
# Algorithmic Governance: Technology, Knowledge and Power

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## INTRODUCTION

We live in an algorithmic society in which a convergence is taking place of the digital and physical worlds (Schuilenburg and Peeters, 2021). In this new reality, algorithms play a decisive role, raising a host of analytical and ethical questions. In the broad sense of the term, algorithms are mathematical procedures for solving a problem by transforming input data into a desired output. Algorithms are everywhere; there are algorithms determining which risk factors are most relevant to the diagnosis of diseases; algorithms assisting in student distribution in a classroom; algorithms predicting where and when criminal activity is likely to occur; algorithms helping people to decide what to watch on Netflix; algorithms detecting possible fraud in social benefits; algorithms identifying privacy vulnerabilities; algorithms optimising routes for waste collection and transportation, and so on. Algorithms are increasingly used throughout the private as well as the public sector in decision-making processes, from criminal justice agencies (e.g., Bennett Moses and Chan, 2018; Hannah-Moffat, 2019; Peeters and Schuilenburg, 2018) to healthcare (e.g., Soltani et al., 2018) and environmental protection (e.g., Granata et al., 2017).

Algorithms are a lot like recipes. When you make your favourite cookies, you use a recipe to make sure you get the crispy chocolate cookies you want. As private and public organisations increasingly turn to the application of algorithms to make smarter, faster, more accurate and consistent decisions, it is important to discern rule-based algorithms from learning algorithms (Lorenz et al., 2020). Rule-based algorithms are ‘digital recipes’ designed by humans – for example, the digitalisation of routine administrative decisions or pre-filled tax forms (Bovens and Zouridis, 2002). By contrast, learning algorithms are dynamic and adaptive recipes, which enables them to autonomously detect patterns and correlations in big amounts of data. They continuously learn and self-correct following the parameters designed into the system (Ávila et al., 2021). An algorithm will, for instance, cook a certain dish without knowing all the required ingredients. This can have countless unforeseen effects whose impact, depending on the context and the nature of the application, can potentially be considerable.

The current excitement surrounding algorithms is largely rooted in the argument that these tools are ways to 'scientize, economize and democratize' (Smith et al., 2017: 261) decision-making processes. There is a strong belief in the added value of algorithms that identify patterns and correlations which cannot be detected by human cognition. Algorithms may also save time and money by improving government efficiency and are often seen as value-neutral ways to generate knowledge and expertise (Christin et al., 2015). In response to the claim that algorithms make decisions more accountable by protecting them against human bias, critics argue that algorithms lead to discriminatory practices because data reflect longstanding institutional biases along income, race and gender lines (Noble, 2019; O'Neil, 2016; Richardson et al., 2019). Furthermore, correct predictions are difficult to make because the algorithms and data used are never neutral. Algorithms are not objective calculating tools. An algorithm is 'set up by developers, analysts and policy makers, which in many cases makes it politically sensitive' (Schuilenburg, 2021a: 83).

In this chapter, we take a broad look at algorithmic systems in the public sector. How do they work? In which domains? How do they create new forms of knowledge? To answer these questions, we look beyond explanations of algorithms that focus solely on their technological qualities. Instead, we address the far-reaching role of algorithms in public domains, both in terms of how algorithms create new forms of knowledge, but also in the way they form their own modes of power. First, we focus on the use of algorithms as a form of ordering society by analysing three conceptualisations: 'algocracy', 'algorithmic regulation' and 'algorithmic governmentality'. Second, we analyse the main activities for which 'algorithm technology' is used in the public sector: automated decisions, automated assessment and automated agency. Next, we analyse how the production of 'algorithmic knowledge' rests on mechanisms of quantification, formalisation and standardisation. Finally, we sketch how 'algorithmic power' is exercised and reproduced rather than possessed. In the conclusion, we sketch the main issues and values at stake in an algorithmically governed society and argue that we are in need of a politicisation of the debate about our algorithmic society.

## ALGORITHMIC GOVERNMENTALITY

Governance has become algorithmic and algorithms govern. As the influence of algorithmic systems in the public and private domain grows increasingly, different scholars are trying to analyse its consequences for the way algorithmic systems regulate or govern behaviour. Despite some conceptual and operational overlap, we discern three conceptualisations: 'algocracy', 'algorithmic regulation' and 'algorithmic governmentality'. How are these concepts distinct, and how are they useful for our understanding of the algorithmic infrastructure of our society?

