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## Data-driven anticipatory governance. Emerging scenarios in data for policy practices

Stefano Maffei , Francesco Leoni  and Beatrice Villari 

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### ABSTRACT

The contemporary technological advancements in information and communication technologies (ICT) enable the employment of non-traditional data sources (e.g. satellite data, sensors, cell phone networks data, social media, etc.) in different aspects of the public sphere. Datafication is changing the relationship between governments and citizens, and the way governments address policy problems. Nowadays, policy-makers are urged to harness data for policies and public service design, while answering at the same time the demand for citizen engagement; as a consequence, innovative government/governance models appeared to connect these two instances. Although it is not a new concept, the model of Anticipatory Governance is particularly worth considering in light of contemporary data availability. Predictive analytics based on data increasingly realizes predictions for public action, although it presents many controversial implications (e.g. the epistemology of data evidence, public trust and privacy). In this article, we address Anticipatory Governance models emerging from data used in futures thinking and policy-making. To understand this phenomenon, we will briefly retrace current paradigms of futures thinking and Anticipatory Governance concerning policy-making, specifying the contemporary perspective design has on these topics. Then, we identify the use of data in futures thinking practices through a systematic literature search. Finally, we will address the challenges and implications of designing data-driven Anticipatory Governance by portraying three scenarios supported by real cases of data for policy-making.

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Anticipatory governance; design for policy; data for policy; futures designing; public policy

## 1. Datafication and new government/governance models

The Digital Revolution has put us in a world where information and communication technologies (ICT) are hyperconnected, performant and almost pervasive. Today it is possible to produce, store and process digital data in a way that has no historical precedent (Hilbert & López 2011; Xindong et al. 2014). It is theorized as the *datafication of society*, in which social phenomena are turned into quantifiable and analyzable formats

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(Mayer-Schönberger & Kenneth 2013). These new data carry the promise of enhancing analytical capacities. The widely cited phrase “data is the new oil,” clearly synthesized this concept: data is a raw material that needs to be extracted and refined in order to create informational value. New data had impacted the policy agenda of governments worldwide (Kim et al. 2014; World Bank Group 2017), pushing them to imagine and address new *types of government and governance*<sup>1</sup>.

Data are expected to bring a new form of knowledge that can inform policy-making in new ways (Longo & McNutt 2018; Mureddu et al. 2012). Datafication promises to revolutionize the process of policy analysis – that traditionally relies on research tools used in the social sciences (e.g. surveys, interviews, polls, etc.; Jarmin & O’Hara 2016) – by allowing *real-time monitoring* for policy interventions (Hemerly 2013; Maciejewski 2017; Mureddu et al. 2012; Schintler & Kulkarni 2014). Despite these potentially disruptive features, new data sources are still scarcely used for policy (Poel et al. 2018; Verhulst et al. 2019). Among the possible causes, there are deficiencies in technical competences and data interoperability protocols in governments (Verhulst et al. 2019). In this scenario, what appears particularly intriguing is the use of predictive analytics (Athey 2017; Engin & Treleaven 2019). Concerning policy-making, these technologies:

can serve as an input into framing a policy problem before it is appreciated as such, indicating where a need is being unmet, or where an emerging problem might be countered early. (Longo & McNutt 2018, p. 374)

While still barely utilized for policy-making, the treatment of large datasets with predictive analytics techniques is a common practice both in the private sector and in the public services provision and management. Practices in the public sector include policing patrolling, planning of health inspections and federal income tax collection (Athey 2017). Predictive analytics can influence policy decisions in many ways. For instance: the UK Government Behavioral Insights Team developed an algorithm based on historical datasets able to define what type of drivers are more likely to get into dangerous accidents (Perricos, & Kapur 2019); the Kenyan Government adopted predictive livestock insurance based on satellite data, to support farmers before droughts damaged them (Bett 2019).

