Ministry of the Economy	Public	Advisor to the Delegate Minister of Innovation and the Digital Economy	Face-to-Face

Design and research tools

To conduct the semi-structured interviews I relied on a topic guide (Appendix A) that I developed on the basis of a pyramidal model (Wengraf, 2001). Using this model, a number of themes were determined along the lines of my research questions and open-ended questions were further formulated. However, a certain amount of flexibility was needed as interviews rarely followed the strict order of the set and new issues were raised and discussed during the course of the interviews. Therefore, my topic guide was by no means set in stone, but rather a flexible guide that made sure all topics and questions were covered, however sinuous and surprising the route may be (Bauer and Gaskell, 2000). After briefly presenting my research project and the different topics it covers, I started by asking a number of introductory questions on the interviewee's organization and their role within it. I then let the interviewee decide on the trajectory of the interview while making sure all the questions on the topic guide were tackled. Adaptability is key during semi-structured interviews. Some interviewees prefer giving succinct answers to precise questions while other will 'think out loud' and discuss topics at length. I worked with Gillham's *Research Interviewing: the Range of Techniques* (2005) to ready myself for the interview process and master the complexities of combining different types of questions during the course of the interviews (probing questions, indirect questions, follow-up questions etc.). Because of the diversity of the profiles, probing and follow-up questions differed substantially from one interview to the other. I was also able to familiarize myself with these aspects of interviewing during a pilot study I conducted in March 2014.

For this research project, I favoured face-to-face interviews at interviewees' workplaces. This is due to the fact that very often professionals speak at conferences under the etiquette of their institution. This undoubtedly has an effect on their discourse and I attempted to reproduce this, though in a limited way, during the interviews. Furthermore, face-to-face interviews make it possible to be more connected with the interviewee (Gillham, 2005) and I found that interviewees were often more comfortable discussing certain topics when they were directly engaging with the interviewer in face-to-face conversation. However, here too, a certain degree of flexibility was needed. For practical reasons I had to conduct two interviews by phone and one interview by Skype. Although these interviews were highly informative, there were drawbacks due to the quality of the recordings.

Finally, all standard ethical procedures were followed in accordance with the 'LSE Research Ethics Policy' and I received full consent to record the interviews and use the transcripts for this paper.

Methodological caveats

Although semi-structured interviews were particularly adapted for this research project, the methodology has its own set of drawbacks. First, a certain number of constraints such as 'time, energy, availability of participants, and other conditions that affect data collection' (Strauss and Corbin, 1998: 16) can hinder the research process. Furthermore, because interviews are a social process, the data they produce is partly determined by the context of the interaction. Responses given by the interviewee are context-specific and are structured by the interviewee's assumptions about the research project and their interlocutor. This can introduce 'bias, error, misunderstanding or misdirection' (Holstein and Gubrium, 1997: 113). Indeed, during the course of the interview, meaning is continuously being mediated and reshaped by the context and social dynamics of the interaction.

For all these reasons, I tried to maintain a high degree of reflexivity at each stage of the research project in order to limit bias and remain mindful of the potential pitfalls of my sampling and interview strategies. For instance, a particular issue arose due to the fact that all the interviews were conducted in a French context. Research in this paper overwhelmingly originates in the United States where the regulatory context differs substantially from that of the European Union. Although this led to some insightful conversations, I had to remain mindful of the European and French regulatory context during the course of the interviews as well as when I analyzed the data. Furthermore, the results of this study are not generalizable as they only offer a glimpse of how Big Data elites in France assess the phenomenon. Finally, this raises the issue of language and translation. Because translation may lead to a partial loss of some of the subtleties of the responses, I worked with the French transcripts and only translated the quotes that are included in the dissertation.

Method of analysis

After transcribing the interviews, I conducted a six-stage thematic analysis (Guest, *et al.*, 2012). I first listened to the interviews and read through the transcripts several times to get an overview of the data and identify different patterns. These patterns were then used to generate the initial coding in order to organize the data under conceptual labels relating to the research questions. These codes enabled me to determine recurring themes in line with the theoretical framework for the study. After having identified a set of potential themes, I further analyzed these themes and determined that four broad thematic areas were of interest to this study. The results and the interpretation of the interviews are reported in the following paragraphs.

