Preprint: Rieder, G.; Simon, J. (2017) Big Data and Technology Assessment: Research Topic or Competitor? In: *Journal of Responsible Innovation* 4(2). doi: 10.1080/23299460.2017.1360718.

Big Data and Technology Assessment: Research Topic or Competitor?

Gernot Rieder and Judith Simon

Abstract

With its promise to transform how we live, work, and think, Big Data has captured the imaginations of governments, businesses, and academia. However, the grand claims of Big Data advocates have been accompanied with concerns about potential detrimental implications for civil rights and liberties, leading to a climate of clash and mutual distrust between different stakeholders. Throughout the years, the interdisciplinary field of technology assessment (TA) has gained considerable experience in studying socio-technical controversies and as such is exceptionally well equipped to assess the premises and implications of Big Data practices. However, the relationship between Big Data as a socio-technical phenomenon and TA as a discipline assessing such phenomena is a peculiar one: Big Data may be the first topic TA deals with that is not only an object of inquiry, but also a major competitor, rivaling TA in several of its core functions, including the assessment of public views and visions, means and methods for exploring the future, and the provision of actionable knowledge and advice for political decision making. Our paper explores this dual relationship between Big Data and TA before concluding with some considerations on how TA might contribute to more responsible data-based research and innovation.

Keywords: Big Data, Technology Assessment, Responsible Research and Innovation, Interdisciplinarity

1. Introduction

Around the globe, the notion of Big Data[1] has captured the imaginations of governments, businesses, and academics. Heralded as a key enabler of public sector innovation (see European Commission (EC) 2015b), a catalyst for economic growth and well-being (see Organisation for Economic Co-operation and Development 2015), and the emblem of a new "data-intensive" scientific paradigm (see Hey et al. 2009), there is hardly a segment of modern society that is not expected to be touched and transformed by the ongoing "Big Data revolution" (Mayer-Schönberger and Cukier 2013). While wrapped in a rhetoric of hype and hope, applications of Big Data are no longer science fiction: From crime and disaster prediction to online advertising, from precision medicine and disease tracking to industry 4.0, from smart cities and climate research to credit and insurance scoring, the use of

[1] Although many definitions have been proposed (see Press 2014), there is "a pronounced lack of consensus about the definition, scope, and character of what falls within the purview of Big Data" (Ekbia et al. 2014). One of the most popular characterizations is Laney's (2012, 2001) notion of the "3Vs", which focuses on *measures of magnitude* and conceptualizes Big Data as growth in data volume, velocity, and variety. Other approaches have shifted the focus from data properties to new *analytical possibilities*, describing Big Data science as a "God's-eye view" (Pentland 2012) that "lets us examine society in fine-grained detail" (Pentland 2014). In contrast to such technology-oriented perspectives, scholars from the social sciences and humanities have pointed to the *cultural dimension* of Big Data, arguing that the real novelty of Big Data lies in the growing significance and authority of quantified information in ever more areas of everyday life (see Leonelli 2014). From this perspective, Big Data constitutes a complex socio-technical phenomenon that rests on an interplay of science, technology, ideology, and mythology (see Jurgenson 2014; boyd and Crawford 2012). It is this latter perspective that will guide our analysis.

computational means to uncover patterns and trends in ever larger haystacks of data has found widespread appeal. Significant investments are being made, underpinned by promissory narratives of efficiency and security, progress and prosperity. To "unlock the value" and "reap [the] benefits" (EC 2016a) of Big Data appears to have emerged as a primary concern of both public and private entities, the incorporation of advanced analytics into virtually all areas of human life already considered a foregone conclusion.

But the rise and spread of Big Data solutionism (see Morozov 2013b) has not remained unchallenged. Observers in the media and academia, but also from watchdog organizations and public interest groups, have called for open debate and critical reflection, pointing to unresolved issues related to privacy and surveillance, bias and discrimination. Put poignantly: What may have started as an advertising campaign for the new "testosterone of business computing" (Vance 2010) soon turned into a heated argument about civil rights and liberties (see Upturn 2014). Though large-scale outcry has been the exception rather than the rule[2], public reactions to the Snowden revelations (see Lyon 2014), NHS England's care.data initiative (see Presser et al. 2015), or Facebook's emotional contagion experiment (see boyd 2016) illustrate a growing discomfort with current data practices. The result is a climate of clash, an atmosphere of intense distrust between different parties and stakeholders with conflicting interests, values, and diverging visions of the future.

The situation is unlikely to resolve itself quickly: As rapid growth in both data generation (see IDC 2014) and the analytics market (see Statista 2016) suggests, at least from a techno-economic perspective, the age of Big Data has only just begun. Processes of datafication and computerization are sure to continue, and it is safe to assume that the combination of declining hardware costs, rising processing power, and ever more sophisticated software solutions will increase the allure of Big Data's 'capture all' imperative. With even more organizations planning to jump on the data train (see Gartner 2015), and many people experiencing a loss of control over their personal information (EC 2015c; PEW 2014), further conflict seems inevitable.

Throughout the years, the interdisciplinary field of technology assessment (TA) has gained considerable experience in studying socio-technical controversies. Extensive research on issues ranging from nuclear power and waste management to genetically modified organisms, geo engineering, stem cell research, and nanotechnology has left the discipline with a broad set of methods and techniques to assess and evaluate the ethical, legal, and social implications of new and emerging technologies. Thereby, the identification of current and future challenges, the facilitation of multi-actor involvement, and the search for both desirable and sustainable solutions has often been of central concern to the field and its scholars.[3] In addition, TA as a concept and practice aims to contribute to the governance of science and technology by (a) adopting an intermediary role and fostering dialogue between policy makers, industry, and the public sphere (see Joss and Bellucci 2002) and (b) providing actionable knowledge and advice for democratic decision making in cases where the stakes are high, facts are uncertain, and values are in dispute (see Klüver et al. 2015; Funtowicz and

[2] Citizens' passivity may have multiple causes. A survey by Turow, Hennessy, and Draper (2015) on consumer data collection in both digital and physical commerce, for instance, finds that people's provision of personal information is not the result of either consent, ignorance, or indifference, but rather a sense of resignation and powerlessness, a feeling that it is futile to even try to manage and control what companies can learn about them.
[3] For an overview of the TA landscape and its various strands, see van Est and Brom (2012) and Grunwald (2009).

Ravetz 1993). Big Data has only recently appeared on the TA agenda[4], but if the "march of quantification" (Gary King, quoted in Lohr 2012) continues, it will probably stay there for a while.

In this article, we seek to explore the relationship between Big Data and TA from two distinct perspectives:

First, we set out to discuss whether and in what ways TA can contribute to the current debate around Big Data. In essence, it is argued that the field's experience in bridging disciplinary boundaries, its proficiency in facilitating (upstream) public engagement, and its expertise in developing deliberative methods for thinking about possible future scenarios may indeed prove a valuable addition to Big Data discourse, providing not only insight into but potentially also a way out of the current climate of clash.

Second, instead of merely conceiving Big Data as a new research topic for TA, we shall consider their relationship as one marked by rivalry and competition. Despite significant epistemic and methodological differences, Big Data's key promise bears striking similarities to that of TA, namely the provision of actionable, future-oriented knowledge. Consequently, the nascent field of Big Data analytics – home to a growing number of software solutions marketed by major IT companies – may soon challenge TA in one of the discipline's core roles and functions: as a scientific advisor to political and bureaucratic decision making. Ultimately, this rivalry could lead to gradual displacement, especially if the computational approach appears to outperform its competitor both practically (e.g., cheaper, faster) and epistemologically (i.e., recommendations believed to be objective and based on numerical facts). The potential consequences of such a shift will be discussed at length.

In a concluding section, we wish to go beyond this scenario of competition and replacement and instead envision possibilities for cooperation and mutual learning between TA and Big Data analytics. Embedding our considerations within the context of RRI, we will inquire how responsibility in data-based research and innovation may be achieved and ponder how more reflexive, inclusive, and participatory modes of computational knowledge generation could actually be put into practice. In particular, we will stress the need for a multidisciplinary research approach, call attention to the politics of participation and the performativity of temporalities, and comment on the chances and pitfalls of collaborative knowledge production.

2. Big Data as a Research Topic for Technology Assessment

Though still relatively new as a topic of investigation, with significant growth in scholarly publications from 2012 onwards (see Singh et al. 2015; Youtie et al. 2017), several TA-related research initiatives examining the rise and impact of Big Data analytics have already been launched. European examples include the Germany-based ABIDA (Assessing Big Data) project[5], the Norwegian Board of Technology's study on data-driven analysis and predictive policing (Teknologirådet 2015), the UK Parliamentary Office of Science and Technology's exploration of Big Data uses across various policy areas[6], or background documents by the European Commission's Unit for eHealth and Health Technology

[4] While explicit references to Big Data were rare in the program of the 1st European TA Conference in Prague in 2013 (see PACITA 2013; Michalek et al. 2014), two years later, at the 2nd European TA Conference in Berlin, the term had become more common and a dedicated session sought to investigate the "Governance of Big Data and the Role of TA" (PACITA 2015).