These examples seem to concretize the concept of *Anticipatory Government* developed in the early ‘90s by *New Public Management* scholars<sup>2</sup>, which obliges us to reflect on how data-driven knowledge can bias decisions and negatively affect society. In this regard, literature that raises criticisms and concerns is abundant. An epistemological conundrum, specifically related to predictive analytics, regards *algorithmic processes* that may confuse *correlation* with *causation* (Athey 2017). Predictive analytics applied to tax evasion can perform data mining on a given dataset, looking for patterns and then isolate those individuals with higher chances of committing tax fraud, without telling us *why* those individuals were chosen (Zarsky 2013). Potential issues also concern *transparency* and *accountability* in the approaches that use data for orienteering governmental decisions, as citizens might ask to justify why they have been subject to targeted policy interventions (Zarsky 2013). Moreover, the fallacy of mathematical-algorithmic models might even lead to privacy and discrimination controversies

(Hemerly 2013; Maciejewski 2017; Schintler & Kulkarni 2014). In light of the scenario so far outlined, the paradigms, modalities and tools of *data-driven Anticipatory Government and Governance* seem to be timely topics. Rather than think “*if*” new data will change policy-making, we should start considering “*how*” this will happen (Giest 2017). We propose to do so by using perspectives from the discipline of design. In this article, we will examine data-driven Anticipatory Governance as a complex system of actors, relationships, processes and technologies that need to be designed.

## 2. Anticipating futures in policy-making

Anticipatory Governance is not a univocal concept. Instead, it evolved throughout decades of theoretical reflection and public initiatives connecting foresight and various governance models (Ramos 2014). In a widely cited paper, Leon Fuerth (who served as national security adviser to former US vice president Al Gore) describes the ideal system of Anticipatory Governance in government. Fuerth defines Anticipatory Governance as “a mode of decision-making that perpetually scans the horizon” and “a scalable system of systems” (Fuerth 2009, p. 30). For this author, its realization encompasses several innovative components: the development of a foresight system, its integration into policy-making, a feedback system to assess predictions, and an overall change in the organizational mindset. The design of this Anticipatory Governance will fundamentally ensure foresight application in the “creation and execution of plans of action. As the result [...] one would expect to find government that is able to sense and execute changes ahead of the cusp of major events” (Fuerth 2009, p. 20).

The centrality of foresight in this perspective should not be unexpected. Foresight activities are today largely integrated into several governments worldwide and applied into several policy domains (e.g. environment, sustainable growth, demographic trends, labor market integration, democracy, equality, social cohesion; Dreyer & Stang 2013). Arguably, foresight in governments represents the most explicit relationship between the act of anticipating the future, the practice of policy-making, and structures of governance. Therefore, to look back at the history of foresight in government is useful for understanding the paradigms and design principles of Anticipatory Governance today.

Foresight emerged during the 1940s–1960s as a tool for strategy-making in US defense policy (Dreyer & Stang 2013; Kuosa 2011). The goal of foresight was, and remains, anticipation rather than an actual prediction. To envision multiple futures supports a wiser course of action in the present. The scenario building techniques initially developed for policy analysis in military defense during the Cold War, are a clear example, still widely used today, of this approach in practice. This strategic orientation toward readiness is also present in relatively recent definitions of foresight in policy:

Foresight in government cannot define policy, but it can help condition policies to be more appropriate, more flexible, and more robust in their implementation, as times and circumstances change ... It is not planning – merely a step in planning. (Coates 1985, p. 343)

Together with the need for developing more adaptable strategies, another historical driver of foresight adoption in policy has been the governments’ interest in

anticipating changes in technological and scientific progress (Miles 2010). In this sense, distinguishing itself from technological forecasting, since the early 90s, technology foresight programs became a tool to inform science, technology and innovation policies and support national innovation systems (Ramos 2014). Later, foresight would have been applied to many policy fields, acquiring increasingly systemic and participative characteristics:

Foresight is a systematic, participatory, future-intelligence-gathering and medium-to-long-term vision-building process aimed at present-day decisions and mobilising joint actions. [...] It brings together key agents of change and various sources of knowledge in order to develop strategic visions and anticipatory intelligence. (Gavigan et al. 2001, p. 4)

During its evolution, foresight practices became more inclusive, as the interaction between diverse expertise and with laypersons was regarded as a source of knowledge in foresight. From strict probabilistic predictions issued by groups of experts, anticipation in government evolved, through foresight, into an engaged practice that might tackle many topics and involve diverse stakeholders (Miles et al. 2008).

