

IMPLEMENTING AND MANAGING ALGORITHMIC DECISION-MAKING IN THE PUBLIC SECTOR

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Abstract. *This paper examines the current evolution of Artificial Intelligence (AI) systems for “algorithmic decision-making” (ADM) in the public sector (§1). In particular, it will focus on the challenges brought by such new uses of AI in the field of governance and public administration. From a review of the rising global scholarship on the matter, three strands of research are hereby expanded. First, the technical approach (§2). To close the gaps between law, policy and technology, it is indeed necessary to understand what an AI system is and why and how it can affect decision-making. Second, the legal and “algor-ethical” approach (§3). This is aimed at showing the big picture wherein the governance concerns arise – namely, the wider framework of principles and key-practices needed to secure a good use of AI in the public sector against its potential risks and misuses. Third, as the core subject of this analysis, the governance approach *stricto sensu* (§4). This aims to trace back the renowned issue of the “governance of AI” to essentially four major sets of challenges which ADM poses in the public management chain: (i) defining clear goals and responsibilities; (ii) gaining competency and knowledge; (iii) managing and involving stakeholders; (iv) managing and auditing risks.*

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1. Introduction

Powered by the remarkable technological advancements and digital transformations we've seen in the last five years,^[2] a new wave of interest and enthusiasm has been dictating the growth in the use of Artificial Intelligence (AI) systems for decision-making in the public sector.^[3] The concept of machines as «Agents»^[4] which take decisions or support decision-making has been long documented in the history of AI,^[5] but now, across first- and second-world governments of all longitudes and ideologies, scholars, policy-makers and practitioners need to rethink how to govern such rapid and systemic changes as a result of the introduction of this new wave of AI.^[6] Meanwhile, a growing number of countries, including China, the United States, and the European Union, have expressly provided in their strategies for the steps (and often also for the means) to implement "algorithmic decision-making" (ADM) in the public sector.^[7]

Against this backdrop, this article summarizes the findings of the Author's research into the governance challenges that public administrations must face when introducing ADM in their operations.

2. Technical background. Artificial Intelligence (AI) and Algorithmic Decision-Making (ADM)

Despite the human temptation to enclose everything in static and clear-cut definitions, Artificial Intelligence (AI) is actually many things. This has brought many misconceptions around its actual features and functioning. A growing strand of research is thus

² MCKINSEY ANALYTICS (2022).

³ WIRTZ ET AL. (2021). See also DJEFFAL (2020), ALEXOPOULOS ET AL. (2019), UBALDI ET AL. (2019).

⁴ RUSSEL & NORVIG (2021), pp. 1–60.

⁵ See TURING (1950), WILKINS (1968), GEMIGNANI (1983), AGRE (1997).

⁶ REICHMAN & SARTOR (2021). See also FINLAY & TAKEDA (2021), FATIMA ET AL. (2020).

⁷ See, among others: MOLINARI ET AL. (2021), pp. 18–29; ADA LOVELACE INSTITUTE ET AL. (2021); OECD (2021), pp. 43–50.

aimed at making a clear and collective understanding of AI, in a way that is both scientifically accurate but also practical for the needs of legal scholars and policymakers.

This brief primer cannot possibly exhaust the subject, on which more comprehensive readings are recommended.^[8] It is necessary, however, to staple several key points.

First, AI is a *vox media*. It refers to both the technologies displaying intelligence and to the research field which studies such technologies. Moreover, the use of the word AI often goes beyond its technical meaning, acquiring a social meaning: an umbrella term to generally indicate the driver of a fourth industrial revolution. This combination of a technical and social nature finally makes the study on AI – and, by extension, AI itself – also context-sensitive and time-sensitive: depending on the context, AI bears very different societal effects, such that not all of them even have a revolutionary impact (think for example of a smart toothbrush, vis-à-vis a smart weapon); depending on the timeframe, AI presents very different technical features because, as every technology, it evolves (in the 80s, for example, a computer would be *per se* considered AI, while today nobody calls it as such). This ultimately stems from the fact that simulating intelligence is an aspirational aim,^[9] which cannot be measured by objective and everlasting parameters. In a more practical and governance-oriented perspective, then, it can be argued that AI refers to a «socio-technological system» or «engineered system», which does not comprise only artificial *Agents* (the machine and its algorithms), but also human *Actors* (technical actors such as project managers and data scientists, social actors such as final users, governments and the general public, and threat actors such as cyber-terrorists) and other critical *Assets* (e.g. data, hardware, environment).^[10]

⁸ See, among others: ROCCO (2022), pp. 3–60; MCKINSEY ANALYTICS (2021); RUSSEL & NORVIG (2021); LESLIE ET AL. (2021), pp. 7–11; SOMOGYI (2021); GAHNBERG (2021); STONE ET AL. (2021); ISO (2021); TENCENT RESEARCH INSTITUTE ET AL. (2021), pp. 1–46; WOLFEWICZ (2021); ENISA (2020); BERTOLINI (2020), pp. 15–32; ICO (2020), pp. 115–122; SAMOILI ET AL. (2020); BERRYHILL ET AL. (2020), pp. 9–71; IBM CLOUD EDUCATION (2021, 2020); AI HLEG (2019); OECD (2019), pp. 19–34; LEHR & OHM (2017), pp. 655–701; MULLAINATHAN & SPIESS (2017); JONES (2017); BOSTROM (2014); MCCARTHY (2007).

⁹ LIPTON (2018).

¹⁰ ROCCO (2022). See also INCOSE (2019) and SPIELKAMP (2019).

Second, different Agents, Actors and Assets make up a large variety of AI systems – each with their own degree of rationality, autonomy, complexity and implications. To this end, the most important variable to expand here is the Agent. AI Agents are essentially defined by their “model”, *i.e.* by their set of rules which instruct them on how to process given inputs (data) into desired outputs (predictions, classifications, recommendations, actions). There are two families of techniques to build such models: Classic Programming (CP), used e.g. in computers and calculators; and Machine Learning (ML), used e.g. in image recognition, voice assistants, natural language processing, predictive systems, and, as anticipated above, for new levels of ADM. This made ML clearly the dominant approach to current AI, and will consequently be the focus of this paper. Because of the time-sensitivity of this field (*supra*), not everyone considers instead CP as a way to build AI anymore. Nonetheless, taxonomies aside, the “older” CP approach remains worth to be explored, especially by the public sector, because it presents undeniable strengths in terms of explainability, certainty, and ease-of-use.

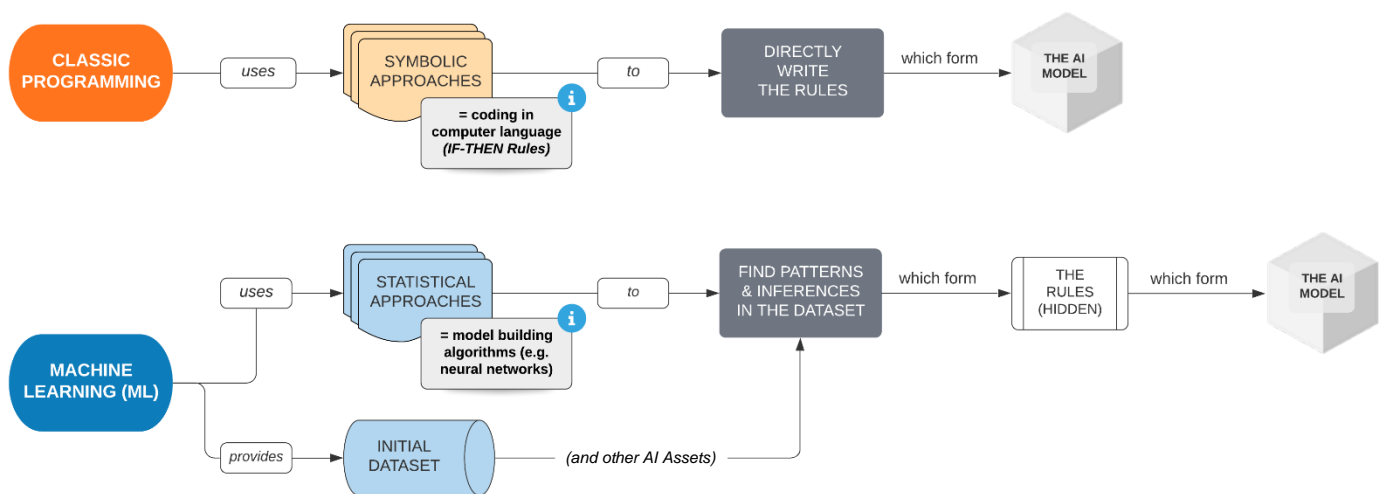


Figure 1 – Building an AI model. Classic Programming (CP) vs. Machine Learning (ML)

Indeed – third key point –, the “newer” Machine Learning approaches carry as many benefits as concerns. The main advantage, as it follows from *Figure 1*, is that ML allows an AI Agent to “learn” (*i.e.* to determine its model) without a human having to manually write down each rule. This is possible thanks to the use of statistical methods – such as linear regression, Bayesian probability, and especially the new “neural network” techniques –, by which the machine can extract information (in form of patterns and inferences) from a given dataset and then use such information as a model to process

“unseen” data as well (= new inputs).^[11] Machine Learning thus enables unprecedented scalability and it overcomes the CP *impasse* in all cases where the models’ rules could not be specified *a priori* because they are not known (e.g. finding consumers’ choices) or because it would be impossible, too complex or too expensive to do so (e.g. determining the best move for every chess position). Moreover, because the extracted knowledge will increase as more data is collected – in the sense that more patterns and inferences will be found, and therefore more “rules” –, ML models can autonomously improve over time through “experience” (i.e. the sheer collection of more data). All these features, however, become conundrums for policymakers and lawmakers, especially in the public sector: the use of statistics strongly implies the presence of technical and human biases, which may go to detriment of individual and societal fairness; complex decision-trees may frustrate the purpose of transparency; unsupervised self-learning may result incompatible with the principle of legal certainty. Considering that the ultimate operational domain of ADM in the public sector may be activities such as crime risk scoring and digital welfare administration,^[12] these few concerns already justify the need for – not only a technical, but also a – legal and justice-oriented understanding of this phenomenon (§3).

In building up towards a “social layer” of ADM,^[13] it is then apt to conclude this primer by recalling that all AI is built by humans: therefore, humans must retain the power to shape and use AI systems in a way that is just, efficient and trustworthy.

¹¹ This process, known as *model training*, is generally operationalised by providing the agent with an initial dataset containing either many past examples of correct outcomes for a given input (so that the agent learns from those answers – so-called “*supervised ML*”), or just loads of unstructured data (so that the agent finds all the possible patterns by itself – so-called “*unsupervised ML*”). The most notable exception to this scheme is “*Reinforcement Learning*” – a sub-category of ML whereby the machine is made to “learn” not via an initial dataset, but by trial and error: if the machine delivers the desired outcome, it is rewarded; otherwise, it is punished (so that it learns how to maximize the reward).

¹² COUNCIL OF EUROPE (2021).

¹³ GASSER & ALMEIDA (2017).

3. Principles for a good use of ADM in the public sector

In the previous section, a “technical approach” was adopted to shed light on the notion(s) of AI and, specifically, of AI systems and ADM. This section now introduces the principles that should govern them, so to lay the theoretical foundation for the specific analysis of the public governance issues in §4. To this end, it is important to recall that discussing of AI principles in a neutral and holistic way would prove useless, as the legal, ethical and socio-economic implications which AI systems raise strictly depend on the sector, purpose and timeframe in which such AI systems are used.^[14]

For this reason, while the Author hopes that many of the following considerations may be applied in the future to further uses and domains of AI (for instance, in too-big-to-fail institutions, and in the so-called private “tech giants”), this paper should be considered as functionally aimed to governing the use of Machine Learning-based AI systems for ADM in the public sector – namely in its political, executive, judiciary and administrative capacity. At the same time, due to the impossibility to create AI silos, this analysis partially touches other technical domains too, to the extent they overlap with ADM. For example, as mentioned before, CP-based AI systems and Computer Vision are often amenable to use for ADM – or anyway as means of algorithmic support to decision-making – in the public sector, sometimes even with better results.

