Administration & Society

The nodality disconnect of data-driven government

Journal:	*Administration & Society*
Manuscript ID	A&S-20-0156.R2
Manuscript Type:	Original Article
Keywords:	big data, government nodality, cybernetic governance, evidence-based policymaking, citizens' segmentation

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Abstract

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Introduction

The reliance on Information and Communications Technology (ICT) in policymaking and in service delivery has been a focal point in public administration, policy studies, and public management for many years, at least since the work undertaken by Dutton and Kraemer in the 1970s (Dutton & Kraemer, 1977; Kraemer & Dutton, 1979). Traditionally, each of these disciplines has considered information to be a means by which to support governments' activities for achieving public purposes (Desouza & Jacob, 2017; Dunleavy, Margetts, Bastow, & Tinkler, 2006; Eggers, Schatsky, & Viechnicki, 2017; Salamon, 2002; Sun & Medaglia, 2019).

Nowadays, government's deployment of the latest technological developments, primarily Artificial Intelligence (AI) and big data techniques (Bright & Margetts, 2016; Clarke & Margetts, 2014; Giest, 2017; Kim, Trimi, & Chung, 2014; C. L. McNeely & J. O. Hahm, 2014), in numerous settings, reinforces the belief that ICT has the potential to affect public administrations as 'information-dependent' institutions (Fleer, 2018). Of particular interest are the data-driven decision-making tools (most notably big data) available to public agencies at present (Mattingly-Jordan, 2018). Thanks to powerful analytics algorithms relying more and more on AI and machine

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learning, which make it possible to extract insights from large, heterogeneous, structured and unstructured datasets, these tools are expected to affect how governments (broadly considered, i.e., without distinction between institutional levels, policy areas, and national and cultural contexts) work and alter the same nature of politics (Cukier & Mayer-Schoenberger, 2013).

In current discourse, big data are portrayed as offering greater precision and predictive powers with which to improve efficiency, safety, wealth generation or resource management (Kim et al., 2014; Manyika et al., 2011). More critical commentators, however, have begun to draw attention to "socioeconomic, cultural, and political shifts that underlie the phenomenon of big data, and that are, in turn, enabled by it" (Ekbia et al., 2015, p. 1527; Lupton, 2015). Algorithmic profiling, the impact on the right of equal treatment, and the dominant position of big internet companies are the areas in which observers identify blind spots in the emerging governance landscape (Royakkers, Timmer, Kool, & van Est, 2018). Thus, there is an urgent need for wider (systemic) reflection on both the promise and the problems of big data in public governance (Desouza & Jacob, 2017; Ingrams, 2019; C. L. McNeely & J. Hahm, 2014).

With this in mind, the present paper conceptually seeks to better understand whether, and on what basis, embedding big data in public action can really have a transformative effect on government, as seems to be implied by the mainstream literature (McAfee, Brynjolfsson, Davenport, Patil, & Barton, 2012; Mergel, Rethemeyer, & Isett, 2016), by asking: *What, if any, is the contribution of big data to the transformation of the role of government in a data-intensive society?*

In trying to answer this question, the article extends past scholarly work to the linkages between 'the digital' and government. It does so by offering a framework of analysis that refers to the 'orders of change' in system development (Baptista, Stein, Klein, Watson-Manheim, & Lee, 2020; Bartunek & Moch, 1987; Kuipers et al., 2014). The article's main stance is that while big data can spur incremental improvements in policymaking and in service delivery — up to a *second-order* change — the possible transformative effect (or *third-order* change) should be found

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elsewhere, i.e. in how the spreading of the use of big data — and its companion data analytics — could challenge government's centrality (or *nodality*) within social systems. This, we argue, should urge government to think strategically about (re)defining its role in the new and emerging scenario.

In what follows, the paper first illustrates the key arguments that have led observers to anticipate a radical change in the public sector because of the rise of big data. Thereafter, following a short methodological section, two widely debated areas of application, namely the use of big data as the basis for evidence-based decision-making and for service delivery, are discussed to show how the use of big data can actually represent a possible step change in the scale, scope and accuracy in government up to a second-order change. The section that follows illustrates how the erosion of government's centrality and a possible shift toward a cybernetic form of governance can imply, under exogenous pressures, a deep transformation in government up to a third-order change. To counteract this potential drift, which challenges the role of government within social systems, it is argued that measures should be taken by government, first of all, to re-establish the fair rules of the game within the big data ecosystem. Some of these measures, including appropriate governance tools, large-scale regulations, and measures aimed at increasing the organizational capabilities of governmental machinery, are discussed in the following.

Focus of the paper

Social researchers' views on the implications of big data for the public sector present a complete spectrum of attitudes and opinions, "from overenthusiastic to ultra-conservative" (Resnyansky, 2019), depending on whether the focus is on the benefits or the risks. These contrasting views underscore the pressing need for wider critical reflection on the nature of big data, both to assess its possible impact and to tease out the epistemological implications that can drive a paradigm shift in science, culture, society and government, based on a new approach for making sense of the world (Kitchin, 2014).

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The discussion herein sets out to expand our thinking beyond the well-known and often examined worries surrounding privacy threats or data protection. A clear and unobstructed view of the nature of the changes spurred by the later digitization of the machinery is a prerequisite for identifying public responses which are better tailored to the times in which we live. If the intertwining of big data and government is to be understood properly, we argue that a simultaneous analysis at both organizational and systemic levels is needed.

Here we use the term 'big data' broadly to indicate the use of analytics algorithms in the overall process of extracting insights from large and heterogeneous datasets, covering both big data management — which involves processes and supporting technologies used to acquire and store data and prepare and retrieve it for analysis — and advanced big data analytics — which refers to underlying techniques used to analyze and acquire 'intelligence' from big data (O'Leary, 2013).

What we are particularly concerned with are the processes that are utilized to collect data from multiple and heterogeneous sources and process it to support public decision-making and service delivery. These operations are based more and more on advanced machine learning algorithms that "find their own ways of identifying patterns, and apply what they learn to make statements about data" (Boucher, 2020, p. 4). Among the different uses of big data analytics, we are more specifically interested in those that derive cognitive insights from data (Davenport & Ronanki, 2018), thanks to the advent of more computational power that has made machine learning — particularly deep learning through neural networks — more broadly deployable in organizations (Batistič & der Laken, 2019; H. J. Watson, 2019). However, we do not intend to address technical details. As nicely summarized by Grimmer (2015, p. 80), for analysis of big data to truly yield answers to society's biggest problems "we must recognize that it is as much about social science as it is about computer science".