ANALYSIS OF INTERVIEWS

Introduction

During the introductory questions many interviewees acknowledged that the study of the social consequences of Big Data in terms of social exclusion has largely remained at the periphery of contemporary debate. ‘There hasn’t been much work done on these issues,’ noted P.N. of Decideo. Although many identified exclusionary dynamics in Big Data, they also often found that the concept might be too broad and its consequences (current or potential) too misunderstood to comprehensively tackle these issues. ‘I think Big Data is too wide. When people say they work with Big Data it doesn’t really mean anything. It’s like saying I work with electricity. There’s no technological unity in its applications,’ remarked D.B. of Tinyclues.

Analysing the concept of Big Data in itself is a challenge. Today, the term is used as a catchall phrase that covers many different realities. H.V. from Etalab claims that Big Data is based on two certainties. First, there are whole new areas of social life that can be datafied. Second, it has become a lot cheaper to store and analyze data. The difficulty in conceptualizing Big Data stems from the fact that it is used to describe both the increased datafication of social life and the technological apparatus used to analyze and gain insight from the data. ‘Many organizations use small data and only a few really qualify for what is commonly ascribed to Big Data,’ noted M.N. of Synomia.

Much of the data currently analyzed by organizations is internal data that is highly structured and analyzing external unstructured data often remains a daunting task. Many interviewees noted that the use of data, whether ‘small’ or ‘big’, is largely in an experimental phase. ‘Hyper-personalization, Internet of things, quantified-self… we’re still in very early stages’ underlined T.C. of APEC. He added that much of this experimenting is conducted in ‘marketing and advertising because unwanted consequences remain relatively harmless’. Although many disagreed with this, pointing to practices such as price discrimination, there was a consensus on the fact that there could be adverse social outcomes if and when the logic behind certain uses of Big Data are expanded to other sectors of the economy such as insurance, healthcare, education etc.

In addition, there was a consensus on the shortcomings of the regulatory framework to tackle both current and future challenges posed by Big Data. The European model posits the protection of 'personal data' as a fundamental right enforced by an independent administrative authority with the power to sanction illegal collection and use of 'personal data'. In France this is enforced by the CNIL [Commission National Informatique et Libertés]. However, the framework, based on the principles of data minimization and purpose limitation, is often ill-suited to effectively tackle these new challenges and is all but antithetical to Big Data, which is founded on data maximization. 'Since 1978 the CNIL looks at the purpose, the proportionality and gives its ok if the project is seen as legitimate, but you're not allowed to use more data than you need to achieve your objectives. This no longer works because data is harvested automatically on an unprecedented scale,' argued H.V. By definition, Big Data analysis is founded on the interconnection and centralization of as much data as possible. Furthermore 'Big Data's finality is imprecise since you look at correlations without stating explicitly where you want to go with the data,' added L.H. of IBM.

This creates a grey area that evades current regulatory frameworks: 'how can you make sure that from the raw data you're allowed to use you're going to inform a decision that you are allowed to inform? That's very complicated because the methods used to get to that information are notoriously difficult to describe. They won't always have the same results and they're built on various theories that are more or less rigorous. I don't think we can regulate that… because it's too abstract, too fluid,' claimed D.B. For these reasons, it was widely acknowledged that technical solutions to collect and analyze data often exceed the CNIL's ability to enforce certain crucial aspects of European regulation, particularly amidst the blurring of the concept of 'personal data'.

In the following paragraphs I will analyze my findings across the four broad thematic areas in line with my literature review and discussed during the course of the interviews.

The Big Data gap and the diffusion-of-innovation discourse

The digital production gap was mentioned at length during the interviews. Although many interviewees acknowledged inequity in online creation and its potential exclusionary consequences, they often rejected its long-term effects and saw it as a temporary phenomenon. Building on a diffusion-of-innovation approach, they often argued that the Big Data gap would subside as access to technology grew and uses were democratized.

Furthermore, because of the craze for Big Data in the private sector, 'data fundamentalism' was recognized as having potentially adverse social consequences as organizations increasingly use and rely on digital data to drive their activity.

> One of the great revolutions with Big Data is our increased capacity to measure and easily acquire data on various aspects of social life. We can measure social interactions that were previously in the shadows. But there's a catch. It's the fact that in our modern and scientific world, we lose interest in what isn't monitored or measured. In that sense, if you can't easily collect information on a population or on a subset of a population then there's a real risk that organizations or social actors might lose interest in these populations. The more we measure and monitor social life, the more we will lose interest in what isn't measured' D.C., Microsoft.