This interactive and participative dimension might be seen as the colliding point between design disciplinary perspective and anticipating futures for policy. Designers traditionally used scenarios “to guide the development of new product or service concepts” (Hines & Zindato 2016, p. 185). While this is a common point between foresight and design, the latter devises more normative and contextualized visions and heavily relies on visual representation and prototypes. Accordingly, the Futures Designing approach develops representations through artifacts and visualizations in a participatory setting (Wilkinson 2017). This allows collective visions to emerge from participants with different cognitive, social, and professional backgrounds:

Design-orientated and vision-based preferred futures are reflexive in that they aim to create reality through a process of bottom-up, goal based incrementalism rather than top-down, grand strategies and detailed blueprints. (Wilkinson 2017, p. 29)

An example of this type of practice has been the initiative “The Future of Gov 2030+ – A Citizen Centric Perspective on new government models”<sup>3</sup>, led by the EU Policy Lab. This project explored the role of citizens in future government models. Six European design schools<sup>4</sup> designed and prototype speculative solutions and services to envision these futures. Futures Designing might offer a useful translational approach, capable of mediating between various types of expertise and evidence for policy purposes (Kimbell 2019).

Other than being instrumentally adopted within practices of Anticipatory Governance, we think design discipline can offer a viewpoint for prefiguring and realizing Anticipatory Governance. This perspective might be further valuable if we consider the possible implications of data and technology in Anticipatory Governance.

### **3. Use of data in futures thinking and futures designing: analysis of practices**

We investigated the use of data in futures thinking practices through a systematic three-step approach. In the first step, we browsed 13 scientific journals, indexed in

scientific databases (WoS, Scopus), considered promising due to their topic focus<sup>5</sup>. Subsequently, we selected an initial group of articles using specific keywords related to our research questions<sup>6</sup>; in order to also include recent experiences, we integrated these data with desk research. This led to the review of initiatives and projects carried out by 34 organizations officially using foresight, almost half of them belonging to the public sector. In the second step, we picked cases from the articles collected, adopting the following eligibility criteria:

1. Explicit use of futures techniques (e.g. foresight)  
We included cases where subjects explicitly used futures techniques and methods to envision possible futures (in particular foresight).
2. The use of data  
We included projects that use data from non-traditional sources (e.g. open data, data exhaust and crowdsourced data) and, consequently, methods and technologies for data collection, analysis and visualization
3. The presence of a participatory setting  
The paradigms of foresight and Anticipatory Governance individuated in the literature review denoted the relevance of participation in contemporary practices of futures thinking. Therefore, to make this inquiry pertinent and useful, we considered only practices with explicit participatory intentions
4. The connection to public bodies and governance processes  
We included initiatives, programs and projects either promoted by or involving public organizations in the process

This sampling intended to select diverse yet comparable practices. We consider the methodology adopted sufficient for an exploratory research from a novel perspective, but another strategy informed by different sources/criteria could have led toward alternative directions. Rather than isolate a representative sample, our scope was to outline that, although certain features equally existed in all the appraised cases, data and data analytics were used in very different ways to change the interplay between participants and the process of futures thinking. These differences can drastically affect the quality of the resulting outputs (e.g. by modifying how participants' perspectives are represented in the overall results or how the interaction among participants is enabled). Consequently, much dissimilar types of evidence can ultimately be offered to policy-makers as outcomes of these processes. The three cases analyzed were chosen to stress this divergence. Since a key attribute of these processes is to extrapolate perspectives from stakeholders with distinctive expertise, we divided participants into three ideal roles: the *experts* (participants possessing knowledge on topic addressed in foresight), the *laypersons* (participants not possessing a specific knowledge on topic addressed in foresight) and the *policy-makers* (as those who might use results of futures thinking practices as a source of knowledge for new policies). For each role, we inferred how data was potentially innovative in the perspective described above (Table 1).

