Dissertation proposal

Big Data in Government:

A social science perspective

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Summary

Big Data analytics, the IT-powered analysis of data in unprecedented volume, velocity and variety, is said to revolutionize all knowledge-based aspects of life, including government and public administration. It is supposed to render currently unnoticed issues visible and currently perplexing problems solvable. However, as a manifestation of the rationalist 'engineering' paradigm of public policy, Big Data negates the idea of 'wicked problems'. Due to sociotechnical processes it may change the way public policy problems are defined and solutions are devised in the political-administrative system. Issues that were hitherto seen as the object of political deliberation may now be perceived as mere questions of data analysis. It may also shift power between policymakers, public managers and analytics departments.

These questions have severe implications for public policy, but the existing Big Data literature fails to address them as it is dominated by the 'engineering' mindset of the IT professionals from whose domain the technology originates. Since sociotechnical considerations are so far absent from the debate, we have no clear idea how Big Data will affect our political-administrative systems and possibly change the way we govern and administer our polities.

In order to close this research gap, I strive to propose a theory of Big Data in government based on first empirical insights into the practice of Big Data from a social science perspective. Following a nested analysis research design, I will employ a mixed-method approach which complements the exploratory richness of small-N case studies with the confirmatory robustness of large-N analyses. Theoretical context is provided from research on evaluation utilization, Science and Technology Studies and the dialogue between the 'wicked problems' literature and the 'engineering' paradigm of public policy.

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1. Introduction

If you believe the current hype,[1] Big Data, the next generation in data analytics, is set out to revolutionize the way we work with information. "Big Data: A Revolution That Will Transform How We Live, Work, and Think"[2] is just one of many book titles spelling out this promise. Since government is a knowledge-based business, the 'revolutionary' effect of Big Data in the public sector could be substantial. With regard to 'wicked problems', the promise of Big Data analytics is to cut through complexity and unravel their wickedness.[3] However, the scarce literature on Big Data's impact on government is characterized by the engineering mindset of the IT professionals from whose domain Big Data originates and which is generally considered outdated in social science.[4] Thus, the sociotechnical and public policy implications of Big Data in government have been neglected so far.

This research project strives to close this gap and to develop a theory of the impact of Big Data on the organization and processes of government.

This proposal is structured as follows: First, I shortly introduce the concept of Big Data and the current state of research on Big Data in government to derive the research gap and my research objective. Second, I present theoretical contextualizations of Big Data in government to highlight the relevance of a sociotechnical approach to the public policy implications of Big Data in government. Finally, I present an outline of my research design.

[1] Gartner 2013
[2] Mayer-Schönberger & Cukier 2013
[3] Satell 2013
[4] Friedmann 1998

2. State of Research

2.1 Big Data[5]

In its essence, Big Data is the analysis of large datasets to identify trends, patterns and anomalies which inform strategic decisions. The novelty of Big Data is based on '3V': *volume, velocity* and *variety*.[6] Volume not only refers to the unprecedented scale of Big Data, but also to working with full datasets rather than partial samples, upending accepted practices of inferential statistics.[7] *Velocity* highlights that Big Data often means (near) real-time monitoring, e.g. with wirelessly connected sensors. *Variety* points towards the varied sources of Big Data, such as social media comments or sensors in the 'internet of things'. In this regard, Big Data is made possible by the growing "datafication"[8] of the world.