On these premises, while the operational domain of ADM has been widely empowered by Machine Learning, less thought has been given until recently to its implications for individuals and society.^[15] The main concern, as argued above, is that ML-backed ADM may become an untamed driver of the decision-making capabilities of a government.

Three indicators, at least, point indeed in that direction. First, ML currently already affects a wide range of public functions and responsibilities: from justice and social security to democracy, local administration, environment, healthcare, taxation, economic

¹⁴ BERTOLINI (2020). See also, recently: EDPB & EDPS (2021), par. 24.

¹⁵ DOS REIS (2019).

affairs and foreign policy.^[16] Second, it is currently spreading fast and at worldwide level, especially driven by the promise of delivering rational outcomes in complex environments.^[17] Third, it is intrinsically disruptive and fraught with critical implications that must be urgently addressed – all the more so, considering that a recent report of the EU Commission’s Joint Research Centre (JRC) has confirmed how the waves of digital transformation in the public sector have often been guided more «by hopes and dreams, rather than confirmed by empirical evidence».^[18] Significant barriers and constraints have proven hard to be overcome for a more diffused adoption of ICT instruments, and now the same could be true for AI: for example, lack of dedicated resources or knowledge, poor data, scepticism, technical illiteracy and misuses.

Ultimately, this shows that we should be cautious towards the “State use of AI”. While still in its infancy, it can already transform many fields of public sector around the globe, but in a way that is not necessarily fair, just, accurate or appropriate. Its use can be pivotal to improve the delivery of public services, to enable more timely and accurate policy responses, to better measure the citizens’ sentiment in their interaction with the government, to deliver tailored recommendations.^[19] However, its use could also be pivotal in amplifying biases which users are unaware of, in creating black boxes, in excluding the voices that are not captured by digital means and further enlarging the digital divide, in frustrating the right to privacy and data protection, in creating lifelong economic and social needs. Governments must be then ready and capable of

¹⁶ See GIRASA (2021), pp. 3–68; WIRTZ ET AL. (2021); MISURACA & VAN NOORDT (2021); DWIVEDI ET AL. (2021); CAHAI (2020); OECD (2019), pp. 47–80.

¹⁷ Use cases include, for example: use of AI chatbots to answer queries from human services case processing officers (Australia); use of AI to analyse medical test results and recommend appropriate treatments (Japan); use of AI to manage traffic lights (Pittsburgh) and reduce traffic congestions (Singapore); use of AI to predict where and when violent crimes are most likely to happen (Chicago); use of AI to predict how diseases spread and infect over time, in particular with regards to the Zika virus in 2015 and to SARS-Cov-2 at the time of writing. See more case studies especially in: ROCCO (2022), pp. 62–69; BALLESTER (2021), pp. 70–72; BANNISTER & CONNOLLY (2020), p. 475; WORLD BANK (2020); MISURACA & VAN NOORDT (2020); TRASYS INTERNATIONAL ET AL. (2020); CHIUSI ET AL. (2020); MIKURIYA & CANTENS (2020); SPIELKAMP (2019); BERRYHILL ET AL. (2019). See also generally the OECD Observatory of Public Sector Innovation at < <https://oecd-opsi.org/innovation-tag/artificial-intelligence-ai/> >, and, with regards to the EU, the CORDIS Database at < <https://cordis.europa.eu> >.

¹⁸ BARCEVIČIUS ET AL. (2019), as cited in MISURACA & VAN NOORDT (2020), p. 15.

¹⁹ HENMAN (2020), MEHR (2017).

accounting not only for the technical layer of AI briefly described in §2, but also for the “social layer” of AI.

Collectively, these realizations draw the *fil rouge* for the creation of a framework of principles and key-practices capable of securing a “good” State use of AI.

On the other hand, there is currently a vast debate on what is exactly a *good* State use of AI and how to secure it. In all likelihood, the reader would receive different answers when asking an engineer, a philosopher, or a legal scholar. From the latter’s perspective, I argue that this use of AI is an exercise of public power, because it can modify and interfere with the legal and socio-economic status of individuals and perhaps of an entire society.^[20] As such, this use should be regulated, restrained, informed and legitimised by a principle of substantive and procedural justice.^[21]

Following this line of reasoning and from the results evidenced by a broad literature review,^[22] this paper proposes a five-folded framework of “proxies” (to the rather abstract concept of Justice) in order to harness ADM in the public sector.

The first two pillars of this framework emerge under the ideal of substantive justice, as capable of securing a “fair” use of AI: 1) the respect of ethics, legality and fundamental rights; and 2) the fostering of welfare and well-being. The other three pillars emerge under the ideal of procedural justice, as capable of securing a “legitimate” use of AI: 3) good governance; 4) explainability; 5) trust and accountability.

Together, these five principles (*Figure 2, next page*) enable a thorough and justice-oriented assessment of the public power under analysis. Thus, they form the

²⁰ See especially SMUHA (2021, 2020).

²¹ Note how the discussion will always focus on ‘good uses’ and ‘bad uses’, not on ‘good AI’ or ‘bad AI’. AI is a neutral technology, and, before that, simply a field of study: hence, it cannot have moral connotations.

²² See, among others, the cited works by MISURACA (*op.vv.*), VAN NOORDT (*op.vv.*), DWIVEDI ET AL. (2021), MEDAGLIA ET AL. (2021), WIRTZ ET AL. (2021, 2018), ZUIDERWIJK (2021), YERLIKAYA & ERZURUML (2021), AL MUTAWA & RASHID (2020), DESOUZA ET AL. (2020), ALBERTI (2019), SUN & MEDAGLIA (2019), LINDGREN (2019), YFANTIS & NTALIANIS (2019), DE SOUSA ET AL. (2019). As for the independent research activity, a pool of approximately 300 contributions has been consulted in ROCCO (2022), on the basis of their relevance and frequency of appearance on Google Search, Google Scholar, SSRN, ScienceGate, AltMetric, the Bocconi University Library and the Digital Library of the University of Sydney.

theoretical basis of this paper's assessment, which will now focus on some of the implications specifically raising under the third principle: good governance.

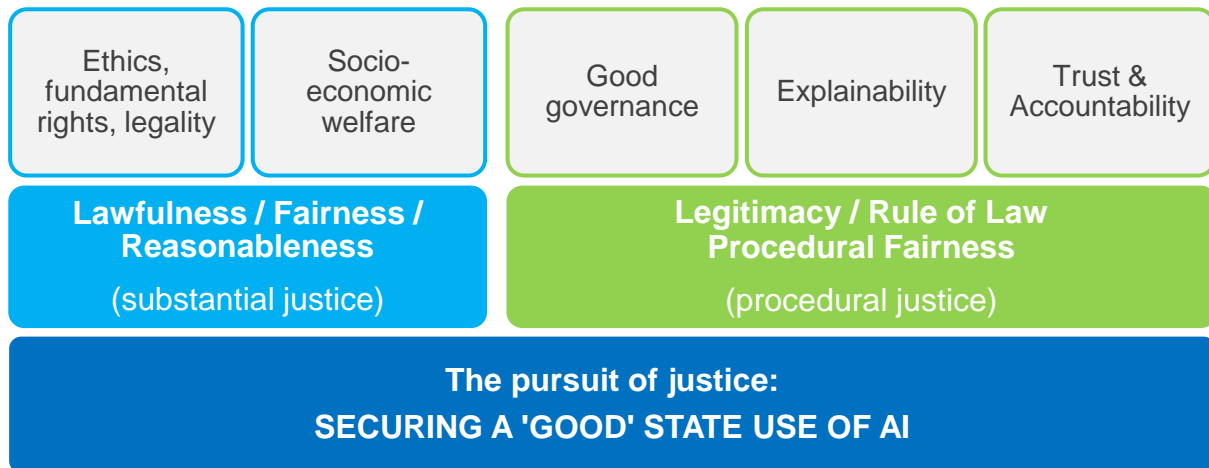


Figure 2 – The five keystones of a “good” State use of AI ^[23]

4. Governing ADM: The challenges in public management

Good governance of an ADM system has many facets. On an abstract level, governance can be defined as the sum of all the processes of social coordination and organization at local, national and international level, aimed at informing the way in which power is concretely exercised.^[24] With regards to the State use of AI, good governance includes then all the efforts that are necessary to confer fairness, effectiveness and trustworthiness to the algorithmically-supported (or algorithmically-made) decisions. This leads to a major theoretical tripartition, between:

- i) data governance (= governance of the AI architecture and infrastructure);
- ii) governance *of* AI (= governance of its adoption in the public sector);
- iii) governance *by* AI (= governance via the adopted AI system).

²³ Rocco (2022), p. 75.

²⁴ See e.g. GAHNBERG (2021), p. 200.

In this paper, we shall focus on the challenges raising from the second “layer” of governance, *i.e.* on the issues in governing the adoption and the implementation of ADM systems in local and national administrations. This is what we refer as “*public management*”.^[25]

The ground zero of any good public management framework is constituted by values. In our case, these values are the principles of substantive justice explored in §3, aimed at securing a fair, lawful and reasonable use of AI: i. ethical and constitutional values (e.g. privacy, beneficence, freedom, democracy, security, dignity, legality, due process of law); ii. socio-economic welfare and wellbeing (e.g. preserving labour, human relationships, and achieving other social development goals).

In order to secure compliance with these principles during the implementation and adoption stage of an AI system in the public sector, it is necessary to look after four families of key governance practices, summarised in the “public management chain”.

This chain consists of: defining clear roles, rules and responsibilities for public officers and servants (§4.1); providing the latter with guidance, skills and literacy (§4.2); managing the multiple and diverse stakeholders involved in an algorithmic decision-making process (§4.3); assessing, auditing and monitoring the risks associated with the employment of such systems in the public sector (§4.4). These steps are an essential pathway to reaching procedural fairness ^[26] – *ergo*, justice – not only in public but also in private management, so they have been long studied. But now the question is how the State use of AI may impact and challenge them.

In approaching them, it should be recalled that the use of ADM in the public sector does not happen in a vacuum, but it is influenced by and will in turn influence manifold contextual factors which lawmakers and policymakers must consider. A recent JRC report gives evidence of at least nine contextual factors.^[27]

²⁵ OJO ET AL. (2019).

²⁶ This is a matter of procedural justice because these aspects do not directly concern any individual, whereas they greatly affect how “good” the final result – in this case, the outcome of ADM – will be.

²⁷ MOLINARI ET AL. (2021), p. 16.

FACTORS	EXAMPLES
POLITICAL	Elected officials endorsing the experimentation of an AI system and/or its embedment in the administrative or policy processes.
ORGANISATIONAL	Support by management and frontline staff involved in the technology and implementation thereof inside the organisational structures.
INFRASTRUCTURAL	Availability of supporting datasets or IT equipment within the organisation adopting or implementing the AI system.
TECHNICAL	Response and efficacy to user needs, and complementarity/interoperability with other IT solutions already in place (of the same or similar kind).
LEGAL	A clear framework incentivising technology innovation while enabling early resolution of legal and regulatory requirements (e.g. data privacy, security).
ETHICAL	Expected and especially unwanted consequences of technology implementation to people, social groups, the environment, etc.
DEMAND-RELATED	Needs expressed by third parties, such as public organisations and/or the civil society interacting with engaged technology solution.
SUPPLY-RELATED	Integration of external IT partners, functional expertise and capacity of the internal staff.
OTHERS	Factors depending, for example, on the specific use (e.g. health) or on a specific geographic location (e.g. cultural factors).

Table 1 – Contextual factors influencing a good governance of AI (from Molinari et al., p. 16)

4.1 Roles, rules, responsibilities

The importance of this first step is manifest each time something wrong or bad happens in uncharted territories. People start questioning how could that have happened, why they were not informed of the risks, who is responsible and so on. All these questions, in a way, reflect the lack of clear roles, rules and responsibilities. And in fact, after such events happen, the general commitment from the authorities is to make all efforts to never repeat the mistake: so begins a general rush to hard or soft law instruments to

determine the three Rs – roles, rules and responsibilities. At the core of public management, thus, lays a State’s anticipatory regulatory power.