### *Algocracy*

The way that algorithmic processes are applied to mine a large volume of digital data to find patterns and correlations within that data is described by sociologist Aneesh (2006, 2009) as 'algocracy'. In his ethnographic study *Virtual Migration* (2009) of Indian workers providing IT and IT-enabled services to US firms, Aneesh departs from a Weberian analysis of bureaucracy and the rise of instrumental reason and shows how a system of governance based on 'rule of the algorithm' adds a new dimension to the already existing bureaucratic (and market) systems of social ordering. In *Wirtschaft und Gesellschaft*, Weber spoke of the bureaucracy in terms of 'authority through knowledge' (2006: 226) and argued that the bureaucracy functions as the prime organisational 'vehicle' for governing through knowledge of citizens and the population as a whole. Even though the concept 'instrumental rationality' (*Zweckrationalität*) only partially captures Weber's perspective on bureaucracies, it makes clear how decisions are made according to laws and coherent rules, such as procedural rules that both define the ends and regulate the ways in which humans act. As such, Weber defined *Technik* as the narrowest form of instrumental rationality, a rationality that can be seen as a way to realise predictable outcomes and reduce uncertainty.

In his reconceptualisation of Weber's thesis that, in a bureaucracy, persons are replaced by positions, Aneesh points out that 'algocratization reduces the power of positions by implementing finely tuned action scripts, almost invariably decentring the authority from the body of a person from the immediate exercise of power' (2006: 130–1). An 'action script', as shown by Madeleine Akrich and Bruno Latour (1992; Ekbia et al., 2015; Matzner, 2017), is not just the set of directions for use, it is rather the 'built-in' nature of 'prescriptions' that impose themselves on the user, inviting one choice of action rather than another. According to Aneesh, as authority is increasingly embedded in the technology itself ('in the underlying code'), technical imperatives have reached a point where they do not require bureaucratic orientation to the same degree any more. In fact, 'programming technologies have gained the ability to structure possible forms of behaviour without a need for orienting people toward accepting the rules' (Aneesh, 2006: 109–10). Accordingly, algorithms now structure and constrain the ways in which humans act (see also Danahar, 2016; Lorenz et al., 2020).

## *Algorithmic regulation*

Scholars like Tim O'Reilly (2013) and Karen Yeung (2017, 2018) have coined the term 'algorithmic regulation' to capture a way of coordinating and regulating social action and decision-making through algorithms, as well as the institutional mechanisms through which the power of algorithms and algorithmic systems can themselves be regulated. Yeung defines algorithmic regulation as 'decision-making systems that regulate a domain of activity in order to manage risk or alter behaviour through continual computational generation of knowledge from data emitted and directly collected (in real time on a continuous basis) from numerous dynamic components pertaining to the regulated environment in order to identify and, if necessary, automatically refine (or prompt refinement of) the system's operations to attain a prespecified goal' (2017: 507). She points out that algorithmic regulation involves three different components: ways of gathering information ('information-gathering and monitoring'), ways of setting standards, goals or targets ('standard-setting') and ways of changing behaviour to meet the standards or targets ('enforcement and behaviour modification'; cf. Hood et al., 2001).

Yeung argues that algorithmic regulation has antecedents in cybernetics. In his ground-breaking book *The Human Use of Human Beings: Cybernetics and Society*, Wiener described cybernetics as a new science 'which includes not only the study of language but the study of messages as a means of controlling machinery and society, the development of computing machines and other such automata, certain reflections upon psychology and the nervous system, and a tentative new theory of scientific method' (1950). Cybernetics focuses on developing positive feedback loops, consisting of input, output and some form of information concerning the effects of the output. According to Yeung (2018: 508), the work of cybernetic analysis makes it possible to identify different systems of algorithmic regulation – e.g., fraud, crime or terrorism prevention – by analysing how each system is configured in relation to the three described components. As to the third component of 'enforcement and behaviour modification', for example, a distinction can be made between automated and recommender decision-making systems, classifying these systems as either reactive systems which administer a specified sanction or decision (e.g., block access to Web content) or pre-emptive systems, based on algorithmically determined predictions of future behaviour (e.g., denying insurance coverage).

### *Algorithmic governmentality*

Other scholars favour the term 'algorithmic governmentality' (Hannah-Moffat, 2019; Henman, 2021; Rouvroy and Berns, 2013; Rouvroy and Stiegler, 2016) to analyse how algorithmic systems govern social reality. The term 'governmentality' refers to the work of Michel Foucault and points to all techniques and procedures that are involved in the managing of social relations in society. Foucault coined the neologism 'governmentality' (*gouvernementalité*) in contrast to the classical liberal-democratic framework, thereby shifting the focus from the legal ('rule of law') and representative ('rule of the people') framework within which political decisions are formulated to a focus on what modern governments actually regulate: the everyday lives of people and their living circumstances (Schuilenburg, 2015: 69–70). For Foucault, governmentality deals with the regulating practices of everyday life, which is concerned with both the techniques of governing, and new forms of power and knowledge production regarding the subjects of government. Antoinette Rouvroy and Thomas Berns rearticulate Foucault's notion of governmentality and define algorithmic governmentality as 'a certain type of (a)normative or (a)political rationality founded on the automated collection, aggregation and analysis of big data so as to model, anticipate and pre-emptively affect possible behaviours' (2013: x).