**Table 1.** Impact of data for participants in futures thinking/futures designing practices analyzed.

Case study	CIVISTI AAL – Vienna	Real cities – Bergamo 2035	Metro futures
Reference	Gudowsky et al. 2017	Andreani et al. 2019	Wilson & Tewdwr-Jones 2019
Use of new data sources and relative technologies	Data analysis applied to citizens' consultations.	Data visualization and simulations for urban design concepts	Prototypal device used for datafication of citizens' suggestions
Effect on experts	Less direct exchange with laypersons' perspectives	Potential emergence of new perspectives by visualizing data of known topics	Less noticeable role in the process
Effect on laypersons	Representativeness mediated by data analysis	Potential engagement on complex topics	Supports proactive role and self-expressivity
Effect on policy-makers	Emerging results from the process are codified insights from large groups consulted	Emerging results are influenced by the data visualization and simulations	Emerging results are extremely heterogeneous, not codified, highly qualitative, and not mediated

In the case of CIVISTI AAL, citizens of Vienna, Austria, were asked about the future of ageing and ambient assisted living (AAL). Their opinions were codified through qualitative content analysis and then further processed through text mining software and network analysis. In this way, it was possible to isolate recurring topics and then submit them to experts for developing recommendations. Data analysis helped to codify the visions of the crowd, making it more accessible throughout the various steps of the process, as well as the final results for possible policy decisions. Arguably, data optimized the process but did not change the fundamental dynamics of citizens' consultation.

In the second case, data generated another type of interplay. Students of the Responsive Environments and Artifacts Lab (REAL) at the Harvard Graduate School of Design devised design concepts on smart city technologies that could change services in the City of Bergamo, Italy. To do so, they developed future urban scenarios and visualized them with modeling and simulations based on available urban data collected (e.g. traffic flow). The engagement of experts and non-experts was heavily mediated by the visual narratives and design choices of those artifacts. The capacity of participants to affect overall future vision was strongly shaped by the mediation of these artifacts. Consequently, we can expect that a possible resulting evidence for policy would be strongly influenced by that visualization as well.

The third case has totally different features. The North East England Passenger Transport Authority promoted an initiative to involve the public in the discussion about the design of the next generation of Tyne and Wear Metro trains in the UK. In MetroFutures, participation was allowed by employing an open hardware device called JigsAudio, designed by the Open Lab of Newcastle University. While low-tech in its appearance (it looks like a wooden jigsaw piece), thanks to an electronic tag on its rear, JigsAudio could "datafy" sketches people made on its surface during organized meetups; in addition to that, via a microphone, they could record a message just by pressing a button. Both sketches and audios were used by people to express ideas on the train service and the design of the internal carriage. By looking at these small-scale experimental



practices, it appears clear that data can have very different effects on the overall Anticipatory Governance in futures thinking processes.

#### **4. Data-driven anticipatory governance: emergent scenarios and design challenges in data for policy**

The cases described in the previous section highlighted how data can be pragmatically applied in diverse ways to futures thinking practices. Technology can enable very diverse roles in these processes, therefore changing resulting evidence for policy. Quite innovative approaches, such as the project in Newcastle, can convey highly qualitative but hardly decodable information. Nonetheless, it can be valuable to individuate unforeseen dimensions of complex policy problems. One might object that the experimental nature of these practices makes them of limited value to policy-makers, who usually act under very different constraints. However, Anticipatory Governance will increasingly offer an opportunity area to create public value through data (van Ooijen, Ubaldi & Welby 2019). Therefore, it might be useful to carefully assess the characteristics of test-bed practices on small scale, and in particular the relation between practices and governance structures, before developing larger initiatives. In this way, policy-makers can innovate without blindly following technological trends or simply replicating solutions that worked in other contexts.