In the private sector, advanced uses of big data have transformed processes and provided the organizational capabilities to tackle key business challenges (Fosso Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015). However, predictive analytics and data-driven strategies also have a

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great deal of potential impact in the public sector (Batistič & der Laken, 2019). First, predictive analytics can increase the quality of scenario planning and result in true evidence-based policymaking (Höchtl, Parycek, & Schöllhammer, 2016, p. 155). Second, citizens can benefit from services that may be proposed proactively as a result of large-scale predictive analytics, based on services used by comparable citizens (ibidem, p. 156). Third, big data and predictive analytics can be used by governments "to enhance transparency, increase citizen engagement in public affairs, prevent fraud and crime, improve national security, and support the well-being of people through better education and health care" (Kim et al., 2014, p. 81).

Here, our point is not to maintain a simplistic thesis, i.e. for or against the use of big data applications. Rather, our aim is to highlight how the effects of 'algorithmization' stemming from big data can be ambivalent, leading to more or less transformative impacts — different 'orders of change' — depending on how tools are used and new technologies are governed. Therefore, we will consider whether, under what conditions, and indeed how the use of big data in the public sphere will drive a change and, if so, what such a change will entail for the 'governmental machinery'.

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Methodological approach

To develop a more nuanced understanding of the intertwining of big data and government, it is first necessary to identify a network of interlinked issues that, together, capture and frame the relationship. For this reason, the present paper adopts a conceptualization approach that "integrates a number of different works on the same topic, summarizes the common elements, contrasts the differences, and extends the work in some fashion" (Meredith, 1993, p. 8).

More specifically, and by adopting Jabareen's definition of a conceptual framework, i.e. "a network, or 'a plane' of interlinked concepts that together provide a comprehensive understanding of a phenomenon" (Jabareen, 2009, p. 51), the paper draws on different social science domains (including public administration, policy studies, and sociology) that become the empirical data of the conceptual analysis carried out to better understand the research object from different perspectives. Hence, although it makes extensive reference to multidisciplinary bodies of knowledge, the paper is neither a literature review nor a meta-review. Rather, the following pages scope the extant research across multiple domains for relevant signposts, leveraging prior research, especially the most cited seminal works concerning the impact of big data on government, and the authors' own knowledge base.

To understand whether the use of big data algorithms in government implies something substantially new or transformational, we refer to the 'orders of change' taxonomy (Baptista et al., 2020; Bartunek & Moch, 1987; Kuipers et al., 2014):

– *First-order* change, which can be found in the introduction of new processes, systems and procedures, without affecting the primary organizational processes and changing the organization. This kind of change includes modifications consistent with an already-present orientation toward events (or 'schemata'), such as the early use of ICT to automatize governmental procedures.
– *Second-order* change, which affects core organizational paradigms, culture, climate, and other behavioral factors. The aim is to try to modify the common organization-wide schemata, as in the use of ICT to implement new user-centric service delivery processes.
– *Third-order* change, which can be found in the transformation of the underlying problem understanding, policy objective, program theory, and even institutional context; this concept implies identity change and many organization/sector-wide changes.

In general, distinguishing between a *before* and an *after* in a change process is difficult and questionable. Nevertheless, the aforementioned taxonomy can be useful for capturing the big picture. In essence, the 'orders of change' view suggests that the focal point should be the impact of big data technologies on the whole machinery of government, and not simply on the programs of individual organizational units.

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The paper frames big data as one of the tools or instruments available to government to address public issues. For the purposes of this discussion, a tool approach (C. C. Hood & Margetts, 2007; Salamon, 2002) is particularly useful for understanding what, if any, differences big data makes to the practice of government. The information sweet spots that steer public action provide a fresh context in which to apply the Nodality–Authority–Treasure–Organization taxonomy developed by Hood in the pre-digital era (1983), and then revisited by Hood and Margetts (2007). The framework (which also goes by the acronym of NATO) identifies four core tools at the disposal of government to monitor society or alter its behavior, and the vital role of ICT therein: i) *Nodality*, meaning the capability to gather, circulate and control information within multiple social and political networks; ii) *Authority*, which is the legal power to require and/or condition behaviors; iii) *Treasure*, meaning the exchangeable assets needed to service policy goals; and iv) *Organization*, referring to the ability to monitor and manage information to guide policymaking. The four basic tools — as pointed out by the authors themselves — consider government to be 'a single analytic entity' (C. C. Hood & Margetts, 2007, p. 173), which is the same perspective that we assume in this paper.

In the following, the effects of the use of big data will be explored in relation to the 'detecting' and 'effecting' capabilities that, according to the NATO framework, for government are "basic for its existence, and certainly for its effectiveness" (C. C. Hood & Margetts, 2007, p. 3). Detector tools are instruments that a government uses for taking in information, whereas effector tools are instruments that it uses to try to make an impact on the world (ibidem). By discussing the dual use of big data as detector tools that support evidence-based decision-making and as effector tools that support personalized service delivery based on citizen segmentation, the next section will provide the first answer to our question, i.e. *What, if any, is the contribution of big data to the transformation of the role of government in a data-intensive society?*

Second-order changes in the big data era

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Evidence-based decision-making

The development of a new data-driven and evidence-based approach to public decision-making and service delivery points to the need to search for usable and relevant information which can be used to help address and resolve problems (Head, 2008, 2016). Big data substantially extend both the quantitative and the qualitative information base for decision-making (Maciejewski, 2016). In addition to the administrative data — which includes governmental records, tracking information, and data from commercial and business sources (Allard et al., 2018) — big data also make the 'digital residues' available to policymakers, i.e. the 'electronic footprints' of behavioral patterns, meanings and memes created by our contemporary civilization (Dunleavy, 2016). Moreover, big data technology enables fragments of heterogeneous information to be matched and linked together to identify faster and better insights. In fact, as "those correlations can be automatically deduced by the application of machine-learning algorithms, data can be observed in its entirety, and analytical results theoretically become available instantaneously" (Höchtl et al., 2016, p. 158).

This opens up "new possibilities for research and evidence-based decision making" (Mergel et al., 2016, p. 932), which makes big data a potentially relevant policy instrument that is expected to enable the production of better decision support information and more informed policymaking to achieve policy goals (Giest, 2017; Janssen & Kuk, 2016; Maciejewski, 2016).

The implicit assumption herein is that "the volume of data, accompanied by techniques that can reveal their inherent truth, enables data to speak for themselves" (Vydra & Klievink, 2019, p. 3) and provides insightful, objective and profitable knowledge. In big data discourse, the reference to data evidence appears to be a means of "underpinning policymaking with scientific or expert evidence, in order to make it more effective, regardless of the political preferences of policymakers or other interested groups" (Poel, Meyer, & Schroeder, 2018, p. 353).