[5] See the ABIDA website: http://www.abida.de/en (accessed 12 Apr. 2017).

[6] See POST's Big Data program website: http://www.parliament.uk/mps-lords-and-offices/offices/bicameral/post/work-programme/big-data/ (accessed 12 Apr. 2017).

Assessment on Big Data in the medical sector (see EC 2014). In the United States, the White House report *Big Data: Seizing Opportunities, Preserving Values* (Executive Office of the President 2014) and the complementary report *Big Data and Privacy: A Technological Perspective* (President's Council of Advisors on Science and Technology 2014) are examples of high-profile technology assessments meant to inform and steer federal S&T policy.[7]

While the initiatives listed above differ in scale and scope, they share the common goal of examining the potential impacts of Big Data from a decidedly *multidisciplinary perspective*. The German ABIDA project, for instance, includes five specialized working groups who are tasked with assessing the opportunities and challenges of Big Data from either an ethical, legal, sociological, economical, or political science point of view.[8] Such multidisciplinary, which has been an integral part of TA programs for decades[9], can contribute to Big Data discourse in two important ways: On the one hand, by bringing together expertise and insights from different fields, TA may provide a synoptic overview of what is often scattered across various disciplinary boundaries. Presented in a concise manner, this collected information may then allow TA scholars to act as "knowledge brokers" (Meyer 2010) between the scientific and the political realm, thus strengthening what to date remains a notoriously difficult relationship (see Wilsdon et al. 2015). On the other hand, the influx of knowledge and know-how from different disciplines may provide a better understanding of the actual significance of Big Data as a complex socio-technical phenomenon. In fact, as review articles such as Ekbia et al. (2015) demonstrate, ethical and legal reflections alone are insufficient to cover the range of conceptual and practical dilemmas surrounding Big Data. And if it is true that modern data analytics will not only "transform how we live, work, and think" (Mayer-Schönberger and Cukier's 2012), but also how we know (Kitchin 2014), judge (Christin et al. 2015), and govern (Rieder and Simon 2016), a concerted scholarly effort seems, indeed, indispensable.

Multidisciplinarity, however, is usually only the first step; the establishment of *interdisciplinary dialogue and collaboration* being the next. Perceived as a chance to transcend research silos and facilitate "more radical interactions between different styles of knowledge" (Stirling 2014), interdisciplinary assessments are expected to provide responses to problems that "are not solvable by an individual scientific discipline alone" (Decker 2001). Such '"wicked" (Rittel and Weber 1973) or "post-normal" (Funtowicz and Ravetz 1993) problem situations have become more frequent in the current "age of uncertainty" (Nowotny et al. 2001), and Big Data is no exception: Tamed by neither existing law (see Barocas and Selbst 2016) nor new regulatory approaches (see Rubinstein 2013), the search for hidden patterns and trends in ever larger – and increasingly diverse – datasets poses a host of intricate ethical and epistemic, social and political, legal, technical, and commercial challenges that evade traditional problem-solving strategies. Though not a panacea, issue-focused interdisciplinary research, as included in many TA programs (e.g., see Decker and Grunwald 2001), can help in finding options for political action, providing practical guidance for problems that do not fit into the functional differentiation of academic disciplines.[10] Yet successful collaboration can be

[7] Another example is the recent report *Big Data: A Report on Algorithmic Systems, Opportunity, and Civil Rights* (Executive Office of the President 2016).
[8] For a concise overview of the ABIDA project, see: http://www.abida.de/en/content/abida-das-projekt (accessed 12 Apr. 2017).
[9] To give but one example, when reporting on the status of the now abolished US Office of Technology Assessment (OTA) back in the early 1980s, Project Director and Senior Analyst Fred B. Wood writes that "OTA's multidisciplinary staff [...] of 80-90 professionals spans the spectrum of physical, life, and social sciences, engineering, law, and medicine." (Wood 1982)
[10] For more on TA's "problem-oriented" version of interdisciplinarity, see Schmidt (2008).

difficult to achieve, requiring significant effort, competence, a certain openness, and time. Especially in Europe, where higher education and research continue to be dominated by scholarly compartmentalization[11], TA might play a crucial role in facilitating such interactions, nourishing a culture of interdisciplinarity ready to support the governance of new and emerging technologies, including Big Data.

While multi- and interdisciplinarity are key constituents, TA projects, including several of the Big Data-oriented initiatives mentioned above, often seek to take an additional step: the implementation of *transdisciplinary engagement*, meaning the active involvement of actors (e.g., laypeople, specialists, interest groups) from diverse social and professional backgrounds, in an effort to broaden the scope, gain new perspectives, and make the borders between science, technology, and society more permeable.[12] Depending on the stage of a techno-scientific development, such participatory approaches may serve two main purposes[13]. On the one hand, in the early stages of development, when a technology is new and societal consequences are difficult to foresee, public engagement – e.g., through scenario exercises (see Selin 2011), group discussions (see Felt et al. 2014), or online deliberation tools (see Rommetveit et al. 2013) – can assist in generating anticipatory knowledge about possible future trajectories and their implications, determining both the plausibility and desirability of an emerging socio-technical arrangement. The focus here is on preparation rather than prediction, on cultivating a capacity to identify viable options and alternatives in times of growing complexity and uncertainty (see Barben et al. 2008). On the other hand, however, when a controversial technology has already become entrenched and ex ante preparation is no longer possible, the involvement of heterogeneous groups of actors can provide a better understanding of the nature of the conflict, that is, the main concerns, the values at stake, the positions taken, the interests involved. Moreover, the inclusion of affected publics can reveal information about problems and issues that may otherwise be overlooked (see Cotton 2014), offering a clearer picture not only of possible, but of actual harms and risks. In sum, participatory engagement can be considered a vital element for a more "anticipatory" (Guston 2014) and "reflexive" (Braun et al. 2010) governance of science and technology, opening both existing conditions and future prospects to broader scrutiny and critical debate. In the case of Big Data, where impacts are already tangible (see O'Neil 2016) but even bigger changes are on the way (see Davenport 2015), such expanded modes of inquiry and reflection could prove essential for more sustainable, socially robust development.

All in all, we believe that TA's experience in multi-, inter-, and transdisciplinary research, its practical expertise in consultation, deliberation, and advice at the science-society-policy interface, can help to address and successfully deal with the manifold challenges posed by Big Data. In turn, the ongoing controversy about Big Data provides an opportunity for TA to prove itself as a theory and

[11] Regarding such compartmentalization in higher education, see Newell (2010); regarding research, see Pan, Boucherie, and Hanafi (2015).

[12] For a deeper, historically grounded discussion of such participatory technology assessment (pTA), see Joss and Bellucci (2002).

[13] In fact, reasons for public participation are manifold (see Wesselink et al. 2011). The argument proposed in this paragraph refers to David Collingridge's well-known "dilemma of control". Collingridge (1980) states: "The social consequences of a technology cannot be predicted early in the life of the technology. By the time undesirable consequences are discovered, however, the technology is often so much part of the whole economics and social fabric that its control is extremely difficult." Like Collingridge, TA searches for ways and means to deal with and, both in theory and practice, overcome this quandary. For an insightful analytical discussion of the dilemma, its assumptions and relationship to TA, see Liebert and Schmidt (2010).

practice, demonstrating its value and relevance for the democratic governance of techno-scientific innovation and change.

Modern data analytics, however, are not only destined to become an important research topic for TA, they may also emerge as a serious competitor to TA, rivaling the field in several of its core competencies, including the assessment of public views and visions (i), means and methods for exploring the future (ii), and the provision of actionable knowledge and advice for political decision making (iii). Following, we shall elaborate on both the programmatic and epistemological similarities and differences between Big Data and TA, highlighting conceptual incommensurabilities as well as the potential for methodological complementarity and research synergy.