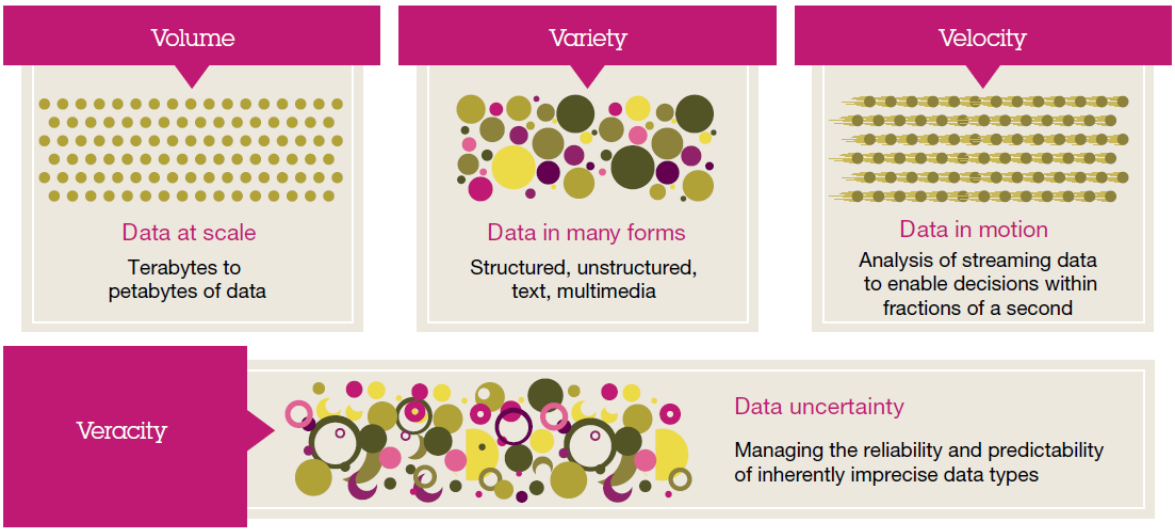

Figure 1: Four dimensions of Big Data (IBM Institute for Business Value 2012, p. 4)

However, Big Data's claim as a 'revolution' goes beyond data volume, "because more isn't just more – more is different".[9] The explosion of sample sizes increases statistical reliability, which leads some authors to predict an "end of theory"[10] where correlation trumps causation. "We can throw the numbers into the biggest computing clusters the world has ever seen and let statistical algorithms find patterns where science cannot."[11] Thus, data-driven 'predictive analytics' allows predicting behavior based on observed correlations, even in absence of any causal model to explain these correlations:

> "Out with every theory of human behavior, from linguistics to sociology. [].Who knows why people do what they do? The point is they do it, and we can track and measure it with unprecedented fidelity. With enough data, the numbers speak for themselves."[12]

[5] Wissenschaftliche Dienste des deutschen Bundestags 2013 provide a concise introduction, as well.
[6] Ward & Barker 2013
[7] Cukier & Mayer-Schönberger 2013
[8] Mayer-Schönberger & Cukier 2013
[9] Anderson 2008b
[10] Anderson 2008a, also Mayer-Schönberger & Cukier 2013
[11] Anderson 2008a
[12] Anderson 2008a

While this provocative view is much debated, it illuminates the data-driven approach to analysis and decision-making that comes along with Big Data.[13]

2.2 Research on Big Data for Government

Research on the effects of Big Data in the public sector is scarce. The existing literature usually offers prognoses rather than findings. Here, two major streams can be identified: The 'incrementalist' stream portrays Big Data as an improved tool for monitoring and evaluation but assumes that the political-administrative system will remain unchanged. In contrast, the 'holistic' stream speculates how Big Data may change structures and processes of the political-administrative system.

The 'incrementalist' view often focuses on individual aspects of Big Data. For example, the McKinsey Global Institute and the Deloitte Analytics Institute view Big Data mostly as a business analytics tool for more efficient resource allocation.[14] The Aspen Institute focusses on the aspect of real-time monitoring („nowcasting") and consequently portrays Big Data as a way to provide more up-to-date data for decision-making.[15] A study by the Australian Government acknowledges all aspects of Big Data, but does not derive any implications for the structure and processes of public policy from these.[16] Common to the 'incrementalist' stream is to recognize how Big Data can improve the input to the policy process, but to treat the political-administrative system as a black box which remains largely unaltered.