The digital production gap can have wide ranging consequences in terms of exclusion from the benefits of the Big Data phenomenon. Interviewees often stated that much of the data produced is skewed in favour of certain populations. This is particularly the case with Big Social Data. Because of the inequalities of access and the differentiated uses of data-producing technologies certain populations are set to reap more benefits from Big Data than others. These range from paying cheaper prices for better-tailored products or services to having greater influence in the marketplace. However, the Big Data gap is seen first and foremost as the result of a generational gap rather than the result of structural inequalities along the lines of socio-economic class and ethnicity. 'Digital natives have a different relationship to data creation,' argued M.L. of Octo Technology. 'Not only do they make better use of the technologies, they're also less concerned about their data being mined by various organizations,' added L.H. Therefore, many see the gap as temporary. As populations gain greater access to technologies and 'acquire the codes of use' (H.V., Etalab), more and more people will create the right data flows. This builds on a market-oriented, diffusion of innovation paradigm that has been dominant in digital divide policy. It posits that inequalities in access and use of technologies are temporary and subside as technologies become more and more widely available (Compaine, 2001). This analysis has been contested by a number of academics (Dutton and Helsper, 2007; Helsper, 2011), with many highlighting that 'any divide in accessing digital technology is not a one-time event but a constantly moving target as new devices, software and cultural practices emerge' (Crutcher and Zook, 2009).

In this context, the question of whether or not certain precautions are taken when data is analyzed by organizations was also addressed. 'One of the problems with Big Data is all the buzz around the phenomenon. Inferring the behaviour of a population by studying tweets is fundamentally biased. Twitter users don't represent Internet users and Internet users don't represent the wider population etc. There is a fundamental skew and certain companies have the feeling that because it can be measured it somehow becomes representative,' warned D.C. In addition to the digital production gap, he believes there is a gap in expertise in organizations to properly draw conclusions from these new sources of data. 'Data analysts are cross-referencing data that have nothing to do with one another, like Customer Relationship Data and Social Network Data,' he added. As a result, there is a risk that misinterpretation may lead to suboptimal decision-making and adverse social consequences. However, not all interviewees agreed as M.N. stressed that the non-representativeness of these new data, their poor quality and the challenges in making sense of them is often the number one reason companies remain sceptical about their use.

Big Data exclusions and discriminatory outcomes: a symptom of wider power asymmetries in the data economy

The crux of the problem regarding the Big Data phenomenon's social exclusions and discriminatory outcomes was linked to the wider power asymmetries in the data economy. The Big Data economy is characterized by profound power asymmetries between its actors.

Three classes of actors are present in the realm of Big Data: the individuals who create data by leaving data trails, the institutions who have the ability to collect and store the data, and the institutions who have the skill and expertise to analyze the data (Manovitch, 2011). The latter two groups, though small in number, hold the most sway. Because data and the ability to draw meaningful inferences from it hold so much value, actors have an economic incentive to create scarcity through monopolization strategies. These monopolization strategies are evident in both the retention of data and the monopolization of skills: 'in Big Data those who possess the most data are the ones who have the greatest power to innovate', noted D.C. Therefore, 'the question is really how certain actors take hold of the data and the technologies. Of course there are organizations that are trying to monopolize the Big Data phenomenon,' insisted H.V. Many interviewees acknowledged that the skills and human capital needed to create value from the data are increasingly monopolized by a small number of actors. 'In particular, I know that in the Valley, at Berkley, at Stanford, people are a little worried because the best researchers, they all go work for Google. And yeah they go because their salary is multiplied by two or three but really they go because they're told… and no true researcher can resist this… you'll be able to access and manipulate 100 times more data' (H.V., Etalab).

However, interviewees were often more struck by the glaring information asymmetries between major actors and individuals due to the growing lack of transparency on how data is harvested, retained and used. Paradoxically, there are also 'more and more actors, more and more intermediaries, and it's getting harder and harder to really trace the movement of the data and ultimately how it is used', stated L.T. of CSC. This leads to what Mark Coté calls 'data motility' or how the data created by individuals increasingly moves autonomously of their control (Coté, 2013). Consumers are largely unaware of what data they have created, how they have created it, who may have access to it and how it is being used. Furthermore, although consumers have the right to access, modify or suppress data, they very rarely exercise these rights rendering these mechanisms all too often inefficient. According to H.V., 'data motility' and the lack of transparency over the outcome of the technologies is leading to the further euphemizing of power. Thus, analysing the Big Data phenomenon through the prism of Gilles Deleuze's 'société de contrôle' ('control society') and further building on Michel Foucault's concept of biopolitique could therefore be a highly enriching path for further research.