Anticipatory regulation – or, put more simply, the determination of the three Rs – ensures that the intended outcomes are achieved, that responsibilities are attributed, and that there is an effective delegation of authority for the AI system to ensure swift operations, timely corrections, and sustained oversight.^[28]

A common counter-argument against anticipatory regulation is that innovation requires freedom – especially from State’s control and regulation. The early call by Facebook’s founder Mark Zuckerberg for the industry to “move fast and break things” epitomizes the importance attached to minimizing legal and governmental constraints.^[29] Although indispensable, legal safeguards might be regarded as unwanted obstacles. However, this argument, besides being intrinsically weaker when it refers to innovation in the public sector, fails to realise that de-regulation (or “freedom”) does not mean less control, but merely a shift of power. In this case, from the hands of governments to those of big-tech executives leading the development of AI systems for the public sector. It is to be questioned if the accumulation of power – and, therefore, of vast amounts of capital – in the hands of few private actors, all the more so when the management of the public sector is involved, is ultimately a positive objective to pursue. Moreover, clarifying the three Rs is essential to remove uncertainty and guarantee a fair trial and adjudication to the AI subjects (*i.e.* to the citizens), while the lack of them also reflects on less opportunities for legislative debate and for public inputs to shape the relevant decision-making systems. This has therefore negative implications on the correct exercise of democracy and on the involvement of all the stakeholders concerned by the State use of AI (*infra*).

Another commonly mentioned issue in anticipatory regulation is the State’s failing at *problem formalisation*. This has to do with poor planning, unrealistic expectations, technological solutionism, lack of diversity and literacy, and with the so-called Collingridge dilemma (*infra*). In general, by problem formalisation (in this context) we mean the act

²⁸ GAO (2021), p. 26.

²⁹ As reported in UNHRC (2019), p. 13.

of translating a legal or policy goal into a measurable target that can be produced by an AI agent.^[30] This should happen obviously at the beginning of the design stage of an AI system, but as Passi & Barocas aptly point out it is actually a practice to cultivate along the entire implementation of an AI system in the public sector.^[31] It is indeed a crucial step, as it represents the injection of *human* policies in an *artificial* system. A poor formalisation of the problem may thus lead to the injection of bad policies, and hence to inconclusive or unfair outcomes. It is imperative, therefore, that when States plan to implement an AI system within the public sector, they formalize the problem at hand (e.g. how to reduce tax frauds) in a way that complies with and enhances justice (§3). In the best scenario, this practice should also be open for public participation and involve a diverse community of stakeholders (see *infra*, §4.3), because «the process of refining vague policy goals and assumptions brings competing values to the fore».^[32]

Furthermore, States must stop short of assuming that such “technical” interventions are appropriate in the first place: technological solutionism or unreasonable expectations may actually be themselves part of the problem – all the more so if they mask the root causes of social inequities and unfairness under a smokescreen of math-washing.^[33]

The regulatory governance process, finally, should take due consideration of the Collingridge dilemma. This dilemma states that «when change is easy, the need for it cannot be foreseen; when the need for change is apparent, change has become expensive, difficult and time consuming».^[34] Thus, when an AI system is at the beginning of its adoption and implementation stage, it can be still easily changed, but so little is known about its possible consequences on a large scale that the social actors cannot adequately anticipate them; conversely, once the system will be deployed on a larger scale, the consequences become known, but it will be too late – or, at best, very difficult – to adapt the technology and avert unwanted effects, because the AI will have become

³⁰ STONE ET AL. (2021).

³¹ PASSI & BAROCAS (2019).

³² STONE ET AL. (2021), p. 64.

³³ *Ibid.* See also EUBANKS (2018).

³⁴ COLLINGRIDGE (1980), p. 11.

socially entrenched.^[35] All this adds up to the issue that, due to the rapid changes in AI technology, government must force themselves to keep up at a faster and faster pace with AI and especially ML.

Against this discouraging backdrop, and given that most of the times it will not be possible to build the AI system in-house anyway, it can be understood why most studies over this aspect of public management converge over the need for an appropriate public procurement framework.^[36] In particular, it should be contemplated how to procure the technology, and whether the current procurement regulations binding the public sector are effective enough in the algorithmic environment. Administration are struggling with procuring from the public sector, as the traditional public procurement processes may not be fit for the iterative process of developing and implementing AI solutions.^[37] Meanwhile, some governments have already started a new season of reforms to encourage trustworthy AI in the public sector: most notably, Canada and the UK were among the earliest in presenting new instruments such as the *Directive on ADM Systems* (Canada), the *Pre-qualified AI Vendor Procurement Program* (Canada), and the *Guidelines on Public Procurement* (UK).

More in general, the World Economic Forum has recently published a set of 10 guidelines which should pave the way for the procurement of the next-generation AI technologies. While they do not specifically target the ADM processes object of this paper's research, they offer an effective outline of the arguments discussed in this section.^[38]

³⁵ BERRYHILL ET AL. (2019), p. 132.

³⁶ Among the wide literature currently blooming on the procurement issues, see, most recently: OECD (2021); CAHAI (2021), p. 11–13; CDDG (2021), p. 48; MCBRIDE ET AL. (2021); WORLD BANK (2020), pp. 49–53; WEF (2020a, 2021).

³⁷ OECD (2021), p. 44.

³⁸ WORLD BANK (2020). Note that in *Table 2* (next page), “RFP” stands for “Request for proposal”.

Guideline	Principles
1. 1. Prescribe a procurement process that defines the scope of problems and opportunities while allowing room for iteration.	<ul style="list-style-type: none"> b. Allow innovative procurement processes for AI systems development. c. Develop a clear focus with a specific problem statement. d. Avoid putting any energy toward defining the details of the solution. e. Support an iterative approach to product development.
2. Produce an RFP that publicly defines the benefits and costs associated with an AI solution while assessing risks.	<ul style="list-style-type: none"> a. Assess why AI is relevant to the problem. Be open to alternative technical solutions. b. Explain which public benefits are the main drivers in the decision-making process when assessing proposals. Consult with external experts if needed. c. Conduct an initial AI risk and impact assessment before starting the procurement process. Ensure that interim findings inform the RFP and revisit the initial assessment at key decision points.
3. Align procurement with relevant existing governmental strategies and contribute to their further improvement.	<ul style="list-style-type: none"> a. Consult relevant government AI initiatives on national, innovation, or industrial strategies. Review any guidance documents informing public policy about emerging technologies. b. Collaborate with other relevant government bodies and institutions to share insights and knowledge.
4. Incorporate potentially relevant legislation, policies, and codes of practice in the RFP.	<ul style="list-style-type: none"> a. Conduct a review of relevant legislation, rights, administrative rules, and other relevant norms that govern the types of data and kinds of applications in scope for the project. b. Consider the appropriate confidentiality, trade-secret protection, and data privacy best practices that may be relevant to AI systems deployment.
5. Articulate the technical and administrative feasibility of accessing relevant data.	<ul style="list-style-type: none"> a. Implement the proper data governance mechanisms at the start of the procurement process. b. Assess whether relevant data will be readily available for the project. c. Define data sharing policies for the vendor(s) during the procurement initiative and subsequent project.
6. Highlight the technical and ethical limitations of intended data uses to minimize issues with bias.	<ul style="list-style-type: none"> a. Consider the susceptibility of data and if the usage of the data is fair. b. Highlight known limitations (e.g., quality) of the data by consulting domain experts and require bidder(s) to describe strategies for addressing these shortcomings. c. Have a plan for addressing relevant limitations as they arise.
7. Work with a diverse, multidisciplinary team.	<ul style="list-style-type: none"> a. Develop ideas and make decisions throughout the procurement process in a multidisciplinary team. b. Require the successful bidder(s) to assemble a team with the right skillset and consult with the established domain experts.
8. Focus on mechanisms of algorithmic accountability and of transparency norms throughout the procurement process.	<ul style="list-style-type: none"> a. Promote a culture of accountability across AI-powered solutions. b. Ensure that AI decision-making is as transparent as possible. c. Explore mechanisms to enable the interpretability of the algorithms internally and externally as a means of establishing accountability and contestability.
9. Implement a process for the continued engagement of the AI provider with the acquiring entity for knowledge transfer and long-term risk assessment.	<ul style="list-style-type: none"> a. Consider that acquiring a tool that includes AI is not a one-time decision. Testing the application over its lifespan, adapting to new models, and extending to new datasets is crucial to success. b. Ask the AI provider to ensure that knowledge transfer and training are part of the engagement. c. Ask the AI provider for insights on how to manage the appropriate use of the application by nonspecialists.
10. Create the conditions for a level and fair playing field among AI solution providers.	<ul style="list-style-type: none"> a. Discover a wide variety of AI solution providers. b. Engage vendors early and frequently throughout the process. c. Ensure interoperability of AI solutions and require open licensing terms to avoid vendor lock-in.

Table 2 – Innovative Procurement Guidelines ^[39]³⁹ *Ibid.*, p. 50.

4.2 Competency and Knowledge

The second key governance practice holds that States must recruit, develop, and retain personnel with adequate, multidisciplinary and up-to-date skills and experiences in the design, development, deployment, assessment, and monitoring of AI systems.^[40] In other words, as public management establishes the governance processes, it must also ensure that the AI system is led by a proficient, diverse and literate team, at all decision-making levels (administrative, governmental, judiciary).

This is necessary for at least three reasons. First, a well-educated and diverse workforce with a degree of specialization in AI (ADM) facilitates the identification of tasks that can be supported or enhanced by AI systems, thus improving the success rate of governments at problem formalisation and at framing clear roles, rules and responsibilities (*supra*). Second, an expert team reduces the risks related to AI safety, including data biases, misuses, manipulations, and violations of equality, fairness and privacy.^[41] And third, a continuous investment on and adjustment of the level of competencies and technical literacy is finally the key to enabling a democracy-oriented and future-proof digital transformation from which society as a whole can benefit.

In parallel with the above, this family of key governance practices should be understood in combination with the idea that knowledge and literacy must also flow towards the citizens. That is to say, knowledge about a certain AI system should not be a prerogative of judges, public servants, governmental institutions, oversight bodies and agencies, *i.e.* of the State, but it should reach the AI subjects as well, *i.e.* the citizens. This calls into relevance the need for robust awareness raising, training and education, especially in schools and especially in favour of potentially marginalised or disadvantaged groups. The aim is not only that to explain how AI systems work, but also and most importantly to explain AI subjects the positive and negative impacts on them and on society. In line with this recognition, this practice represents ultimately also a first

⁴⁰ GAO (2021), p. 27.

⁴¹ See BALLESTER (2021), p. 73; BANERJEE ET AL. (2018).

form of abidance to – and perhaps the very foundation – of the fourth keystone of a good State use of AI (§3): transparency. Notwithstanding this, as transparency falls outside of the scope of this paper, we shall focus here on knowledge and technical literacy from the perspective of the AI user, *i.e.* of civil and public servants.

In this regard, it must be first of all pointed out that, in practice, the presented propositions clash with the observation that «the human talent deficit is the government’s most conspicuous AI deficit and the greatest inhibitor to buying, building, and fielding AI-enabled technologies».^[42] Many public bodies, courts, and agencies have already manifested great difficulty in obtaining tech talents and promoting awareness and literacy for governing the “first generation” of ICT systems.^[43] With the advent of second-wave AI systems, powered by ML, this inadequacy is obviously emphasised and may result fatal in highly-sensitive ADM matters such as law enforcement and criminal adjudication. Even having a “human in the loop” to correctly implement the AI system may not be sufficient to ensure good governance, if the human is not endowed with the needed knowledge, information and expertise.^[44] In fact, we might as well say that AI is not only as good as its data, but also as good as its user.

