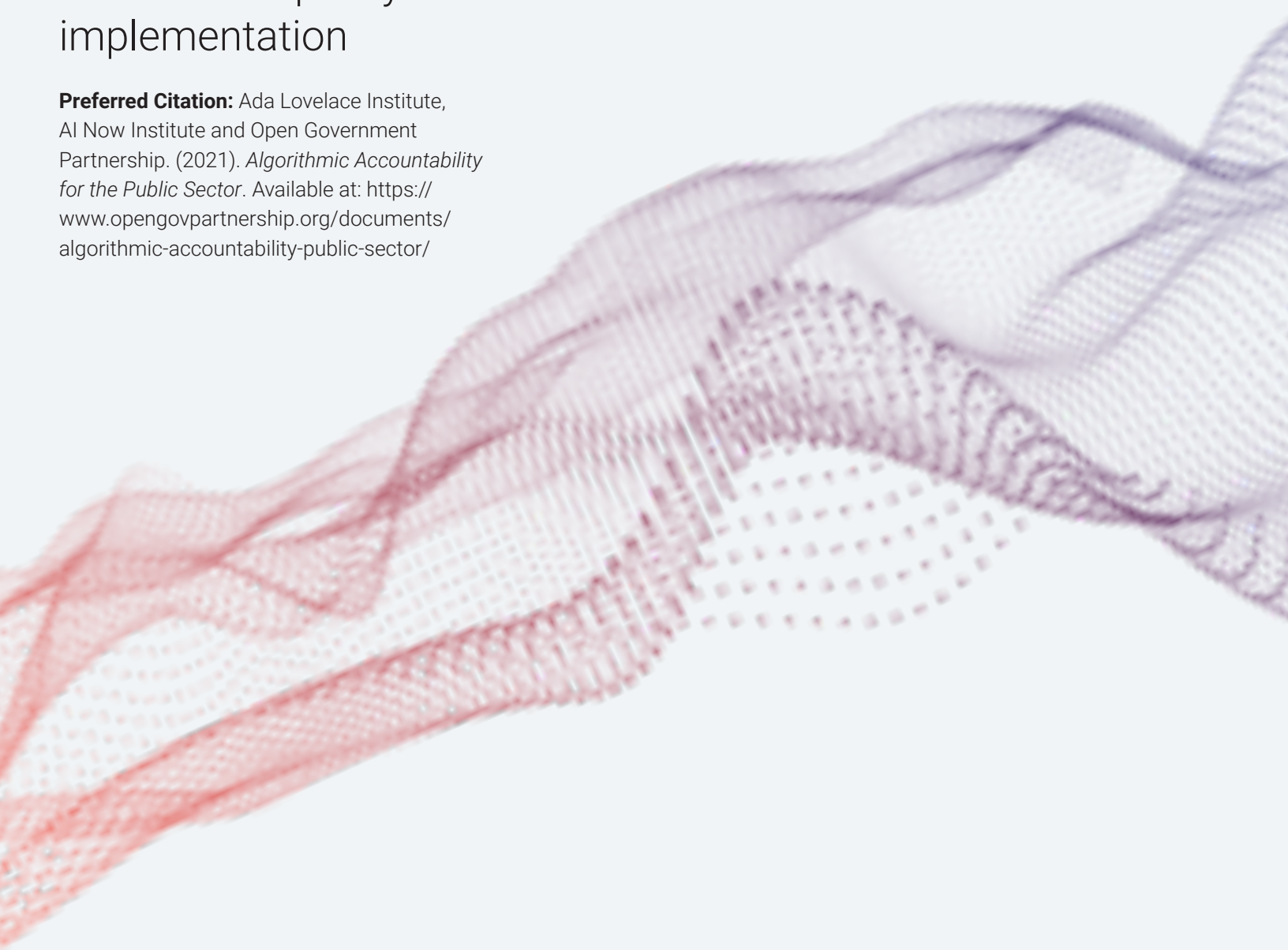


Algorithmic accountability for the public sector

August 2021

Learning from the first wave of policy implementation

Preferred Citation: Ada Lovelace Institute, AI Now Institute and Open Government Partnership. (2021). *Algorithmic Accountability for the Public Sector*. Available at: <https://www.opengovpartnership.org/documents/algorithmic-accountability-public-sector/>



Contents

Executive summary	3
How to read this report	5
Introduction	7
Methodology	8
Mapping algorithmic accountability policy interventions	13
Learning from the first wave of algorithmic accountability policy implementation	36
Conclusions and priorities for future research	54
Appendix 1: Expanded table of the first wave of policy mechanisms	57
Appendix 2: OGP commitments on open algorithms	65
Select bibliography	66
Project team	69

Executive summary

The Ada Lovelace Institute (Ada), AI Now Institute (AI Now), and Open Government Partnership (OGP) have partnered to launch this first global study to analyse the initial wave of algorithmic accountability policy for the public sector.