The information asymmetries between major actors in the data economy and individuals often make it very difficult for individuals to uphold their rights. This led many interviewees to underline the shortcomings of the recent application of the 'right to be forgotten'. 'Greater transparency will create a more serene environment, not just offering the possibility for some, more informed or with greater cultural capital, to remove data from time to time,' criticized P.N. These dynamics undermine the very 'ideological linchpin of a market economy' that is consumer sovereignty (Manzerolle and Smeltzer, 2010) and highlight the urgency of what F.M. of the Ministry of the Economy called the 'enlightened collective negotiation' in the Big Data economy, echoing Antonio Casilli's appeal for the 'launch of collective negotiations' (Casilli, quoted by H.V.).

Calls for consumer sovereignty and greater data transparency

Many interviewees underlined the difficulty in applying traditional proprietary concepts to data creation mechanisms. The individual ownership of data is challenging for two reasons. First, because of the non-exclusive nature of data, traditional proprietary models can't apply. The very nature of digital data evades all of the proprietary concepts of the French legal system underlined F.M. Therefore, it is difficult to envision a legal solution that reinforces individual control over the use of their data through ownership mechanisms. Furthermore, ‘there is a real problem in the valuation of data,’ stressed L.T. An individual’s data on its own holds very little value. It is only once it can be crossed with multiple sources that it becomes valuable. In addition, individuals are often unaware of which data are being harvested by organizations – ‘we don’t know what it is exactly we’re selling when we’re creating data trails,’ added F.M. Nevertheless, interviewees acknowledged that regaining consumer sovereignty is paramount to avert the negative consequences linked to digital exclusion and Big Data’s disparate impacts.

In their article 'Big Data for all: privacy and user control in the age of analytics', the authors suggest that ‘individuals must be offered meaningful rights to access their data in a usable, machine-readable format’ (Tene and Polonetsky, 2013: 242), in order to place the individual at the epicentre of data flows. This belief has fostered research in what has been dubbed ‘Human-Data Interaction’ (HDI). HDI ‘arises from the need, both ethical and practical, to engage users to a much greater degree with the collection, analysis, and trade of their personal data, in addition to providing them with an intuitive feedback mechanism’ (Haddadi, *et al.*, 2013: 3). It aims to give individuals greater control over the visibility, scope and use of their personal data all along the data supply chain. Ultimately, HDI’s ambition is to enable people to regain sovereignty over the signals they emit and how their digital image is used. It ‘aims to understand both raw and derived data out there about individuals, the way in which and by whom they are used, and how people might desire and act to influence and ideally benefit from the data and their use’ (Mortier, *et al.*, 2013: 1).

The concepts of consumer sovereignty in the data ecosystem and HDI have been at the heart of various projects like ‘ProjectVRM’ (Vendor Relationship Management’) from the Harvard Berkman Center, which looks to ‘provide customers with tools that provide both independence from vendor lock-in and better ways of engaging with vendors—on terms and by means that work better for both sides’ (Berkman Center for Internet and Society, 2014). Many interviewees saw great opportunity in the concept of Vendor Relationship Management. ‘We can really work on empowering individuals by granting them access to their data and let them determine the type of service they wish to have by accepting certain transfers of data to different organization in a conditioned, temporary and reversible way,’ stated H.V. ‘I think these are the political struggles we need to engage in in the future,’ he added. A.D. of Nugg.ad pointed to start-ups like Personal.com that are also building business plans on the idea that both individuals and companies can benefit from consumer access and control of personal information (Kang, *et al.*, 2012).

