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Big Data – Automated Decision-Making in Public Policy

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Central Definition/Definition(s)

Automated decision-making, ADM, is decision-making that is performed by automated or automatic processes. This means that the activity of making decisions is, to some extent, delegated to technology in the form of algorithms, models and systems. ADM is associated with increased digitalization of society in large, including the public sphere, public policy and public administration. In general, ADM is based on *data-driven* information practices and technologies, that are instated to facilitate analyses of data to inform and/or utilize decision-making. For certain technologies, upon which some ADM-systems are based, access to large amounts of data is required. This connects it to the development of *big data*, referring to the collection, analysis and use, of big sets of digital data produced by digitalization and datafication of everything from healthcare and welfare provisions, to geographical movements and social relationships.

Main text

Historical/generic aspects

Automation is not a new phenomenon, but it has received increased scholarly and public attention the last decades. This is due to technological advancements and a rising number of development projects and implementations of automation of administrative and policy related tasks, as well as the introductions of data governance frameworks, such as the General Data Protection Regulation, GDPR, in the European Union. This shift towards automation goes together with an ideological understanding of the digital society, and a policy push to make the most out of the possibilities brought about by digital technologies and data collection. This push is prevalent in public vision papers, strategies and policies, as well as in practice. It is part of developments such as the E-government, algorithmic government, the digital government, the digital public sector or, in some contexts, the data welfare state (Andreassen et al., 2021). ADM could be part of developing and establishing (new) public policy directions, by data-driven analysis, believed to result in improvement by more evidence-based decisions. However, more focus is dedicated to ADM as administrative tool in the fulfilment of public policy.

Prior to digitalization, major life-changing decisions were generally made by human discretion, even though the process could be aided by technology to greater or lesser extent. Today, on the other hand, our lives are increasingly affected by algorithmic-, model-, software-, system-, or machine-supported/translated/made decisions. This is done by different sorts of activities that could gravely impact our lives, and that are referred to as, to some degree, automated decision-making. It includes activities going by the name of automated eligibility, ranking algorithms, social sorting, prediction models, red flagging and many more (Eubanks, 2017: 3; Kaun, 2021). Additionally, ADM is part of legislative conceptualization. In the GDPR, article 22 specifies the right to choose not to be subject to solely automatic processing of personal data, that has legal effects on the individual. This also includes profiling. Attention has been devoted to the inclusion and definition of the term *solely*, that is indicating that profiling and decisions based on personal data could be fully or partly automated, and that the article only applies in the former case. Moreover, GDPR, entails the right to have a human reassessment of algorithmic decisions (Kaun, 2021; Früh et al., 2019).

The motivations for introducing ADM in the public policy realm are manifold. The most prominent being that it is argued to provide for better decision-making by an increase in efficiency, consistency and fairness. These motivations are part of a policy ideal, to make the most out of digitalization, optimization and technology, and by so, save or make better use of public resources and provide better service. By this reasoning, the development of ADM is fueled by a scarcity of resources, both in terms of staffing shortages, and increased costs and insufficient funding of public administration and the public sector in total (Andreassen et al., 2021). The hope is to be saving, or at least more efficiently using, public resources by utilizing new technologies and specifically delegating decision-making to ADM, fully or partly. However, a hope for ADM is that it will also increase evidence-based decision-making by (big) data analysis, resulting in improved decision-making and policy-making, better distribution of resources for where they are most needed, as well as increased equality in the execution of public policy. It is also argued to provide consistency and transparency, in comparison to human judgements, although many argue that it on the contrary risk leading to unforeseen consequences and increased opacity (McNeely and Hahm, 2014; Andreassen et al., 2021; Früh et al., 2019).

A presumption for ADM, besides the utilization of data-driven analysis, is the benefits of avoiding the "human factor", by characterizing it as being a cause for inefficiency, inconsistency and discriminatory treatment. Critiques against this reasoning can be summed up as: 1) ADM could still be demanding a lot of work and resources, but perhaps of other groups than before, doing development and maintenance work, 2) data-driven decision-making builds upon the historical data of human decisions, and human choices in model building, hence is not free from human (miss)judgements, 3) ADM has been proven to in some cases create new unforeseen problems or unfair treatments in algorithmic decision-making.