This study aims to understand the challenges and successes of algorithmic accountability policies from the perspectives of the actors and institutions directly responsible for their implementation on the ground.

This executive summary highlights the key findings from this study, which:

- presents and analyses evidence on the use of algorithmic accountability policies in different contexts from the perspective of those implementing these tools
- explores the limits of legal and policy mechanisms in ensuring safe and accountable algorithmic systems
- provides practical guidance to the policymakers, civil society, public officials and agencies responsible for implementing related policy tools and commitments
- outlines some open questions and future directions for the research community in this field.

The report identifies eight different forms of algorithmic accountability policies currently being implemented in the public sector. As a relatively new area of technology governance, these policies vary widely, as does the vocabulary used to describe them. The report outlines the following policy mechanisms and analyses their intentions, aims, assumptions and impacts:

1. Principles and guidelines
2. Prohibitions and moratoria
3. Public transparency
4. Impact assessments
5. Audits and regulatory inspection
6. External/independent oversight bodies
7. Rights to hearing and appeal
8. Procurement conditions

Building on the analysis of this evidence, the report sets out six lessons for policymakers, proposing key factors in the effective deployment and implementation of algorithmic accountability policies.

These lessons represent initial learnings from the first wave of algorithmic accountability policy for the public sector. The aim of this study was not to definitively evaluate particular algorithmic accountability policies, and this report acknowledges that abstract findings of effectiveness will have little value in situated local or national contexts. Measuring 'effectiveness' holistically requires a more significant investment of time, and deep engagement with affected communities, and the policies we review here are relatively new (concentrated within the last two to three years), making it difficult to assess their intermediate or long-term effects.

With the above in mind, the key lessons of this report are:

1. Clear institutional incentives and binding legal frameworks can support consistent and effective implementation of accountability mechanisms, supported by reputational pressure from media coverage and civil society activism.
2. Algorithmic accountability policies need to clearly define the objects of governance as well as establish shared terminologies across government departments.
3. Setting the appropriate scope of policy application supports their adoption. Existing approaches for determining scope such as risk-based tiering will need to evolve to prevent under- and over-inclusive application.
4. Policy mechanisms that focus on transparency must be detailed and audience appropriate to underpin accountability.
5. Public participation supports policies that meet the needs of affected communities. Policies should prioritise public participation as a core policy goal, supported by appropriate resources and formal public engagement strategies.
6. Policies benefit from institutional coordination across sectors and levels of governance to create consistency in application and leverage diverse expertise.

How to read this report

If you are a policymaker...

- Our goal with this report is to help you identify potential mechanisms for holding the use of public sector algorithms more accountable, increasing public trust in these systems and mitigating potential harms.
- Start with the table on [page 9](#) mapping different kinds of algorithmic accountability mechanisms that have made up the 'first wave' of algorithmic accountability policy, then read about each mechanism in more detail, starting on [page 57](#).
- While reading this report, keep in mind that mechanisms for enabling algorithmic accountability are nascent, context-specific and that there is no silver-bullet solution to hold algorithmic systems accountable. Consider each mechanism described in this report as a tool in a toolbox, and that the use of different mechanisms can amplify their effect.
- Also keep in mind that there is no objective or holistic assessment of the effectiveness of each mechanism, and that you will need to evaluate how each mechanism should be translated to your specific policy context. While the examples described in this report can be illustrative, they may require fine-tuning to fit your needs.
- When considering how to fine tune these mechanisms to your needs, visit [page 36](#) to learn about the six lessons to be drawn from the first wave of algorithmic accountability policies. These lessons provide some generalisable considerations for factors that might affect the implementation of algorithmic accountability policies in your jurisdiction.

If you are a researcher...

- The report provides an empirical perspective on how assumptions about algorithmic accountability described in academic and policy literature play out in practice, and highlights the various factors that public officials negotiate when implementing algorithmic accountability policies.
- Visit our table on [page 9](#) to view our high-level findings, then visit [page 57](#) to learn about each mechanism in more detail. Our lessons from the first wave of algorithm accountability policies can be found on [page 36](#).
- This report acknowledges that more research is needed into the effectiveness and externalities of specific algorithmic accountability mechanisms. Our hope is that future research will help evaluate these systems within their situated national and local contexts.
- This report is focused on the North American and European policy contexts due to the greater number of implemented policies in these regions, and is missing critical perspectives from the Global South. We encourage more research into wider and emerging policy contexts.

If you are in civil society...