Public organizations commonly resort to external data sources, such as hybrid cross-sectoral intermediaries, i.e. think tanks, social enterprises, and other third-sector organizations (Williamson, 2014), to find an evidence base for policymaking; therefore, there is always the risk that these data

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are bias-affected. However, when the evidence base comes from traditional data intermediaries, governmental organizations can also evaluate its reliability and validity through the trustworthiness of a reduced number of (often prequalified) providers. This gives governmental organizations some (direct or indirect) control over the data sources on which they base their decisions.

Conversely, the big data era multiplies the potential data providers that can also operate as secondary providers, the trustworthiness of which is much more difficult for government to ascertain, and this implies a possible reduction of government's control over the data sources. Furthermore, current discourse assigns a crucial role to technologies as instruments that not only make the data management processes more efficient, but also ensure the data's objectivity. Hence, the generation, collection, storage, and processing of big data are conducted using information systems and algorithms that, as technological artefacts, are perceived as being *neutral*, or at least more neutral than humans.

Nevertheless, "transforming big data into information and insights … depends on who decides what data is worth, what is included, what is excluded, how data are aggregated …. there are political decisions to be made not only in interpreting the data, but also in gathering it; the algorithms used to capture insights from big data reflect specific conceptions of social phenomena, including preconceptions about factors of importance, expected correlations, or contested assumptions" (Vydra & Klievink, 2019, p. 3). These assumptions are, however, not transparent; they are embedded in the logic underlying the analytics algorithms. This logic is most often unknown to governmental organizations, therefore heightening the risk of policy decisions being shaped by biased data.

In sum, the multiple information sources available to public administrations in the big data era can strengthen government's detecting capability, thus amplifying the efficiency and efficacy of decisional processes. This can prompt a step change in scale, scope and accuracy (Schroeder, 2014) in many public service sectors, while also inducing changes in the patterns and nature of work as well as in organizational schemata, to which a second-order change amounts (Baptista et al., 2020).

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This, however, comes at a price: the possible reduction of government's control over the data sources on which its decisions are based.

Citizen segmentation in service delivery

Big data are expected to provide governments with powerful tools with which to better assess 'the will of the people' and to "ensure that their policies — and the subsequent provision of public goods and services — reflect the preferences of their citizens" (Desouza & Jacob, 2017, p. 1053). The segmentation of recipients, based on data analytics algorithms, gives a new sense of citizens' centricity in service delivery through a better understanding of their needs, preferences and behaviors, which allows for the deeper personalization of interventions (Pencheva, Esteve, & Mikhaylov, 2020, p. 9). Moreover, "big data makes it possible to understand which incentives will work and under what circumstances, and to design policy and administrative change in a way that is realistic, legitimate and efficient" (Clarke & Margetts, 2014, p. 403).

User/consumer segmentation is quite a common practice in the business world, wherein the use of big data analytics for customer segmentation has reached highly advanced levels of sophistication. Mergel, Rethemeyer, and Isett (2016) report that (as of 2014) the nine largest private data brokers hold more than 3,000 data segments (i.e. variables) that can be used to classify individuals, and thus to "create highly specific segmentations and to tailor products and services precisely to meet those needs" (Manyika et al., 2011, p. 5). This is claimed to also be of value for policymaking and for service delivery. As Pirog put it, having "access to more complete or comprehensive data on citizens, and having a fuller picture of individuals should, all other things being equal, improve public policy" (Pirog, 2014, p. 537).

Among the big data enthusiasts, Manyika et al. go further by claiming that the user/consumer segmentation approach "can be revolutionary (…) in the public sector where the ethos of treating citizens in the same way is commonplace" (2011, p. 5). Contrary to what the above authors claim, however, treating citizens as customers is not so commonplace and what 'revolutionary' can mean

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in this context requires a much deeper explanation. This is an old and ongoing debate in public administration, at least since the emergence of the New Public Management reform rhetoric some 30 years ago.

As already highlighted by Fountain in 2001, "the growing replacement of the term 'citizen' with 'customer' and the idea that government agencies should be 'customer-focused' — that is, that public managers should view their clients as customers and serve them using management concepts drawn from effective private sector service firms — demand close scrutiny" (Fountain, 2001, p. 56). In her critical analysis of the customer orientation transposed to the public sector, Fountain observes that the service models may produce improvements in the operational performance of public organizations, but that "those improvements do not replace political outcomes that render some customers much less powerful than others" (Fountain, 2001, p. 58). This is because public agencies routinely serve a variety of target populations with possibly conflicting interests. Hence, since agencies cannot pick and choose their customers, they must mediate the conflicting interests of different groups in order to avoid increased political inequality. This is a typical aspect of the policy and administrative discretion (Lipsky, 1980), which is a crucial part of a public administrator's job (Sowa & Selden, 2003) — one that the growing algorithmization of policy and administrative processes tends to eclipse and erode.

Customer hyper-segmentation in the business world enables firms to offer highly-customized products or services to very small groups of consumers, and even to selectively target and satisfy individual tastes and needs. However, when hyper-segmentation is applied in the public sphere, e.g. to social policies and health care, it risks exacerbating the risk of inequalities, bumping it up from the level of potential conflict between groups of citizens to the much more critical level of conflict between the needs and preferences of the *single* citizen. Considering the service recipient as a cluster of (potentially conflicting) needs that are to be selectively satisfied risks the subversion of public purposes, such as fairness, and recognition of the holistic nature of citizens' satisfaction.

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In sum, big data give government a precision tool with which to better hone and target public interventions and craft a more effective citizen-centric approach to service design and delivery, which can sensibly enhance government's effecting capability. This, as already observed, can represent a step change in scale, scope and accuracy beyond simple incremental improvements.

In the original NATO language, the use of big data can lead to the 'sharpening' of government's tools by enhancing both its detecting and its effecting capabilities up to second-order changes, as described by (Kuipers et al., 2014). However, the use of such data can also have far-reaching consequences for the administrative machinery as ICT increasingly becomes a *driving* tool for the design and implementation of targeted public policies. The flipside is that big data would give ICT artefacts a more penetrative changing role, even beyond second-order changes — one that we believe deserves close scrutiny.

Big data and third-order change

Loosing nodality in the big data era

In contemporary government, as Peters (2012) points out, information is power. A crucial problem, then, is "how that information is used and the extent to which information is processed and politicized prior to being acted upon" (p. 126). The current big data ecosystem — in which a multiplicity of actors interact with one another to exchange, produce and consume data (Oliveira, Barros Lima, & Farias Lóscio, 2019) — is characterized by a systemic information asymmetry.

Currently, in the big data ecosystem an increasingly central role is played by certain big tech companies — the big five (Facebook, Amazon, Apple, Microsoft, and Google) — and a few others; these organizations not only provide government with the technological tools (algorithms) necessary to manage big data, but also collect themselves and produce huge amounts of data that government can use in its policymaking processes. The contract between the Australian government and Amazon to store data from the coronavirus tracking app has caused quite a stir. The same happened when the Canadian government and Amazon signed the contract for the supply of

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medical equipment. In this case, the renunciation of the use of the public postal service has raised strong doubts. Both examples remind us that, in the information-intensive society, the power of government as the central actor within social systems (i.e. its nodality) can be eroded, as other (private) actors can take the stage.