3. Big Data as a Competition for Technology Assessment

3.1. The assessment of public views and visions

While TA was initially conceived as a "rational-scientific tool" (Thompson Klein 2001) that would provide policy makers with "competent, unbiased information" concerning "probable impacts of technology"[14], the field's focus has since shifted from mere risk-based assessments to greater consideration of public acceptance (see Assefa and Frostell 2007) and social desirability (see Bennett and Sarewitz 2006). Supported by a broad variety of survey and engagement methods[15], numerous research projects have sought to investigate people's values and beliefs, but also their hopes and concerns regarding specific techno-scientific developments. However, there are certain problems: Quantitative survey research, for instance, has been criticized for relying on narrow 'tick-box' questionnaires that fail to account for the plurality and complexity of laypeople's thinking (see Macnaghten et al. 2010) and for the particular 'versions of reality' such surveys enact (see Law 2009). Qualitative engagement exercises, in comparison, have come under fire for being slow and time-consuming[16], for granting too much authority to the new "experts of community" (Rose 1999) and their "technologies of participation" (Chilvers and Kearnes 2016), and for issues of legitimacy and representativeness (see Lafont 2015).

In view of such criticism, the growing interest in digital methods for controversy mapping, opinion mining, and sentiment analysis should not come as a surprise.[17] Paired with the epistemic promises of Big Data (see Rieder and Simon 2017; Kitchin 2014) such computational techniques may indeed seem like an offer too good to refuse: Advertised as fast and cheap, Big Data tools promise real-time analysis, claiming to provide guidance and orientation at a bargain price. Furthermore, by gleaning data from online sources – e.g., from social networking sites such as Facebook or Twitter –

[14] Quoted from the U.S. Congress Technology Assessment Act of 1972, Public Law 92-484, § 2(d) and § 3(c), which created the now defunct Office of Technology Assessment (OTA), see: https://www.gpo.gov/fdsys/pkg/STATUTE-86/pdf/STATUTE-86-Pg797.pdf (accessed 12 Apr. 2017).

[15] For a selective overview of public engagement methods, see Parliamentary Office of Science and Technology (2001); for a review and critical discussion of large-scale survey research – and its paradigms – see Bauer (2008).

[16] For a list of participatory methods, including time and cost estimates, see Involve (2005) and the Participation Compass: http://participationcompass.org/article/index/method (accessed 12 Apr. 2017).

[17] As an indication of this interest in a European policy context, consider studies such as the commissioned report Big Data Analytics for Policy Making (EC 2016b), events such as the EurActiv stakeholder workshop Big Data & Policy Making, see http://www.euractiv.com/section/digital/video/big-data-and-policy-making/, or research initiatives such as the Framework Programme 7 projects SENSEI, see http://www.sensei-conversation.eu/, and EuroSentiment, see http://eurosentiment.eu/ (all accessed 12 Apr. 2017).

computational methods are said to bridge the qualitative-quantitative divide, capturing an entire conflict or debate in full detail. Finally, presented as a disinterested reading of reality, the Big Data marketing narrative feeds into the ideal of "mechanical objectivity" (Daston and Galison 2010), thus seemingly solving the problem of individual or institutional research bias by purely technical means. While scholars from different disciplinary backgrounds have pointed out the practical limitations and conceptual flaws of this heralded methodological revolution (e.g., see Crawford 2013; Mustafaraj et al. 2011), the ability to measure public attitudes directly and without delay presents a compelling prospect for a political system facing issues of trust and uncertainty. And even though TA's role in facilitating public participation in science and technology governance goes well beyond the collection of views and opinions, the systematic monitoring of user-generated online data for feedback gathering and trend analysis may soon give traditional engagement methods a run for their money. In a society where more and more of people's interactions have migrated to the Web, the opportunities for such research proliferate – and policy makers are taking note (see Grubmüller et al. 2013). The question of how TA should respond to this challenge will thus be crucial to the field's future development.

3.2. Means and methods for exploring the future

Technology assessment's relationship to the future is the next potential site of competition. As mentioned above, the orientation towards the future is a central element of TA and has been a guiding issue from its very beginning. Yet, following some disillusionment with positivistic and deterministic "prognosticism" (Grunwald 2009), there has been a shift from notions of early warning and control to those of shaping and designing (see Grunwald 2014). The future orientation of TA becomes obvious both in methodology and conceptual work: On the one hand, empirical studies on the societal impacts of technology make use of an abundance of foresight methods such as Delphi surveys, roadmapping exercises, or scenario development (see Porter 2010). On the other hand, conceptual work on technology futures has blossomed in recent years, and there have been numerous attempts – both from within and beyond TA – to conceptually grasp the dynamic and performative relationships between past, present, and future (see Esposito 2007; Brown and Michael 2003). Two prominent non-deterministic approaches at the core of the TA movement are the concept of "anticipatory governance" (Guston 2014) and the notion of "technology futures" (Grunwald 2012). While the former advocates broad-based capacity building to manage emerging technologies as long as such management is still possible (see Guston 2008), the latter stresses the value of technology futures as a common point of reference between developers, political actors, and the wider public, thus emphasizing their contribution to a sustainable co-evolution of technology and society by stimulating critical reflection and debate (see Grunwald 2012). What unites the two approaches – and TA foresight practices in general – is an understanding of the future as open and malleable, as something that can be steered and shaped, not "determined by natural necessities, but contingent and influenced by human action" (Voß et al. 2006). Avoiding any 'crystal ball ambitions', contemporary TA conceptualizes foresight and anticipation as a fundamentally democratic practice, an inclusive societal learning process that is meant to reduce the costs of learning by trial and error.

The reduction of costs through future-oriented analysis is also one of the main selling points of Big Data. The methods employed, however, differ considerably: Instead of deliberative foresight, Big Data specializes in predictive forecasting; instead of negotiating plausible future scenarios, Big Data technologies estimate probable future trajectories. In essence, historical and near-time data are used to identify patterns and trends, marking an epistemological shift from futures as socially created (see Adam 2005) to the future as an object of machine calculation. The spirit of positivism thus returns (see Jurgenson 2014), and it appears more powerful than ever, fueled by a massive increase in data availability and advanced tools and techniques to process and leverage them. The real challenge for TA, however, is arguably not so much the upcoming field of data science[18], but, once again, the Big Data imaginary, which promises almost universal applicability (see Anderson 2008) and the restoration of certainty in uncertain times (see Hardy 2013). By rendering the future knowable and its outcome optimizable[19], Big Data "revitalize[s] the promise of prediction across social, political, and economic worlds" (Aradau and Blanke 2016), becoming both product and enabler of a new "regime of futurity" (Ekbia et al. 2014), in which slower and less accurate methodologies are considered obsolete. In a society that increasingly thinks and lives towards the future, that is marked by a constant need to conquer and colonize the 'not yet' (see Adams et al. 2009), technology assessment's deliberative modes of future engagement may soon find themselves outgunned and outpaced by the grand claims of the algorithmic forecasting industry. Once again, an open discussion of how TA as a future-oriented discipline should and could respond to this challenge seems paramount.

3.3. The provision of actionable knowledge and advice

While "anticipating future developments and their impacts" is a key objective of TA, the field also seeks to "accommodate such insights in decision making and its implementation" (Rip 2012). The focus on providing actionable knowledge for political decision making has been a major concern of TA since its formal inception in the 1970s. Back then, the now defunct Office of Technology Assessment (OTA) was commissioned to advise the US Congress in matters of science and technology. While the executive branch of the US government could rely on an extensive apparatus of departments and agencies, Congress as the legislative branch was lacking such resources. Thus, a crucial function of OTA was to re-establish the knowledge/power balance between the government's legislative and executive branches (see Sadowski 2015; Bimber 1996). The focus on actionable knowledge, however, becomes apparent not only in the specific case of parliamentary TA, which aims to "strengthen representative democracy by timely informing MPs about the potential social impacts of technological change" (van Est and Brom 2012), but also when participatory TA is used as a means to mediate between the interests of different stakeholders, for instance in the context of selecting sites for nuclear waste disposal (see Hocke and Renn 2009). The distinction between consultation, on the one hand, and decision making, on the other, is crucial for the disciplinary self-understanding of TA. In order to remain trustworthy in its advisory function, TA aims at providing independent, high-quality knowledge about techno-scientific developments and their potential social, ethical, and legal implications. It does not, however, actively participate in the decision making process.[20] Moreover, TA as a discipline is well aware that the impact of its advice varies greatly and is hard to predict. While some reports may directly influence parliamentary decisions, others may get tucked away in filling cabinets, never to be read again. This relative openness and uncertainty should not be seen as a failure

[18] Data scientists are usually well aware of the various limitations of their craft. For a balanced account of prediction in the era of Big Data, see Silver (2012).
[19] Consider, for instance, IBM's advertising slogan for their predictive analytics products, which prompts customers to "optimize the future with better decisions today". See: http://www.ibm.com/analytics/us/en/technology/predictive-analytics/ (accessed 12 Apr. 2017).
[20] For an overview of the different practices and institutions of parliamentary TA in Europe, see Nentwich (2016).

of the discipline, but as a testimony to its facilitative and supportive rather than deciding societal function.