Rouvroy and Berns discern three stages of algorithmic governmentality. The first stage is the collection and automated storage of unfiltered mass data by public and private parties. The second stage consists of the automated processing of these mass data to identify all kinds of correlations between them. They refer to this as 'automated knowledge production', which means that it requires minimal human intervention. At the third stage, probabilistic statistical knowledge is used to anticipate individual behaviours and associate them with profiles defined based on correlations discovered through datamining. With regard to the third stage, it is important to realise that the action that is undertaken to govern no longer takes place on the basis of an external norm (e.g., a law or an average), but rather realizes an effect by deriving norms from statistical data and subsequently spreading these norms over the population with the aim of identifying anomalies that deviate from the expected and normal patterns. For example, it is not the criminal but the future criminal who is the object of analysis in algorithmic systems such as predictive policing. As such, algorithmic governance produces, in the words of Rouvroy and Berns, an 'actuality with a "memory of the future"' (2013: xix).

Despite the subtle differences of the three distinguished conceptualisations, it is crucial to understand that they aim to describe the same phenomenon: the widespread use of algorithms to detect patterns and correlations in human behaviour in order to improve decision-making processes. Although the boundaries between the described concepts are not precise, we favour in this chapter the term 'algorithmic governance' as it opens up new layers of analysis of the governance of society through particular modes of power–knowledge relations and ways of forming new subjects. For a better understanding of this, we first need to acquire a deeper understanding of how 'algorithmic technologies' are used to complement, compete with or even replace human decision-making, human assessment and human agents. Hereby, we focus on the public sector.

## ALGORITHMIC TECHNOLOGY

Algorithms are not a recent invention nor are algorithm-based technologies new in government and public administration. Especially since the 1990s, the digitalisation of government and use of computer algorithms have accelerated dramatically. Building upon the digitalisation of files and information into databases, simple bureaucratic decision-making procedures were automated by converting procedural decision trees into computer-programmed algorithms. Public organisations started to automate routine large-scale, decision-making procedures, such as pre-filled tax returns, automated processing of traffic fines, and determining the eligibility for student grants and welfare benefits (Bovens and Zouridis, 2002). By then, it had already become clear that automation of decision-making procedures had a profound impact on organisational practices. To put it simply, computer screens replaced paper and automated decision trees replaced human case assessment. System designers became key organisational actors. Data became a crucial resource (Bovens and Zouridis, 2002; Landsbergen, 2004).

Since the 1990s, new technological advancements have transformed government far beyond the simple automation of existing bureaucratic decision-making procedures. In order to distinguish the digitalisation wave of the 1990s from more recent innovations, some authors argue for referring to the former as 'information systems', while reserving the term 'algorithmic systems' for applications of dynamic learning algorithms (Lorenz et al., 2020; cf. Yeung, 2018). In this chapter, we opt for a broad conceptual approach to algorithmic applications, including both rule-based and learning algorithms. We argue that, despite their differences, these applications are bound together by a shared governmentality that renders the subjects of governing calculable, and relies on machinic judgement and categorisation. More specifically, they allow for concrete manifestations of automation to complement, compete with, or even replace human decision-making (*automated decisions*), human assessment (*automated assessments*) and human agents (*automated agents*).

### *Automated decisions*

Algorithms are used for administrative decision-making and status determination of citizens as eligible for access to rights and services or as obliged to comply with regulation (such as taxation). At least three ways can be discerned in which algorithms replace human decision-making. First, digital portals and other e-services transform the interaction between citizens and government by fully digitalising both the supply- and the demand-side – for instance, when paying taxes online or when applying for municipal services or social benefits (Dunleavy et al., 2006; Lindgren et al., 2019; Reddick, 2005). Currently, digitalisation has advanced to the point that certain standard administrative procedures require no human actor at all. In some cases, citizens do not even need to apply or fill in any form to receive government services that are, instead, triggered automatically by changes in a person's status, such as old-age benefits or child benefits (Larsson, 2021; Scholta et al., 2019).

Automated administrative decisions are also increasingly embedded in broader information architectures (Yeung, 2011, 2018). Supra-organisational information systems function as an infrastructure that allows for the free flow of information, but also guides and constrains its use (Bowker and Star, 2000; Cordella, 2010).

Second, whereas the first generation of automated decision-making remained confined to single-organisation automation, the second generation expanded automation to data-sharing in 'chain decisions'. An organisational chain concerns independent organisations that cooperate in a predefined sequential process towards a collective result (Grijpink, 1997; Peeters, 2020; Widlak et al., 2021). In these chains, data is shared according to a harmonised legal framework and harmonised data definitions (Van Eck, 2018; Zouridis et al., 2020). Cooperation between police force and public prosecutor office on processing criminal cases is a typical example of a chain in which data can be shared to coordinate and automate decision-making processes.