Actually, the risk of government to loose its centrality was already anticipated by Hood and Margetts at the dawning of the big data era (the term 'big data' made its first appearance in 2005): "If those developments continue in the future, we might expect to find government to be decreasing nodal in the Google-search sense ….. The algorithms that … powerful multinational corporations use are more tightly guarded than any state secret against the strategizing of those who want to …. maximize *their* nodality" (C. C. Hood & Margetts, 2007, pp. 190, original emphasis).

What is distinctive for the current scenario in comparison to the era in which the NATO framework was originally developed is, first and foremost, the fact that government has little direct control over the sheer volume of information of potential public interest and the proprietary analytics algorithms used by big tech companies. The exploitation of the various forms of data that platforms collect on consumers and business users explains, to a good extent, the current dominance that these firms enjoy (Khan, 2018). Second, in the contemporary world, the contexts in which data are generated and processed — whether through commercial platforms or public institutions — "all appear to be interchangeable" (Van Dijck, 2014, p. 204). In the past the public sector served as "the repository for most of the stored data in the world", while "the advent of the information economy resulted in a dramatic role reversal" (Andrejevic, 2020, p. 85). For example, in the field of national security, governmental agencies have found ways in which to piggyback on the data collection practices of major tech players (ibidem), and in many countries worldwide, taxation authorities regularly use data from social media in the fight against tax evasion. In parallel, in some areas the role of public services is being questioned by the presence of digital giants (OECD, 2019).

Within a few years a sort of continuum between public and private social actors, and from state to international level, was created (Scott, Cafaggi, & Senden, 2011). In this ecosystem of supply,

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demand and exchange, which are fueled by growing piles of online metadata, social agents and online platforms, are "inevitably interconnected, both on the level of infrastructure and on the level of operational logic" (Van Dijck, 2014, p. 204). This would entail, at least tendentially, a broader picture of governance arrangements generated outside of the global public sphere, with a shift toward "a polycentric perspective that sees the state as a part of a broader and more complex social governance system" (Aligica, 2017, p. 542).

In such a polycentric context, important reconfigurations of power are emerging. The differential power of tech players and other unaccountable actors is partly a consequence of the orders of magnitude that they have reached, thanks to their levels of digitization, intermediation capacity, and global integration. In the emerging scenario, in which nodality will vary according to the extent to which citizens and public opinion trust the institutions involved (Van Dijck, 2014), the problem for government lies in how to preserve centrality as the guarantor of fundamental values and rights in modern society. This would require government to progressively change not only its capabilities and operational modes, but also its steering model and its role and purpose, i.e. to deal with questions such as 'what is government?' — this can lead to third-order changes.

A step toward 'cybernetic governance'?

Our illustration has shown how the massive algorithmization tends to transform ICT from a *supporting* tool into a *driving* tool for the design and implementation of public policies. This raises the problem of what impact the use of big data algorithms can have on public governance, since different forms of governance can be distinguished based on the "extent to which information drives decisions or is only part of a decision process that also involves a number of more deliberative and politicized elements" (G. Peters, 2012, p. 113).

We shall attempt to answer the above question by relating the use of big data algorithms to the reduction of complexity of the information-intensive environment. Borrowing from (Luhmann, 1993), Kallinikos (2011, p. 23) characterizes technology broadly as a system organized along the

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lines of *functional simplification* and *functional closure* (italics in the original). The former principle takes the shape of "a set of operations being lifted out of the surrounding institutional and organizational complexity … as simplified causal and … procedural sequences ...", while functional closure implies "the very decoupling of the operations of the technical system from the wider organizational and social relations within which the system itself is embedded" (Kallinikos, 2005, p. 190). Big data algorithms are premised upon functional simplification and closure. In particular, the (apparent) objectivity of the algorithms makes it difficult for public officials to contend with the algorithmically-generated evidence, thus diminishing unwanted and uncontrolled interferences from outside of the system, according to the 'let the data speak for themselves' principle (or functional simplification, in Luhmann's words). Yet big data algorithms mark a crucial shift: they can shape the scene for decision-making and policymaking *outside* of decision-makers' sphere of influence, i.e. outside of the public realm. In addition, unlike previous problem-solving tools working on the basis of *recognized* rules, big data management and data analytics algorithms are "opaque, inscrutable black boxes" (Yeung, 2018), whose inferential engine often operates without regard for human comprehension (Burrell, 2016) (or the functional closure principle, in Luhmann's words).

"The unlimited technicization of work processes" (Luhmann, 2018, p. 302) led by functional simplification and closure legitimizes the question of whether big data applications, once they become a 'universal standard of rationality' (Townley, 2008), will accelerate the transition to a 'cybernetic approach to governance'. Simply put, this conception emphasizes the responsiveness of the public sector to changing social and economic conditions as depending upon information processing, just as physical mechanisms for cybernetic controls involve receiving and processing adequate information from the environment and then making the appropriate decisions based on that information (B. G. Peters, 2012; p. 121).

It may be easy to initially shrug this account off as unrealistic, especially when comparing the contemporary steering models to the distinctive attributes of the cybernetic ideal type, i.e. a closed-system vision, a rather linear conception of control, a clear capacity of control, and programmed-in-

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advance decisions with regard to changed states. Per contra, the plausibility of a cybernetic conception of governance cannot be ruled out in the event that the use of big data and automated analytics in government takes an impetuous turn; in other words, ICT applications not only shape the decisional field and present recommendations to human decision-makers (as in prescriptive and predictive analytics), but also autonomously *take action* based on the results of their analysis.

To gain a sense of the scope of this transformation, it is helpful to go beyond the visible manifestations of the technologies in use to consider what patterns and logics are related to the decoupling of technical operations from the wider organizational and social relations within which such a technical system is embedded (Kallinikos, 2011, p. 77). In this regard, the displacement of social processes — including social deliberation — with automatic systems can be traced back to three interrelated 'built-in tendencies' or 'biases' (in Andrejevic's words) of big data: pre-emption, operationalism and environmentality. Table 1 provides an overview of these biases.