- Our goal for this report is to synthesise different algorithm accountability mechanisms that are being implemented in the public sector. Many of these mechanisms have been developed by leveraging civil society expertise, and seek to enable an ecosystem of accountability that realises the vital role civil society organisations play in holding algorithms accountable.
- Visit [page 13](#) to read about the different mechanisms we have identified and find case study examples of these mechanisms in practice.
- Visit [page 36](#) to read about our lessons and what role civil society organisations might play in enabling algorithm accountability mechanisms in your region.

Introduction

Governments around the world are increasingly turning to algorithms to automate or support decision-making in public services. Algorithms might be used to assist in urban planning, prioritise social-care cases, make decisions about welfare entitlements, detect unemployment fraud or surveil people in criminal justice and law enforcement settings. The use of algorithms is often seen as a way to improve, increase efficiency or lower costs of public services.

Growing evidence suggests that algorithmic systems in public-service delivery can cause harm and frequently lack transparency in their implementation, including opacity around decisions about whether and why to use them. Most countries have yet to resource efforts to raise awareness and engage the wider public about the use of algorithms in public service delivery.

In recognition of these conditions, regulators, lawmakers and governmental accountability organisations have turned to regulatory and policy tools, hoping to ensure ‘**algorithmic accountability**’ across countries and contexts. These responses are emergent and fast evolving, and vary widely in form and substance – from legally binding commitments, to high-level principles and guidelines. Lessons from their early implementation raise important challenges and pose questions about the future of governing algorithmic systems.

While there have been some efforts to evaluate algorithmic accountability within particular institutions or contexts,¹ there have been few systematic and cross-jurisdictional studies of the implementation of these policies. This report, commissioned by the Ada Lovelace Institute, AI Now Institute and the Open Government Partnership is the first study to evaluate this initial ‘wave’ of algorithmic accountability policy for the public sector across jurisdictions.

This report contains three sections:

1. Outlines the methodology of this study, including its scope and limitations, how we define key terms and concepts used, the questions that prompted this study and the gaps in existing research which it attempts to address.
2. Provides an indicative typology of the different kinds of policy mechanisms that are being used by governments to ensure algorithmic accountability, and scrutinises the claims and assumptions that these mechanisms make. It includes case studies of the mechanisms in use.
3. Presents the findings from our qualitative study of the implementation of algorithmic accountability policies in different jurisdictions, and outlines the factors which appear to affect the implementation of policies, including key challenges, tensions and debates that have arisen in their implementation.

¹ For instance: Young, M., Katell, M., and Krafft, P.M., (2019) ‘Municipal surveillance regulation and algorithmic accountability.’ *Big Data & Society*. Vol.6 No.2. Available at: <https://journals.sagepub.com/doi/full/10.1177/2053951719868492>

Methodology

This report examines the implementation of algorithmic accountability policies by governments in various jurisdictions. The findings of this report are based on:

- A database of more than 40 examples of algorithmic accountability policies at various stages of implementation, taken from more than 20 national and local governments (see table 1 below).
- Semi-structured interviews with decision-makers and members of civil society closely involved with the implementation of algorithmic accountability policies in the UK, Netherlands, France, New Zealand, Canada and Chile, as well as at the local level in Amsterdam City and New York City.
- Feedback received at a workshop with members of the Informal Network on Open Algorithms² that are implementing commitments focusing on algorithmic accountability through their OGP action plans.
- Feedback from participants of a private roundtable at RightsCon 2021 with public officials and members of civil society organisations from many of the countries reviewed in this report.
- A review of existing empirical studies on the implementation of algorithmic accountability policies in various jurisdictions.

The focus of the report is government policies designed to guide the use of algorithmic systems by the various government agencies and institutions that broadly comprise the ‘public sector’. By focusing on implemented policies, it excludes draft or planned policies such as draft EU AI regulation or the proposed US Algorithmic Accountability Act.³

2 Open Government Partnership (2021) *Open Algorithms Network*. Available at: <https://www.opengov-partnership.org/about/partnerships-and-coalitions/open-algorithms-network/>

3 European Commission., (2021). Proposal for a regulation of the European Parliament and of the Council on laying down harmonised rules on artificial intelligence (Artificial Intelligence Act) and amending certain union legislative acts. Available at: <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX-%3A52021PC0206>; United States Congress. (2019) H.R.2231: Algorithmic Accountability Act of 2019. Available at: <https://www.congress.gov/bill/116th-congress/house-bill/2231>