A third, currently emerging generation of automated decision-making uses algorithms on the level of networks (Widlak et al., 2021). Here, the analogy with a supply chain is lost because there is no clear sequential process, no common objective and often no harmonisation of legal frameworks and data definitions between organisations that cooperate in information architectures. A good example is the Dutch government's system of registrations of vital statistics. In this centralised registration system, authentic data on citizens, businesses, geographical locations, buildings, vehicles and so on is gathered and subsequently automatically shared with a large variety of public and private organisations to allow for the execution of their primary processes (Peeters and Widlak, 2018). Rather than each organization having its own client registration, they all tap into a more complete, reliable and up-to-date 'basis registration'.

### Automated assessments

Algorithms are also used for statistical data analysis. Here, algorithms enhance, complement and sometimes replace human assessment. By exploiting their potential to analyse more data in less time and with more variables (Kitchin, 2014), automated data analysis has become a powerful business model that underpins and strengthens 'surveillance capitalism' (Zuboff, 2019) of Facebook, Google, credit card companies, and other digital platforms. Furthermore, the 'proliferation of scoring and ranking citizens' (Harcourt, 2015: 205) has also transformed governments' efforts to predict, nudge and constrain human behaviour (Danaher et al., 2017). Data and the algorithms processing these data have become a crucial commodity for companies and governments alike. Where algorithms are put to use for commercial benefit by the former, the latter tap into the potential of algorithms for anticipation. Without aiming to be exhaustive, four key areas can be identified where risk analysis and identification of data patterns infuse government interventions and lead to automated assessments.

First, algorithmic systems are used for automated resource allocation. Based on data analyses of risk factors, governments identify 'hot spots' and allocate police surveillance to these places (Bennett Moses and Chan, 2018; Perry et al., 2013; Smith and O'Malley, 2017; Van Brakel, 2016; Williams et al., 2017), priorities for regulatory oversight (Coglianese and Lehr, 2017; Yeung, 2018; Yeung and Lodge, 2019), possible cases of welfare or tax fraud (Engin and Treleaven, 2019; Van Eck, 2018), but also optimise routes for municipal waste collection (Karadimas et al., 2007) and fire safety inspections (Engin and Treleaven, 2019). Second, algorithmic systems can be used to make individualised assessments and evaluations, including enhancing teacher performance evaluations (O'Neill, 2016), risk assessment in child protection services (Gillingham, 2016), and probation and parole decisions in criminal justice (Berk, 2012; Berk and Bleich, 2013; Douglas et al., 2017; Goel et al., 2016; Kleiman et al., 2007). Behavioural intervention is a third area in which automated assessment is increasingly applied. A first step here is pattern detection in group behaviour – for instance, in the urban governance of busy city centres or traffic situations (Morozov and Bria, 2018; Sadowski and Pasquale, 2015; Vanolo, 2014) – followed up by the design of nudging interventions to alter people's behaviour (McGuire, 2018; Pali and Schuilenburg, 2020; Peeters and Schuilenburg, 2018; Ranchordás, 2020). Fourth, algorithm systems are used to model and simulate the need for and the consequences of physical – infrastructural – interventions in the public space, such as in the planning of road construction or large-scale maintenance work and inspection (Spencer et al., 2019).

These and other applications of automated assessment are characterised by their anticipatory objectives. Through statistical modelling, algorithms detect patterns in large data sets and analyse individual cases in relation to those patterns (Hannah-Moffat, 2019). For instance, variables such as age, gender, educational level, consumer behaviour and income may be used to construct profiles regarding an individual's possible (future) behaviour (Aradau and Blanke, 2017; Koopman, 2019). Rather than the more service-oriented application of algorithms in automated decision-making, the focus here is mostly on control, ranging from the control of traffic flows to the identification of risky individuals. Moreover, algorithms used for risk assessment often rely on machine learning rather than rule-based models. The latter analyse data according to the statistical model designed in by humans, whereas the former learn to detect new patterns in the data and adapt their statistical model accordingly (Binns, 2018).

### *Automated agents*

Algorithm-based technology can also be used to take over tasks of human agents. The use of military drones is one of the more controversial examples of using robots rather than humans for interventions (Citron and Pasquale, 2014). Similar technologies are also applied in more mundane settings, with potentially disrupting effects. The robotisation of manufacturing jobs and industrial logistics, for instance, is increasingly and fundamentally changing production processes and labour markets (Agarwal, 2018). In the public sector, robotisation is still an emerging phenomenon. However, its impact can already be seen in the replacement of frontline helpdesks for government information, permission requests or virtual social care assistance by AI-guided chatbots (Androutsopoulou et al., 2019), the use of surveillance drones in the public domain by police forces (West and Bowman, 2016), robotised street sweeping and public toilet cleaning (McGuire, 2021), and the use of robots for healthcare and elderly care assistance (Nielsen et al., 2016; Wirtz et al., 2019).