In the case of Big Data, the distinction between consultation and decision making is far less obvious: While Big Data technologies are said to provide insight and guidance for human decision making, they are increasingly used to generate decision recommendations or even take action on their own (see Citron and Pasquale 2014). What can thus be observed is a gradual shift from description (i.e., data reporting) and prediction (i.e., identifying trends) to prescription and automation (see Davenport 2015). Whereas prescriptive analytics are meant to suggest actions and "tell you what to do" (Davenport 2013), the move towards automation shifts the power – and burden – of decision making from the human actor to ever smarter programs and machines. In the latter case, algorithmic systems do not merely participate in decision processes, but perform certain actions with no or minimal human intervention. And even though a fully automated state may still be a distant utopian or dystopian vision (see Forster 1909), there is clear indication that the demand for such solutions in the public sector is growing (see Hartzog et al. 2015). In such a context, a major task for TA will be to critically assess and question the "prominence and status acquired by data as a commodity and recognized output" (Leonelli 2014) as well as to challenge the "widespread belief that large data sets offer a higher form of intelligence […], with an aura of truth, objectivity, and accuracy" (boyd and Crawford 2012). In addition, however, the field will also have to develop strategies to maintain its relevance in a crisis-ridden political environment that longs for seemingly clean, unambiguous knowledge and advice. To be blunt, the recent push for "data for policy" (EC 2016c) and "evidence-informed decision making" (EC 2015a) does not aim to raise the budget for traditional public engagement exercises, but encourages the development of computational solutions that may make such methodologies appear increasingly redundant. Going forward, fast-paced innovation and the ongoing datafication of society will make this an even more pressing matter of concern.

4. Discussion: Towards Responsible Data-Based Research and Innovation

The relationship between Big Data as a complex socio-technical phenomenon and TA as a discipline assessing such phenomena is a peculiar one: Big Data may be the first topic TA deals with that is not only an object of inquiry, but also a major competitor, rivaling TA in several of its core functions. Having outlined a narrative of competition in the previous section, we now want to conclude by sketching an alternative way forward, one that considers the relationship between Big Data and TA with respect to the concept of RRI. In essence, we believe that TA's focus on multi-, inter-, and transdisciplinary research, its reflexive orientation towards the future, and its practical expertise in providing policy advice, can help to address and successfully deal with the manifold challenges posed by Big Data. In doing so, TA-based analysis may provide valuable insight and support for the alignment of Big Data governance with the aims and goals of RRI, a widespread policy agenda the European Commission broadly defines as "an approach that anticipates and assesses potential implications and societal expectations […], with the aim to foster the design of inclusive and sustainable research and innovation" (EC n.d. b). While we do not wish to engage in a detailed discussion of RRI as a concept and funding strategy (see, however, Simon 2017; 2015), we do seek to highlight a number of central issues and concerns that may require special attention when moving Big Data under the RRI umbrella.

4.1. Multidisciplinarity beyond ELSIfication

As the range of topics and issues covered in journals such as *Big Data & Society* indicates, the scope and complexity of the Big Data phenomenon extends well beyond the purview of any single academic discipline. Meaningful assessments of societal impacts will thus require the collaboration of researchers from different fields, not only contributing their domain-specific knowledge, but also engaging in cross-disciplinary investigations, considering complex socio-technical entanglements from various angles and perspectives. As argued, TA as an analytic practice is well equipped for such a task, but the selection of the relevant scientific disciplines is both crucial and tricky and should be made with care (see Decker 2004). While the choice ultimately depends on the question to be answered and the problem to be solved, in the case of Big Data, the scope of traditional ELSI research often will not suffice. In particular political (Morozov 2013a), economic (Newman 2015), and epistemic (Rieder and Simon 2017) premises and implications should be taken into account, and some technical expertise may prove necessary when dealing with matters related to advanced computational methods such as data mining or machine learning (e.g., see Barocas and Selbst 2016; Burrell 2016). Thus, in order to truly grasp the impacts and consequences of Big Data and path the way for more responsible data-based research and innovation, finding the 'right' research partners and establishing a high-quality exchange relationship will be key.

4.2. Public Engagement and the Politics of Participation

The idea(l) of RRI emphasizes the need for "deepening the relationship between science and society" (European Parliament and Council 2013) by "includ[ing] multi-actor and public engagement in research and innovation" (EC n.d. b), fostering "dialogues between researchers, policy makers, industry and civil society organizations, NGOs, and citizens" (EC n.d. a). While the general aim of "bringing on board the widest possible diversity of actors" (EC n.d. a) may be democratically laudable, and TA certainly has a lot to offer in this regard (see Section 2), the specific modes and modalities of engagement remain a major issue of concern. Despite a rhetoric of openness and inclusion, consultation exercises are frequently designed as one-way, top-down public education approaches where participants are taught about scientific facts, expert knowledge is given primacy over lay expertise, and a strong commitment to consensus stifles deliberative disagreement. Given Big Data's now well-documented potential for causing harm (see O'Neil 2016) and people's growing discomfort with the widespread application and impact of data analytics in numerous areas of life (see Pew 2015), such strategies of appeasement seem both futile and utterly misplaced. Instead, controversies should be embraced as sites of social learning where citizens can share and discuss their experiences with specific services and applications (see Rip 1986). Moreover, measures should be taken that the outcomes and findings of deliberative engagements can actually affect the regulation of new and emerging technologies, which means that even stopping certain developments – e.g., through temporary or permanent moratoria – must be considered a real option. Otherwise, public consultation and stakeholder involvement risks becoming a farce and may rightly be accused as a means to silence critical voices and fabricate consent.

4.3. Performative Temporalities and Contestable Futures

As outlined in Section 3, TA and Big Data practices share a common interest in the future. While Big Data is mainly discussed as a forecasting technology that may soon "predict our every move" (Hassani and Silva 2015), TA is rooted in the broader and less determinant but equally forward looking tradition of foresight (see Harper 2013), focusing on different stakeholder's visions, expectations, and fears rather than statistical patterns. From a TA perspective, the future cannot be discovered, but has to be created and constructed – for instance through scenario building – resulting in a plurality of possible futures and paths that are open to public scrutiny and deliberation. In addition, TA emphasizes the interconnectedness between past, present, and future, acknowledging that we can only think about futures according to our present-day's knowledge and that the ways how futures are constructed are decisive for their content (see Grunwald 2010). Such a reflexive stance may prove valuable when assessing the performativity and politics of Big Data forecasts, which are marked by a shift from prediction to prescription, no longer limited to the confines of prognosis, but actively telling people "what they should be doing next" (Eric Schmidt, quoted in Jenkins 2010). Ultimately, Big Data's predictive power may enable a "new philosophy of preemption" (Kerr and Earle 2013), which forestalls (human) action based on algorithmic estimates. If we allow such systems of digital regulation to proliferate, we need to be very sure about their epistemological premises as well as their potential ethical, social, and political implications.

4.4. Actionable, Situated, and Inclusive Knowledge

Given the prevalent "trust in numbers" (Porter 1995) within political and administrative circles, on the one hand, and Big Data proponents' claims of predictive superiority and analytical neutrality (see Anderson 2008), on the other, TA may soon face a new competitor in providing guidance and support for public policy. But policy makers should be aware that the very kind of knowledge they receive may differ considerably between the two approaches: While TA focuses on collective problem solving, discussions and critical deliberation (see Abelson et al. 2003), Big Data methods tend to look at networks and opinions from a distance (see Moretti 2013). Two-way interactions, mutual learning, and external subject-matter expertise are key elements of TA, but much less so in data mining and computational analytics.

However, rather than substituting one for the other, we believe that both fields can learn and benefit from one another. For instance, whereas Big Data methods could expand the breadth of traditional scoping exercises (see Gandomi and Haider 2015), facilitate the tracking of trends (Nguyen et al. 2016) and public sentiment (see Cambria et al. 2014), and help map the dynamics of controversies over time (see Lansdall-Welfare 2014), TA could use its methodological know-how, its reflexive capacities, and its experience in policy advice to make Big Data RRI-ready.[21] In the end, diligently supervised mixed-methods approaches could contribute to the theoretical and methodological development of both fields as well as to the general advancement of responsible data-based research and innovation.