Table 1: The first wave of policy mechanisms

Name of policy/mechanism	Jurisdiction (Country)	Year
General Data Protection Regulation	EU	2016
French Digital Republic Act	France	2016
Act CXII of 2011 on the Right to Informational Self-Determination and Freedom of Information	Hungary	2018
Impact Analysis Guide for the development and use of systems based on artificial intelligence in the public sector	Mexico	2018
Advisory Council on the Ethical Use of AI and Data	Singapore	2018
California State Bill No. 10	USA	2018
Automated Decision-Making: Better Practice Guide	Australia	2019
AI Procurement Source List	Canada	2019
Directive on Automated Decision Making	Canada	2019
Moratorium on Facial Recognition	Morocco	2019
Fair Algorithms Starter Kit	Netherlands	2019
Policy letter on AI, public values and human rights	Netherlands	2019
Data Ethics Advisory Group	New Zealand	2019
Principles for the Safe and Effective Use of Data and Analytics	New Zealand	2019
Testing New Technologies for Automation in Public Administration	Sweden	2019
Ethical AI Toolkit	UAE	2019
Artificial Intelligence Strategy for the Digital Government	Uruguay	2019
Automated Decisions Task Force	USA	2019
House Bill No. 118 on Pretrial Risk Assessments	USA	2019
City of Helsinki AI Register	Finland	2020
Guidance on Algorithms in the Public Sector	France	2020
Tamil Nadu Safe and Ethical Use of AI	India	2020
Amsterdam Algorithm Register	Netherlands	2020
Algorithm Charter for Aotearoa New Zealand	New Zealand	2020
Swedish National Auditor Office Report on Automated Decision-Making in Public Administration	Sweden	2020
Draft AI Auditing Framework	UK	2020
Guidelines For AI Procurement	UK	2020
Review into Bias in Automated Decision-Making	UK	2020
West Midlands Data Science Ethics Committee	UK	2020
AI in Government Act	USA	2020
Algorithms Management and Policy Manager	USA	2020
Executive Order 13960	USA	2020
Public Oversight of Surveillance Technologies Act	USA	2020
Nantes Algorithm Registry	France	2021
Standard Clauses for Fair Algorithms	Netherlands	2021
Understanding Algorithms Report	Netherlands	2021
Data Ethics Framework	UK	2021
Ethics, Transparency and Accountability Framework for Automated Decision-Making	UK	2021
Registry of Algorithms	Canada	2021

For an expanded version of this table, see [page 57](#).

The report recognises that policies, standards and regulations that impact on the design and development of algorithmic systems in the private sector are part of a broader ecosystem but does not analyse their use and effects. While acknowledging that they may impact on the public sector indirectly, this report focuses specifically on policies that aim to govern the use of algorithmic systems in the public sector, and considers policy or regulations that are intended for both the public and the private sector.

The study also excluded policies and laws that generally cover issues like data protection or administrative decision-making frameworks, which might incidentally govern particular aspects of the use of algorithmic systems in the public sector, but have not been explicitly designed or used for this purpose.

Definitions

The term **algorithm** describes a series of steps through which particular inputs can be turned into outputs. An **algorithmic system** is a system that uses one or more algorithms, usually as part of computer software, to produce outputs that can be used for making decisions. We use a functional definition of an algorithmic system, as a system that uses automated reasoning to aid or replace a decision-making process that would otherwise be performed by humans. It is important to note that all algorithmic systems encompass different kinds of human intervention – whether at the stage of design, or in the way they are eventually used. In our analysis, we consider the technical as well as social, cultural, legal and institutional contexts where algorithms are embedded, as important determinants of how these systems are used and governed.

In this report, we use the term ‘**algorithmic accountability policies**’ to identify the set of policies oriented towards ensuring that those that build, procure and use algorithms are eventually answerable for their impacts. This terminology builds on the widely used definition of **accountability** provided by Professor Mark Bovens, which describes accountability as a relationship between the *actors* who use or design algorithmic systems, and *forums* that can enforce standards of conduct. This definition of accountability encompasses both the requirement that actors are answerable and can justify their use of algorithmic systems, and also that they can face consequences for such use.⁴

We focus here on accountability mechanisms created or channelled through law and policy. Mechanisms that have emerged to hold algorithmic systems accountable to the contexts and communities they are meant to serve, including tech-worker organising and whistleblowing, community organisers, civil society organisations and investigative journalism, are not examined in this study.

4 Bovens, M., (2007) ‘Analysing and assessing accountability: A conceptual framework 1.’ *European Law Journal*. Vol.13. Issue: 4pp. 447-468. Available at: <https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1468-0386.2007.00378.x>

Research questions and evidence

Section two seeks to answer the following questions:

- What are the kinds of policy responses from governments towards algorithmic accountability?
- What are their aims and assumptions?
- What are the (explicit or implicit) theories of change that they rely on?