Without proper interventions, a blind implementation of AI in the public sector will render the latter increasingly dependent on external AI consultants. While this may represent a chance for independent and impartial auditing, it also poses serious risks of vendor lock-in and opacity, due to the limited internal understanding.^[45] The bottom line, therefore, is that the lack of adequate capacities and knowledge within the public sector directly translates into a lack of good governance and reflects on a dire lessening of the other keystones of justice as well – such as explainability and accountability.^[46] What is worse, the States (or, at regional level, the courts and the other public bodies) that will be most affected by this shortcoming are also the ones that would most need AI and AI literacy, as they would keep failing to catch up.^[47] While courts

⁴² US NSCAI (2021), p. 3.

⁴³ MOLINARI ET AL. (2021), p. 35.

⁴⁴ UNESCO (2019), Annex p. 10. See also UNESCO (2021).

⁴⁵ MOLINARI ET AL. (2021), p. 35. On the consequences for the judiciary, recall the case *State v. Loomis*.

⁴⁶ ANANNY & CRAWFORD (2016).

⁴⁷ This dilemma is known as the “regional innovation paradox”. See MUSCIO ET AL. (2015).

and public administration have been to some extent forced to accelerate the innovation process due to COVID-19, it is yet to be proved whether this trend will actually lead to profound reforms and will finally manage to turn Artificial Intelligence as an augmentation of human knowledge – and not the other way round.

The issue of low technical literacy and overall capacity within the public administration carries along a series of further causes for concern. A first already anticipated consequence stems from the lack of expert human resources. The shortage of experienced persons causes more hindrances and mistakes, as the experimental results brought by Janssen^[48] and Busch^[49] confirm that more experienced users (respectively, in the two experiments, immigration officers and judges) make better and faster decisions than those without any experience in the use and functioning of ADM systems. A second concern, as Berryhill notes, is that «certain skills may be difficult to build internally, but it may also be challenging to obtain them externally».^[50] This comes from inadequate procurement processes, but also from poor collaboration with the academia, the industry and the civil society (§4.3). In this context, financial feasibility becomes a strongly related challenge: on the one hand, the investment for creating a sophisticated technological infrastructure to store and collect data is huge; on the other, there is a high demand for a limited number of AI experts, which causes skyrocketing costs of education and salaries.^[51] Finally, building a good leading team at all levels of ADM is complicated by the required multi-disciplinarity and diversity that should be pursued. In cases where it is not possible or appropriate to rely on external AI skills (e.g. for security matters), governments must be all the more prepared to face the challenges in recruiting expertise and develop in-house capacity. This does not mean that public servants and authorities must become or replace technical experts, but it will require the ability of them to act as interlocutors and translators between the many contextual factors interacting in the algorithmic environment (see *Table 1*, p. 8) and to combine them with an understanding how public administration and the judiciary work.

⁴⁸ JANSSEN ET AL. (2020).

⁴⁹ BUSCH (2017).

⁵⁰ BERRYHILL ET AL. (2019), p. 121.

⁵¹ WIRTZ ET AL. (2018), p. 602.

The lack of adequate competency and literacy is further aggravated by two apparently contradictory – and yet often coexistent – biases. As all biases, they deserve a separate discussion because of their accentuated harm to society and individuals. Leslie calls them “decision-automation bias” and “automation-distrust bias”.^[52]

AI users affected by the *decision-automation bias* «become hampered in their critical judgment and situational awareness as a result of an overconfidence in the objectivity, or certainty of the AI system». ^[53] In other words, decision-automation bias is the result of an excessive reliance on the results of an ADM system. Implementers lose the capacity to identify and respond to the faults, errors, or deficiencies, becoming victims of an ‘out-of-loop syndrome’. ^[54] This is where Floridi’s feared degradation and deskilling of critical thinking ^[55] hampers the user’s ability to complete the tasks that have been automated. As we can imagine, the effects of this bias on the AI actors reverberate in an even worse way on the general public that is subject to the biased decision.

At the other extreme – hence the contradictory aspect – unexperienced or low-skilled users of an ADM system may tend to disregard the latter’s contributions to evidence-based reasoning in its entirety as a result of their distrust or scepticism about AI technologies.^[56] In other words, while the bias above is essentially a result of over-reliance or over-compliance with an ADM system, this *automation-distrust bias* occurs because of an over-prioritisation of prudence, human expertise and common sense. This makes the AI user fail to see how decision-support systems may in fact help the public authorities and civil servants reduce implicit cognitive shortcomings and understand complex patterns. This bias is unfortunately consolidated by the all too familiar heuristics of availability and anchor: «stakeholders initially consider decision making aids trustworthy, then after observing that errors happen they distrust even the most reliable applications, ... [putting] the whole system at risk». ^[57]

⁵² LESLIE (2019), p. 21. See also ICO (2020); BULLOCK ET AL. (2020); BURTON ET AL. (2020); COBBE (2019).

⁵³ ICO (2020), p. 78.

⁵⁴ *Ibid.*, p. 79.

⁵⁵ FLORIDI ET AL. (2018). See also MÖKANDER ET AL. (2021), BANNISTER & CONNOLLY (2020), FLORIDI ET AL. (2020), MITTELSTADT ET AL. (2016) and MCBRIDE ET AL. (2014).

⁵⁶ ICO (2020), p. 79.

⁵⁷ MISURACA & VAN NOORDT (2020), p. 48.

Finally, as AI becomes cheaper and more entrenched within the public administration, it is important to mention the “non-technical” literacy that governments must build. These are the skills that are needed on the side-lines of the above discussion, in order to deliver the tasks that the AI cannot deliver. For example, the ability to make fair decisions out of scarce data; the ability to compensate for the computers’ lack of emotional intelligence; the ability to think laterally to solve an unprecedented issue. Thus, the implementation of ADM in the public sector entails a two-fold change in the user of the resulting socio-technological system: on the one hand, the development of technical skills and literacy; on the other, the enhancement of those intrinsically human features that AI cannot (yet) simulate.

4.3 Stakeholders

The main objective of the third family of key governance practices in the public management chain is to include a diverse community of stakeholders throughout the entire lifecycle of an AI system.^[58] This entails establishing collaborative processes and multidisciplinary teams, involving subject experts in crucial fields such as data science, software development, civil liberties, legal risks, and risk management.^[59]

Involving co-designers from the very beginning of the implementation process will help formalize problems more proactively and effectively (§4.1), while also lowering risks and their repercussion on the involved stakeholders. For example, as the CAHAI suggests, open participatory workshops may be used to discover which aspects of front-end workers’ jobs should remain human and which ones would instead benefit from ADM.^[60] By building active listening and understanding of the final user needs, States increase their success in governing the final AI system, not only in terms of efficiency and work optimisation, but also in terms of legitimacy and workforce motivation, which

⁵⁸ GAO (2021), p. 26.

⁵⁹ *Ibid.*

⁶⁰ CAHAI (2021), p. 19.

in turn also lowers the risks of decision-automation bias and automation-distrust bias. Moreover, the active involvement of all stakeholders – especially of the AI subjects, *i.e.* the citizens – is *per se* an essential step to the well-functioning of a democracy. In line with this recognition, a deep public oversight on “where, when and how” ADM systems are used in government services is fundamental to secure democracy against the more powerful tools that ML provides to interfere with citizens’ freedom and self-determination.

However, engaging with the citizens, the civil servants, and especially with the industry, raises several issues that can hinder collaboration success. A first issue is the different environment surrounding public and private organizations. While public organizations are accountable to their users and to the citizens at large, private organizations respond to their shareholders. This can lead to clashes in aligning the interests of the different partners engaged in the collaboration.^[61] For instance, public and private actors will tend to manifest divergent approaches to managing risks, as the political and legal risks are not easy to be reconciled with the economic and reputational risks about which companies care the most. This adds up to different organizational structures and to the fact that such strategic collaborations have been often driven by mere opportunism. Against this background, collaborations with the academia present instead better and quicker opportunities, as the latter’s organizational differences can be aligned under a shared mission: the pursuit and promotion of social good.^[62]

Another commonly reported cause of failure in stakeholder involvement is the lack of collaborative culture, even within the public sector itself.^[63] AI projects are often of collaborative nature, especially in the early phase of collecting the data (hence the rise of data sharing policies such as the Open Government Data policy, or “OGD”). Yet, organisations have to be willing to share the data, whereas research has found a discouraging lack of unity among different agencies and sometimes even within the same administration.^[64] The causes and reasons put forward by interviewed public servants

⁶¹ MIKHAYLOV ET AL. (2018), p. 12.

⁶² *Ibid.*

⁶³ CAMPION ET AL. (2020), p. 32.

⁶⁴ *Ibid.*

are disparate. For example, the lack of quality data standards and data-sharing agreements. Most interestingly, though, it was also pointed out that many employees and agencies got “burned” in the past with data sharing, especially because of data protection violations – a clear reference to the manifold sanctions issued by data protection authorities especially across Europe due to poor data management. Thus, as long as the current uncertainty persists as to how much data to share, what data and how, one of the most immediate effects of this grey area is the chilling effect on potentially beneficial collaborations. In the case of a future AI Authority,^[65] this should become an important *memento*: for States, which cannot elude the constitutional protection of personal data under the claim of better governing AI; but also for the regulating authority itself, which should set out clear and effective rules if it does not want to uselessly thwart innovation, as it partially happened with the previous wave of data regulation.

Finally, the issues in cross-sectoral collaboration and the lack of a collaborative culture within the public sector itself reflect at the international level. An evident aspect which characterizes the current political strategies is indeed the competition between States, the rush to becoming “the first and the best” in AI implementation.^[66] While this may well be a positive driver attached to innovation and growth, Franke suggests caution, as this strategy might turn in a far-from-positive form of «AI Nationalism».^[67] That is neither certain nor inevitable, but recent developments especially in the US, in the EU and in China should keep everyone alert. Thinking only within one’s own borders has been long proven a poor and detrimental practice towards good and sustainable innovation.^[68] Nationalism does not promote collaboration, does not foster interdisciplinary research and it does not solve jurisdictional discrepancies. Instead, it exploits these factors (or the lack thereof), increasing the risk of a “rush to the bottom” towards unfair AI. In an all-too-known pattern common to taxation, competition and international criminal law, States try to prevail economically or strategically over others, so they reduce the regulatory and legal constraints in order to incentivize forum shopping practices

⁶⁵ As proposed, for instance, in the new European Commission’s Artificial Intelligence Act of April 2021.

⁶⁶ See e.g. the suggestive title and objective proposed in the latest report of the US NSCAI (2021).

⁶⁷ FRANKE (2021), pp. 17–18.

⁶⁸ UN (2015).

from big companies, and in the end an anti-Pareto development occurs, as many individuals end up being worse, and no one (except said companies) will be better.

Lack of diversity represents a further widespread challenge. This topic has been dealt in multiple occasions along this section. To just gather the various arguments on this matter, this paragraph shares the insightful review of Professor Alston, who reports: «values underpinning and shaping the new technologies are unavoidably skewed by the fact that there is a diversity crisis in the artificial intelligence sector across gender and race. Those designing artificial intelligence systems in general, as well as those focused on the welfare state, are overwhelmingly white, male, well-off and from the global North. No matter how committed they might be to certain values, the assumptions and choices made [...] will reflect certain perspectives and life experiences».^[69]

To conclude the discourse on stakeholder management, it is apt to recall the chart of external factors that a good governance framework must deal with (*Table 1, p. 8*). One of the most overlooked aspect is in fact the dialogue with political powers. Political will and executive support are necessary to provide the representative legitimacy that fuels public trust, interest, and therefore, at the end of the day, the success of an AI project. As one of Campion's interviewed managers sharply comments, «If the mayor is reaching out directly saying "I want this done", then doors open pretty quickly ... If that is not the case, you can be knocking on the door for a long time and not get anyone».^[70]

4.4 Risks

The final step in the public management chain for a good governance of ADM systems is assessing and managing risks, as complemented by the auditing and monitoring activities. The objective is as straightforward as challenging: to systematically and continuously identify, analyse, prevent and mitigate risks.^[71] Although this rationale echoes

⁶⁹ UNHRC (2019), p. 22.

⁷⁰ CAMPION ET AL. (2020), p. 33. See also CAMPION ET AL. (2021).