Tab. 1. Built-in tendencies of big data and their effects (authors' own, based on (Andrejevic, 2020))

Bias	**Description**	**Displacement effect**
Pre-emption	Extensive monitoring and predictive analysis	Number crunching vs. comprehension
Operationalism	Automated responses	Acting vs. understanding
Environmentality	Monitoring and shaping the conduct of individuals	Regulation of effects vs. regulation of causes

First, big data impose a logic of pre-emption to simulate future scenarios, from crime to terrorism, and from natural disasters to pandemics, so as to act on them in the present, i.e. before they can strike. Shifting the focus from the past (historical data) to the future displaces narratives of causation (Andrejevic, 2020, p. 77). Second, the predicted operationalization of monitoring enabled by digital automation has the effect of eliciting and modeling reality, and renders problematic domains actionable (ibidem p. 97). In this way, the argument as the main form of motivation for decisions is abandoned. Third, and finally, the imperative of total information capture and tracking transforms the environment into a 'sensorized space' (p. 39), populated with devices capable of

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detecting and discerning signals and patterns of behavior (Van Dijck, 2014, p. 198), and modulating the context accordingly. In this case, automated detection implies the potential displacement of human intervention; in other words, agency is absent, or at least reduced. In NATO's words, not only does technology sharpen government's detecting and effecting capabilities, it is also the technological system itself that ideally acts as both a detector and an effector.

An ever-going trend is demonstrated by the well-known State vs. Loomis case concerning a citizen arrested in Wisconsin (US) for driving a car involved in a former shooting case. The arrested was sentenced six years of detention on the basis of his potentiality to re-offend algorithmically calculated by a closed-source risk assessment software (COMPAS). One consequence of the use of algorithms that are insensitive to the fundamental norms in the US legal system is that "the Court in effect outsourced its decision making, …. consequently undermining its public accountability" (Liu, Lin, & Chen, 2019, p. 133).

In essence, the increasing use of big data and AI-based artefacts in governmental machinery can question fundamental principles of public administration — including control, discretion and accountability — as well as the role of policymakers and that of public officials. In other words, the far-reaching consequences of the emergent algorithmization of policy and administrative processes will urge government to think strategically about its purpose and role within social systems, which can lead to third-order changes.

Regaining nodality

Developing an appropriate governance framework

Two mutually-reinforcing factors emerge from the increasing use of big data — and its companion, AI-based data analytics — that, if not governed, can have far-reaching, critical consequences for government. As discussed above, the potential — and, regarding many aspects, already actual — erosion of government's nodality and the possible emergence of a cybernetic mode of governance

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can significantly reduce the role of government in the information-intensive society. As seen in the State vs. Loomis case, “ill-informed deference to the privately made machines marginalizes the role of public authority and public scrutiny in government” (Liu et al., 2019, p. 138). However, even when government decides to rely on private firms’ consultancy to elaborate algorithms which might serve in public decision-making, the public sector has additional duties of accountability to the citizens (Gualdi & Cordella, 2021).

Under different forms and with gradations varying in different sociopolitical contexts, the centrality of government within social systems is a value that should be preserved for a number of reasons, including (van Wynsberghe, 2020): the need to protect people; the need to create a level playing field; the need for the development of a common set of rules for all stakeholders to uphold; protection from negative outcomes that may result from new and emerging technologies; and the interest of the state, given that the new technologies are being used in state-governed areas (such as prisons, taxes, educational systems, etc.).

To retain nodality, government would have to reposition itself to take back its role as the regulator of the social system and the guarantor of public values, while also maintaining political agency and democratic accountability (Nemitz, 2018). This could require government to transform itself, up to a third-order change, to adapt to the new contextual conditions. However, if government wants to steer the change rather than to submit to it, the conditions for rebalancing the power relationships within the big data ecosystem must be re-established to allow government to operate on an equal footing with the private players.

Industry self-regulation in many cases can be (and has been) an advantageous complement to government policies (OECD, 2015). However, in the big data ecosystem self-regulation by single companies or industry branches risks being ineffective due to the massive concentration of information industries removing market-led pressures toward self-governance (Koene et al., 2019; Nemitz, 2018).

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An obvious alternative for government would be to resort to market-based mechanisms to negotiate better terms, and to establish rules limiting the scope of non-disclosure and trade secrets (Liu et al., 2019). When codified as prerequisites in order to bid for government contracts these requirements take on the form of co-regulation (Koene et al., 2019). However, also contractual regulation and co-regulation risk being ineffective due to the information asymmetry that would allow private players to use their informational advantage to water down contractual specifications and standards (Hirsch, 2011).

Another option, although not free from problems, could be establishing a clear governance framework for algorithmic transparency and accountability to be adopted by business and governmental organizations that use advanced data-processing algorithms (European Parliament, 2019; H. Watson, 2019).

The strong information and power asymmetry between public and private actors within the big data ecosystem makes it unlikely that single governments will be able to succeed in setting such regulation and enforcing it in global enterprises. The limited room for unilateral maneuvering in relation to these phenomena requires governments to coordinate their efforts at the supranational level.

In Europe, the EU Parliament has taken the lead in defining a new governance framework in a series of coordinated reports prepared for the Directorate-General for European Parliamentary Research Services (EPRS) (Boucher, 2020; Koene et al., 2019; van Wynsberghe, 2020). In particular, based on a review and analysis of existing proposals for the governance of algorithmic systems, Koene et al. (2019) identify a number of possible governance measures that, when implemented, can help governments to regain a central role in the big data ecosystem.

Excluding the state ‘appropriation’ of big data infrastructure, which is unfeasible in Western liberal democracies, governments can adopt measures related to (Koene et al., 2019, pp. 45-50):

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- Information, which means providing the users of algorithmic decision-making systems with a general understanding of algorithmic processes and specific information regarding a particular application of algorithmic decision-making;
- Command-and-control regulation through legislative measures, as exemplified by the EU General Data Protection Regulation (GDPR) that, by defining measures dealing with the protection of personal data, also provides some response to the search for more accountability relating to algorithmic decision-making (Brand, 2020);
- Incentives through funding and taxes — individual countries have begun introducing digital tech company taxes, and a global tech tax compact is back in vogue again (Dignam, 2020) — as part of an incentivizing structure for promoting the use of transparency- and accountability-enabling methods such as voluntary certification against transparency standards and performance auditing;
- Public investments on big data infrastructures (most notably platforms and certified data sets to train the algorithms), which would give back to the public some control power on the ecosystem (Nogarede, 2021). While unlikely in the cost-containment scenario of the past, this measure has recently become feasible (at least in Europe) as a part of the Next Generation EU package.