In this concluding section, we have argued that Big Data practices may clearly benefit from the insights and experience of TA and have pointed towards certain issues and concerns that may prove crucial when seeking to align Big Data research with central RRI tenets. While our analysis had a critical edge and sought to debunk certain exaggerated hopes and claims mainly voiced by industry stakeholders, we do wish to acknowledge the great social, economic, and academic opportunities that Big Data and

[21] In this respect, TA could also learn from the digital methods community, which has employed Web-based tools to map controversies around, e.g., global warming (Weltevrede and Borra 2016), biofuels (Eklöf and Mager 2013), or GM food (Marres and Rogers 2000), embracing the epistemic opportunities of online data mining while remaining attentive to potential limitations and the perils of competitive marketization (see Rieder and Sire 2014).

related methods provide. There is no doubt that Big Data tools can be used for the common good, but there are pitfalls along the way that must be thoroughly understood and addressed. Thus, while opportunities should be exploited, this needs to be done in a responsible, socially sustainable manner. Throughout the paper, we have also argued that Big Data poses a considerable challenge to TA, rivaling the field in several core functions, including the assessment of public views and visions, means and methods for exploring possible future trajectories, and the provision of actionable knowledge and advice for political decision making. We believe that in order to stay in the game, TA will have to engage with the new methods and techniques offered by Big Data technologies. Such an engagement should include, but not be limited to, critical reflection. Instead, TA should consider forming coalitions of mutual learning, for instance by including data scientists into future project designs, thereby expanding its multidisciplinary expertise by yet another approach. What we propose is a third way between industry hype and Big Data doom and gloom, one that acknowledges the value of data science as a powerful epistemic practice, that is open to the opportunities granted by the proliferation of digital (social) data, and that takes a proactive stance in developing tools and methods that function as best practice examples. If done right, modern data analytics could become an ally rather than a competitor to the field of technology assessment, potentially extending the scope, speed, and quality of discourse, dispute, and trend analysis. If disregarded and left to the proprietary discretion of commercial products, however, Big Data may not only grow to challenge the TA community, but could also pose a considerable threat to the core principles of Responsible Research and Innovation.

Funding

This work was supported by Austrian Science Fund (AT) [grant number P 23770].

Notes on contributors

Judith Simon is Full Professor for Ethics in Information Technologies at the University of Hamburg. She is co-editor of the journals "Philosophy & Technology" and "Big Data & Society". She also serves on the executive boards of the International Society for Ethics and Information Technology (inseit.net) and the International Association for Computing and Philosophy (iacap.org).

Gernot Rieder is a PhD fellow at the IT University of Copenhagen. His dissertation investigates the rise of Big Data in public policy and the social, ethical, and epistemological implications of data-driven decision making. Gernot serves as an assistant editor for the journal "Big Data & Society".

References

Abelson, Julia; Forest, Pierre-Gerlier; Eyles, John; Smith, Patricia; Martin, Elisabeth; Gauvin, Francois-Pierre (2003) Deliberations about Deliberative Methods: Issues in the Design and Evaluation of Public Participation Processes. In: *Social Science & Medicine* 57(2), 239–251.

Adam, Barbara (2005) *Futures in the Making: Contemporary Practices and Sociological Challenges*. Paper presented at the ASA conference. Available at: http://www.cardiff.ac.uk/socsi/futures/conf_ba_asa230905.pdf (accessed 12 Apr. 2017).

Adams, Vincanne; Murphy, Michelle; Clarke, Adele E. (2009) Anticipation: Technoscience, Life, Affect, Temporality. In: *Subjectivity* 28(1), 246-265.

Anderson, Chris (2008) The End of Theory: The Data Deluge Makes the Scientific Method Obsolete. In: *Wired*. Available at: https://www.wired.com/2008/06/pb-theory/ (accessed 12 Apr. 2017).

Aradau, Claudia; Blanke, Tobias (2016) Politics of Prediction: Security and the Time/Space of Governmentality in the Age of Big Data. In: *European Journal of Social Theory* 20(3): 373-391.

Assefa, Getachew; Frostell, Björn M. (2007) Social Sustainability and Social Acceptance in Technology Assessment: A Case Study of Energy Technologies. In: *Technology in Society* 29(1), 63-78.

Barben, Daniel; Fisher, Erik; Selin, Cynthia; Guston, David H. (2008) Anticipatory Governance and Nanotechnology: Foresight, Engagement, and Integration. In: Hackett, Edward J.; Amsterdamska, Olga; Lynch, Michael; Wajcman, Judy (Eds.) *The Handbook of Science and Technology Studies*. Third Edition. Cambridge, MA: MIT Press, 979-1000.

Barocas, Solon; Selbst, Andrew D. (2016) Big Data's Disparate Impact. In: *104 California Law Review* 671-732.

Bauer, Martin W. (2008) Survey Research and the Public Understanding of Science. In: Bucchi, Massimiano; Trench, Brian (Eds.) *Handbook of Public Communication of Science and Technology*. London: Routledge, 111-130.

Bennett, Ira; Sarewitz, Daniel (2006) Too Little, Too Late?: Research Policies on the Societal Implications of Nanotechnology in the United States. In: *Science as Culture* 15(4), 309-325.

Bimber, Bruce (1996) *The Politics of Expertise in Congress. The Rise and Fall of the Office of Technology Assessment*. New York: State University of New York Press.

boyd, danah (2016) Untangling Research and Practice: What Facebook's "Emotional Contagion" Study Teaches Us. In: *Research Ethics* 12(1): 4-13.

boyd, danah; Crawford, Kate (2012) Critical Questions for Big Data. In: *Information, Communication & Society* 15(5), 662-679.

Braun, Kathrin; Moore, Alfred; Herrmann, Svea Luise; Könninger, Sabine (2010) Science Governance and the Politics of Proper Talk: Governmental Bioethics as a New Technology of Reflexive Government. In: *Economy and Society* 39(4), 510-533.

Brown, Nik; Michael, Mike (2003) A Sociology of Expectations: Retrospecting Prospects and Prospecting Retrospects. In: *Technology Analysis and Strategic Management* 15(1), 3-18.

Burrell, Jenna (2016) How the Machine 'Thinks': Understanding Opacity in Machine Learning Algorithms. In: *Big Data & Society* 3(1), 1-12.

Cambria, Erik; Rajagopal, Dheeraj; Olsher, Daniel; Das, Dipankar (2014) Big Social Data Analysis. In: Akerkar, Rajendra (Ed.) *Big Data Computing*. Boca Raton, FL: CRC Press, 401-414.

Chilvers, Jason; Kearnes, Matthew (2016) Participation in the Making. Rethinking Public Engagement in Co-Productionist Terms. In: Chilvers, Jason; Kearnes, Matthew (Eds.) *Remaking Participation. Science, Environment and Emergent Publics*. Abingdon: Routledge, 31-63.

Christin, Angèle; Rosenblat, Alex; boyd, danah (2015) *Courts and Predictive Algorithms*. Workshop Primer. Available at: http://www.datacivilrights.org/pubs/2015-1027/Courts_and_Predictive_Algorithms.pdf (accessed 12 Apr. 2017).

Citron, Danielle K.; Pasquale, Frank (2014) The Scored Society: Due Process For Automated Predictions. In: *Washington Law Review* 89(1), 1-33.

Collingridge, David (1980) *The Social Control of Technology*. London: Frances Pinter.

Cotton, Matthew (2014) *Ethics and Technology Assessment: A Participatory Approach*. Heidelberg; New York: Springer.

Crawford, Kate (2013) The Hidden Biases in Big Data. In: *Harvard Business Review*. Available at: https://hbr.org/2013/04/the-hidden-biases-in-big-data (accessed 12 Apr. 2017).

Daston, Lorraine J.; Galison, Peter (2010) *Objectivity*. New York: Zone Books.

Davenport, Thomas H. (2015) The Rise of Automated Analytics. In: *The Wall Street Journal*. Available at: http://blogs.wsj.com/cio/2015/01/14/the-rise-of-automated-analytics/ (accessed 12 Apr. 2017).

Davenport, Thomas H. (2013) Analytics That Tell You What To Do. In: *The Wall Street Journal*. Available at: http://blogs.wsj.com/cio/2013/04/03/analytics-that-tell-you-what-to-do/ (accessed 12 Apr. 2017).

Decker, Michael (2001) Preface. In: Decker, Michael (Ed.) *Interdisciplinarity in Technology Assessment. Implementation and its Chances and Limits*. Wissenschaftsethik und Technikfolgenbeurteilung Band 11. Berlin: Springer, IX-X.

Decker, Michael (2004) The Role of Ethics in Interdisciplinary Technology Assessment. In: *Poiesis & Praxis* 2, 139-156.

Decker, Michael; Grunwald, Armin (2001) Rational Technology Assessment as Interdisciplinary Research. In: Decker, Michael (Ed.) *Interdisciplinarity in Technology Assessment. Implementation and its Chances and Limits*. Wissenschaftsethik und Technikfolgenbeurteilung Band 11. Berlin: Springer, 33-60.