As outlined above, this research was conducted through document analysis, literature review and qualitative interviews. We collated and created a database of more than 40 publicly available examples of algorithmic accountability policies from more than 20 national and local jurisdictions (see table 1). We coded and analysed these documents to understand common themes, which were used to create the indicative typology of policy mechanisms in this section of the report.

Section three of this report seeks to answer the following questions:

- What do we know about the implementation of algorithmic accountability policies, and how do we know it?
- What factors affect the implementation of algorithmic accountability policies in achieving their stated goals?

Building on the categorisation and assessment of the ‘first wave’ of policy responses, this section seeks to understand how these policies have been implemented in various jurisdictions, and what we can learn from their implementation so far.

An initial review of literature indicated that, while a range of scholarship exists on understanding algorithmic accountability in the context of law and government policy, there have been few systematic studies of the implementation of algorithmic accountability policies. As such, our study seeks to both coalesce the evidence about implementation available through a diverse but fragmented literature, as well as build an empirical base of evidence for the purpose of this analysis.

In order to understand how algorithmic accountability policies have been implemented, we conducted semi-structured interviews with decision-makers and members of civil society closely involved with the implementation of algorithmic accountability policies in the UK, Netherlands, France, New Zealand, Canada and Chile, as well as at the local level in Amsterdam City and New York City. We also presented preliminary findings and received feedback at a workshop with countries that are part of the Informal Network on Open Algorithms convened by Open Government Partnership (OGP), which are implementing commitments focusing on algorithmic accountability through their OGP action plans.

We reviewed existing empirical studies on the implementation of algorithmic accountability policies in various jurisdictions. These include reports by civil society actors who have closely followed policy implementation (e.g. the shadow report of the New York ADS Task Force),⁵

5 Richardson, R (ed.). (2019) *Confronting Black Boxes: A Shadow Report of the New York City Automated Decision System Task Force*. AI Now Institute, Available at: <https://ainowinstitute.org/ads-shadowreport-2019.pdf>.

documents released by governments describing the design and implementation of policies (e.g. a white paper on algorithm registers by Amsterdam City, Helsinki and Saidot)⁶ and academic literature and empirical studies of policy implementation in particular contexts (e.g. studies on the Data Ethics Framework in the UK).⁷

The implementation of algorithmic accountability policies varies widely across social, economic, legal and political contexts. Owing to this, evaluating or analysing these policies without recognising the contexts in which they are implemented tends to be inadequate. Consequently, instead of offering prescriptions, or rigid normative evaluations of particular policies in the abstract, the focus of this study is on understanding and analysing the factors that have shaped the implementation of algorithmic accountability policies in various jurisdictions.⁸

In section three, we seek to describe and analyse how these factors may operate in particular contexts, and how they might enable or disable the objectives that these policies set out to achieve.

Limitations

This research was constrained by its relatively short time frame and available resources, and we acknowledge that important examples of algorithmic accountability policies, or literature and evidence on policy implementation, may not be covered in this review. Moreover, the study was limited by the kinds of access we were able to secure to interview public officials and experts, to gather data about implementation.

The majority of our evidence base, including both the review of literature and the empirical study, is in the context of algorithmic accountability policy from the Global North. Most examples of current algorithmic accountability policy interventions are from governments in the US, Europe and other Global North contexts, and there is limited evidence of interventions from the Global South. The few policies from the Global South that we do analyse (for example, from India and Uruguay) do not alter our analysis significantly, but we recognise that a systematic analysis of algorithmic accountability policies in the Global South might reveal very different policy approaches, priorities and factors affecting their implementation.

6 Haataja, M., van de Fliert, L., and Rautio, P., (2020). *Public AI Registers: Realising AI transparency and civic participation in government use of AI*, Saidot. Available at: <https://ai.hel.fi/wp-content/uploads/White-Paper.pdf>

7 Domagala, N. (2020). 'Data ethics in practice: challenges and opportunities for a data ethics policy function in the public sector' Presented at the Data for Policy 2020, Zenodo. Available at: <https://zenodo.org/record/3967224>

8 Drawing from methodologies used by impact evaluation studies in other domains, for eg. See: Gaventa, J., and McGee, R., (2013). 'The impact of transparency and accountability initiatives.' *Development Policy Review*. Vol. 31.: s3-s28. Available at: https://assets.publishing.service.gov.uk/media/57a08aabd915d622c00084b/60827_DPRGaventaMcGee_Preprint.pdf

Mapping algorithmic accountability policy interventions

This section builds a typology of eight policy mechanisms through which governments have sought to achieve algorithmic accountability in the public sector, and analyses their underlying assumptions and theories of change.