Implementing new organizational capabilities

Interestingly, the recent EPRS governance measures leverage three basic tools — nodality (information), authority (command and control) and treasure (incentives and public investments) — informing the NATO framework. To be effective, however, the aforementioned means should be implemented 'on the ground', which requires complementing them with appropriate organizational actions (i.e. the fourth NATO tool of government) to be taken by each governmental unit. The options, which can be divided into interventions of lower and higher intensity, measured against the extent to which they depart from the organizational status quo, include:

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- Capacity-building programs, e.g. action plans coupled with adequate investments in the key assets and resources required (technologies, skills, and technical knowhow) to develop the new technical and functional roles that are, at present, unevenly spread in the public sector, including data cleaners, algorithm writers, data visualizers, and designers of the interfaces of systems that gather and output data (Kennedy, Poell, & van Dijck, 2015);
- Large-scale retraining programs for mid-career workers to match the shifts in skill requirements. Once the gaps in organizational and knowledge capacities are filled, data workers might create spaces in which to exercise some agency in their work (Kennedy et al., 2015). These first two steps will enable government to bring in-house vital skills and knowhow to reorient and rescale its capabilities, moving more upstream and, ultimately, strengthening its negotiating position with big tech companies;
- Decision-making procedures that ensure the ongoing involvement of human decision-makers ('human in the loop'), including engineers, product managers, user experience researchers, and legal professionals. This is a viable strategy with which to validate models and double-check results from AI solutions (Chui et al., 2018, p. 41). More interdisciplinary efforts, including the involvement of social scientists and of experts in the organizational and societal implications of ICT, are essential when it comes to managing the inherent risks of opaque algorithms.

All of the above suggests that there is no quick fix that can be implemented to regulate and steer big data and AI developments in a way that furthers the public interest while unlocking the potential of these technologies (Cate, 2016; Guihot, Matthew, & Suzor, 2017), without forgetting that part of the challenge of effectively regulating those developments lies in identifying opportunities for regulatory agencies to influence other actors when the traditional NATO tools of government are limited (Guihot et al., 2017, p. 429). In this sense, the large-scale approach recently adopted by the European Union in attempting to shape the behaviors of big tech companies is a

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clear policy signal to all of those involved in the big data and AI industry that the topic of governance in the data-intensive era is high on the policy agenda (Royakkers et al., 2018).

Yet more needs to be done to proactively safeguard governmental nodality in what is largely "an unregulated field" (Guihot et al., 2017, p. 386). As observed recently by (Brand, 2020) and (Etzioni, 2018), what are important to establish on a global scale are appropriate frameworks not for the sake of regulating the use of technology, but in order to protect society from potential harm, without forgetting that the ongoing evolution requires not only continuous consideration of suitable legal arrangements, but also a deep transformation of government both at the (macro) policy level and at the (micro) organizational level.

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Conclusions

This paper addresses several crucial questions raised by the use of big data and AI-based data analytics in government. However, as is often the case with technological innovations that penetrate nearly all facets of organizations, whether big data delivers on its promise is far from assured. Obviously, this introduces another veil of uncertainty into the public sphere.

To fully appreciate the impact of big data in government, it is necessary to understand at least two potential manifestations of the effects of these data:

– An *organizational* transformation, to match and combine big data into well-established practices and public values, in order to leverage the increase *in the scale and scope* of the efficacy of the core tools deriving from the use of big data to support public decision-making and service delivery processes (second-order change).

– A progressive change of the governmental *identity*, to cope with the emergent cybernetic mode of governance and the potential erosion of nodality, and to re-establish, under new conditions, the central role of government (third-order change).

Drawing on the NATO framework, we have also argued for a more multidimensional look at big data, recognizing how the real game is played at the level of governmental nodality, as well as advocating the need for appropriate strategies that incorporate this aspect.

In essence, what government can learn from the data-intensive digital whirlpool into which it has been plunged is that it is unwise to focus exclusively or prevalently on the first- and second-order change effects. That would allow the real implications of big data for the public sector to slip by unnoticed, and would lead to the vision, mission and strategies of government paying the ultimate price. Of course, we are not any closer to a quick solution, but we have distilled several principles for action in an information-intensive society.

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Acknowledgments

The authors thank the Editor-in-chief and reviewers of *Administration and Society* for their insightful comments and suggestions on earlier versions of the paper. Author'names are listed alphabetically indicating equal contribution to the research.

References

Aligica, P. D. (2017). Public Administration and the Classical Liberal Perspective: Criticism, Clarifications, and Reconstruction. *Administration & society, 49*(4), 530-551. doi:10.1177/0095399715581044

Allard, S. W., Wiegand, E. R., Schlecht, C., Datta, A. R., Goerge, R. M., & Weigensberg, E. (2018). State Agencies' Use of Administrative Data for Improved Practice: Needs, Challenges, and Opportunities. *Public Administration Review, 78*(2), 240-250. doi:10.1111/puar.12883

Andrejevic, M. (2020). *Automated media*. New York: Routledge.

Baptista, J., Stein, M.-K., Klein, S., Watson-Manheim, M. B., & Lee, J. (2020). Digital work and organisational transformation: Emergent Digital/Human work configurations in modern organisations. *The journal of strategic information systems, 29*(2), 101618. doi:10.1016/j.jsis.2020.101618

Bartunek, J. M., & Moch, M. K. (1987). First-Order, Second-Order, and Third-Order Change and Organization Development Interventions: A Cognitive Approach. *The Journal of Applied Behavioral Science, 23*(4), 483-500. doi:10.1177/002188638702300404

Batistič, S., & der Laken, P. (2019). History, Evolution and Future of Big Data and Analytics: A Bibliometric Analysis of Its Relationship to Performance in Organizations. *British journal of management, 30*(2), 229-251. doi:10.1111/1467-8551.12340

Boucher, P. (2020). *Artificial intelligence: How does it work, why does it matter, and what can we do about it?* Brussels: European Parliamentary Research Service, Scientific Foresight Unit (STOA), PE 641.547, European Union.