⁷¹ GAO (2021), p. 28.

in all the steps previously discussed, its importance is such that it gives rise to an entire family of key governance practices – and to an entirely separate set of concerns.

Essentially, the above proposition stems from the observation that every algorithmic model bears an intrinsic risk of impacting a keystone of substantive justice, with consequences that may range from unimportant to literally existential.^[72] Therefore, States must consider – prior to, during, and after the implementation of an ADM system – whether a particular use case is appropriate in light of the level of risk it entails and, accordingly, of the potential individual, collective and societal harm it may cause. In so doing, risk management should be precise and effective, distinguishing between risks associated to an entire AI system and risks associated with specific practices, between subjective and objective values, between danger and actual harm, between the convenience of *ex-ante* rather than *ex-post* prohibitions, and, in summation, it should factor in all the considerations made thus far.

The benefits of a good risk management process range from a better alignment with ethics and legislation to a sharper increase in public trust and transparency. This has also economic implications, as such processes can help unlock economic growth. They can help balance conflicts of interest, and help human decision-makers to allocate accountability. Finally, of course, a good risk management framework provides AI users and auditors with the instruments to relieve and anticipate negative consequences on substantive justice, respectively after and before they happen.^[73]

It must be clear from the outset, though, that risk management is not something that provides an immediately applicable “answer sheet” or immediately direct benign effect to citizens, otherwise it would have been numbered as a substantive principle. Instead, as a procedural *meta-value*, risk management could more aptly be seen as a playbook: that is to say, as a dynamic and dialectic process between the controller and the controlled, and not as a monolith to be implemented “as is”.^[74] For the same reasons, it is impossible in any case to obtain risk-free AI systems: what risk management aims at,

⁷² BANNISTER & CONNOLLY (2020), p. 483

⁷³ MÖKANDER ET AL. (2021), pp. 13–14.

⁷⁴ *Ibid.*, p. 16.

instead, is providing useful information and raising awareness about what may cause harm, incorporating an active feedback into the implementation and governance processes and thus better informing the continuous re-design and re-assessment which ADM systems must go through.^[75]

Ultimately, following the principles recently proposed by Mökander et al.,^[76] an effective risk management framework should meet seven criteria: (1) *holistic*, i.e. it treats the ADM system as a socio-technological system; (2) *traceable*, i.e. it assigns responsibilities and documents decisions to enable follow-ups; (3) *accountable*, i.e. it links risk-enhancing behaviours to proportional sanctions; (4) *strategic*, i.e. it aligns the ethical and legal values with policies, organisational strategies and incentives; (5) *dialectic* and (6) *continuous*, i.e. it conceives auditing as a dynamic, collaborative and on-going process; (7) *transformative*, i.e. it provides feedbacks to inform the re-design of ADM systems.

The reception of risk management as a governance practice and of its founding principles formulated above has been much on the rise in the latest legislation and soft-law.^[77] A risk-based approach was notably one of the key features of the GDPR, and it may now become a decisive factor for AI systems too, at least according to the Final Proposal of the European Commission for a Regulation laying down harmonised rules on Artificial Intelligence (“Artificial Intelligence Act”).^[78] Unsurprisingly, most of the ADM applications concerning the public sector are therein categorised as high risk: biometric identification, management of critical infrastructure, education, employment, welfare

⁷⁵ *Ibid.* See also n. 26: PASSI & BAROCAS (2019).

⁷⁶ *Ibid.*

⁷⁷ See e.g. CAHAI (2020), pp. 12–13.

⁷⁸ See EUROPEAN COMMISSION (2021), *ARTIFICIAL INTELLIGENCE ACT*, pp. 1–16 (Explanatory Memorandum) and *Recital 14*. The latter in particular explains the famous partition in “three + one” categories of risk – three envisaged in the Act, plus an implicit one, gathering the residual cases. «In order to introduce a proportionate and effective set of binding rules for AI systems, a *clearly defined risk-based approach should be followed*. That approach should tailor the type and content of such rules to the intensity and scope of the risks that AI systems can generate. It is therefore necessary to *prohibit certain artificial intelligence practices*, to *lay down requirements for high-risk AI systems* and obligations for the relevant operators, and to *lay down transparency obligations for certain [other] AI systems*»: at *Recital 14* (emphasis added). See also EUROPEAN COMMISSION (2020).

adjudication and social security, law enforcement, migration and border control, administration of justice and democratic processes.^[79]

However, while many entities worldwide have started adopting or drafting high-level principles for implementing trustworthy and equitable AI through a risk-based approach – such as the new EU proposal just shown –, according to the US Government Accountability Office (GAO) much still has to be researched and done to operationalise the actual activities of risk assessment, auditing and monitoring.^[80]

Indeed, besides the difficulties of risk-assessment in itself, further degrees of complexity arise due to the algorithmic environment in which this set of practices would have to operate.^[81] First, governments would need to move as fast as the innovation and digital transformation processes go – which is currently, according to many commentators, unbearably fast for the bureaucratic system of a State and perhaps even irreconcilable with the State's responsibility to ensure, above all and before anything else, the respect for legality, democracy and the rule of law. Technical complexity also makes it difficult to audit a system without perturbing it, and increases the risk that sensitive data may be exposed during the process, due to the privileged access that must be granted to auditors. Third, the discussed Collingridge Dilemma (§4.1) hampers *in itinere* attempts at managing and containing the risks of an AI system which has already become entrenched in society, while *ex-ante* “laboratory attempts” to determine the level of risk may lose their soundness once the system is actually put to use on a large scale. Fourth, the risk-management practice inevitably imposes substantial costs in terms of investment and time. As such, it might be disproportionate for smaller public bodies and it may unreasonably hinder innovation and adoption. Fifth, in the quite common case of relying on public procurement, externally-built AI systems are unsurprisingly much more difficult to secure, because of the limited access to key information. In lack of an appropriate set of provisions equipping governments with adequate instruments to enable public oversight (e.g. access to data and models),

⁷⁹ *Ibid.*, Annexes II and III.

⁸⁰ GAO (2021), p. 74. See also MÖKANDER ET AL. (2021), p. 3.

⁸¹ See for an early analysis GREEN & CHEN (2019).

effective and verifiable risk management may remain a far fetch for outsourced ADM systems. Moreover, there is always the risk of adversarial behaviour during audits,^[82] as it happened with the infamous diesel-gate scandal that has recently engulfed Volkswagen. Sixth, the current asymmetries in knowledge and expertise, and consequently in power over AI systems (§4.2), combined with a substantial lack of transparency, often translates in poor risk management and in a drift of responsibility away from private actors, who may thus prevent corrective steps from being taken. Finally, organisational and institutional constraints, such as the lack of an auditing and monitoring system “by default and by design” and the lack of an independent and international watchdog authority or organisation, increase the risk of AI nationalism and of a rush to the bottom.

Against this backdrop, the question arises as to how to convert good propositions into actions, *i.e.* how to *concretely* measure and tackle the risks brought by an AI system.

From a high-level stance, qualitative assessments are the best (if not the only) option. They consist in documenting the processes and outcomes, and subsequently recording, testing, and monitoring the documented activities.^[83] In the process, clear questions are asked to the AI users (if possible, yes/no questions are to be preferred) to tackle specific concerns: e.g., “does [a given algorithmic decision] deal with special categories of personal data, as defined by applicable legal norms?”^[84] Despite the lack of quantifications, this methodology may prove itself effective in providing the answers we seek, by making more visible – and therefore more solvable – the negative implications that an ADM system may have. Qualitative assessments also satisfy the goal of risk auditing, as they allow the monitoring of the input, throughput and output of an ADM system. Moreover, they provide a first form of transparency as well – as it is already the case, for instance, with the duty to keep a Records of Processing Activities (Article 30 GDPR). Finally, judging from the answers given by the AI user to the

⁸² For an early theorisation of behavioural impacts over decisions, see KAHNEMAN & TVERSKY (1979).

⁸³ Documentation is here considered a risk management activity, and not a transparency mechanism, because not all these documents need to be distributed externally or to be made accessible to anyone.

⁸⁴ For more examples and a more thorough qualitative checklist for risk management purposes see, most recently, LOI ET AL. (2021), GAO (2021), and BERRYHILL (2019).

qualitative assessment, and from how easy it was for the user to complete the assessment, governments and auditors can get a good baseline for a further evaluation and comparison of different risks carried by different AI systems: for instance, between CP-based systems and ML-based one; between fully-automated ADM and support ADM.

Less promising are instead the efforts currently made worldwide to build a quantitative approach to risk management.^[85] This paper shares, in fact, the concerns raised lastly by Loi as to the appropriateness of such methodologies in the algorithmic environment – especially in light of the principles of substantive justice on which such environment should be based (§3). First of all, current tools of quantitative nature, aimed at *quantifying* risks, still actually rely on subjective assessments: for example, asking whether the likelihood of risk or of harm is “occasional” or “probable” or whether the impact is “low”, “moderate” or “high”. However, they fail to specify concrete, precise and verifiable criteria on which these judgements should be made. Moreover, conflicts in the final evaluation may occur when different criteria are given very different values: for example, if the potential negative impact of an ADM system is very low, but the risk of that impact happening is very high, how should the system be classified? Using one of the most standard formulas for risk assessment (*quantification of risk* \times *probability of risk*), in such cases we should be expected to treat such an AI system exactly as one that has, conversely, a very high negative impact with a very low chance of happening. This does mathematically make sense, and it represent a good rule of thumb in situations fraught with high uncertainty. However, playing the game of averages may lead to paradoxical outcomes, epitomized by the famous “oven-feet and freezer-head” problem: *«I really don't trust statistics much. A man with his head in a hot oven and his feet in a freezer has statistically an average body temperature»*.^[86]

Even taking into consideration more sophisticated calculations, it is unclear whether a utilitarian approach may be considered acceptable under substantive justice in the first

⁸⁵ On this strand of approaches, see e.g. the Government of Canada's indications contained within the Appendix B of the “*Directive on Automated Decision-Making*”; the Government of New Zealand's “*Algorithm Charter for Aotearoa New Zealand*” under the voice ‘Assessing Likelihood and Impact’; the World Economic Forum's “*AI Procurement Guidelines*” recalled earlier in this section; and ENISA's Risk Quantification Frameworks developed for events such as a data breach or a cyberattack.

⁸⁶ BUKOWSKI (allegedly). See also UNHRC (2019), p. 17.

place. In the European Union, for instance, a utilitarian measure (e.g. the amount of people affected, the probability of the bad event occurring) cannot in principle run counter to the rights-based and justice-based approach on which the Charters hinge, even when the final assessment would favour the majority.^[87] Likewise, the Council of Europe has recently stressed that human rights must apply «regardless»,^[88] and that in case of «significant *human rights risks* that cannot be mitigated» (again reference is made only to the human rights framework, not to utilitarian factors) «the algorithmic system should *not be implemented or otherwise used by any public authority ...* and should be discontinued at least until adequate measures for risk mitigation have been taken». ^[89]

The strict prohibition of certain AI systems because they are deemed *a priori* as incompatible with the human rights framework (see Title II of the Artificial Intelligence Act) goes evidently in the same direction. Should this Act be approved, the prohibition would apply to any AI system causing or being likely to cause physical or psychological harm by (a) subliminally distorting a person's behaviour; (b) exploiting the vulnerabilities of specific group of persons; or (c) scoring the trustworthiness of the individual in a society in a way that legitimizes correlation over causation or unjustified or disproportionate treatments; additionally, the use of (d) real-time biometric identification systems in publicly accessible spaces for the purpose of law enforcement would be allowed only to the extent strictly necessary to pursue certain objectives listed by the Act itself (e.g. searching for missing children).^[90] Even for ADM systems that pose more tolerable risks, the European Commission imposes legally mandated conformity assessments and/or voluntary adherence to an ethics-based auditing.^[91]

Finally, the same kind of qualitative risk-management framework seems to be currently emerging in bottom-up approaches. The dialogue between courts, legislators and with the data protection authorities, in particular, offer plenty of lessons that should be learnt

⁸⁷ LOI ET AL. (2021), p. 17.

