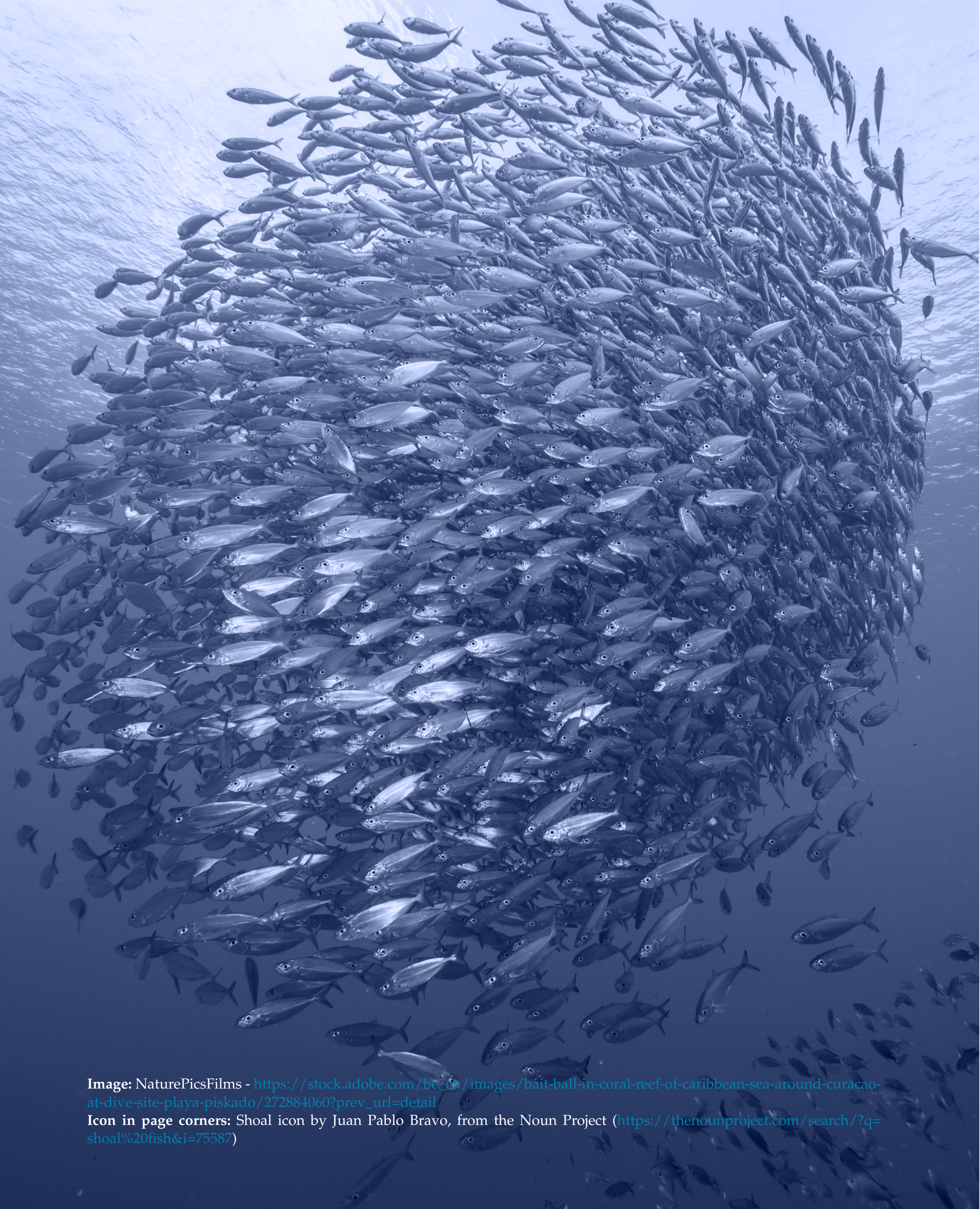

Image: NaturePicsFilms - https://stock.adobe.com/be_en/images/bait-ball-in-coral-reef-of-caribbean-sea-around-curacao-at-dive-site-playa-piskado/272884060?prev_url=detail
Icon in page corners: Shoal icon by Juan Pablo Bravo, from the Noun Project (https://thenounproject.com/search/?q=shoal%20fish&i=75587)

Chapter 9

The Big Data and Artificial Intelligence: Opportunities and Challenges to Modernise the Policy Cycle

Authors: Massimo Craglia, Jiri Hradec, Xavier Troussard

Key takeaways

- Big data is not just another type of evidence: with AI developments, it offers potential for radical transformation of policy environments, making them more in tune with a fast-changing world.
- If designed with accountability and transparency at their core, big data and AI can modernise the policy cycle, e.g., by customising policy interventions and offering their faster evaluation and adaptation.
- By putting individuals' needs in the centre, these innovations can help design policies more attuned with diverse needs or location specificities, also helping solve the problem of silent and overlooked groups.
- Such methods can only succeed if a trustworthy social contract for sharing and using data by governments is established. In turn, a more responsive policy environment can strengthen active citizenship and communication between the authorities and the public.