Design and implementation challenges, in other words *how to realize these practices*, are the key elements to be addressed by practitioners. We will consider some of them by envisioning three scenarios of data-driven Anticipatory Governance, based on real case examples of data and analytics technologies used in the public sector to act on the future.

##### **4.1. The policy dashboard scenario: data-driven anticipatory governance within government**

The availability of new sources of data and the better use of public data (i.e. generated by governments) will increasingly create the conditions for a data-driven Anticipatory Governance connecting various subjects within government. We can expect that governments will increasingly address policy issues on a precise topic (e.g. energy, environment, poverty, etc.) through data, either by merging internal data sources (e.g. from governmental departments/organizations and public agencies) or by accessing official/non official sources (e.g. telecommunications company data or internet-mined data). In this sense, forecasting can support foresight and lead to the formulation of policies.

Take, for example, The National Energy Analytics Research (NEAR) by the Department of Industry, Science, Energy, and Resources of the Australian Government (International Energy Agency 2019): NEAR's goal is to understand the national energy system and its evolution; in order to enhance the governmental analytical and forecasting capacities, it collects data both from energy infrastructures (e.g. the electric system grid) and individual consumption through the participation of volunteers. NEAR's platform publicly offers both raw dataset and data visualizations on various themes about the energy sector.



In this scenario, the main design challenge is to ensure data transparency, clarity and accountability in the agenda setting and policy formulation phases. All stakeholders, regardless of their expertise, should be able to understand data and easily connect them to the phenomena they describe. Therefore, competences in information/interface design and data visualization are essential.

#### ***4.2. The data collaboratives scenario: public-private partnership for data-driven anticipatory governance***

Governments will not always possess all the data needed to forecast policy issues, which are in most cases owned by the private sector (Susha et al. 2017). Consequently, data exchange practices among various stakeholders (e.g. public and private sectors, but also the civil society) are necessary and can become a framework for a new model of data-driven Anticipatory Governance. Data will be proactively and consensually shared among all parties owning them, so they can be collectively used to monitor the current state of things and to adapt to possible future changes. One example is The Center of Humanitarian Data, managed by the United Nations Office for the Coordination of Humanitarian Affairs<sup>7</sup>. The Center is committed to inform decision-making in the humanitarian sector by integrating multiple types of data (e.g. migration flow monitoring, financial tracking, etc.) from partner organizations worldwide. The Center recently started to explore the use of predictive analytics for humanitarian response, with the aim to share results and models in a transparent way throughout its community.

In this scenario, the challenge for a successful Anticipatory Governance regards data fruition (as in the previous scenario), but also the co-creation process that will make data sharing meaningful for all the actors involved. In fact, while legal and privacy issues on data exchange can be addressed by specific regulations (e.g. the GDPR<sup>1</sup>) and sharing can be achieved through partnership strategies (Susha et al. 2017), just getting the data would not be enough. The process of data exchange will have to be translated into a co-created sense-making process oriented toward the future. This requires a system with moments of collective exploration (e.g. of existing datasets and sources) and interaction points ensuring data flows correctly between all the actors involved (e.g. monitoring system). In other words, this data-driven Anticipatory Governance model could be treated as a collaborative service design problem. This might require prefiguring specific conditions and interactions that will take place when a policy arrives at its implementation phase.

#### ***4.3. The collective imaginaries scenario: data-driven anticipatory governance with citizens***

Is it possible to have a data-driven Anticipatory Governance model that includes a large group of citizens? While, to the best of our knowledge, explicit cases in this sense are scarce, recent practices seem to suggest this area might grow. Technologies for open consultations are a noteworthy step in this direction. The participatory agenda

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<sup>1</sup>The General Data Protection Regulation (GDPR) is a European Union regulation for personal data processing and privacy adopted on 2016

setting project vTaiwan (Hsiao et al. 2018) supported citizens in submitting future proposals and discussing on present issues. vTaiwan is an officially recognized service of the Taiwanese Government: both a multi-step process (encompassing online and offline activities) and a technological stack composed by open-source tools for digital discussion and data analysis. During the process, as citizens' perspectives emerge during digital conversations, they are analyzed through machine learning. This helps to form working groups characterized by a common vision.