This review of a range of international policies and mechanisms reveals substantial variation in their aims and approaches towards algorithmic accountability. To analyse and evaluate their implementation, it is necessary to understand what algorithmic accountability policies attempt to achieve, and how they seek to achieve it. What are the policy mechanisms, tools and frameworks leveraged by different governments to ensure algorithmic accountability? What are the intended objectives of these mechanisms, and how are these objectives sought to be achieved – in short, what is the ‘theory of change’ (the description of how the activities in an intervention will lead to desired outcomes) that they rely on?

The literature on this subject uses a variety of names and terms for these emerging policy mechanisms, and there is a lack of a shared vocabulary for their constitutive elements.

Within these parameters, we’ve developed a typology in which we examine eight different emerging policy mechanisms used towards algorithmic accountability, which are differentiated according to their aims, claims and assumptions:

4. Principles and guidelines
5. Prohibitions and moratoria
6. Public transparency
7. Impact assessments
8. Audits and regulatory inspection
9. External/independent oversight bodies
10. Rights to hearings and appeal
11. Procurement conditions

Each mechanism is illustrated with a case study, which explores the implementation of these mechanisms in specific contexts, including the challenges and successes faced in their implementation.

1. Principles and guidelines

Some of the policy documents we examined provide non-binding, normative guidance on ethical principles and values for public agencies to follow. These documents vary in form, but generally identify high-level policy goals, and how they might be implicated in the use of algorithmic systems by public agencies. In some cases, these documents also provide implementation guidance on how such principles may be implemented in the design or use of an algorithmic system by a public agency. These guidelines provide normative standards against which agencies or the public can evaluate the use of algorithmic systems.

Theory of change and assumptions

Policies that articulate high-level principles or guidelines are generally not intended to be binding, and are issued as normative standards against which agencies can assess their own use of algorithmic systems. Often, as non-binding and standalone principles, these do not create any enforceable obligations, but they can provide useful aids and guidance for public agencies confronted with questions about the appropriate use of algorithmic systems. They can also serve as declarations of intent about broader goals of administrations in the development of public policy for algorithmic systems.⁹

Some scholars have pointed to the relative ineffectiveness of ethics statements and principles as mechanisms for effective accountability of algorithmic systems, and criticised the recent policy focus on ethical guidelines as a means to avoid regulation and legally binding accountability mechanisms by prioritising self-regulation without accountability.¹⁰ Others have focused on how governments can build more constructive and mutually supportive interfaces between standards of professional ethics and regulation.¹¹

Ethical and value-based guidelines and principles form part of a number of existing policies on algorithmic accountability. Uruguay's AI Strategy for Digital Government,¹² for example, outlines several guiding principles for the use of AI in government, including 'general interest', 'respect for human rights', 'transparency' and 'privacy by design'.

-
- 9 Taylor, L., Leenes, R., and Schendel, S., (2017). 'Public Sector Data Ethics: From Principles to Practice', *Tilburg University*. Available at: <https://research.tilburguniversity.edu/en/publications/public-sector-data-ethics-from-principles-to-practice>
 - 10 Metzinger, T., (2019). 'Ethics Washing Made in Europe'. *Der Tagesspiegel*. 18 April. Available at: <https://www.tagesspiegel.de/politik/eu-guidelines-ethics-washing-made-in-europe/24195496.html>; Hagedorff, T., (2020). 'The ethics of AI ethics: An evaluation of guidelines.' *Minds and Machines* 30.1 pp.99-120. Available at: <https://link.springer.com/article/10.1007/s11023-020-09517-8>
 - 11 Delacroix, S., and Wagner, B., (2021). 'Constructing a mutually supportive interface between ethics and regulation.' *Computer Law & Security Review* 40. Available at: <https://www.sciencedirect.com/science/article/pii/S0267364920301254>
 - 12 Digital Government Agency. (2020). *Artificial Intelligence Strategy for Digital Government* Government of Uruguay

In some cases, declarations of principles are accompanied by guidance on how these principles may be implemented in the design or use of algorithmic systems. For example, the UK Data Ethics Framework¹³ provides points of intervention and checklists for implementation of data ethics into the functioning of data usage in public agencies. Similarly, the Australian Ombudsman's Better Practice Guide on Automated Decision-Making articulates administrative legal principles applicable to agency decisions made with the use of algorithmic systems, and also provides guidance on how they might be applied on a case-to-case basis.¹⁴

Case study: --- UK Data Ethics Framework

The UK Data Ethics Framework is a document produced by the UK Government, first published in 2018, and updated in 2020.¹⁵ It provides guidance on 'appropriate and responsible data use' within the government and public sector, which includes guidance on the algorithmic processing of data. The framework emphasises three overarching principles – transparency, fairness and accountability – and provides actionable guidance on how these principles can be translated into specific actions taken by agencies while using data in the course of a project.