Ekbia, Hamid; Mattioli, Michael; Kouper, Inna; Arave, G.; Ghazinejad, Ali; Bowman, Timothy; Suri, Venkata Ratandeep; Tsou, Andrew; Weingart, Scott; Sugimoto, Cassidy R. (2014) Big Data, Bigger Dilemmas: A Critical Review. In: *Journal of the Association for Information Science and Technology* 66(8), 1523-1545.

Eklöf, Jenny; Mager, Astrid (2013) Technoscientific Promotion and Biofuel Policy: How the Press and Search Engines Stage the Biofuel Controversy. In: *Media, Culture & Society* 35(4), 454-471.

Esposito, Elena (2007) *Die Fiktion der Wahrscheinlichen Realität*. Frankfurt am Main: Suhrkamp.

van Est, Rinie; Brom, Frans (2012) Technology Assessment as an Analytic and Democratic Practice. In: Chadwick, Ruth; Callahan, Dan; Singer, Peter (Eds.) *Encyclopedia of Applied Ethics*. 2nd Edition. San Diego: Academic Press, 306-320.

European Commission (n.d. a) *Public Engagement in Responsible Research and Innovation*. Available at: https://ec.europa.eu/programmes/horizon2020/node/766 (accessed 12 Apr. 2017).

European Commission (n.d. b) *Responsible Research & Innovation*. Available at: https://ec.europa.eu/programmes/horizon2020/en/h2020-section/responsible-research-innovation (accessed 12 Apr. 2017).

European Commission (2016a) *European Cloud Initiative to Give Europe a Global Lead in the Data-Driven Economy*. Press Release. Available at: http://europa.eu/rapid/press-release_IP-16-1408_en.htm (accessed 12 Apr. 2017).

European Commission (2016b) *Big Data Analytics for Policy Making*. Report. Available at: https://joinup.ec.europa.eu/sites/default/files/dg_digit_study_big_data_analytics_for_policy_making.pdf (accessed 12 Apr. 2017).

European Commission (2016c) *Data for Policy: An Increasingly Global Affair*. Conference Announcement. Available at: https://ec.europa.eu/digital-single-market/en/news/data-policy-increasingly-global-affair (accessed 12 Apr. 2017).

European Commission (2015a) *Data for Policy: When the Haystack is Made of Needles*. Call for Contributions. Available at: https://ec.europa.eu/digital-single-market/news/data-policy-when-haystack-made-needles-call-contributions (accessed 12 Apr. 2017).

European Commission (2015b) *ICT-Enabled Public Sector Innovation in Horizon 2020*. Available at: https://ec.europa.eu/digital-single-market/en/ict-enabled-public-sector-innovation-horizon-2020 (accessed 12 Apr. 2017).

European Commission (2015c) *Special Eurobarometer 431 – Data Protection*. Report. Available at: http://ec.europa.eu/public_opinion/archives/ebs/ebs_431_en.pdf (accessed 12 Apr. 2017).

European Commission (2014) *The Use of Big Data in Public Health Policy and Research. Background information document*. Available at: http://ec.europa.eu/health/ehealth/docs/ev_20141118_co07b_en.pdf (accessed 12 Apr. 2017).

European Parliament and Council (2013) *Regulation (EU) No 1291/2013 of the European Parliament and of the Council of 11 December 2013 establishing Horizon 2020 – the Framework Programme for Research and Innovation (2014-2020) and repealing Decision No 1982/2006/EC Text with EEA relevance*. Available at: http://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32013R1291&from=EN (accessed 12 Apr. 2017).

Executive Office of the President (2016) *Big Data: A Report on Algorithmic Systems, Opportunity, and Civil Rights.* Available at: https://obamawhitehouse.archives.gov/sites/default/files/microsites/ostp/2016_0504_data_discrimination.pdf (accessed 12 Apr. 2017).

Executive Office of the President (2014) *Big Data: Seizing Opportunities, Preserving Values.* Available at: https://obamawhitehouse.archives.gov/sites/default/files/docs/big_data_privacy_report_may_1_2014.pdf (accessed 12 Apr. 2017).

Felt, Ulrike; Schumann, Simone; Schwarz, Claudia; Strassnig, Michael (2014) Technology of Imagination: A Card-Based Public Engagement Method for Debating Emerging Technologies. In: *Qualitative Research* 14(2), 233-251.

Forster, Edward M. (1909) *The Machine Stops*. Available at: https://en.wikisource.org/wiki/The_Machine_Stops (accessed 12 Apr. 2017).

Funtowicz, Silvio O.; Ravetz, Jerome, R. (1993) Science for the Post-Normal Age. In: *Futures* 25(7), 739-755.

Gandomi, Amir; Haider, Murtaza (2014) Beyond the Hype: Big Data Concepts, Methods, and Analytics. In: *International Journal of Information Management* 35(2), 137-144.

Gartner (2015) *Gartner Survey Shows More Than 75 Percent of Companies Are Investing or Planning to Invest in Big Data in the Next Two Years*. Available at: http://www.gartner.com/newsroom/id/3130817 (accessed 12 Apr. 2017).

Grubmüller, Verena; Götsch, Katharina; Krieger, Bernhard (2013) Social Media Analytics for Future Oriented Policy Making. In: *European Journal of Futures Research* 1(20), 1-9.

Grunwald, Armin (2014) Technology Assessment for Responsible Innovation. In: van den Hoven, Jeroen; Doorn, Neelke; Swierstra, Tsjalling; Koops, Bert-Jaap; Romijin, Henny (Eds.) *Responsible Innovation 1: Innovation Solutions for Global Issues*. Dordrecht: Springer, 15-32.

Grunwald, Armin (2012) *Technikzukünfte als Medium von Zukunftsdebatten und Technikgestaltung*. Karlsruhe: KIT Scientific Publishing.

Grunwald, Armin (2010) Future. In: Guston, David H. (Ed.) *Encyclopedia of Nanoscience and Society. Volume 1*. Los Angeles: SAGE, 265-267.

Grunwald, Armin (2009) Technology Assessment: Concepts and Methods. In: Meijers, Anthonie (Ed.) *Philosophy of Technology and Engineering Sciences.* Handbook of the Philosophy of Science. Volume 9. Amsterdam: Elsevier, 1103-1146.

Guston, David H. (2014) Understanding 'Anticipatory Governance'. In: *Social Studies of Science* 44(2), 218-242.

Guston, David H. (2008) Preface. In: Fisher, Erik; Selin, Cynthia; Wetmore, James M. (Eds.) *The Yearbook of Nanotechnology in Society. Volume 1: Presenting Futures*. New York: Springer, V-VIII.

Hardy, Quentin (2013) Why Big Data is not Truth. In: *The New York Times*. Available at: http://bits.blogs.nytimes.com/2013/06/01/why-big-data-is-not-truth/ (accessed 12 Apr. 2017).

Hartzog, Woodrow; Conti, Gregory; Nelson, John; Shay, Lisa A. (2015) Inefficiently Automated Law Enforcement. In: *Michigan State Law Review* 2015(5), 1763-1796.

Harper, Jennifer C. (2013) *Impact of Technology Foresight.* Nesta Working Paper 13/16. Available at: http://www.nesta.org.uk/sites/default/files/1316_impact_of_technology_foresight_final_version.pdf (accessed 12 Apr. 2017).

Hassani, Hossein; Silva, Emmanuel S. (2015) Forecasting with Big Data: A Review. In: *Annals of Data Science* 2(1), 5-19.

Hey, Tony; Tansley, Stewart; Tolle, Kristin (Eds.) (2009) *The Fourth Paradigm. Data-Intensive Scientific Discovery*. Redmond: Microsoft Research.

Hocke, Peter; Renn, Ortwin (2009) Concerned Public and the Paralysis of Decision-Making: Nuclear Waste Management Policy in Germany. In: *Journal of Risk Research* 12(7-8), 921-940.

International Data Research (IDC) (2014) *The Digital Universe of Opportunities: Rich Data and the Increasing Value of the Internet of Things*. Available at: www.emc.com/leadership/digital-universe/2014iview/executive-summary.htm (accessed 12 Apr. 2017).

Involve (2005) *People & Participation. How to Put Citizens at the Heart of Decision-Making*. Available at: http://www.involve.org.uk/wp-content/uploads/2011/03/People-and-Participation.pdf (accessed 12 Apr. 2017).

Jenkins, Holman W. (2010) Google and the Search for the Future. In: *The Wall Street Journa*l. Available at: http://www.wsj.com/articles/SB10001424052748704901104575423294099527212 (accessed 12 Apr. 2017).