This scenario is perhaps the most difficult to realize, because the key design challenge here is to accomplish wide participation while overcoming inherent technological barriers posed by data usage (e.g. the technical competences and data literacy). One strategy could be to design participatory schemes able to bring together skilled/unskilled citizens, even if this might create unbalanced roles in the process. Several experiments can inspire this design approach: one example is the EU funded project *Making Sense*, which developed participatory sensing activities on environmental issues in several municipalities in Europe (Coulson et al. 2018). There, a group of citizens used open source technologies to record environmental data (e.g. sound pollution), thus contributing to collective awareness and existing evidence on these issues in their local communities. It should be noted that these activities were part of a broader project of common consciousness and exploration. Data collection technology was just a way – together with futures thinking tools as fictional newspapers (Making Sense 2018, p.126) – to develop a concerted, proactive perspective on the future. To design this data-driven Anticipatory Governance model, competences in experimental practices and citizen engagement technologies are needed. This type of experimentation may be used to make new policy ideas emerge in agenda setting or in the evaluation of existing policy interventions.

## 5. Conclusions

Like any other disruptive technological innovation, datafication offers both drawbacks and opportunities for future-oriented government and governance practices. On the one hand, we can expect that the adoption of predictive analytics will allow continuous forecasting of immediate futures to optimize the use of specific policy instruments and governmental functions; on the other, the value of new data sources for policies will push governments and other societal actors toward new innovative practices of data collection, sharing and use. Their goal will be to prepare themselves for what the future holds, developing collective anticipatory capacities in the present: we can look at them as models of data-driven Anticipatory Governance, in which the use of new data sources enables governance settings oriented toward the future. Our analysis of futures thinking practices using data pointed out that this might unfold in quite unexpected fashions. Even on the small and experimental scale, various uses of data can very differently affect the interplay between the actors involved in anticipating futures. Consequently, the resulting evidence for policy emerging from these processes can greatly change from case to case.

In light of this, we advocate the collection of extensive empirical knowledge from experimentation that use anticipation and data for policy purposes. This will definitely

require multidisciplinary dialog, focused on the design features of data-driven Anticipatory Governance models. Design for policy and Futures Designing for policy are still in an early stage. Nonetheless, the design disciplinary perspective can offer a useful vantage point to outline challenges and underlying design paradigms of data-driven Anticipatory Governance. In this article, we considered some of them through three different scenarios; we hope that we offered policy practitioners a refreshing stimulus to reflect on the complex relationship between data, policy and futures thinking.

## Notes

1. Respectively defined as “*the office, authority or function of governing*” and “*set of decisions and processes made to reflect social expectations through the management or leadership of the government*” (Fasenfest 2010, p. 771)
2. See Osborne and Gaebler (1992)
3. See more at: <https://blogs.ec.europa.eu/eupolicylab/futurgov>
4. Authors of this article were involved in the initiative as one of the design schools. Our results can be seen at: [servicedesignmaster.com/futuregov2030](http://servicedesignmaster.com/futuregov2030)
5. The journals selected were: Cities; Computers, Environment and Urban Systems; Design and Culture; European Journal of Futures Research; Futures; Government Information Quarterly; International Journal of Forecasting; Journal of Futures Studies (issues from 2015 to 2019); MIT Press Journals (the general online archive); Omega – The International Journal of Management Science; Research Policy; Technological Forecasting and Social Change; Technology Analysis & Strategic Management
6. The keywords used were: “anticipatory governance”; “participatory foresight”; “urban foresight”; “foresight” and “open foresight”
7. See: <https://centre.humdata.org/predictive-analytics>

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