The framework emphasises that agencies should understand and articulate the public benefit of using data-based systems, comply with legal requirements of privacy and equality, review data for bias and limitations and ensure organisational diversity.

A review of the Data Ethics Framework by Natalia Domagala¹⁶ of the UK's Government Digital Service, revealed some of the challenges with its implementation.¹⁷ Domagala's review (released in 2020 prior to the revision of the Data Ethics Framework) included a survey of public agencies utilising the framework and found that some of the major obstacles towards its implementation included lack of clear mechanisms to ensure implementation, the saturation of conflicting or overlapping ethical guidance in the area, lack of diversity and lack of skills and awareness about the framework.

13 UK Government. (2021). Department for Digital, Culture, Media and Sport. Data Ethics Framework. (2021) Available at: <https://www.gov.uk/government/publications/data-ethics-framework>.

14 Commonwealth Ombudsman. (2019). *Automated Decision-Making Better Practice Guide* Government of Australia. Available at: <https://www.ombudsman.gov.au/publications/better-practice-guides/automated-decision-guide>

15 UK Government. (2021). Department for Digital, Culture, Media and Sport. Data Ethics Framework. (2021) Available at: <https://www.gov.uk/government/publications/data-ethics-framework>.

16 Head of Data Ethics, UK Government Digital Service

17 Domagala, N., (2020). 'Data ethics in practice: challenges and opportunities for a data ethics policy function in the public sector' Presented at the Data for Policy 2020, *Zenodo*. Available at: <https://zenodo.org/record/3967224>

2. Prohibitions and moratoria

Some jurisdictions have banned or prohibited the use of particular kinds of ‘high risk’ algorithmic systems. In some cases, prohibitions are framed as temporary moratoria, which are intended to lapse once appropriate safeguards and accountability mechanisms are designed and implemented. Prohibitions and moratoria have been most prominently applied to facial recognition technologies used by law enforcement, and in some cases, by local governments in the USA.

Theory of change and assumptions

Prohibitions and moratoria are utilised in situations where the perceived risk or harm of using a particular algorithmic system, in a specific context, is considered to be too high to justify its use. In some cases, these prohibitions are expressly time-limited and are framed as temporary moratoria, with the intention that the prohibitions will be lifted when certain conditions regarding the use of the algorithmic system are met. Legal prohibitions in the use of algorithmic systems are usually outcomes of advocacy efforts from civil society, who have sought to establish ‘red lines’ on the use of technologies after documenting their harms or risks, such as threats to privacy or discriminatory use, or where risks and harms are perceived to be great enough to warrant precaution, especially until it is possible to establish systems of accountability for their use.¹⁸

The prohibitions and moratoria documented in this study have emerged mostly in response to the use of particular technologies in specific sectors and contexts. Examples of prohibitions include bans on the use of facial recognition technology (‘FRT’) by several local city and county governments in the USA, including San Francisco, Oakland and Seattle.¹⁹ In some cases, prohibitions are framed as moratoria – in that the technology’s use is to be kept in abeyance until specific conditions are met, including implementing stricter regulations on use. Such moratoria have been implemented in Morocco,²⁰ by the national privacy regulator, as well as by some states and local governments in the USA, for example the three-year moratorium on FRT in police body cameras, enacted in California.²¹

18 c.f. Harwell, D., (2021). ‘Civil rights groups ask Biden administration to oppose facial recognition’. *Washington Post*. 17 Feb 2021 Available at: <https://www.washingtonpost.com/technology/2021/02/17/facial-recognition-biden/>; Surveillance Oversight Technology Project (STOP), ‘Ban The Scan’, Available at: <https://www.stopspying.org/ban-the-scan>.

19 Electronic Privacy Information Centre, “State Facial Recognition Policy”, <https://epic.org/state-policy/facialrecognition/>

20 National Control Commission for the Protection of Personal Data, Morocco. (2020). ‘Press release of 30/03/2020: Press release accompanying the publication of deliberation No. D-97-2020 du 26/03/2020’. (In French) Available at: <https://www.cndp.ma/fr/presse-et-media/communique-de-presse/661-communique-de-presse-du-30-03-2020.html>

21 California Legislative Information. (2019). *AB-1215 Law enforcement: facial recognition and other biometric surveillance*. Available at: https://leginfo.ca.gov/faces/billNavClient.xhtml?bill_id=201920200AB1215.

While moratoria are often passed on the assumption that accountability frameworks might be implemented during the time of the prohibition, this may not always transpire. In Morocco, for example, the moratorium on FRT came to an end in December 2020, without accountability mechanisms specific to facial recognition technology being implemented in the interim.