Science for Policy Handbook
http://dx.doi.org/10.1016/B978-0-12-822596-7.00009-7

We are living through a period of intense digital transformation of our society, in which the integration of different technologies, such as artificial intelligence (AI), sensor networks, blockchain, 3D printing and others, with digital data is changing every aspect of our daily lives. The power of integrating different data streams to profile customers and users, predict their behaviour and customise services is becoming increasingly evident to business and some government agencies with both positive outcomes in terms of personalised services and also negative ones in terms of manipulation and control for both commercial and political gain (see for example, Krumm, 2011; Zuboff, 2015).

We are living through a period of intense digital transformation of our society, in which the integration of different technologies, such as artificial intelligence (AI), sensor networks, blockchain, 3D printing and others, with digital data is changing every aspect of our daily lives.

In this chapter, we discuss the opportunities and challenges of using big data and AI to modernise the entire policy cycle, from anticipation to design, implementation, monitoring and assessment. It could be a peculiar example of cocreation of knowledge and making policymaking, as well as evidence, more dynamic. We show in particular how the concept of profiling can be applied to official statistics and other data sources to develop policy interventions targeted to the groups and areas needing them the most. This form of 'personalised' policy recognises the need to put individuals at the centre of the policy debate, addressing their needs, expectations and perceptions. The approach described shifts the traditional knowledge used to inform policy by combining both objective and subjective measures of need and by increasing the granularity of evidence to the level of the individual. This may have consequences to how we define knowledge gaps, commission new research or request scientific/research support. Before exploring the topic, it may be useful to briefly introduce the two key concepts, big data and AI, because they do not always have agreed definitions.

Big data is generally referred to by using the 3Vs: Volume, Velocity and Variety (Laney, 2001). This definition points out that big data does not simply mean big datasets or many datasets (big Volume) but also rapidly changing, next to real-time data (big Velocity) and great heterogeneity (big Variety). In general, it refers to the enormous increase in range of data sources, from space, social media, the public and private sectors and the ability to integrate the data and generate new insights typically for commercial purposes. This definition and others that have added other Vs, such as Veracity, Value and Visualisation (Nativi et al., 2015), are based on a technical perspective. Other authors take a more social and political perspective focussing on Big data and 'datification' as the transformation of our everyday life into quantifiable, measurable and therefore controllable data (Mayer-Schoenberger and Cukier, 2013; van Dijck, 2014), which may lead to forms of surveillance capitalism (Zuboff, 2015).

Big data is generally referred to by using the 3Vs: Volume, Velocity and Variety

The definition of AI also lacks clear boundaries. Traditionally, AI refers to machines or agents that are capable of observing their environment, learn, and based on the knowledge and experience gained, take intelligent action, or propose decisions. This is a rather old-fashioned definition, and with the emergence of new algorithms, the definition has become rather blurred to include areas of AI, such as machine learning (ML), deep learning, reinforcement learning, neural networks and robotics, and key fields of application such as natural language processing, image and speech recognition, computer vision and so on.

The interest in AI is rather recent even if the underlying methods date back to the 1950s. This new found interest in AI, and ML in particular, results from the convergence of three developments: (i) increased access to cheap computing storage and processing capabilities, (ii) increased availability of big data on which to train algorithms and address previously hard problems such as object recognition from digital images and machine translation and (iii) improved algorithms and increased access to specialised open source ML software libraries that make the creation and testing of ML algorithms easier. These trends started to come together around 2012, and since then, we have seen a rapid development of AI.[1] As in the case of Big data discussed above, we can contrast this technical perspective of AI with more political ones, which see Big data and AI as part of the same narrative of 'dataism', as the new authority of data and algorithm on human society (Harari, 2015; van Dijck, 2014).

In this chapter, we want to consider the potential use of Big data and AI to modernise the policy cycle. Why would we want to do that? Because there is an increasing gap between the speed of the policy cycle and that of technological, and social, change. Using the example of the INSPIRE Directive (EC, 2007), which addresses data, standards and technology to share environmental information, it started being discussed in the year 2000, was formulated in 2002–03, was adopted in 2007 and has an implementation roadmap that will end in 2019–20. During these 20 years, computing power has increased about 10,000 times and data availability more than 100,000 times (based on Kambala et al., 2014). Many jobs of today did not exist 20 years ago, and over the next 20 years, we will see even further changes in the job market and social practices. How can we formulate meaningful policy in this context? We are always playing catch up rather than being able to guide the processes. Therefore, the question is can we leverage AI and Big data to govern *with* the digital transformation, in addition to shaping the governance *of* digital transformation? What would governing with AI and Big data look like?