These technologies move beyond algorithmic assessment that seeks to optimise governmental operations through the Internet-of-Things like applications of urban waste management, water management and resource allocation. Instead, robots are 'autonomous agents' (Vogl et al., 2020). This means that they have the potential to select and subsequently implement interventions without any human presence or interference. Currently, there is a broad spectrum of levels of robot autonomy and levels of human override and oversight designed into the algorithms of automated agents (Citron and Pasquale, 2014; Danaher, 2016; Young et al., 2019).

## ALGORITHMIC KNOWLEDGE

The way that algorithmisation plays out in specific contexts depends on the design variables of algorithmic technologies and on the organisational conditions in which they are deployed and in which 'human-algorithm interaction' (Van Eijk, 2021) takes place. However, following the argument that an underlying 'algorithmic governmentality' binds together all algorithmic applications, we identify three shared characteristics of the knowledge that algorithms produce. In turn, this knowledge infuses new power relations, which we will explore in the next paragraph.

## *Input: calculation and classification*

Algorithms require quantification of input data and, hence, produce quantified outcomes. Rather than human judgement of individual cases, algorithms classify cases according to predefined procedural steps in automated decision-making and according to statistical pattern detection and profiling in automated assessment. Judgement becomes 'machinic' (Henman, 2021; Peeters and Schuilenburg, 2018). Algorithmic outcomes are, therefore, determined by the characteristics of the input data and the throughput procedures. This has led scholars to focus on the quality of input data that governments already have, share, compare and gather from 'public' sources through data mining of people's online behaviour (Couldry and Mejias, 2019; Harcourt, 2015). Especially in algorithmic risk assessments, there are concerns that variables used for pattern detection are also proxies for race, gender, inequality and marginalisation (Maurutto and Hannah-Moffat, 2006).

In recent years, different scholars have pointed out that algorithmic knowledge may exacerbate existing social inequalities and generate forms of systemic discrimination (Ávila et al., 2021; Hannah-Moffat and Maurutto, 2010). The use of 'dirty data' (biased, inaccurate, unlawful) as both input and output of policing practices, for example, may contribute to over-policing of high-poverty and non-white urban areas (Richardson et al., 2019), to bail and sentencing decisions biased against minority defendants (Angwin et al., 2016), to higher error rates for minorities in facial recognition algorithms (Buolamwini and Gebru, 2018), and to negative effects for students from disadvantaged backgrounds in algorithm-assisted assessments for university admissions (Broussard, 2020). These and other concerns also apply to machine learning algorithms that may simply find new proxies for reflecting the same unjust socio-economic inequalities (Binns, 2018; Van Eijk, 2017).

Furthermore, there are concerns regarding the very premise of quantification itself. 'Reducing humans to a percentage' (Binns et al., 2018) conflicts with individual justice and the idea that each case should be assessed on its own merits (Binns, 2019; Van Eijk, 2021). For instance, using an assessment of how many characteristics a person shares with a group of individuals that is known to reoffend in sentencing and probation decisions can be questioned on both moral and legal grounds (Hannah-Moffat, 2013; Simmons, 2018: 1076; Ward, 2011: 106), because 'the riskiness attributed to an individual is not his or her own, but the average of a group in which he or she is included for purposes of statistical analyses' (Tonry, 2019: 446). Also, algorithmically producing the 'other' as an anomaly based on a set of variables statistically associated with certain behaviour (Aradau and Blanke, 2017) raises the question whether algorithmic assessments are compatible with the idea of rehabilitation and agency (Van Eijk, 2021) as the outcomes challenge the legal paradigm of the autonomous subject that may change his or her own future self (McNeill, 2006).

## *Throughput: opacity and closure*

Algorithmic decision-making and assessment are a form of formalisation. Algorithms – just like any other form of information technology – are tools for simplification and closure of throughput procedures (Kallinikos, 2005). Simplification takes place by breaking down a task or problem into a set of sequentially performed operations. Closure complements this by protecting the operations from human interference through isolation (Cordella and Tempini, 2015: 281). This efficiency comes at a price. Concerns are raised about organising meaningful oversight and accountability (Bullock, 2019; Busuioc, 2020; Diakopoulos, 2014). More specifically, accountability problems can emerge, first, because many algorithms are developed and sold by private companies that protect the workings of their algorithms by proprietary laws (Carlson, 2017; Pasquale, 2015).