Functional aspects – the automated decision-making in practice
ADM could be based on complex data-driven analyses, or be simple automatic rule-based tasks performed on digital data as input. In discourse, conceptualization and practice, ADM is associated with the increasing development and implementation of Artificial Intelligence, AI, even though it is not in all cases classified as based on such technologies. Another adjacent concept is robotic process automation, RPA, which refers to the automation of workflows (Roehl, 2022). In ADM, the level of automation, autonomy and complexity varies. It can be automation of simple rule-based decision-making task, in the form of decision trees, such as the automatic approval of social benefit applications, based on set parameters for qualification (Kaun, 2021). However, it can also be ADM in the form of complex analytical judgements, where multiple factors are taken into account and the judgement can be adaptive to changing conditions, and the updated execution or outcome be autonomously performed. ADM could also take the form of data-driven prediction, leading to, more or less automated, preventative actions being taken. Regardless of level of complexity, ADM can have unforeseen effects.

In practice, ADM requires stages of activities to work, in short: data collection and analysis, designing and building of models and algorithms, followed by output in the form of decision-support or decision-making. Correspondingly, (administrative) decision-making itself also requires collection and assessment of relevant data and information, followed by design or development of course of action, and lastly the choice or decision, where a particular course of action is decided upon (Roehl, 2022: 38). For reaching goals of efficiency and optimization, ADM is often associated with large-scale performance of systems and decision-making, also entailing vast reaching impacts and/or impact on large groups. While this is part of the beneficial aims of implementing ADM, it does include the risk of flawed or discriminatory outcomes affecting many people in a short amount of time. Dignitary concerns can also be raised as the people to serve are increasingly taking the form of data points to process, rather than humans to support.

The datafication and digitalization within public policy are however foundational necessities for enabling automated decision-making (McNeely and Hahm, 2014). With the term "dataism", van Dijck refers to the ideological belief in objective quantification and tracking, as well as trust in the institutions that collect, analyses, and make use of data (van Dijck, 2014). This data paradigm can be found both in research and public policy. It builds upon ideas of data as objective and raw – a belief that is contested. Further it is founded on activities of data collection that is often critiqued for being surveillance, both state surveillance and tracking and collection performed by private companies for the purpose of commodification (van Dijck, 2014). Still, the datafication of the public sector originates also from the understanding of data providing for more accurate and complex insights into human behavior, that is possible to reach by data-driven analyses, definitions and predictions (Andreassen et al., 2021). These are arguments for the benefits of data-driven public policy and ADM. Yet, Eubanks (2017: 12-13) stresses how these developments risk making social problems into systems engineering problems, and that it is perceived to be within that realm that all solutions are to be found. A matter of concern is further that automation has been claimed to more often disadvantage poor or working-class citizens (Eubanks, 2017).

There is however an expectation that ADM will contribute to increased fairness in decision-making of public policy, and that a datafied public government can assist in discovering systemic bias in decision-making processes. Nevertheless, one reason for the recent public and scholarly spur of interest in ADM is that cases of mistreatment by the use of ADM or algorithmic systems have been brought to public attention. One such case receiving much attention is from the United Kingdom, where a model was use to predict student grades, and accordingly offered spots for university admissions. It caused public outrage since it turned out to be discriminatory, by basing predictions on historical data and thereby disadvantaging students from schools with previous lower number of A-grades (Kaun, 2021). This is one example of how automation of policy in how to deal with physical restrictions due to Covid-19 (limiting possibilities for students to take the usual grading exams), leaned too heavily on technical solutionism rather than including important social and economic factors of the problem at hand.

Moreover, datafication and ADM is argued to frequently follow commercial logics of data capture and development of proprietary systems (Andreassen et al., 2021). As such, ADM can become part of an intricate relationship between public policy and commercial actors, such as private system developers. This happens as system development often takes place outside of the public entities, or in cooperation with external actors, and possibly by actors with other aims or value systems. In many cases, it takes the form of commercial startups and pilot projects, together with the public sector. Causes for caution, within this development, is the potential lack of transparency and insight, lack of long-term commitments (while being funded by public resources), and the risk of value discrepancy (profit versus human values) between the actors

(Kaun, 2021). ADM in public policy is assumed to embody public values for the public good, which potentially could be challenging, if performed in joint endeavors with private contractors.