⁸⁸ COUNCIL OF EUROPE (2020): *CM/Rec(2020)1*, p. 12.

⁸⁹ *Ibid.*, p. 10.

⁹⁰ EUROPEAN COMMISSION (2021): ARTIFICIAL INTELLIGENCE ACT, Article 5.

⁹¹ MÖKANDER ET AL. (2021), p. 10.

and transferred to the new wave of AI systems. The French Data Protection Authority (CNIL), for example, has recently expressly devised frameworks of substantive justice to which data processing procedures must align with.^[92] Especially in light of the last consideration, it is important however not to misread the risk-management framework as a mere form of privacy management. While it is true that many risks originate from or pertain to privacy and security issues, this practice must concern *all* aspects of substantive justice – from privacy and security to equality and fairness. An exclusive focus on only one or a few of the discussed keystones may lead to a sub-optimisation of the original problem and paradoxically cause more problems than it aims to solve.^[93]

On the other hand, perhaps going partially against the argument defended thus far, it would still not be much sensible to prohibit *tout court* public and private actors from measuring also utilitarian factors (or any other factor outside of substantive justice, ethics and the human rights context), such as the size of the impact, the chance of actual harm and the amount of people involved. Indeed, such considerations become inevitable on some occasions, and they provide anyway valuable additional information to AI users, AI subjects, and external or internal auditing parties. In certain conditions, it becomes unfair *not* to use them: risk-management tools that focus only on qualitative assessments, indeed, may provide little incentives for the public actors and thus incentivise a form of “rights minimalism”. From the Data Protection Impact Assessment (Article 35 GDPR) to the sanctioning and pre-sanctioning decisions issued every day by criminal courts, many risk management processes rely currently on manifold criteria, not all of which are based exclusively on human rights considerations. Rather, what is and should remain undisputable, is that fundamental rights and human rights must form the bedrock of any assessment. This does not automatically prevent from the possibility to refine a risk-management process through other considerations too.

The last piece of a good risk management framework, finally, is the safety assessment. As Leslie describes it, a safe AI (ADM) system is one that prioritises «accuracy,

⁹² *Ibid.*

⁹³ *Ibid.*

reliability, security, and robustness».^[94] The risk management challenge here is therefore how to audit, monitor and ensure the fulfilment of these four operational objectives. The discussion over these factors is mostly a matter of technical nature. As such, it mostly falls outside of this paper's scope of research. A few points, however, are to be brought to the attention of the legal and policymaking scholarship, with the firm understanding that an interdisciplinary cooperation with the science and engineering field is all the more so inevitable.

Accuracy is the rate at which a model generates the correct output – or, said otherwise, the deviance from the expected outcome. Its importance is clear in light of the constitutional framework on which the first keystone of substantive justice is founded (§3): poor accuracy is indeed a direct driver of discriminatory harm and potentially existential threats for an individual, as it increases the chance of ADM delivering false positives (e.g. judging an innocent as likely to commit crime again) and false negatives (e.g. excluding a poor from welfare benefits). *Reliability* is instead the capacity of an AI system to behave exactly as intended and anticipated: it is therefore a measure of consistency, which translates in legal terms to the crucial need of ensuring the principle of legality (and, specifically, legal certainty). *Security* is a broad goal, encompassing the protection against cyber-attacks and other negative externalities and threats, as well as ensuring the integrity of the information processed and produced by an AI system and the confidentiality thereof (including personal data protection).^[95] *Robustness*, finally, indicates that an AI system can work safely also under harsh conditions, such as errors, unforeseen use cases or blatant abuses: from a legal perspective, this becomes especially relevant in order to determine the level of responsibility and accountability of the AI manufacturer, in cases where such issues arise. In more general terms, the legal and policy importance of these safety principles emerges from the conclusive consideration that all the procedural keystones of good governance, explainability and accountability (§3) are impaired when any of these metrics is lessened.^[96]

⁹⁴ LESLIE (2019), p. 30.

⁹⁵ For an extensive mapping of the security objective, see ENISA (2020), pp. 25–29, 43 ss. As an outline, the document presents a high-level partition into nine categories of threat: i) nefarious activity & abuse; ii) eavesdropping; iii) interception and hijacking; iv) physical attacks; v) unintentional damage; vi) failures or malfunctions; vii) outages; viii) disasters; ix) legal threats and reputational loss.

⁹⁶ *Ibid.*, pp. 25–26.

5. Conclusions

This paper tried to provide a comprehensive overview of the public management issues which arise within the wider framework of good governance of ADM systems. In doing so, it has first explored the technical nature of this field (§2), then it offered a holistic outlook of the principles of substantive and procedural justice which AI calls into question when “interacting with the social world” ^[97] (§3), finally it delved into the issue known as the “governance of AI” (§4).

Many trends, lessons and recommendations can be pinpointed from this analysis.

On the first strand of research, it has emerged that AI is best defined (for governance and policymaking purposes) as an “engineered system”, *i.e.* as a socio-technological system which comprises Agents, Actors and Assets. Within this system, the way in which the Agents’ models are built heavily influences the final outcome. In particular, the models which are built following the Machine Learning (ML) approach bear new fascinating, yet concerning, results. They can improve autonomously overtime, and do not need an expert human programmer to manually write down the rules guiding the artificial agent. This gives rise to several challenges in the field of law and policy, especially when ML is used to inform decision-making processes (so-called ADM) within the public sector, in its political, executive, administrative and judiciary capacity.

On the second strand of research, it has emerged that the manifold governance challenges concerning AI systems lay on a wide legal and ethical framework of principles. Tackling such principles in a general and subject-neutral way, however, would prove useless, because the implications that we address depend on the sector, purpose and timeframe in which the AI system is used. Thus, the scope of research was restricted (with all due exception) to the use of ML-based AI systems in the public sector for the purpose of ADM. This specific use of AI was deemed indeed as intrinsically disruptive, in a way that is not necessarily fair, just, accurate or appropriate. To identify an appropriate network of principles capable of harnessing such use of AI, the paper followed

⁹⁷ SELBST ET AL. (2019).

the consideration that the latter is an exercise of public power, and therefore it must be regulated, restrained, informed and legitimised by a general principle of substantive and procedural justice. On this basis, five operative values are identified: 1) ethics, legality and fundamental rights; 2) welfare and wellbeing; 3) good governance; 4) explainability; 5) trust and accountability.

On the third strand of research, it has emerged that the principle of good governance is at risk on multiple sides. Three crucial pillars are: i) governing the data and the external environment of an AI system; ii) governing the adoption and implementation of an AI system in the public sector; iii) governing the *res publica* throughout the adopted and implemented AI system. From a deeper examination of the challenges affecting the second pillar – also known as the “public management” –, mixed results are drawn. The paper runs through four families of key governance practices, characterising the “public management chain”: 3.1) defining clear roles, rules and responsibilities; 3.2) building up knowledge, literacy and internal capacity; 3.3) stakeholders’ management and involvement; 3.4) risk assessment, auditing and monitoring. As for the first key practice, three shortcomings have been evidenced: the fight of private companies against anticipatory regulation; States’ failure at problem formalisation; the need for a renovated public procurement framework of ADM systems. As for the second key practice, several factors have driven the poor internal capacity of the public sector: deficit of human resources and expertise; excessive dependency on external consultants; difficulty in retrieving and holding highly-demanded AI experts within public administrations; difficulty in setting together a diverse and multi-disciplinary workforce; decision-automation bias and decision-distrust bias. As for the third key practice, cross-sectoral collaborations, the collaborative nature within the public sector itself, and the well-functioning of a democracy were found somewhat lessened to several extents; in addition, the sector lacks data management, diversity, and solid involvement of political power. The fourth key practice, finally, brings positive results on the qualitative assessments front, whereas quantitative assessments still raise practical issues in their conformity with a human rights and justice-based framework.

References & Bibliography

- Ada Lovelace Institute, AI Now Institute & Open Government Partnership. (2021). *Algorithmic accountability for the public sector. Learning from the first wave of policy implementation*. (D. Joshi, T. Basu, J. Brennan, & A. Kak, Eds.) Retrieved from <http://www.opengovpartnership.org/documents/algorithmic-accountability-public-sector/>
- Agre, P. E. (1997). Lessons learned in trying to reform AI. In G. Bowker, S. L. Star, L. Gasser, & W. Turner, *Social Science, Technical Systems, and Cooperative Work: Beyond the Great Divide*, 131. Psychology Press.
- AI HLEG (High-Level Expert Group on Artificial Intelligence). (2019). *A definition of AI: Main capabilities and scientific disciplines*. European Commission. Publications Office of the European Union.
- Al Mutawa, M., & Rashid, H. (2020). Comprehensive Review on the Challenges that Impact Artificial Intelligence Applications in the Public Sector. *Proceedings of the 5th NA International Conference on Industrial Engineering and Operations Management*. Detroit.
- Alberti, I. (2019). The Double Side of Artificial Intelligence in the Public Sector. *Acta Universitatis Sapientiae, Legal Studies*, 8(2), 151-165. <https://doi.org/10.47745/AUSLEG.2019.8.2.01>
- Alexopoulos, C., Lachana, Z., Androutsopoulou, A., Diamantopoulou, V., Charalabidis, Y. K., & Loutsaris, M. A. (2019). How Machine Learning is Changing e-Government. *ICEGOV '19: Proceedings of the 12th International Conference on Theory and Practice of Electronic Governance* (pp. 354-363). Melbourne: ACM. <https://doi.org/10.1145/3326365.3326412>
- Ananny, M., & Crawford, K. (2016). Seeing without knowing: Limitations of the transparency ideal and its application to algorithmic accountability. *New Media & Society*, 20(3), 973-989. <https://doi.org/10.1177/1461444816676645>

- Areiqat, A. Y., & Alheet, A. F. (2021). Artificial Intelligence and Its Impact on Public Management and Decision-Making. In A. Hamdan, A. E. Hassanien, A. Razzaque, & B. Alareeni, *The Fourth Industrial Revolution: Implementation of Artificial Intelligence for Growing Business Success* (pp. 231-240). Springer. https://doi.org/10.1007/978-3-030-62796-6_13
- Ballester, O. (2021). An Artificial Intelligence Definition and Classification Framework for Public Sector Applications. *DG.O '21: 22nd Annual International Conference on Digital Government Research* (pp. 67-75). Omaha, NE (USA): ACM. <https://doi.org/10.1145/3463677.3463709>
- Banerjee, S., Pradeep Kumar, S., & Bajpai, J. (2018). A comparative study on decision-making capability between human and artificial intelligence. In N. Hoda, V. Sharma, & S. Goel, *Nature inspired computing: Proceedings of CSI 2015* (pp. 203-210). Springer.
- Bannister, F., & Connolly, R. (2020). Administration by algorithm: A risk management framework. *Information Polity*, 25(4), 471-490. <https://doi.org/10.3233/IP-200249>
- Barcevičius, A. E., Cibaitė, G., Gineikytė, V., Klimavičiūtė, L., Matulevič, L., Misuraca, G., & Vanini, I. (2019). *Exploring Digital Government transformation in the EU*. JRC. <https://doi.org/10.2760/17207>
- Barocas, S., Hood, S., & Ziewitz, M. (2013). *Governing algorithms: A provocation piece*. <https://doi.org/10.2139/Ssrn.2245322>
- Berryhill, J., Heang, K. K., Clogher, R., & McBride, K. (2019). *Hello, World: Artificial Intelligence and its Use in the Public Sector*. OECD Working Papers on Public Governance. OECD Publishing. <https://doi.org/https://doi.org/10.1787/19934351>