Furthermore, it is essential that individuals regain control over the inferences that are drawn from their personal data and the decisions that these inferences inform. By disclosing the rationale behind their decision-making process and clearly establishing how personal data is used, companies have the possibility of building greater trust with their consumer base at a time of heightened consumer angst over privacy invasion. Ultimately, increased transparency and consumer sovereignty would create the conditions for greater data quality by preserving its contextual integrity, would ensure better inferences as well as greater oversight from regulatory bodies and would enable consumers to collectively regain bargaining power in the data economy. However, interviewees recognized that these mechanisms of consumer empowerment would suffer first and foremost from a lack of awareness and understanding in the data economy from both the political class and the wider civil society. 'If data was open to consumers, how many would really engage in these practices,' asked L.T.

The difficult case for algorithmic accountability

In conjunction with consumer sovereignty, certain authors have been making a case for algorithmic accountability. This, in turn, is raising a number of questions on the nature and extent of the oversight of these often-complex proprietary tools. 'The analytics algorithms themselves must become less opaque – what data are they consuming, what methods are they using to draw inferences. This is often in direct tension with the fact that these processes represent core intellectual property of the companies that implement and run them, and so cannot easily be made public' (Mortier, *et al.*, 2013: 1). Numerous authors who have attempted to study settings where algorithms are central have criticized their secrecy and inscrutability (Hargittai, 2000, Van Couvering, 2007). However, it is believed that greater scrutiny would 'discourage unethical, if not illegal, classifications and provide individuals with the due process opportunity to challenge decisions made about them by algorithm-driven machines' (Tene and Polonetsky, 2013: 263). In addition, because they formalize and systematize decision-making mechanisms, it seems that algorithms could be a godsend for due process.

However, delving into the black box of algorithmic rule raises a number of challenges that have yet to be fully addressed. First, their complexity may often hinder attempts to unpack their rationale. Many interviewees underlined the difficulty in establishing methods of algorithmic oversight in the case of Big Data analytics. 'Who really understands how they work', asked M.L. 'There are just a handful of people who really know how they function and with the development of machine learning, nobody understands what's really going on, not even the developers', he added. This raises another issue. Many patterns and correlations detected by Big Data analytics may be counterintuitive and making sense of the result may prove difficult. 'Usually the models are in line with our intuition, often with greater precision, but sometimes they go against our intuition. We're sometimes tempted to change our decision because of counterintuitive results… but it's difficult,' recognized D.B. Even though French law requires human intervention when individuals are impacted by automated decision mechanisms, how does one reverse a potentially adverse outcome if it is difficult to make sense of the mechanism that lead to that result? D.B. underlined yet another issue: 'There is another paradox that is difficult to explain. Imagine that an insurer wants to identify the 10 per cent of people who have five times more risk in order to determine a price discrimination scheme. In reality there isn't just one algorithm that can determine the 10 per cent of the population and the different algorithms might point to relatively different populations. How then do you understand equity when you have to arbitrarily decide between two results that are both technically valid?'

This particular example further highlights how algorithms are often difficult to diagnose and their outcomes problematic to challenge. A number of other challenges have recently been underlined in an article entitled 'Governing algorithms: a provocative piece' (Barocas, *et al.*, 2013). Given the multitude of economic sectors and environments in which algorithms are deployed, is the expertise needed to diagnose them context-specific? Who should have the authority to carry out such diagnoses? Furthermore, as the number of actors increases between developers and the final users (data brokers, user experience designers etc.), it is increasingly difficult to identify the party responsible for the technology's adverse outcomes. It appear clear, however, that putting too much emphasis on algorithmic accountability runs the risk of fetishizing a technology and deferring responsibility of its adverse outcomes on an abstract or complicated notion. Therefore, it may be constructive to shift the focus from algorithmic accountability to the power relations involved in the construction of these algorithms.

CONCLUSION

This study has aimed to explore the social consequences of Big Data and the phenomenon's potential to aggravate structural inequalities. It offers a multidisciplinary analysis of the exclusionary dynamics of Big Data by building on the concept of social exclusion. First, this study sought to structure and analyze literature on the social consequences of Big Data in terms of social exclusion and its potential for discriminatory outcomes. Second, it looked to investigate how those who hold a privileged position in the field of Big Data appraise the phenomenon's social impact and furthermore to assess their recommendations on how to tackle Big Data's exclusionary dynamics. To achieve this, semi-structured elite interviews were conducted over a period of a month in Paris. Thus, this study offers a snapshot of how French elite actors in the Big Data field evaluate the exclusionary dynamics of Big Data in a French and European regulatory framework. Nevertheless, given the large quantities of research data acquired, the interviews offered a range of opinions from which it was possible to draw a number of findings.