In contrast, the 'holistic' stream stresses possible changes in the structure and processes of political-administrative system due to Big Data. Policy papers by the London-based think tank Policy Exchange, the United Nations' Global Pulse program, and the World Economic Forum propose fundamental changes to the way policymakers and public managers conduct business.[17] Central to their argument is the idea of 'agile public policy', which replaces the classic policy sequence of 'planning – implementation – evaluation' with a more responsive, iterative and data-driven process.[18] Borrowing terminology from software development,[19] this is likened to the 'waterfall model' versus 'agile development'.[20] While these are mere thought experiments, it is striking they are neither discussed in the light of 'wicked problems' nor that the proposed shift from deliberative to more managerial policy processes, redistributing power from the legislative to the executive branch, is problematized.[21]

2.3 Research Gap & Objective

Big Data may change the way public policy problems are defined and solutions are derived. It may shift power between policymakers, public managers and analytics departments. Issues that were hitherto seen as the object of political deliberation may now be perceived as mere questions of data analysis. These

[13] Bollier 2010
[14] Manyika et al. 2011, Deloitte 2011
[15] Bollier 2010
[16] Australian Government Information Management Office 2013
[17] Yiu 2012, UN Global Pulse 2012, World Economic Forum 2012
[18] UN Global Pulse 2012
[19] Beck et al. 2001
[20] [citation needed] Robert Kirkpatrick at Strata 2011
[21] Bogumil 1997

questions have severe implications for public policy, but neither stream in the Big Data literature addresses them. In short, sociotechnical considerations and their public policy implications are so far absent from the debate.

In order to close this research gap, observations and subsequent theorization of Big Data's impact on structures and processes in government are necessary. Hence, this research project aims to produce first empirical insights and theoretical approaches for a social science perspective on Big Data.

3. Big Data for Government in Theoretical Context

Although little is known about the practice of Big Data in government, it can still be linked to long-standing paradigms, research streams and theories.

3.1 Big Data as an 'engineering' approach to public policy

Big Data can be seen as the continuation of the age-old dream to replace politics with knowledge,[22] which is already familiar from the Age of Enlightenment, the planning euphoria of the 1960s and 1970s, and more recent concepts like 'evidence-based policymaking'[23] or 'results-based management'[24] of the New Public Management movement. This "engineering" model of public policy is built on the belief in the data-based solubility of social problems.[25] 'Social engineering'[26] of this kind may be understood as the antithesis to the idea of 'wicked problems' in public policy.[27] Even the Big Data-inspired idea of 'agile public policy', can be linked back to CAMPBELL's "reforms as experiments" from 1969, which sought to instill scientific experimentation in public policy.[28] In their seminal paper on 'wicked problems', RITTEL & WEBER criticize this 'engineering' paradigm, pointing out how the range of possible solutions to a problem hinges on its definition, which is in turn highly arbitrary and/or dependent on the individual and social context.[29] This perspective urges us to consider and examine Big Data's influence on how public managers and politicians define problems and which strategies they employ to arrive at possible solutions.[30]

3.2 Big Data as a question of evaluation utilization

Big Data can be seen as the latest tools for monitoring and evaluation and therefore be examined in the light of 'research of evaluation utilization'.[31] This field of study scrutinizes how evaluations and similar products of scientific inquiry are utilized in the political-administrative system. Its findings highlight the importance of processes and actors in the utilization or non-utilization of evaluations.[32] For example, it has shown that the impact of evaluation results hinge less on the quality and convincibility of the evaluation than on the intentions of key actors in the policy process.[33] Roughly summarized, research on evaluation utilization finds that the impact of monitoring and evaluation is mostly determined by its social context. This points my inquiry into the practice of Big Data in government towards the intentions, perception, and utilization of Big Data by different actors in the political-administrative system.