- Bertolini, A. (2020). *Artificial Intelligence and Civil Liability*. Committee on Legal Affairs (JURI), Policy Department for Citizens' Rights and Constitutional Affairs. European Parliament.
- Bostrom, N. (2014). *Superintelligence: Paths, Dangers, Strategies*. Oxford University Press.
- Bullock, J. B., Young, M. M., & Wang, Y.-F. (2020). Artificial intelligence, bureaucratic form, and discretion in public service. *Information Polity*, 25(4), 491-506. <https://doi.org/10.3233/IP-200223>
- Burton, J. W., Stein, M.-K., & Jensen, T. B. (2020). A systematic review of algorithm aversion in augmented decision making. *Journal of Behavioral Decision Making*, 33(2), 220-239. <https://doi.org/10.1002/bdm.2155>
- Busch, P. A. (2017). The Role of Contextual Factors in the Influence of ICT on Street-Level Discretion. *Proceedings of the 50th Hawaii International Conference on System Sciences*. Hawaii: HICSS. <https://doi.org/10.24251/HICSS.2017.358>
- CAHAI (Ad Hoc Committee on Artificial Intelligence). (2020). *Feasibility study on Artificial Intelligence*. Council of Europe. CAHAI(2020)23.
- CAHAI (Ad Hoc Committee on Artificial Intelligence). (2021). *Artificial Intelligence in Public Sector*. Council of Europe, Policy Development Group. CAHAI-PDG(2021)03.
- Calo, R. (2017). Artificial Intelligence Policy: A Primer and Roadmap. *UC Davis School of Law Review*, 51(2), 399-435. Retrieved from https://lawreview.law.ucdavis.edu/issues/51/2/Symposium/51-2_Calo.pdf
- Campion, A., Gasco-Hernandez, M., Mikhaylov, S. J., & Esteve, M. (2021). Overcoming the challenges of collaboratively adopting Artificial Intelligence in the public sector. *Social Science Computer Review*. <https://doi.org/10.1177/0894439320979953>

- Campion, A., Hernandez, M.-G., Mikhaylov, S. J., & Esteve, M. (2020). *Managing Artificial Intelligence Deployment in the Public Sector*. IEEE Computer Society. <https://doi.org/10.1109/MC.2020.2995644>
- Chiusi, F., Fischer, S., Kayser-Bril, N., & Spielkamp, M. (2020). *Automating Society Report 2020*. AlgorithmWatch.
- Cobbe, J. (2019). Administrative law and the machines of government: judicial review of automated public-sector decision-making. *Legal Studies*, 39(4), 1-20. <https://doi.org/10.1017/lst.2019.9>
- Collingridge, D. (1980). *The Social Control of Technology*. Frances Pinter.
- Council of Europe. (2020). *Recommendation CM/Rec(2020)1 of the Committee of Ministers to member States on the human rights impacts of algorithmic systems*. Council of Europe. CM/Rec(2020)1.
- Council of Europe. (2021). *Declaration by the Committee of Ministers on the risks of computer-assisted or artificial-intelligence-enabled decision making in the field of the social safety net*. Council of Europe. Decl(17/03/2021)2.
- de Sousa, W. G., de Melo, E. R., Bermejo, P. H., Farias, R. A., & Gomes, A. O. (2019). How and where is artificial intelligence in the public sector going? A literature review and research agenda. *Government Information Quarterly*, 36(4). <https://doi.org/10.1016/j.giq.2019.07.004>
- Desouza, K. C., Dawson, G. S., & Chenok, D. (2020). Designing, developing, and deploying artificial intelligence systems: Lessons from and for the public sector. *Business Horizons*, 63(2), 205-213. <https://doi.org/10.1016/j.bushor.2019.11.004>
- Djeffal, C. (2020). Artificial Intelligence and Public Governance: Normative Guidelines for Artificial Intelligence in Government and Public Administration. In T. Wischmeyer, & T. Rademacher, *Regulating Artificial Intelligence* (pp. 277-293). Springer. https://doi.org/10.1007/978-3-030-32361-5_12

- dos Reis, J. C., Espirito Santo, P., & Melao, N. (2019). Impacts of Artificial Intelligence on Public Administration: A Systematic Literature Review. *14th Iberian Conference on Information Systems and Technologies (CISTI)*. Coimbra. <https://doi.org/10.23919/CISTI.2019.8760893>
- Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., . . . Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57. <https://doi.org/10.1016/j.ijinfomgt.2019.08.002>
- EDPB & EDPS. (2021). *Joint Opinion 5/2021 on the proposal for a Regulation of the European Parliament and of the Council laying down harmonised rules on artificial intelligence (Artificial Intelligence Act)*. Publications Office of the European Union.
- ENISA (European Union Agency for Cybersecurity). (2020). *AI Cybersecurity Challenges. Threat Landscape for Artificial Intelligence*. (A. Malatras, & G. Dede, Eds.) <https://doi.org/10.2824/238222>
- Eubanks, V. (2018). *Automating inequality: How high-tech tools profile, police, and punish the poor*. St. Martin's Press. <https://doi.org/10.5555/3208509>
- European Commission. (2020, February 19). White Paper. On Artificial Intelligence - A European approach to excellence and trust. COM(2020)65. Retrieved from https://ec.europa.eu/info/sites/default/files/commission-white-paper-artificial-intelligence-feb2020_en.pdf
- European Commission. (2021, April 21). Artificial Intelligence Act. *Proposal for a Regulation of the European Parliament and of the Council laying down harmonised rules on Artificial Intelligence and amending certain Union legislative acts*. COM/2021/206 final. Retrieved from <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52021PC0206>

- Fatima, S., Desouza, K. C., & Dawson, G. S. (2020). National strategic artificial intelligence plans: A multi-dimensional analysis. *Economic Analysis and Policy*, 67, 178-194. <https://doi.org/10.1016/j.eap.2020.07.008>
- Finlay, R., & Takeda, H. (2021). Reflections on Decision-Making and Artificial Intelligence. In B. Braunschweig, & M. Ghallab, *Reflections on Artificial Intelligence for Humanity* (pp. 68-75). Springer. https://doi.org/10.1007/978-3-030-69128-8_5
- Floridi, L., Cows, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., . . . Vayena, E. (2018). AI4People – An Ethical Framework for a Good AI Society: Opportunities, Risks, Principles, and Recommendations. *Minds and Machines*, 28(4), 689-707. <https://doi.org/10.1007/s11023-018-9482-5>
- Floridi, L., Cows, J., King, T. C., & Taddeo, M. (2020). How to Design AI for Social Good: Seven Essential Factors. *Science and Engineering Ethics*, 26, 1771–1796. <https://doi.org/10.1007/s11948-020-00213-5>
- Franke, U. (2021). *Artificial Intelligence diplomacy. Artificial Intelligence governance as a new European Union external policy tool*. European Parliament, DG for Internal Policies, Policy Department for Economic, Scientific and Quality of Life Policies. Publications Office of the European Union. <https://doi.org/10.2861/745637>
- Gahnberg, C. (2021). What rules? Framing the governance of artificial agency. *Policy and Society*, 40(2), 194-210. <https://doi.org/10.1080/14494035.2021.1929729>
- GAO (U.S. Government Accountability Office). (2021). *Artificial Intelligence: An Accountability Framework for Federal Agencies and Other Entities*. GAO-21-519SP.
- Gasser, U., & Almeida, V. A. (2017). A Layered Model for AI Governance. *IEEE Internet Computing*, 21(6), 58-62. <https://doi.org/10.1109/MIC.2017.4180835>

- Gemignani, M. (1983). Laying down the law to robots. *San Diego Law Review*, 21(5), 1045-1059.
- Girasa, R. (2020). *Artificial Intelligence as a Disruptive Technology – Economic Transformation and Government Regulation*. Palgrave Macmillan. <https://doi.org/10.1007/978-3-030-35975-1>
- Green, B., & Chen, Y. (2019). Disparate Interactions: An Algorithm-in-the-Loop Analysis of Fairness in Risk Assessments. *FAT* '19: Proceedings of the 2019 Conference on Fairness, Accountability, and Transparency*. New York: ACM. <https://doi.org/10.1145/3287560.3287563>
- Henman, P. (2020). Improving public services using artificial intelligence: possibilities, pitfalls, governance. *Asia Pacific Journal of Public Administration*, 42(4), 209-221. <https://doi.org/10.1080/23276665.2020.1816188>
- IBM Cloud Education. (2021, March 12). *Supervised vs. Unsupervised Learning: What's the Difference?* Retrieved from IBM Analytics: <https://www.ibm.com/cloud/blog/supervised-vs-unsupervised-learning>
- IBM Cloud Education. (2020, September 21). *Unsupervised Learning*. Retrieved from IBM Analytics: <https://www.ibm.com/cloud/learn/unsupervised-learning>
- IBM Cloud Education. (2020, August 19). *Supervised Learning*. Retrieved from IBM Analytics: <https://www.ibm.com/cloud/learn/supervised-learning>
- IBM Cloud Education. (2020, July 15). *Machine Learning*. Retrieved from IBM Analytics: <https://www.ibm.com/cloud/learn/machine-learning>
- ICO (Information Commissioner's Office). (2020). *Explaining decisions made with AI*. ICO / The Alan Turing Institute.
- INCOSE (International Council on System Engineering). (2019). *Systems Engineering and System Definitions*. (H. Sillitto, J. Martin, D. McKinney, R. Griego, D. Dori, D. Krob, . . . S. Jackson, Eds.) Open Access. Retrieved from

https://www.incose.org/docs/default-source/default-document-library/final_-se-definition.pdf?sfvrsn=340b9fc6_0

ISO. (2021). ISO/IEC DIS 22989. *Artificial intelligence concepts and terminology*. ISO/IEC JTC 1/SC 42.

Janssen, M., Hartog, M., Matheus, R., Ding, A. Y., & Kuk, G. (2020). Will Algorithms Blind People? The Effect of Explainable AI and Decision-Makers' Experience on AI-supported Decision-Making in Government. *Social Science Computer Review*, 1-16. <https://doi.org/10.1177/0894439320980118>

Jones, M. T. (2017, December 5). *Models for machine learning*. Retrieved from IBM Analytics: <https://developer.ibm.com/articles/cc-models-machine-learning/>

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, 47(2), 263-292. <https://doi.org/10.2307/1914185>

Lehr, D., & Ohm, P. (2017). Playing with the Data: What Legal Scholars Should Learn About Machine Learning. *UC Davis School of Law Review*, 51(2), 653-717.

Leslie, D. (2019). *Understanding artificial intelligence ethics and safety. A guide for the responsible design and implementation of AI systems in the public sector*. The Alan Turing Institute. <https://doi.org/10.5281/zenodo.3240529>

Leslie, D., Burr, C., Aitken, M., Cowls, J., Katell, M., & Briggs, M. (2021). *Artificial intelligence, human rights, democracy, and the rule of law: a primer*. Council of Europe / Alan Turing Institute.

Lindgren, I., Madsen, C. O., Hofmann, S., & Ulf, M. (2019). Close encounters of the digital kind: A research agenda for the digitalization of public services. *Government Information Quarterly*, 36(3), 427-436. <https://doi.org/10.1016/j.giq.2019.03.002>

Lipton, Z. C. (2018, June 5). *From AI to ML to AI: On Swirling Nomenclature & Slurried Thought*. Retrieved from ApproximatelyCorrect:

<http://approximatelycorrect.com/2018/06/05/ai-ml-ai-swirling-nomenclature-slurried-thought/>

Loi, M., Mätzener, A., Müller, A., & Spielkamp, M. (2021). *Automated Decision-Making Systems in the Public Sector: An Impact Assessment Tool for Public Authorities*. AlgorithmWatch.

McBride, K., van Noordt, C., Misuraca, G., & Hammerschmid, G. (2021). Towards a Systematic Understanding on the Challenges of Procuring Artificial Intelligence in the Public Sector. *SocArXiv Papers*(Pre-print). <https://doi.org/10.31235/osf.io/un649>

McBride, S. E., Rogers, W. A., & Fisk, A. D. (2014). Understanding human management of automation errors. *Theoretical Issues in Ergonomics Science*, 15(6), 545-577.

McCarthy, J. (2007, November 12). *What is Artificial Intelligence?* Computer Science Department. Stanford University. Retrieved from <http://www-formal.stanford.edu/jmc/whatisai.pdf>

McKinsey Analytics. (2022). *The Internet of Things: Catching up to an accelerating opportunity*. McKinsey. Retrieved from: <https://www.mckinsey.com/business-functions/mckinsey-digital/our-insights/iot-value-set-to-accelerate-through-2030-where-and-how-to-capture-it>

McKinsey Analytics. (2021). *An executive's guide to AI*. McKinsey.