Brand, D. (2020). Algorithmic Decision-making and the Law. *JeDEM - eJournal of eDemocracy and Open Government, 12*(1), 114-131. doi:10.29379/jedem.v12i1.576
Bright, J., & Margetts, H. (2016). Big Data and Public Policy: Can It Succeed Where E-Participation Has Failed? *Policy & Internet, 8*(3), 218-224. doi:10.1002/poi3.130
Burrell, J. (2016). How the machine 'thinks': Understanding opacity in machine learning algorithms. *Big Data & Society, 3*(1), 2053951715622512.
Cate, F. H. (2016). Big data, consent and the future of data protection. In C. R. Sugimoto, H. R. Ekbia, & M. Mattioli (Eds.), *Big Data Is Not a Monolith* (pp. 3-19). Cambridge: The MIT Press.
Chui, M., Harryson, M., Manyika, J., Roberts, R., Chung, R., & van Heteren, A. (2018). *Notes from the AI frontier. Applying AI for social good*: McKinsey Global Institute.
Clarke, A., & Margetts, H. (2014). Governments and Citizens Getting to Know Each Other? Open, Closed, and Big Data in Public Management Reform. *Policy & Internet, 6*(4), 393-417. doi:10.1002/1944-2866.POI377
Cukier, K., & Mayer-Schoenberger, V. (2013). The Rise of Big Data: How It's Changing the Way We Think About the World. *Foreign Affairs, 92*(3), 28-40.
Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review, 96*(1), 108–116.
Desouza, K. C., & Jacob, B. (2017). Big Data in the Public Sector: Lessons for Practitioners and Scholars. *Administration & Society, 49*(7), 1043-1064. doi:10.1177/0095399714555751
Dignam, A. (2020). Artificial intelligence, tech corporate governance and the public interest regulatory response. *Cambridge journal of regions, economy and society, 13*(1), 37-54. doi:10.1093/cjres/rsaa002
Dunleavy, P. (2016). 'Big data' and policy learning. In G. Stoker & M. Evans (Eds.), *Methods that Matter: Social Science and Evidence-Based Policymaking* (pp. 143-168). Bristol: The Policy Press.
Dunleavy, P., Margetts, H., Bastow, S., & Tinkler, J. (2006). New Public Management Is Dead. Long Live Digital-Era Governance. *Journal of Public Administration Research and Theory, 16*(3), 467-494. doi:10.1093/jopart/mui057
Dutton, W. H., & Kraemer, K. L. (1977). Technology and urban management: the power payoffs of computing. *Administration & Society, 9*(3), 305-340.
Eggers, W. D., Schatsky, D., & Viechnicki, P. (2017). *AI-augmented government. Using cognitive technologies to redesign public sector work*. Retrieved from
Ekbia, H. R., Mattioli, M., Kouper, I., Arave, G., Ghazinejad, A., Bowman, T., . . . Sugimoto, C. R. (2015). Big data, bigger dilemmas: A critical review. *Journal of the Association for Information Science and Technology, 66*(8), 1523-1545.
Etzioni, O. (2018). Point: Should AI technology be regulated? yes, and here's how. *Communications of the ACM, 61*(12), 30-32.
European Parliament. (2019). *A governance framework for algorithmic accountability and transparency*. Brussels: EPRS | European Parliamentary Research Service.
Fleer, P. (2018). The technology of information, communication, and administration: An entwined history. *Administration & Society, 50*(9), 1210-1212
Fosso Wamba, S., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015). How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. *International journal of production economics, 165*, 234-246. doi:10.1016/j.ijpe.2014.12.031
Fountain, J. E. (2001). Paradoxes of Public Sector Customer Service. *Governance, 14*(1), 55-73. doi:10.1111/0952-1895.00151
Giest, S. (2017). Big data for policymaking: fad or fasttrack? *Policy Sciences, 50*(3), 367-382. doi:10.1007/s11077-017-9293-1
Grimmer, J. (2015). We Are All Social Scientists Now: How Big Data, Machine Learning, and Causal Inference Work Together. *PS: Political Science & Politics, 48*(1), 80-83. doi:10.1017/S1049096514001784
Gualdi, F., & Cordella, A. (2021). *Artificial Intelligence and Decision-Making: the Question of Accountability*. Paper presented at the 54th Hawaii International Conference on System Sciences, Maui, Hawaii.

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Guihot, M., Matthew, A. F., & Suzor, N. P. (2017). Nudging robots: Innovative solutions to regulate artificial intelligence. *Vanderbilt Journal of Entertainment & Technology Law, 20*(2), 385-456.

Head, B. W. (2008). Three Lenses of Evidence-Based Policy. *Australian Journal of Public Administration, 67*(1), 1-11. doi:10.1111/j.1467-8500.2007.00564.x

Head, B. W. (2016). Toward More “Evidence-Informed” Policy Making? *Public Administration Review, 76*(3), 472-484. doi:10.1111/puar.12475

Hirsch, D. (2011). The Law and Policy of Online Privacy: Regulation, Self-Regulation, or Co-Regulation? *Seattle University Law Review, 34*(2), 439-480.

Hood, C. (1983). *The tools of government*. London: Macmillan.

Hood, C. C., & Margetts, H. Z. (2007). *The Tools of Government in the Digital Age*. Basingstoke: Palgrave Macmillan.

Höchtl, J., Parycek, P., & Schöllhammer, R. (2016). Big data in the policy cycle: Policy decision making in the digital era. *Journal of organizational computing and electronic commerce, 26*(1-2), 147-169.

Ingrams, A. (2019). Big Data and Dahl's Challenge of Democratic Governance. *Review of Policy Research, 36*(3), 357-377. doi:10.1111/ropr.12331

Jabareen, Y. (2009). Building a Conceptual Framework: Philosophy, Definitions, and Procedure. *International Journal of Qualitative Methods, 8*(4), 49-62. doi:10.1177/160940690900800406

Janssen, M., & Kuk, G. (2016). The challenges and limits of big data algorithms in technocratic governance. *Government Information Quarterly, 33*(3), 371-377. doi:10.1016/j.giq.2016.08.011

Kallinikos, J. (2005). The order of technology: Complexity and control in a connected world. *Information and Organization, 15*(3), 185-202. doi:10.1016/j.infoandorg.2005.02.001

Kallinikos, J. (2011). *Governing through technology: information artefacts and social practice*. Basingstoke: Palgrave Macmillan.

Kennedy, H., Poell, T., & van Dijck, J. (2015). Data and agency. *Big Data & Society, 2*(2), 1-7. doi:10.1177/2053951715621569

Khan, L. (2018). Sources of Tech Platform Power. *Georgetown Law Technology Review, 2*(2), 325-334.

Kim, G.-H., Trimi, S., & Chung, J.-H. (2014). Big-data applications in the government sector. *Communications of the ACM, 57*(3), 78-85.

Kitchin, R. (2014). Big Data, new epistemologies and paradigm shifts. *Big Data & Society, 1*(1), 1-12. doi:10.1177/2053951714528481

Koene, A., Clifton, C., Hatada, Y., Webb, Helena, Patel, M., . . . Dillon. (2019). *A governance framework for algorithmic accountability and transparency*. Brussels: European Union

Kraemer, K., & Dutton, W. (1979). The interests served by technological reform. The case of computing. *Administration & Society, 11*(1), 80-106.

Kuipers, B. S., Higgs, M., Kickert, W., Tummers, L., Grandia, J., & Van Der Voet, J. (2014). The management of change in public organizations: a literature review. *Public Administration, 92*(1), 1-20. doi:10.1111/padm.12040

Lipsky, M. (1980). *Street-level bureaucracy: Dilemmas of the individual in public services*. New York: Russel Sage Foundation.

Liu, H.-W., Lin, C.-F., & Chen, Y.-J. (2019). Beyond State v Loomis: artificial intelligence, government algorithmization and accountability. *International journal of law and information technology, 27*(2), 122-141. doi:10.1093/ijlit/eaz001

Luhmann, N. (1993). *The sociology of risk* Berlin: Walter der Gruyter.