[22] Torgerson & Lasswell 1986
[23] e.g. Sanderson 2002
[24] Thiel & Leeuw 2002 for a concise overview and interesting take on results-based management in the public sector.
[25] Weiss 1979
[26] Tönnies 1905 is a classic representative of this school; a critique for example Scott 1998
[27] Conklin et al. 2007
[28] Campbell 1969
[29] Rittel & Webber 1973
[30] Head & Alford 2013
[31] Stamm 2002 provides a useful summary of the research on evaluation utilization.
[32] Wollmann 2013 conveniently summarizes the literature.
[33] Stamm 2002

3.3 Big Data in Science and Technology Studies' perspective

As a technical instrument, Big Data can be approached from Science and Technology Studies. In contrast to research on evaluation utilization, Science and Technology Studies argue that technical tools shape the social context in which they are employed: "Change the instruments, and you will change the entire social theory that goes with them."[34] BOYD & CRAWFORD reflect this process with regard to Big Data: "Big Data creates a radical shift in how we think about research. [].Big Data reframes key questions about the constitution of knowledge, the processes of research, how we should engage with information, and the nature and the categorization of reality."[35] This sociotechnical approach suggests that technological innovations, once they become integral part of a social context, alter the mental models and paradigms of the involved individuals.[36] As a consequence, role perceptions and social practices within an organization change. To sum it up, Science and Technology Studies' body of literature provides theories of how Big Data may influence the ways actors define and approach issues and subsequently change roles, structures and processes of their social context to suit their altered mental models.

3.4 Conclusion to the Theoretical Context

While the three theoretical approaches to Big Data in government outlined above may not be exhaustive, they point towards several key issues: First, Big Data can be placed in the 'engineering' paradigm of public policy, a specific way to define and approach the solution of problems. Science and Technology Studies highlights how an instrument like Big Data can change mental models and underlying social theories of involved actors. This is of consequence, because, as SCOTT argued, 'how the state sees' determines how government works and acts.[37]

Second, research on evaluation utilization and Science and Technology Studies suggest opposing directions of influence: While one stresses that the impact of technological tools is determined by their social context, the other proposes that social contexts are changed by the tools used. These complex social dynamics have to be carefully disentangled, both on the organizational and individual level.

[34] Latour 2009, p. 9
[35] Boyd & Crawford 2012, p. 665
[36] Pasmore 1995
[37] Scott 1998

4. Guiding Questions

As outlined before, my research objective is to produce empirical insights and subsequent theory-building on Big Data in government. In such an exploratory, theory-building effort, research questions are only of preliminary nature to "guide data collection and analysis".[38]

My overarching research question reads: *How does Big Data impact government?*

In the light of the theoretical context outlined above, more concrete sub-questions read:
How does Big Data change the way policy problems are defined and solutions are developed?
How does Big Data change distributions of power within the political-administrative system?
How do structures and processes within the political-administrative system consequently change?

With the goal of theory-generation in mind, further questions are:
What factors determine the scope of Big Data's impact on government, especially with regard to policy formulation? What processes are central to this impact?

[38] Yin 2009, p. 14

5. Research Design

To approach my exploratory, theory-generating effort with as much rigor as possible, I follow LIEBERMAN's "nested analysis", which lays out a research process which switches between (exploratory) small-N analyses and confirmatory large-N analyses.[39] In line with this layout, I propose a three-step approach for my project:

1. Initial large-N analysis of Big Data projects in government on the basis of documents and other publicly accessible information to a) test initial hypotheses, b) create a preliminary typology of Big Data projects in government, and c) inform the case selection process.
2. Small-N analysis of deliberately selected Big Data projects to conduct "causal-process observation",[40] resulting in the generation of more sophisticated hypotheses from the within-case analysis as well as the between-case comparison.
3. Large-N analysis, probably based on an own survey, to test the hypotheses generated in the small-N analysis.