A second issue emerges because of the possible inherent opaqueness of algorithms. They analyse amounts of data that humans cannot process and use complex pattern analyses that humans cannot reproduce (Binns, 2018; Kitchin, 2014). Especially machine learning algorithms are vulnerable to this, since they adapt without human interference and sometimes even without humans being able to reproduce their statistical model (Ford, 2018). Algorithms, then, become a rationalising force that goes beyond human reason. A third issue of algorithmic accountability is not whether an algorithm can *in principle* be explained, but whether users and affected subjects can get a *meaningful* explanation that they understand (Edwards and Veale, 2017). The relevant question here is if the street-level bureaucrats, social workers, judges and police officers understand the workings and implications of algorithmic outcomes – and if the defendants, social benefit recipients and taxpayers subjected to them understand how and on which grounds decisions are made (Peeters, 2020; Ribeiro et al., 2016).

Accountability is a key hallmark of administrative decision-making under the 'rule of law' (Busuioc, 2020; Widlak et al., 2021). The aforementioned concerns regarding algorithmic accountability are, therefore, directly related to issues of procedural fairness, administrative justice and principles of good governance (Van Eck, 2018). It is impossible to determine whether a decision was reached according to legal requirements of due process if either the validity of the input data is unknown or if the validity of the statistical model underlying an algorithmic assessment cannot be tested (Ponce, 2005; Smith et al., 2017). This, moreover, may affect people's trust in government as a competent and benevolent actor (Meijer and Grimmelikhuijsen, 2021). Specifically, a lack of meaningful accountability exacerbates common information asymmetry problems between government and citizens, thereby undermining the legitimacy of algorithmic applications (Busuioc, 2020).

### *Output: default and discretion*

Algorithmic knowledge tends towards output standardisation. This applies directly to automated decision-making by rule-based algorithms, but also indirectly to automated assessment where algorithmic predictions and profiles provide defaults for human decision-making at street-level (Henman, 2021; Peeters and Schuilenburg, 2018). As Mark Bovens and Stavros Zouridis (2002) argued, the introduction of automated decisions in traditional bureaucracies reduces discretion at street-level – and, to a certain extent, also at managerial level (Wesche and Sonderegger, 2019) – in favour of a system-level bureaucracy in which soft- and hardware designers become key organisational players (cf. Landsbergen, 2004). Recent developments in assessment algorithms indicate not only a further shift of discretion to data analysts, but also to algorithms themselves as they are able to identify new patterns through machine learning (Hannah-Moffat, 2019).

In administrative decision-making, discretion at street-level is considered a key mechanism to counterbalance the tendencies of bureaucratic standardisation. As digital discretion (Busch and Henriksen, 2018), automated discretion (Zouridis et al., 2020) and artificial discretion (Young et al., 2019) replace human discretion – or reduce the practical possibilities for exerting human discretion (Peeters, 2020) – concerns rise about the ability of public organisations to treat individual citizens fairly (Peeters and Widlak, 2018), to identify and correct administrative errors and their consequences for citizens (Widlak and Peeters, 2020) and to safeguard citizens' administrative rights (Van Eck, 2018). This affects governments' ability to be held accountable for algorithmic outcomes.

In algorithmic assessments, the generated knowledge contributes to standardisation because it sets a default for action by human decision-makers: 'it circumvents and avoids reflexive human subjects, feeding on infra-individual data which are meaningless on their own' (Rouvroy and Berns, 2013: x). In the literature on algorithmic applications in the public sector, three mechanisms stand out (Peeters, 2020). First, human decision-makers have a 'bounded rationality' (Simon, 1947), which limits their capacity to understand complex algorithmic calculations (Bainbridge, 1983: 776) and may cause misinterpretation of algorithmic outcomes, such as confusing correlation with causation (Hannah-Moffat, 2013) and risk with blame (Monahan and Skeem, 2016). Second, human decision-makers exhibit 'satisficing behaviour' (Simon, 1947), meaning that people, acting within a context of practical constraints and organisational expectations, are more inclined to follow algorithmic outcomes as an attractive default for action rather than challenge them (Eubanks, 2018; Peeters and Widlak, 2018; Villani, 2018: 124). Finally, human operators tend to see algorithms as rational, scientific and value-neutral and, therefore, as a good basis for legitimising actions and decisions (Silver, 2000; Zerilli et al., 2019: 555). This 'automation bias' (Cummings, 2006) is especially common among officials, designers and analysts, but much less so among citizens (Burton et al., 2020; Moon and Welch, 2005; Moynihan and Lavertu, 2012).

## ALGORITHMIC POWER

As algorithms assume a dominant role in the mediation of power in our society, it becomes increasingly important to understand how this power functions and what its actual and potential social effects are. As argued above, algorithmic governance is a practice in which the digital and physical worlds are colliding. The invisibility of the structuring power of algorithms is a key feature that has been discussed by different authors (e.g., Amoore, 2013; Beer, 2009; Bucher, 2018; Introna, 2016). Nigel Thrift (2004) speaks of a 'technological unconscious' that underpins a society of ubiquitous media in which power, as Scott Lash argues, 'is increasingly *in* the algorithm' (2007: 71) or operates '*through* the algorithm' (Beer, 2009). Power is thought of in relation to invisible codes or embedded in 'black-box' algorithms (Pasquale, 2015). Nevertheless, algorithms have very real consequences in everyday life. Paraphrasing the work of Gilles Deleuze on Foucault (1986), it can be argued that algorithmic power is a virtuality that has its own consistent reality and creates a whole variety of actuals.