First, although a number of academics have been warning of the pitfalls of data invisibility and the potential adverse effects of the Big Data gap, many interviewees saw this exclusionary mechanism as temporary. Building on a diffusion of innovation model, they often argued that digital production gaps would subside, as greater access to technologies would enable individuals to create the right data trails. This techno-centric and market-oriented approach has been criticized by a number of researchers and underlines the need for further research on the impact of digital exclusions as the marketplace and the public sphere are increasingly remodelled by Big Data.

Second, a majority of interviewees identified the blatant power asymmetries in the data economy as responsible for Big Data's adverse social externalities. Because data monopolization strategies hinder oversight mechanisms and undermine consumer sovereignty, many interviewees recognized that it was becoming increasingly urgent to launch collective negotiations between the different actors in the data economy. To tackle 'data motility', interviewees mentioned various empowerment mechanisms, which focus on greater transparency and individual control over the signals they emit and the inferences that are drawn from their personal data. However, they were quick to underline that these mechanisms would suffer from a lack of awareness in the wider civil society and that a number of challenges had yet to be addressed to properly implement such policies. Similarly, implementing greater algorithmic accountability was seen as highly problematic due to algorithms' increasing autonomy and the difficulty in creating efficient oversight mechanisms.

To conclude, this study underlines the importance of tackling the growing power asymmetries between those who create data trails and the organizations that have the ability to collect, store and analyze digital data. Thus, policy initiatives should focus on creating an environment in which individuals can collectively regain bargaining power as well as foster projects bent on insuring greater awareness and transparency in the data economy. In addition to strengthening Open Data initiatives, the budding field of human-data interaction may offer a promising path to achieve greater individual control over data creation mechanisms and data portability. However, additional research is needed to address HDI's many challenges. These include consumer data visualization and making sense of complex mechanisms as well as the nature of the technical infrastructure and the institutional framework to drive such interactions.

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APPENDIX A: Topic Guide

Interview Topic Guide

Title: Big data exclusions and disparate impact: investigating the exclusionary dynamics of the Big Data phenomenon.

Project description: The Big Data phenomenon has given rise to much debate in various academic fields as well as in business, government and in the wider civil society. It is often highlighted that huge benefits stem from the insights of Big Data, like advances in medicine, transportation, education and improved product offerings among others. However, the study of the social consequences of Big Data has so far remained at the periphery of contemporary debates. This project analyses the Big Data phenomenon through the prism of social exclusion and addresses the various mechanisms by which the use of Big Data leads to unequal social outcomes. By conducting semi-structured elite interviews of Big Data professionals, this dissertation seeks to shed light on how elite actors in the field of Big Data assess the phenomenon's exclusionary dynamics and furthermore how they believe these dynamics might be addressed.

1- Introductory Questions

Can you start by giving me additional information on your organisation's activities?

What is your role within the organisation?

2- Defining Big Data

The term of Big Data is everywhere. It's a catch all phrase in the media, it's a sales argument in the private sector, it is source of angst in the wider society etc. What is it exactly, how would you define it?

Can you unpack the concept? What is the nature of the phenomenon?

What are the major issues regarding Big Data in your organisation today?

In your opinion, what are the major challenges linked to Big Data today in developed countries?

3- Big Data's benefits to consumers and citizens

Can you spell out how Big Data and Big Data analytics can benefit consumers and citizens?

Which conditions must be met for Big Data to benefit society at large?

4- Big Data and social exclusions

In your opinion, is Big Data an inclusive or exclusive phenomenon? Is the Big Data phenomenon today socially empowering?

Do the benefits mentioned previously, that stem from Big Data and Big Data analytics, impact all consumers and citizens in the same way? Is it fair to say that there are winners and losers in Big Data? Why?

Can digital exclusions have an impact on Big Data's social outcomes? Can this entrench existing inequalities? Can it create new ones? If so, how can this be adequately addressed?

Can the categorization of individuals lead to new forms of discrimination? Can behavioural targeting have discriminatory outcomes? If so, how can this be adequately addressed?

Do power asymmetries in the data economy lead to adverse social outcomes?

How can greater transparency be achieved in the data economy?

Which measures must be taken to reduce the exclusionary dynamics of Big Data and create a more inclusive phenomenon?