Medaglia, R., Gil-Garcia, J. R., & Pardo, T. A. (2021). Artificial Intelligence in Government: Taking Stock and Moving Forward. *Social Science Computer Review*, 1-18. <https://doi.org/10.1177/08944393211034087>

Mehr, H. (2017). *Artificial Intelligence for Citizen Services and Government*. Ash Center for Democratic Governance and Innovation. Harvard Kennedy School.

- Mikhaylov, S. J., Esteve, M., & Campion, A. (2018). Artificial intelligence for the public sector: opportunities and challenges of cross-sector collaboration. *Philosophical Transactions of the Royal Society A*, 376(2128). <https://doi.org/10.1098/rsta.2017.0357>
- Mikuriya, K., & Cantens, T. (2020). If algorithms dream of Customs, do customs officials dream of algorithms? A manifesto for data mobilisation in Customs. *World Customs Journal*, 14(2), 3-22.
- Misuraca, G., & Álvarez, T. (2021). *Governing algorithms: perils and powers of AI in the public sector*. Digital Future Society.
- Misuraca, G., & Kuziemski, M. (2020). AI governance in the public sector: Three tales from the frontiers of automated decision-making in democratic settings. *Telecommunications Policy*, 44(6). <https://doi.org/10.1016/j.telpol.2020.101976>
- Misuraca, G., & van Noordt, C. (2020). *AI Watch. Artificial Intelligence in public services. Overview of the use and impact of AI in public services in the EU*. European Commission, Joint Research Centre (JRC). Publications Office of the European Union. <https://doi.org/10.2760/039619>
- Misuraca, G., van Noordt, C., & Boukli, A. (2020). The use of AI in public services: results from a preliminary mapping across the EU. *International Conference on Theory and Practice of Electronic Governance*. Athens. <https://doi.org/http://dx.doi.org/10.1145/3428502.3428513>
- Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. *Big Data & Society*(July-December), 1-21. <https://doi.org/10.1177/2053951716679679>
- Mökander, J., Morley, J., Taddeo, M., & Floridi, L. (2021). Ethics-Based Auditing of Automated Decision-Making Systems: Nature, Scope, and Limitations. *Science and Engineering Ethics*, 27(44). <https://doi.org/10.1007/s11948-021-00319-4>

- Molinari, F., Van Noordt, C., Vaccari, L., Pignatelli, F., & Tangi, L. (2021). *AI Watch. Beyond pilots: sustainable implementation of AI in public services*. JRC126665. Publications Office of the European Union. <https://doi.org/10.2760/440212>
- Mullainathan, S., & Spiess, J. (2017). Machine Learning: An Applied Econometric Approach. *Journal of Economic Perspectives*, 31(2), 87-106. <https://doi.org/10.1257/jep.31.2.87>
- Muscio, A., Reid, A., & Leon, L. R. (2015). An empirical test of the regional innovation paradox: can smart specialisation overcome the paradox in Central and Eastern Europe? *Journal of Economic Policy Reform*, 18(2), 153-171. <https://doi.org/10.1080/17487870.2015.1013545>
- OECD. (2019). *Artificial Intelligence in Society*. OECD Publishing. <https://doi.org/10.1787/eedfee77-en>
- OECD. (2021). *State of Implementation of the OECD AI Principles: Insights from National AI policies*. OECD Digital Economy Papers, No. 311. OECD Publishing.
- OECD.AI (2021), powered by EC/OECD (2021), *Database of national AI policies*, accessed on 27/03/2022, <https://oecd.ai/>
- Ojo, A., Mellouli, S., & Zeleti, F. A. (2019). A Realist Perspective on AI-era Public Management. *DG.O '19: Proceedings of the 20th Annual International Conference on Digital Government Research*. Dubai: ACM. <https://doi.org/10.1145/3325112.3325261>
- Passi, S., & Barocas, S. (2019). Problem Formulation and Fairness. *FAT* '19: Proceedings of the 2019 Conference on Fairness, Accountability, and Transparency*. Atlanta: ACM. <https://doi.org/10.1145/3287560.3287567>
- Qian Sun, T., & Medaglia, R. (2019). Mapping the challenges of Artificial Intelligence in the public sector: Evidence from public healthcare. *Government Information Quarterly*, 36(2), 368-383. <https://doi.org/10.1016/j.giq.2018.09.008>

- Reichman, A., & Sartor, G. (2021). Algorithms and Regulation. In H.-W. Micklitz, O. Pollicino, A. Reichman, A. Simoncini, G. Sartor, & G. D. Gregorio, *Constitutional Challenges in the Algorithmic Society* (pp. 131-181). Cambridge University Press. <https://doi.org/10.1017/9781108914857.009>
- Rocco, S. (2022, forthcoming). *State use of AI. On the application of algorithmic decision-making in the public sector and in the judiciary* (pp. 1-308).
- Russell, S. J., & Norvig, P. (2021). *Artificial Intelligence: A Modern Approach* (4th ed.). Pearson.
- Samoili, S., López Cobo, M., Gómez, E., De Prato, G., Martínez-Plumed, F., & Delipetrev, B. (2020). *AI Watch. Defining Artificial Intelligence. Towards an operational definition and taxonomy of artificial intelligence*. European Commission, Joint Research Centre (JRC). Publications Office of the European Union. <https://doi.org/10.2760/382730>
- Selbst, A. D., Boyd, D., Friedler, S. A., Venkatasubramanian, S., & Vertesi, J. (2019). Fairness and Abstraction in Sociotechnical Systems. *FAT* '19: Proceedings of the 2019 Conference on Fairness, Accountability and Transparency*. ACM. <https://doi.org/10.1145/3287560.3287598>
- Smuha, N. A. (2020). Beyond a Human Rights-Based Approach to AI Governance: Promise, Pitfalls, Plea. *Philosophy & Technology*, 1-14. <https://doi.org/10.1007/s13347-020-00403-w>
- Smuha, N. A. (2021). Beyond the individual: governing AI's societal harm. *Internet Policy Review*, 10(3). <https://doi.org/10.14763/2021.3.1574>
- Somogyi, Z. (2021). *The Application of Artificial Intelligence. Step-by-Step Guide from Beginner to Expert*. Springer. <https://doi.org/10.1007/978-3-030-60032-7>
- Spielkamp, M. (2019). *Automating Society - Taking Stock of Automated Decision-Making in the EU*. AlgorithmWatch.

- Stone, P., Altman, R., Brynjolfsson, E., Conitzer, V., Gray, M. L., Grosz, B., . . . Wajcman, J. (2021). *Gathering Strength, Gathering Storms: One Hundred Year Study on Artificial Intelligence (AI100)*. Stanford University.
- Tencent Research Institute, CAICT, Tencent AI Lab, Tencent Open Platform. (2021). *Artificial Intelligence*. Springer / China Renmin University Press. <https://doi.org/10.1007/978-981-15-6548-9>
- TRASYS International, Vucheva, M., Rocha, M., Renard, R., & Stasinopolous, D. (2020). *Study on the use of innovative technologies in the justice field – Final Report*. European Commission, Directorate-General for Justice and Consumers, Unit B.3. Publications Office of the European Union. <https://doi.org/10.2838/585101>
- Turing, A. M. (1950). Computing Machinery and Intelligence. *Mind*, 59(236), 433-460. <https://doi.org/10.1093/mind/LIX.236.433>
- Ubaldi, B., Le Fevre, E. M., Petrucci, E., Marchionni, P., Biancalana, C., Hiltunen, N., . . . Yang, C. (2019). State of the art in the use of emerging technologies in the public sector. *OECD Working Papers on Public Governance*, No. 31, 1-74. <https://doi.org/10.1787/932780bc-en>
- UN (United Nations). (2015). *Resolution adopted by the General Assembly on 25 September 2015. Transforming our world: the 2030 Agenda for Sustainable Development*. A/RES/70/1.
- UNESCO. (2019). *Preliminary study on the technical and legal aspects relating to the desirability of a standard-setting instrument on the ethics of Artificial Intelligence*. 206 EX/42.
- UNESCO. (2021). *Draft text of the Recommendation on the ethics of Artificial Intelligence*. SHS/IGM-AIETHICS/2021/JUN/3 Rev.2.
- UNHRC (United Nations Human Rights Council). (2019). *Report of the Special Rapporteur on extreme poverty and human rights*. By Philip Alston. United

- Nations, General Assembly. A/74/493. Retrieved from <https://digitallibrary.un.org/record/3834146?ln=en>
- US NSCAI (National Security Commission on Artificial Intelligence). (2021). *Final Report*. NSCAI. Retrieved from <https://www.nsc.ai.gov/2021-final-report/>
- van Noordt, C., & Misuraca, G. (2020). Exploratory Insights on Artificial Intelligence for Government in Europe. *Social Science Computer Review*, December, 1-19. <https://doi.org/10.1177/0894439320980449>
- van Noordt, C., Medaglia, R., & Misuraca, G. (2020). Stimulating the Uptake of AI in Public Administrations: Overview and Comparison of AI Strategies of European Member States. *EGOV-CeDEM-ePart*. Linköping: Digital Government Society.
- WEF (World Economic Forum). (2020a). *Unlocking Public Sector AI— AI Procurement in a Box: AI Government Procurement Guidelines*. S. Gerdon, E. Katz, E. LeGrand, G. Morrison, & J. T. Santeli (Eds.). WEF Publishing. Retrieved from <https://www.weforum.org/reports/ai-procurement-in-a-box>
- WEF (World Economic Forum). (2020b). *Unlocking Public Sector AI— AI Procurement in a Box: Workbook*. S. Gerdon, E. Katz, E. LeGrand, G. Morrison, & J. T. Santeli (Eds.). WEF Publishing. Retrieved from <https://www.weforum.org/reports/ai-procurement-in-a-box>
- Wilkins, L. T. (1968). Computer Impact on Public Decision Making. *Public Administration Review*, 28(6), 503-508. <https://doi.org/10.2307/973327>
- Wirtz, B. W., Geyer, C., & Weyerer, J. C. (2018). Artificial Intelligence and the Public Sector – Applications and Challenges. *International Journal of Public Administration*, 42(7), 596-615. <https://doi.org/10.1080/01900692.2018.1498103>
- Wirtz, B. W., Langer, P. F., & Fenner, C. (2021). Artificial Intelligence in the Public Sector - a Research Agenda. *International Journal of Public Administration*, (forthcoming issue), 1-27. <https://doi.org/10.1080/01900692.2021.1947319>

- Wolfewicz, A. (2021, July 20). *Deep learning vs. machine learning – What's the difference*. Retrieved from Levity.AI: <https://levity.ai/blog/difference-machine-learning-deep-learning>
- World Bank. (2020). *Artificial Intelligence in the Public Sector. Maximizing Opportunities, Managing Risks*. K. Farooq & B. Sołowiej (Eds.). International Bank for Reconstruction and Development / The World Bank.
- Yerlikaya, S., & Erzuruml, Y. Ö. (2021). Artificial Intelligence in Public Sector: A Framework to Address Opportunities and Challenges. In A. Hamdan, A. E. Hassanien, A. Razzaque, & B. Alareeni, *The Fourth Industrial Revolution: Implementation of Artificial Intelligence for Growing Business Success* (pp. 201-216). Springer. https://doi.org/10.1007/978-3-030-62796-6_11
- Yfantis, V., & Ntalianis, K. (2019). Exploring the Adoption of the Artificial Intelligence in the Public Sector. *International Journal of Machine Learning and Networked Collaborative Engineering*, 3(4), 210-218. <https://doi.org/10.30991/IJMLNCE.2019v03i04.003>
- Zuiderwijk, A., Chen, Y.-C., & Salem, F. (2021). Implications of the use of artificial intelligence in public governance: A systematic literature review and a research agenda. *Government Information Quarterly*, 38(3). <https://doi.org/10.1016/j.giq.2021.101577>