In this chapter, we conceptualise algorithmic power in terms of techniques, as concrete forms of interventions on individual bodies, souls or populations. In this way, algorithmic power is closely related to the entire body of questions that are provoked by 'sovereignty, discipline, and governmental management, which has the population as its main target and apparatuses of security as its essential mechanism' (Foucault, 2009: 107–8). Whereas sovereignty is about the punitive power of the law and the institution of the state, and the aim of discipline is to produce efficient and self-controlled individuals, security focuses on the population in general and the risk management of the future (Foucault, 1975, 1976, 1982, 2008; Schuilenburg, 2021b). Identifying the differences between these three mechanisms is not only an academic exercise, but is reflected in the use of algorithms in existing governmental practices. For example, how does algorithmic power contribute to a disciplinarian mechanism to encourage 'proper' conduct? How does algorithmic power relate to the general aim of security to create risk-free environments without the danger of crime or disorder? While it is beyond the scope of this chapter to make an exhaustive list of the effects of algorithmic power in governmental practices, the following case illustrates how algorithmic power adds new layers to already existing power mechanisms and intensifies sovereign, disciplinary and security relations.

## Algorithmic power in operation: predictive policing

The technique of predictive policing represents arguably the biggest shift in policing since the criminal justice system began accepting social science and other expert evidence more than a century ago (e.g., Ferguson, 2017; Perry et al., 2013; Smith et al., 2017; Van Brakel, 2016). The term 'predictive policing' became famous worldwide in 2008, when police commissioner William Bratton of the Los Angeles Police Department (LAPD) spoke at a public meeting about the department's success in tackling high-impact crimes, including assaults and gang violence in the city, by using the software package PredPol (Predictive Policing). This software allowed the LAPD to predict where and when crime would occur based on historical crime data. PredPol is no longer the only predictive policing program. Today, there are predictive systems with names such as HunchLab (Philadelphia), Palantir (New Orleans), Precobs (Germany), ProMap (UK), KeyCrime (Italy), Maprevelation (France) and CAS (the Netherlands). In relation to the question of power, it can be argued that predictive policing is a form of state surveillance (*sovereign power*), which operates, through algorithmic data-driven technologies for the purposes of prediction and prevention of risks (*security*), while – at the same time – the discretionary space of police officers at street-level is diminished by the fixed outcomes of the data analysis (*disciplinary power*).

Predictive policing is a consequence of increased technological opportunities, and of governmental efforts to pre-empt risks as opposed to merely responding to events by primarily repression-driven penalties. Predictive policing programs must be 'trained' on historical police data, in combination with the proximity of various risk factors, before they can forecast future crimes. Although we might be inclined to see the power enacted in these programs purely as techniques of *security* to prevent future crimes, several aspects of a *sovereign* conception of power are still central to predictive policing. This is first and foremost because the outcomes of predictive policing are used by the police as 'an investigative resource' (Sheehey, 2019) for patrolling the streets in marked police-cars within a given area. As such, predictive policing is still part of a 'law-and-order' politics of the state to maintain public order and security.

At the same time, decision-making processes in predictive policing programs increasingly move away from professional assessment by police officers. Instead, the algorithmic outcomes provide a default for action and thus legitimacy for the use of force. They discipline the process of decision-making because the outcomes do not 'argue' but rather present a 'truth' to police officers at street-level. In this context, we have used the term 'machine justice' (Peeters and Schuilenburg, 2018) and pointed out the paradox that although the machine learning ability of algorithms suggests that the decision-making process is in constant flux, the use of algorithms in daily practice leads to more rigid and standardised behaviour by police officers. Understood as a 'rationalising force' (Pasquale, 2015: 15), algorithms both constrain and guide the behaviour of the people working with them and the people subjected to them. In terms of *disciplinary* power, this means that they standardise decisions in a similar way as the rational rules and procedures of the classic bureaucracy, as analysed by Weber.

Finally, this new way of policing aims to make the future secure and safe by transforming the whole population into the object of analysis and intervention. In Chicago, for example, an algorithmically derived 'heat list' ranks people at risk of becoming victims or perpetrators of gun violence (e.g., Ferguson, 2017; Sheehey, 2019). The underlying assumption is that both crimes and criminal behaviour are to a large extent predictable, because criminals with a distinguishable profile tend to commit the same type of crime, at roughly the same location and time of the day (Bennett and Chan, 2018). The implications of such developments are wide-ranging, especially considering that techniques of *security* no longer focus on the physical body of the individual. The centrality of the physically embodied human subject is disappearing and is being substituted with data representations via techniques of security (Schuilenburg, 2021a). In this context, critical scholars speak of 'the New Jim Code' to refer how algorithms reproduce existing inequities in society by obscuring their reproduction of historical systems of discrimination (Benjamin, 2019). This raises a host of questions which have been largely ignored in social sciences. Does this form of algorithmic governance involve some kind of liability, for instance of the person who designed the algorithm of a predictive policing program?