The actual research process may deviate from this process according to LIEBERMAN's decision tree for nested analysis (see Figure 2)

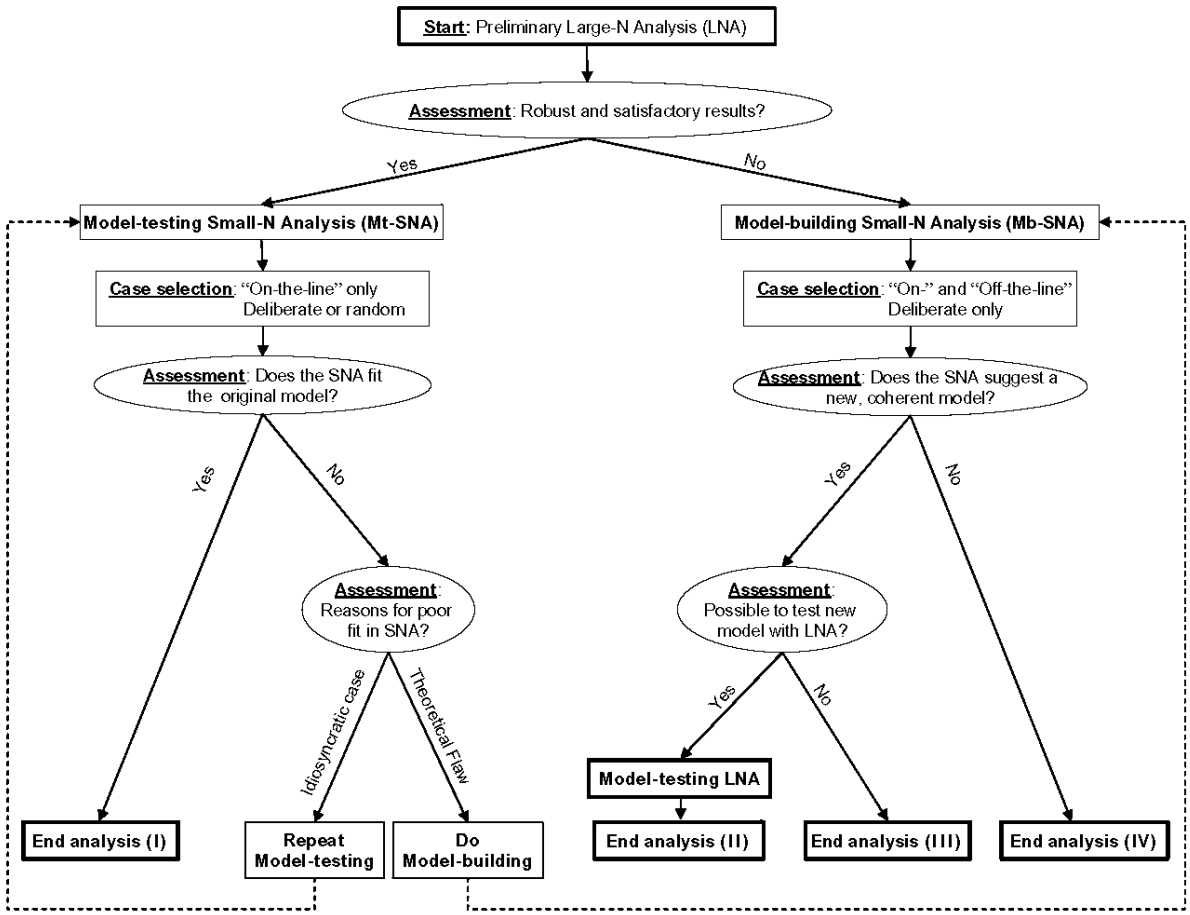

Figure 2: Decision tree of the Nested Analysis Approach (Lieberman 2005, p. 437)

[39] Lieberman 2005
[40] Lieberman 2005, p. 440ff

5.1 Initial large-N analysis

For the initial large-N analysis, I construct a database of Big Data projects in government. Given the public sector Big Data initiatives in existence and in development around the world,[41] sufficient cases are available. To preserve time and resources, only publicly accessible information is used in the database at this stage. Interesting dimensions are e.g. stated goals of the project, stressed aspects of Big Data, organizational setup, who initiated the project, etc. Additional contextual data allows to control e.g. for effects of administrative cultures, constitutional types or democratic development.