Luhmann, N. (2018). *Organization and decision*. Cambridge: Cambridge University Press.

Lupton, D. (2015). *Digital sociology*. Abingdon: Routledge.

Maciejewski, M. (2016). To do more, better, faster and more cheaply: using big data in public administration. *International Review of Administrative Sciences, 83*(1_suppl), 120-135. doi:10.1177/0020852316640058

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., & Hung Byers, A. (2011). *Big data: the next frontier fon innovation, competition and productivity*: McKinsey Global Institute.

Mattingly-Jordan, S. (2018). Reasserting the Refounding. *Administration & Society, 50*(5), 653-678. doi:10.1177/0095399718770392

For Peer Review

McAfee, A., Brynjolfsson, E., Davenport, T. H., Patil, D., & Barton, D. (2012). Big data: the management revolution. *Harvard Business Review, 90*(10), 60-68.

McNeely, C. L., & Hahm, J. (2014). The Big (Data) Bang: Policy, Prospects, and Challenges. *Review of Policy Research, 31*(4), 304-310. doi:10.1111/ropr.12082

McNeely, C. L., & Hahm, J. O. (2014). The Big (Data) Bang: Policy, Prospects, and Challenges. *Review of Policy Research, 31*(4), 304-310. doi:10.1111/ropr.12082

Meredith, J. (1993). Theory building through conceptual methods. *International Journal of Operations & Production Management, 13*(5), 3-11.

Mergel, I., Rethemeyer, R. K., & Isett, K. (2016). Big Data in Public Affairs. *Public Administration Review, 76*(6), 928-937. doi:10.1111/puar.12625

Nemitz, P. (2018). Constitutional democracy and technology in the age of artificial intelligence. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 376*(2133), 20180089. doi:10.1098/rsta.2018.0089

Nogarede, J. (2021). *Governing Online Gatekeepers - Taking Power Seriously*. Brussels: The Foundation for European Progressive Studies.

O'Leary, D. E. (2013). Artificial Intelligence and Big Data. *IEEE Intelligent Systems, 28*(2), 96-99. doi:10.1109/MIS.2013.39

OECD. (2015). *Industry Self Regulation: Role and Use in Supporting Consumer Interests* (OECD Ed.). Paris: OECD.

OECD. (2019). *Vectors of digital transformation* (OECD Ed.). Paris: OECD.

Oliveira, M. I. S., Barros Lima, G. d. F., & Farias Lóscio, B. (2019). Investigations into Data Ecosystems: a systematic mapping study. *Knowledge and information systems, 61*(2), 589-630. doi:10.1007/s10115-018-1323-6

Pencheva, I., Esteve, M., & Mikhaylov, S. J. (2020). Big Data and AI – A transformational shift for government: So, what next for research? *Public Policy and Administration, 35*(1), 24-44. doi:10.1177/0952076718780537

Peters, B. G. (2012). Information and governing: cybernetic models of governance. In D. Levi-Faur (Ed.), *The Oxford Handbook of governance* (pp. 113-128). Oxford: Oxford University Press.

Peters, G. (2012). Information and governing: cybernetic models of governance. In D. Levi-Faur (Ed.), *The Oxford Handbook of governance* (pp. 113-128). Oxford: Oxford University Press.

Pirog, M. A. (2014). Data will drive innovation in public policy and management research in the next decade. *Journal of Policy Analysis and Management, 33*(2), 537-543. doi:10.1002/pam.21752

Poel, M., Meyer, E. T., & Schroeder, R. (2018). Big Data for Policymaking: Great Expectations, but with Limited Progress? *Policy & Internet, 10*(3), 347-367. doi:10.1002/poi3.176

Resnyansky, L. (2019). Conceptual frameworks for social and cultural Big Data analytics: Answering the epistemological challenge. *Big Data & Society, 6*(1), 2053951718823815.

Royakkers, L., Timmer, J., Kool, L., & van Est, R. (2018). Societal and ethical issues of digitization. *Ethics and Information Technology, 20*(2), 127-142.

Salamon, L. M. (Ed.) (2002). *The tools of government. A Guide to the New Governance*. Oxford: Oxford University Press.

Schroeder, R. (2014). Big Data and the brave new world of social media research. *Big Data & Society, 1*(2), 2053951714563194.

Scott, C., Cafaggi, F., & Senden, L. (2011). The conceptual and constitutional challenge of transnational private regulation. *Journal of law and society, 38*(1), 1-19.

Sowa, J. E., & Selden, S. C. (2003). Administrative Discretion and Active Representation: An Expansion of the Theory of Representative Bureaucracy. *Public Administration Review, 63*(6), 700-710. doi:10.1111/1540-6210.00333

Sun, T. Q., & Medaglia, R. (2019). Mapping the challenges of Artificial Intelligence in the public sector: Evidence from public healthcare. *Government Information Quarterly, 36*(2), 368-383. doi:10.1016/j.giq.2018.09.008

Townley, B. (2008). *Reason's Neglect. Rationality and Organizing*. Oxford: Oxford University Press.

For Peer Review

Van Dijck, J. (2014). Datafication, dataism and dataveillance: Big Data between scientific paradigm and ideology. *Surveillance & society, 12*(2), 197-208.
van Wynsberghe, A. (2020). *Artificial intelligence: From ethics to policy*. Brussels: European Parliamentary Research Service, Scientific Foresight Unit (STOA), PE 641.507, European Union.
Vydra, S., & Klievink, B. (2019). Techno-optimism and policy-pessimism in the public sector big data debate. *Government Information Quarterly*. doi:10.1016/j.giq.2019.05.010
Watson, H. (2019). Update tutorial: Big Data analytics: Concepts, technology, and applications. *Communications of the Association for Information Systems, 44*(1), 364-379.
Watson, H. J. (2019). Update Tutorial: Big Data Analytics: Concepts, Technology, and Applications. *Communications of the Association for Information Systems, 44*, 364 – 379.
Williamson, B. (2014). Knowing public services: Cross-sector intermediaries and algorithmic governance in public sector reform. *Public Policy and Administration, 29*(4), 292-312. doi:10.1177/0952076714529139
Yeung, K. (2018). Algorithmic regulation: A critical interrogation. *Regulation & Governance, 12*(4), 505-523.

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Tab. 1. Built-in tendencies of big data and their effects (authors' own, based on Andrejevic (2020))

Bias	**Description**	**Displacement effect**
Pre-emption	Extensive monitoring and predictive analysis	Number crunching vs. comprehension
Operationalism	Automated responses	Acting vs. understanding
Environmentality	Monitoring and shaping the conduct of individuals	Regulation of effects vs. regulation of causes

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