## CONCLUSION

In this chapter, we have provided an overview of algorithmic applications in the governing of society and analysed which new forms of power/knowledge are associated with them. More specifically, we argue that algorithms are the prime *technology* that underpins the automated decision-making of bureaucratic 'decision factories' (Bovens and Zouridis, 2002), the automated assessment of risky individuals in enforcement and regulation (Yeung, 2018), and the automated agency of robotised public services (Vogl et al., 2020). Despite their differences, the underlying algorithmic governmentality that characterises these applications has a profound impact on the governing of society. For instance, at a macro level, algorithms infuse new ways of managing urban spaces and organising information architectures. At a meso level, algorithms change organisational power dynamics as new actors, such as system designers and data analysts, shift discretionary power away from both street-level and managerial level. And at a micro level, algorithms may replace human agency or provide a default for human decisions to follow-up on algorithmically produced calculations.

These transformations are a consequence of the knowledge/power configurations that algorithms create. In terms of *algorithmic knowledge*, the use of algorithms implies quantification, formalisation and standardisation. Social reality is made calculable through automated 'decision trees' and through statistical models that find patterns in big data. This allows algorithmic technologies to classify individual cases, either in terms of their formal status as eligible for public services (e.g., Peeters and Widlak, 2018) or in terms of their 'riskiness' for deviant behaviour (e.g., Aradau and Blanke, 2017). The quantification of social reality is, thereby, linked to a formalisation of judgement. Algorithms operate, by definition, without human intervention. Human oversight and override may or may not be organised into an algorithmic system, but the outcomes of the algorithm itself are always the result of a formalised computer procedure or statistical analysis (e.g., Pasquale, 2015). This, in turn, logically contributes to output standardisation. Either algorithms autonomously produce decisions or interventions based on its internal calculations and classifications, or they provide a legitimate default for human follow-up decisions (e.g., Peeters, 2020).

*Algorithmic power* is – at the same time – applied for specific functions and objectives. Where algorithms are used by private companies for commercial benefits, governments tend to use algorithm-fuelled technologies for purposes of control. On the one hand, algorithms promise to make routine administrative decision-making, the organisation of public services (e.g., chatbots and waste-collection routes), and the management of the public domain (e.g., traffic flows) more efficient. On the other hand, this quest for collective efficiency is combined with singling out risky individuals or specific population groups through algorithmic assessment. For instance, predictive policing aims to find patterns in historical crime data to allocate police surveillance capacity where crimes are more likely to be committed as well as construct profiles of risk offenders. Thereby, *algorithmic power* expands and underpins already existing techniques of sovereignty (surveillance), security (crime prevention) and discipline (of police professionals) (Henman, 2021; Rouvroy and Berns, 2013; Schuilenburg, 2015, 2021b).

As algorithms increasingly enhance, complement, and sometimes replace human agency in the governing of society, it is important to remember that human decision-makers are no saints either (Coglianese, 2021). In fact, there is evidence that people might prefer being subjected to automated decisions if they fear discrimination by human agents (Miller and Keiser, 2021). Furthermore, algorithms might improve procedural justice for low-complexity tasks (Nagtegaal, 2021), although 'algorithm aversion' is also reported (Burton et al., 2020). It is, however, undeniable that algorithmic applications have an impact on procedural, social and individual justice (Danaher, 2016). In this chapter, we have documented various of the existing concerns, including racially biased data (Ávila et al., 2021), accountability gaps (Busuioc, 2020), and reduction of discretionary space at the street-level of public organisations (Widlak et al., 2021).

We cannot, therefore, leave the integration of algorithmic applications in the governance of society to system designers and data analysts alone. A 'politicization of the debate about the algorithmic society' (Schuilenburg and Peeters, 2021: 119) is needed to develop organisational checks and balances against the unintended consequences of automation, and to weaponise citizens to legally defend themselves against unfair treatment. This means, for example, that the design process of algorithmic applications in the field of safety and security must be designed with 'care' and sensibly to democratic values such as 'respect for human autonomy', 'prevention of harm', 'fairness' and 'explicability' (High-Level Expert Group on Artificial Intelligence, 2019). It also means that the design process should be participatory and involve all parties in diagnosing the problems before the design of the technology takes place. Here, the emphasis lies on a bottom-up approach, operating from the lowest level, resting upon the input of knowledge and experience by, for instance, concerned residents of local communities in security governance, in order to balance the benefits of technological innovation with the risk of harm from unintended consequences.

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