Different meanings/definitions/use

One conundrum of the concept of ADM is that, while it at a first encounter might seem to facilitate precision, it is still vague in all of its parts. The automated/automatic aspect of ADM, has been interpreted in various ways. That is, the concept is used in scholarly research and public practice by referring to a variety of applied models and systems, ranging from full large-scale automation to decision-support, or informing, systems. Hence, it differs how much human involvement there actually is in this phenomenon called automated decision-making. To what extent is the process actually automated or automatic? Does the process constitute the making of a decision? Could it be called a decision without human discretion involved? There is an ongoing negotiation of what the concept of ADM holds within public policy, especially as considered a sociotechnical concern which is interpreted differently by different actors. Depending on who you ask, it is comprehended as a robot, code, decision tree, interface, service automation, rule-based expert model, decision support, machine learning model, neural networks, or other types of processes or objects (Kaun, 2021; Roehl, 2022).

Although much of research into ADM do not fully distinguish the level of human involvement, some try to conceptualize types of ADM. An adjacent conceptualization is bureaucracy on street-level (no automation), screen-level (semi-automated decision-support), or system-level (full automation) (Roehl, 2022: 41-42). As ADM is often only separated on three general levels of technological applications: no automation, semi-automated decision-support or fully automated decision-making, Roehl (2022) argues for a more detailed classification of automated administrative decision-making, AADM. He distinguishes six types of configuration of decision authority and organizational practices, including: minimal automation, acquisition and presentation of data, suggested procedural steps, supported decisions, automated decisions and autonomous decisions (Roehl, 2022). By this conceptualization we can reach greater understanding of the decision-making processes at hand, the sociotechnical dimensions such as the role of technology in the process, and of the potential impact of the activity. The six types correspond with grades of human involvement and responsibility, or degrees of action. A closely connected concept in regards to that is the human in-the-loop (Roehl, 2022). That is, humans are in some way or another still part of the process, and working together with the decision-making technology.

In many cases, some part(s) of a decision-process is automated, while the final step of the operation is conducted by a human operator. One way it has been conceptualized, is as augmented decision-making, due to the perceived complementary capabilities provided by algorithmic data analysis and decision-support. In ADM, to keep a human-in-the-loop is commonly portrayed as safeguard, yet, even if a human is the operator of a certain important step of a decision, studies have shown the tendency of what is called automation bias. It refers to that humans are, especially regarding routine tasks, over-relying on the judgments produced by algorithmic systems, as decision authority have been delegated to technology (Roehl, 2022: 49). A risk is that humans become mere operators of automated decisions, and not personify the intended qualities of keeping a human in-the-loop. Still, one could also ask; what human is to be kept in the loop? In principle, just treatment by public services, or humane policy directions that are to be implemented, in the use of ADM, could require to go outside of the given set of rules. Eubanks argues that by the use of technology, the possibility to perform some degree of human discretion is in some cases also moved, from social servants to engineers and private contractors, ending up in exacerbated discriminatory decision-making (Eubanks, 2017: 81). From a sociotechnical perspective, it is also argued that as human judgements are needed in the different stages of developing and utilizing ADM, one could argue that a process is never fully automated decision-making, when the whole life cycle of its operation is taken into account. Further, it could also be argued that decision-making has to be a deliberate conscious action, and that it, if fully automated, seize to be decision-making but rather algorithmic computation or operationalization. Another line of argument is that for automation to be possible, the decisions already have had to been made (Früh et al., 2019). By that reasoning, decision-making rather occurs in the agreement on requirements, making of systems and processes of setting parameters, implying that decision-making is not actually delegated. However, the validity of the conceptual distinctions depends on how decision-making is thought of, and with what level of autonomy a system is operating.