A cluster analysis[42] of the database can yield an initial typology of Big Data projects in government. If the data proves to be conclusive enough, initial hypotheses drawn from the theoretical context and existing literature on Big Data in government can be tested with comparative methods, e.g. fuzzy-set or regression analysis. Most importantly, the database is essential to the case selection process as cases can be identified as critical, extreme or typical.

5.2 Model-building small-N analysis

In the selected case studies, the goal is to generate hypotheses by exploration. As research methods, interviews with involved actors, semi-structured as well as narrative, and the analysis of internal documents are robust ways to arrive at the "thick description"[43] necessary to gain insight into social practices of Big Data. This is likely to be an iterative process in the vein of grounded theory approaches.[44] Additionally, the empirical studies on evaluation utilization[45] suggest the use of standardized surveys and tests to gain insight on actors' attitudes towards an evaluation tool and their information processing behavior. WESTBROOKS & BRAITHWAITE's sociotechnical study on the introduction of new information technologies in a medical facility also employs social network analysis to document how roles and patterns of interaction have changed due to the new technology.[46] This may be considered for my case studies as well. However, while the current surge in Big Data projects provides attractive research opportunities to accompany the introduction of Big Data in new organizational settings, I cannot rely on the availability of such cases.

Once the data is gathered, hypotheses can be generated from within-case analysis through process tracing[47] as well as from between-case analysis through pattern matching.[48]

5.3 Confirmatory large-N analysis

To put the hypotheses generated in the small-N analysis to the test, a final large-N analysis is conducted. The operationalization of qualitatively generated hypotheses from a small-N setting necessarily means a

[41] e.g. USA (Executive Office of the President of the United States 2012), United Nations (UN Global Pulse 2012), Australia (see Australian Government Information Management Office 2013) and the United Kingdom (Gov.uk 2014); for broader overviews of emerging public sector Big Data efforts, see e.g. BITKOM 2012, Oracle 2012, Center for Digital Government 2013
[42] Kaufman & Rousseeuw 2005
[43] Kohlbacher 2006
[44] e.g. Suddaby 2006, Orton 1997
[45] e.g. Dickey 1980; Weiss & Bucuvalas 1980
[46] Westbrook & Braithwaite 2007
[47] Muno 2009
[48] Eisenhardt & Graebner 2007

reduction in subtlety and granularity. However, the large-N analysis adds considerable robustness to the hypotheses and reduces the danger of falling victim to idiosyncrasies of cases.

For the large-N analysis, the existing database of Big Data projects in the public sector is complemented with responses from a survey that explicitly contains items that operationalize the hypotheses generated in the small-N analysis. A probable challenge here is to elicit sufficient responses to the survey.

On the basis of this survey, the initial typology of Big Data projects can be refined. More importantly, my hypotheses can be tested with correlation analysis and similar statistical methods. Those hypotheses that remain robust in the large-N analysis can be used with confidence in formulating a theory of Big Data in government.

Annex I: Project Schedule

This research project is broken down into eight phases over the course of 36 months. In addition to the three steps presented in the research design, time is dedicated to additional literature research and refinement of theory and methodology, organizational matters, as well as writing up and presenting my findings. The phases are:

1. Revision of theoretical context and methodology
2. Compilation of database of Big Data projects in government
3. Initial large-N analysis of database: test initial hypotheses, construct preliminary typology
4. Preparation of case studies: case selection, methodological refinement, field access, logistics
5. Conduct case studies: data collection, analysis, hypothesis generation
6. Preparation of large-N analysis: operationalization of hypotheses, formulation of survey
7. Conduct and analyze large-N survey
8. Present and disseminate findings

Phase	Months
1	1-3
2	4-6
3	7-8
4	9-10
5	11-23
6	24-26
7	27-30
8	31-36

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