Joss, Simon; Bellucci, Sergio (2002) *Participatory Technology Assessment: European Perspectives*. Centre for the Study of Democracy. Gateshead: Athenaeum Press.

Jurgenson, Nathan (2014) View from Nowhere. In: *The New Inquiry*. Available at: https://thenewinquiry.com/essays/view-from-nowhere/ (accessed 12 Apr. 2017).

Kerr, Ian; Earle, Jessica (2013) Prediction, Preemption, Presumption. How Big Data Threatens Big Picture Privacy. In: *Stanford Law Review Online* 66, 65-72.

Kitchin, Rob (2014) Big Data, New Epistemologies and Paradigm Shifts. In: *Big Data & Society* 1(1), 1-12.

Klüver, Lars; Nielsen, Rasmus Øjvind; Jørgensen, Marie Louise (2015) *Policy-Oriented Technology Assessment Across Europe. Expanding Capacities*. Houndmills: Palgrave Macmillan.

Laney, Doug (2012) Deja VVVu: Others Claiming Gartner's Construct for Big Data. In: *Gartner Blog Network*. http://blogs.gartner.com/doug-laney/deja-vvvue-others-claiming-gartners-volume-velocity-variety-construct-for-big-data/ (accessed 12 Apr. 2017).

Laney, Doug (2001) 3D Data Management: Controlling Data Volume, Velocity, and Variety. In: *META Group. Application Delivery Strategies*. https://blogs.gartner.com/doug-laney/files/2012/01/ad949-3D-Data-Management-Controlling-Data-Volume-Velocity-and-Variety.pdf (accessed 12 Apr. 2017).

Lansdall-Welfare, Thomas; Sudhahar, Saatviga; Veltri, Giuseppe A.; Christianini, Nello (2014) On the Coverage of Science in the Media: A Big Data Study on the Impact of the Fukushima Disaster. In: *Proceedings of the 2014 IEEE International Conference on Big Data*, 60-66.

Lafont, Christina (2015) Deliberation, Participation, and Democratic Legitimacy: Should Deliberative Mini-Publics Shape Public Policy? In: *The Journal of Political Philosophy* 23(1), 40-63.

Law, John (2009) Seeing Like a Survey. In: *Cultural Sociology* 3(2): 239-256.

Leonelli, Sabrina (2014) What Difference Does Quantity Make? On the Epistemology of Big Data in Biology. In: *Big Data & Society* 1(1), 1-11.

Liebert, Wolfgang; Schmidt, Jan C. (2010) Collingridge's Dilemma and Technoscience. An Attempt to Provide a Clarification from the Perspective of the Philosophy of Science. In: *Poiesis & Praxis* 7, 55-71.

Lohr, Steve (2012) The Age of Big Data. In: *The New York Times*. Available at: http://www.nytimes.com/2012/02/12/sunday-review/big-datas-impact-in-the-world.html?_r=0 (accessed 12 Apr. 2017).

Lyon, David (2014) Surveillance, Snowden, and Big Data: Capacities, Consequences, Critique. In: *Big Data and Society* 1(2): 1-13.

Macnaghten, Phil; Davies, Sarah; Kearnes, Matthew (2010) Narrative and Public Engagement: Some Findings from the DEEPEN Project. In: von Schomberg, René; Davies, Sarah (Eds.) *Understanding Public Debate on Nanotechnologies. Options for Framing Public Policy*. Luxembourg: Publications Office of the European Union, 13-29.

Marres, Noortje; Rogers, Richard (2000) Depluralising the Web and Repluralising Public Debate: The Case of the GM Food Debate on the Web. In: Rogers, Richard (Ed.) *Preferred Placement: Knowledge Politics on the Web*. Maastricht: Jan van Eyck Editions, 113-135.

Mayer-Schönberger, Viktor; Cukier, Kenneth (2013) *Big Data. A Revolution That Will Transform How We Live, Work, And Think*. New York: Houghton Mifflin Harcourt.

Meyer, Morgan (2011) The Rise of the Knowledge Broker. In: *Science Communication* 32(1), 118-127.

Michalek, Tomáš; Hebáková, Lenka; Hennen, Leonhard; Scherz, Constanze; Nierling, Linda; Hahn, Julia (2014) *Technology Assessment and Policy Areas of Great Transitions*. Proceedings from the PACITA 2013 Conference in Prague. Available at: http://www.pacitaproject.eu/wp-content/uploads/2014/11/Conference-Book.pdf (accessed 12 Apr. 2017).

Moretti, Franco (2013) *Distant Reading*. London: Verso.

Morozov, Evgeny (2013a) The Real Privacy Problem. In: *MIT Technology Review*. Available at: https://www.technologyreview.com/s/520426/the-real-privacy-problem/ (accessed 12 Apr. 2017).

Morozov, Evgeny (2013b) *To Save Everything, Click Here. The Folly of Technological Solutionism*. New York: Public Affairs.

Mustafaraj, Eni; Finn, Samantha; Whitlock, Carolyn; Metaxas, Panagiotis T. (2011) *Vocal Minority Versus Silent Majority: Discovering the Opinions of the Long Tail*. Paper presented at the 2011 IEEE International Conference on Privacy, Security, Risk, and Trust, and IEEE International Conference on Social Computing, 103-110.

Nentwich, Michael (2016) *Parliamentary Technology Assessment Institutions and Practices. A Systematic Comparison of 15 Members of the EPTA Network*. ITA manu:script 16-02. Available at: http://epub.oeaw.ac.at/ita/ita-manuscript/ita_16_02.pdf (accessed 12 Apr. 2017).

Newell, William H. (2010) Undergraduate General Education. In: Frodeman, Robert; Thompson Klein, Julie; Mitchman, Carl; Holbrook, Britt J. (Eds.) *The Oxford Handbook of Interdisciplinarity*. New York: Oxford University Press, 360-371.

Newman, Nathan (2015) *Data Justice: Taking on Big Data as an Economic Justice Issue*. Data Justice Report. Available at: http://www.datajustice.org/sites/default/files/Data%20Justice-%20Taking%20on%20Big%20Data%20as%20an%20Economic%20Justice%20Issue.pdf (accessed 12 Apr. 2017).

Nguyen, Khanh-Ly; Byung-Joo, Shin; Yoo, Seong Joon (2016) Hot Topic Detection and Technology Trend Tracking for Patents Utilizing Term Frequency and Proportional Document Frequency and Semantic Information. In: *Proceedings of the 2016 International Conference on Big Data and Smart Computing (BigComp)*, 223-230.

Nowotny, Helga; Scott, Peter; Gibbon, Michael (2001) *Re-Thinking Science: Knowledge and the Public in an Age of Uncertainty*. Cambridge: Polity Press.

O'Neil, Cathy (2016) *Weapons of Math Destruction. How Big Data Increases Inequality and Threatens Democracy*. New York: Crown.

Organisation for Economic Co-operation and Development (2015) *Data-Driven Innovation: Big Data for Growth and Well-Being*. Paris: OECD Publishing.

PACITA (2015) *The Next Horizon of Technology Assessment. 2nd European TA Conference.* Book of Abstracts. Available at: http://berlinconference.pacitaproject.eu/wp-content/uploads/2015/02/Book-of-Abstracts-UPDATED3.pdf (accessed 12 Apr. 2017).

PACITA (2013) *Technology Assessment and Policy Areas of Great Transitions. 1st PACITA Project Conference.* Book of Abstracts. Available at: http://www.pacitaproject.eu/wp-content/uploads/2013/03/Book-of-abstracts-Prague.pdf (accessed 12 Apr. 2017).

Pan, Lei; Boucherie, Sacha; Hanafi, Shereen (2015) *Interdisciplinary Research: How Do 9 Nations Compare?* Elsevier Connect. Available at: https://www.elsevier.com/connect/interdisciplinary-research-how-do-9-nations-compare (accessed 12 Apr. 2017).

Parliamentary Office of Science and Technology (2001) *Open Channels: Public Dialogue in Science and Technology*. Report No. 153. Available at: http://www.parliament.uk/documents/post/pr153.pdf (accessed 12 Apr. 2017).

Pentland, Alex (2014) *Social Physics. How Good Ideas Spread – The Lessons from a New Science*. New York: Penguin Press.

Pentland, Alex (2012) Society's Nervous System: Building Effective Government, Energy, and Public Health Systems. In: *IEEE Computer* 45(1), 31-38.

Pew Research Center (2015) Americans' Attitudes about Privacy, Security and Surveillance. Available at: http://www.pewinternet.org/files/2015/05/Privacy-and-Security-Attitudes-5.19.15_FINAL.pdf (accessed 12 Apr. 2017).