National differences

Globally, there are some national differences in how ADM has been developed, implemented, incorporated and received, in public policy and practice. Much research has focused on cases of flawed or discriminatory ADM in public service in the United States and the United Kingdom (Eubanks, 2017; Andreassen et al., 2021). In the Nordic countries, there is generally a high level of public trust in institutions and their data collection, in addition to that much data on citizens are already collected as part of how these welfare states functions. This is often put forward as a solid foundation for implementing ADM. Further, the Nordic countries have ambitious visions and national public policies regarding digitalization and to become world-leading in using digital technologies (Andreassen et al., 2021). Other cases attended to have been ADM in social security and education, in the Netherlands, Australia, and the Nordic countries. Further, scholars have focused on sorting by employment services in Austria and Finland, and many examples from the criminal justice system, including surveillance, prediction and datafication as crime-solving and crime-preventing measures, but also datafication of prisons in the United States as well as Sweden (Roehl, 2022; Andreassen et al., 2021). Yet, from a critical perspective, Eubanks (2017: 199-200) argues that high-tech severe social sorting of people, which could be part of some ADM processes, develops foremost in totalitarian governed countries with high inequality. Here we have to attend to what it is that the technology at hand does, and how, to decipher how it fits into the specific public policy and whom is benefiting from its use.

Some national differences could be due to variances in regulation. A stronger protection of individuals' personal data might impact the development of certain ADM-systems, such as GDPR within the European Union (Andreassen et al., 2021). In general, regulations and social (non-)acceptance can contribute to certain ADM processes not being implemented, even though they could be technically feasible and possibly resource effective. Generally, global differences concerning ADM have also been ascribed to levels of trust in technology and trust in the state and public policy. There are also differences with regards to what expectations the citizens have on the behaviors and values of governmental institutions. It involves trust in data collection and state control, but also regulations and beliefs of openness (see for example the Swedish principle of public access to information, Offentlighetsprincipen)(Kaun, 2021; Andreassen et al., 2021).

Comments

The challenges of data-driven public policy and ADM within the public policy domain, are many. They are practical (ensuring validity of data, robustness of systems, develop scalable models) as well as value-based and regulatory controlled (safeguarding legal action, preventing discriminatory outcomes). ADM is plentiful with both promise and problems, as was and still is the case with big data in general (McNeely and Hahm, 2014), with cases that could be argued to support both its benefits and its downsides. If the developments of ADM continue, we most certainly have yet to see the full implications of it in public policy. Hopefully, research into that can be supported by approaching a common understanding of the concept of ADM.

Cross references

- Big Data – Consulting the Public in Public Policy
- Evidence-based Policy-Making
- Public-Private-Partnership in Public Policy

References

Andreassen R, Kaun A and Nikunen K (2021) Fostering the data welfare state: A Nordic perspective on datafication. *Nordicom Review* 42(2): 207-223.

Eubanks V (2017) *Automating inequality : how high-tech tools profile, police, and punish the poor.* New York, NY: St. Martin's Press.

Früh A, Thouvenin F, Rudolph T, et al. (2019) Towards principled regulation of automated decision-making (ADM)– A workshop report. *Center for Information Technology, Society, and Law (ITSL), University of Zürich*. DOI: ttps://doi.org/10.5167/uzh-183655

Kaun A (2021) Suing the algorithm: the mundanization of automated decision-making in public services through litigation. *Information, Communication & Society*. DOI: 10.1080/1369118X.2021.1924827. 1-17.

McNeely CL and Hahm J-o (2014) The Big (Data) Bang: Policy, Prospects, and Challenges. *Review of Policy Research* 31(4): 304-310.

Roehl UBU (2022) Understanding Automated Decision-Making in the Public Sector: A Classification of Automated, Administrative Decision-Making. In: Juell-Skielse G, Lindgren I and Åkesson M (eds) *Service Automation in the Public Sector : Concepts, Empirical Examples and Challenges*. Cham, Switzerland: Springer.

van Dijck J (2014) Datafication, dataism and dataveillance: Big data between scientific paradigm and ideology. *Surveillance and Society,* 12(2): 197-208.