We sketch a scenario below starting from the assumption that computing is not an issue as it is now ubiquitously available through different forms of cloud computing. In the near future, more decentralised forms of computing at the edge of the network will also emerge by preprocessing data at the level of sensors, vehicles and mobile devices. We also start from the assumption that data, whether collected by or contributed to public authorities, will be linked and exploitable for public good without jeopardising the rights of companies and individuals, including the protection of private data. Finally, we recognise that AI is at the present time largely focussing on ML and related algorithms that are trained on the data to find patterns and rules, predict future behaviours and responses and adapt or 'learn' based on feedback loops.

[1] For further reading on the subject, see http://publications.jrc.ec.europa.eu/repository/bitstream/JRC113826/ai-flagship-report_online.pdf.

A first step for transforming public policies would be to exploit the full potential of administrative data to orchestrate policy evaluation into regular and short feedback loops. Through fine-grained administrative data, it is possible to individualise key characteristics like age, gender, residence location and socioeconomic profile and start measuring the impact of public policies on different groups, going beyond correlation towards causality. A new short cycle of adaptation could be foreseen in new types of regulatory instruments sensitive to impact results. There is already available experience in implementing counterfactual impact evaluation and exploiting the potential of administrative data linkages. Future developments will depend on data availability as well as changes in legislative approaches, aligning with the requirements associated to the regulation of complex systems: probe, test and adapt.

When bringing AI into the picture, we can progress the transformation of public policymaking even further. We are concerned at the present time with the notion of 'algorithmic' governance, i.e., being ruled by decisions taken or informed by machines on the basis of algorithms (i.e., rules) that we do not understand and are not accountable. There is a clear need for accountability, transparency, oversight, testing for biases and explainability of algorithms but that does not mean that we should reject the use of algorithms outright to support decision-making processes. In fact, we can posit that a set of legal implementing rules expressed in computer code (i.e., as algorithms) could be clearer and more verifiable than expressed in legal language, with the advantage of being more programmable and adaptable, for example, to maximise effectiveness and fairness of implementation whilst maintaining the objective of the legal act constant.

We can think of this with analogy of European Directives, where we agree on the objective to be reached (the *What*) and then leave the Member States to transpose the Directive in their national laws so that they can adapt the implementation (the *How*) to their institutional system and national characteristics. So why not think of redesigning the policy so that we agree on the objective in such a way that the implementation shall vary according to different circumstances, for example, different areas and different groups of people or firms, to maximise efficiency of resources, effectiveness of outcomes and fairness in implementation? If the implementing measures (rules) were expressed as ML algorithms, we could also from the outset design the policy so that it does not need revision unless the objective has changed, but is constantly adapting to changing reality and 'learning' based on the feedback loop from implementation.

Aside from more flexible, adaptive and responsive policies, we can also think of more targeted policies based on needs and location. We may be comfortable with personalised services (e.g., loans, insurance, recommendations about books, films or music and in the near future personalised medicine) and less so with personalised/targeted marketing, but how would we feel about 'personalised' government policies? The answer may well be more about our trust in government and whether we feel it has our best interest at heart, than about concepts, methods, or technology. Therefore, it probably varies from country to country, level of government and historical period.

The issues about designing 'personalised', 'need-based' policies are being addressed in the Digitranscope[2] project and in leading centres like the Alan Turing Institute in the United

[2] https://ec.europa.eu/jrc/communities/community/digitranscope.

Kingdom, which has a dedicated programme about data science for public policy.[3] The key point is to identify individual needs and then target policy intervention around such needs whilst being in full respect of privacy protection. This can be done through anonymised processes and under governance protocols protecting from various types of potential abuses or violations. Administrative data management and new forms of social contracts around data sharing between citizens, public authorities and private companies are key aspects of this area of development, and many countries are exploring innovative approaches as a result of the AI revolution.

To identify the needs of individuals and groups in specific geographical areas for different public policy areas of intervention such as housing, social care, education or energy, we can use several data sources and strategies:

- Infer need by integrating and analysing all the data relevant to a policy issue that are already held by government at different levels: This is technically possible as we (almost) all have unique identifiers like tax codes or digital IDs that allow to link the files held by different government departments (the so-called administrative data linkage). In most countries, it is not done because of legal, cultural and organisational barriers/sensitivities although there is a policy push by European Commission to introduce the 'Once Only' principle, already applied in Estonia, whereby a government should not ask citizens or firms for information it already has. This implies a much greater degree of good data management and data sharing across government than is the case in most countries at the present time, but it seems to be a direction for future development.
- Infer need by disaggregating anonymised group data that are published by statistical offices: National and local statistics are typically published at small area units of approximately 200–500 people. For each area, many variables are available about the population, households, families and buildings. These variables can be disaggregated to the level of (artificial) individuals based on a set of rules, so that when reaggregated at the small area unit, they give the same set of statistics as those published. The (imputed) characteristics of these (artificial) individuals can then be aggregated into families and households and assigned to buildings and dwellings, so that again when reaggregated, they return the official published data. This technique is already well used for policy modelling and assessment, for example, to compare the outcome of a policy intervention on a certain group with nonintervention on a group having similar characteristics or for modelling emissions from individual transportation (see, for example, Chapter 18).
- Ask people to express their needs: Traditionally, this is done through postal, telephone or online surveys, which can be done more frequently and on questions already targeted on different groups based on some degree of profiling from one or two above. This would have the advantage of making the questions more pertinent and eliciting not just 'need' but also the equally important 'perception of need'. As an example, there could be a set of questions about level of satisfaction with the local school, and journey to it only addressed to families with young children, and access to healthcare targeted to the elderly, etc., and avoid questions that do not apply to the groups imputed from one to two above.

[3] https://www.turing.ac.uk/research/research-programmes/public-policy.

- Establish a social platform, encourage people to create their profiles and then gather data from the interaction among people and between people (or firms) and the platform: This is equivalent in a public space to what is done by all social media platforms that are based on content created by the users and then enriched with labels and context by the user interactions. This is crucial for training ML algorithms: not just raw data but semantically enriched, contextualised data. Public administrations cannot do that on their own, they need users to do it, but of course, they need to provide the right incentives to get people (or firms) to create and maintain their profiles and use the platforms, maintain accountability and trust and so on. This is a rich matter of ongoing research also in many experiences with citizen-generated content and citizen science where motivation, incentives and sustainability are key concerns.

Unlike traditional surveys, the combination of the methods highlighted above would also allow to identify the groups that do not respond or participate and try to understand better the reasons behind this, reducing the problem of the 'silent and overlooked' groups. If carefully developed and adequately communicated and explained, these methods could be used to customise policy intervention according to the need (and perception thereof), develop powerful feedback mechanisms to policy planning and implementation and reinforce bidirectional communications between citizens and the government leading to greater accountability, increased trust and more active citizenship. Algorithms finding commonalities among the citizens will help us identify 'communities' of shared needs and interests, to which we can tailor policies so that they do to impose obligations on those that do not need to be affected.

Last but not least, it is now possible in a digitally transformed society to do any of the points above considering real people in the real physical world, artificial individuals in the real world, artificial individuals in a virtual world (e.g., avatars) or real individual interacting with a virtual replica of the real world. An example of the latter is the Digital Twin of the Netherlands created in Minecraft by a public–private partnership between the Dutch Cadastre, Dutch Waterboards, the Free University of Amsterdam and Geodan, a private company. Geocraft.nl[4] is a 1:1 model of the Netherlands where every building is represented based on the official cadastre and recreated by more than 20,000 children over a period of 4 years. The opportunities for a new form of participation and policy design are illustrated from an experiment done in June 2018 in the south of Amsterdam, where 500 children came together with the local administration, industry and academics to use this virtual model in Minecraft to help design their vision of the future for their neighbourhood.[5] This experiment is now being replicated in Warsaw with the engagement of local schools.

Combining the approaches described above, it is possible to gather knowledge about objective/relative and perceived needs and design policy interventions that address those who need them most in the geographical areas that need them most.

These policy interventions can be modelled and tested in advance using randomised control trials techniques in both physical and virtual environments and then deployed and monitored so that the feedback from implementation adapts the policy intervention in next to real time, a form of 'policy that learns' similar to the approach in ML, where algorithms learn from the

[4] https://www.youtube.com/watch?v=R-xVyyliS4ghttps://geocraft.nl/.

[5] https://www.youtube.com/watch?v=WkKHReQ8wyE&feature=youtu.be.

data. Moreover, because we are designing from the outset policies that target specific groups in specific areas, we can assess with much greater transparency their impacts and include also the feedback of the policy recipients themselves. This creates new opportunities for public participation also in the ex-post policy assessment described in Chapter 18. Last but not least, as the case of South Amsterdam mentioned above, we can involve the recipients of intervention in the policy design process, and who better than children are the most impacted by the future.

Of course, using AI and Big data for new forms of policy design and evaluation as described here may have negative and unintended consequences from the point of view of security, privacy and social equity. It is for this reason that we are running policy experiments to ask the questions that may help us identify positive directions of travel, blind alleys or no-go areas. On the other hand, more targeted and transparent policy design and impact assessment could force politicians and decision-makers in the industry to be more accountable about their promises and citizens and firms to become more conscious about their responsibilities. This in turn could contribute to improving that dialogue between citizens and institutions that Vesnic-Alujevic et al. (2019) advocate as crucial in meeting the future challenges in society.