Pew Research Center (2014) *Public Perceptions of Privacy and Security in the Post-Snowden Era*. Available at: http://www.pewinternet.org/files/2014/11/PI_PublicPerceptionsofPrivacy_111214.pdf (accessed 12 Apr. 2017).

Porter, Alan L. (2010) Technology Foresight: Types and Methods. In: *International Journal of Foresight and Innovation Policy* 6(1).

Porter, Theodore M. (1995) *Trust in Numbers: The Pursuit of Objectivity in Science and Public Life*. Princeton: Princeton University Press, 36-45.

President's Council of Advisors on Science and Technology (2014) *Big Data and Privacy: A Technological Perspective.* Available at: https://obamawhitehouse.archives.gov/sites/default/files/microsites/ostp/PCAST/pcast_big_data_and_privacy_-_may_2014.pdf (accessed 12 Apr. 2017).

Press, Gil (2014) 12 Big Data Definitions: What's Yours? In: *Forbes*. Available at: https://www.forbes.com/sites/gilpress/2014/09/03/12-big-data-definitions-whats-yours/#3bec4cba13ae (accessed 12 Apr. 2017).

Presser, Lizzie; Hruskova, Maia; Rowbottom, Helen; Kancir, Jesse (2015) Care.data and Access to UK Health Records: Patient Privacy and Public Trust. In: *Technology Science*. Available at: http://techscience.org/a/2015081103/ (accessed 12 Apr. 2017).

Rieder, Bernhard; Sire, Guillaume (2014) Conflicts of Interest and Incentives to Bias: A Microeconomic Critique of Google's Tangled Position on the Web. In: *New Media & Society* 16(2), 195-211.

Rieder, Gernot; Simon, Judith (2017) Big Data: A New Empiricism and its Epistemic and Socio-Political Consequences. In: Pietsch, Wolfgang; Wernecke, Jörg; Ott, Maximilian (Eds.) *Berechenbarkeit der Welt? Philosophie und Wissenschaft im Zeitalter von Big Data*. Wiesbaden: Springer VS, 85-105.

Rieder, Gernot; Simon, Judith (2016) Datatrust: Or, the Political Quest for Numerical Evidence and the Epistemologies of Big Data. In: *Big Data & Soci*ety 3(1), 1-6.

Rip, Arie (2012) Futures of Technology Assessment. In: Decker, Michael; Grunwald, Armin; Knapp, Martin (Eds.) *Der Systemblick auf Innovation. Technikfolgenabschätzung in der Technikgestaltung*. Berlin: edition sigma, 29-39.

Rip, Arie (1986) Controversies as Informal Technology Assessment. In: *Science Communication* 8(2), 349-371.

Rittel, Horst W. J.; Webber, Melvin M. (1973) Dilemmas in a General Theory of Planning. In: *Policy Sciences* 4, 155-169.

Rommetveit, Kjetil; Gunnarsdóttir, Kristrun; Jepsen, Kim Sune; Bertilsson, Thora Margareta; Verrax, Fanny; Strand, Roger (2013) The Technolife Project: An Experimental Approach to New Ethical Frameworks for Emerging Science and Technology. In: *International Journal of Sustainable Development* 16(1/2), 23-45.

Rose, Nikolas (1999) *Power of Freedom. Reframing Political Thought*. Cambridge: Cambridge University Press.

Rubinstein, Ira (2013) Big Data: The End of Privacy or a New Beginning? In: *International Data Privacy Law* 3(2), 74-87.

Sadowski, Jathan (2015) Office of Technology Assessment: History, Implementation, and Participatory Critique. In: *Technology in Society* 42, 9-20.

Schmidt, Jan C. (2008) Towards a Philosophy of Interdisciplinarity. An Attempt to Provide a Classification and Clarification. In: *Poiesis & Praxis* 5(1), 53-69.

Selin, Cynthia (2011) Negotiating Plausibility: Intervening in the Future of Nanotechnology. In: *Science and Engineering Ethics* 17, 723-737.

Silver, Nate (2012) *The Signal and the Noise. Why So Many Prediction Fail – But Some Don't*. New York: Penguin Press.

Simon, Judith (2017). Value-Sensitive Design and Responsible Innovation. In: Hansson, Sven O. (Ed.) *Methods for the Ethics of Technology*. London: Rowman and Littlefield International, 219-236.

Simon, Judith (2015) Distributed Epistemic Responsibility in a Hyperconnected Era. In: Floridi, Luciano (Ed.) *The Onlife Manifesto: Being Human in a Hyperconnected Era*. Charm: Springer, 145-159.

Singh, Vivek Kumar; Banshal, Sumit Kumar; Singhal, Khushboo; Uddin, Ashraf (2015) Scientometric Mapping of Research on 'Big Data'. In: *Scientometrics* 105(2), 727-741.

Statista (2016) *Forecast of Big Data Market Size, Based on Revenue, from 2011 to 2026 (in Billion U.S. Dollars)*. Available at: http://www.statista.com/statistics/254266/global-big-data-market-forecast/ (accessed 12 Apr. 2017).

Stirling, Andy (2014) Disciplinary Dilemma: Working Across Research Silos Is Harder than It Looks. In: *The Guardian*. Available at: https://www.theguardian.com/science/political-science/2014/jun/11/science-policy-research-silos-interdisciplinarity (accessed 12 Apr. 2017).

Teknologirådet (2015) *Predictive Policing: Can Data Analysis Help the Police to Be in the Right Place at the Right Time?* Available at: https://teknologiradet.no/wp-content/uploads/sites/19/2013/08/Predicitve-policing.pdf (accessed 12 Apr. 2017).

Thompson Klein, Julie (2001) The Discourse of Transdisciplinarity: An Expanding Global Field. In: Thompson Klein, Julie; Grossenbacher-Mansuy, Walter; Häberli, Rudolf; Alain, Bill; Scholz, Roland W.; Welti, Myrtha (Eds.) *Transdisciplinarity: Joint Problem Solving among Science, Technology, and Society*, 35-44. Basel: Spring Basel AG.

Turow, Joseph; Hennessy, Michael; Draper, Nora (2015) *The Tradeoff Fallacy. How Marketers Are Misrepresenting American Consumers and Opening Them Up to Exploitation*. A Report from the Annenberg School for Communication. Available at: https://www.asc.upenn.edu/sites/default/files/TradeoffFallacy_1.pdf (accessed 12 Apr. 2017).

Upturn (2014) *Civil Rights, Big Data, and Our Algorithmic Future. A September 2014 Report on Social Justice and Technology*. Available at: https://bigdata.fairness.io/wp-content/uploads/2015/04/2015-04-20-Civil-Rights-Big-Data-and-Our-Algorithmic-Future-v1.2.pdf (accessed 12 Apr. 2017).

Vance, Ashlee (2010) EMC Takes a Big-Data Swipe at Oracle, H.P. and I.B.M. In: *The New York Times*. Available at: http://bits.blogs.nytimes.com/2010/10/13/emc-takes-a-big-data-swipe-at-oracle-h-p-and-i-b-m/ (accessed 12 Apr. 2017).

Voß, Jan-Peter; Truffer, Bernhard; Konrad, Kornelia (2006) Sustainability Foresight: Reflexive Governance in the Transformation of Utility Systems. In: Voß, Jan-Peter; Bauknecht, Dierk; Kemp, René (Eds.) *Reflexive Governance for Sustainable Development*. Cheltenham: Edward Elgar, 162-188.

Weltevrede, Esther; Borra, Erik (2016) Platform Affordances and Data Practices: The Value of Dispute on Wikipedia. In: *Big Data & Society* 3(1): 1-16.

Wesselink, Anna; Paavola, Jouni; Fritsch, Oliver; Renn, Ortwin (2011) Rationales for Public Participation in Environmental Policy and Governance: Practitioners' Perspectives. In: *Environment and Planning A* 43(11): 2688-2704.

Wilsdon, James; Doubleday, Robert; Hynard, James (2015) Future Directions for Scientific Advice in Europe. In: Wilsdon, James; Doubleday, Robert (Eds.) *Future Directions for Scientific Advice*. Cambridge: Centre for Science and Policy. Available at: http://sro.sussex.ac.uk/54004/4/future-directions-for-scientific-advice-in-europe-v10.pdf (accessed 12 Apr. 2017).

Wood, Fred B. (1982) The Status of Technology Assessment. A View from the Congressional Office of Technology Assessment. In: *Technological Forecasting and Social Change* 22, 211-222.

Youtie, Jan; Porter, Alan L.; Huan, Ying (2017) Early Social Science Research about Big Data. In: *Science and Public Policy* 44(1), 65-74.