Prohibitions and restrictions on use have been implemented through legislation, as evidenced in facial recognition bans and the surveillance oversight mechanisms in US cities, as well as being adopted as a matter of executive policy, for example, by the Vancouver Police Department,²² or through the actions of data regulators, as in the case of Morocco.

Case study: --- Community surveillance oversight by local governments in the USA

A number of local governments in the USA have enacted bans or moratoria on the use of algorithmic technologies used for surveillance by law enforcement. While the focus of these laws is specifically on questions of privacy, these issues have substantial overlap with questions of algorithmic accountability.²³

Prohibitions on the use of facial recognition technology have been enacted by at least 13 local governments in the US. These prohibitions are generally established within legislation, although many laws have specified limited exemptions from the prohibition, such as information obtained from FRT by third parties. For example, a San Francisco bill that bans the use of facial recognition technologies only applies to its use by municipal agencies and excludes use by federal agencies (such as in the ports and airports). The bill led to the disabling of a police department system whose use was previously unknown to the city council and public, but also led to a subsequent exemption to allow municipal authorities to use city-issued Apple iPhone devices that came with a 'face unlock' feature.²⁴

Although most of these laws are relatively recent (San Francisco was the first city to ban FRT, in 2019), and their effect on the use of FRT is not yet clearly established, the scope and reach of the prohibitions and the availability of exemptions are issues that continue to be contested between civil society groups advocating for the non-use of these systems, and government agencies.

22 Short, B. (2021). 'The First Moratorium on Facial Recognition in Canada'. *Open Media*. 28 April Available at: <https://openmedia.org/article/item/the-first-police-moratorium-on-facial-recognition-in-canada>.

23 Degroff, S, & Fox Cahn, A., (2021). 'New CCOPS On the Beat'. Surveillance Technology Oversight Project and Hogan Lowells. Available at: <https://www.stopspying.org/ccops>.

24 Simonite, T., and Barber, G., (2019). 'It's Hard to Ban Facial Recognition Tech in the iPhone Era.' *Wired*. 19 December. Available at: <https://www.wired.com/story/hard-ban-facial-recognition-tech-iphone/>

3. Transparency mechanisms

Transparency mechanisms provide information about algorithmic systems to the general public (e.g. affected persons, media or civil society) so that individuals or groups can learn that these systems are in use, and demand answers and justifications related to such use.

Ensuring transparency, in different forms, is a core feature of several algorithmic accountability policy measures. In this section we focus particularly on mechanisms for establishing public access to information about algorithmic systems and processes. These mechanisms may stand-alone, or be embedded within broader mechanisms of algorithmic accountability.

Public transparency mechanisms should also be distinguished from hearing and explanation rights that provide an individual with a right to an explanation of a specific algorithmic decision made about them.

Examples of transparency mechanisms include:

- public registries of algorithmic systems, which are aimed at civil society and citizens
- requirements for source code transparency, which apply to computational algorithmic systems
- explanations of algorithmic logics (purportedly allowing the public and policymakers to ‘understand’ how an algorithmic decision was reached).

Theory of change and assumptions

Transparency is a necessary condition for accountability, however, the links between transparent processes or outcomes, and accountable relations are not always well established. Public access to information can enable responses from particular actors within the general public (affected persons, media, civil society, etc.). This delivers the possibility of accountability and answerability to people who can use the information to hold public agencies or other actors accountable for their use of algorithmic systems. Transparency mechanisms assume that a critical audience can be enlisted, which is able to understand the information, and empowered to respond to it in order to produce accountability and answerability.²⁵

A number of the policies reviewed attempt to foster public access to information about algorithmic systems used by the public sector. The specific requirements of transparency mechanisms, including the kinds of information required to be published, or the form in which they are intended to be published, differ widely across jurisdictions.

Some requirements focus on transparency of the source-code and the operating logic of algorithmic systems. Article L-312-1-3 of the French Digital Republic Bill,²⁶ for example, requires public sector agencies to ‘make publicly available, in an open and easily re-usable format, the

25 Kemper, J, and Kolkman, D., (2019). ‘Transparent to whom? No algorithmic accountability without a critical audience.’ *Information, Communication & Society*. Vol. 22. No. 14.pp. 2081-2096. Available at: <https://www.tandfonline.com/doi/full/10.1080/1369118X.2018.1477967>

26 Republique Francaise. (2016). *The Digital Republic bill – Overview*. Available at: <https://www.republique-numerique.fr/pages/in-english>

rules defining the main algorithmic processing used in the accomplishment of their mission when such processing is the basis of individual decisions'. In compliance with this law, the source code of some algorithmic systems, like the tax and benefits calculator, has been published online.²⁷ Similarly, the Canadian ADM Directive requires custom source code owned by the Canadian Government to be made public, subject to certain exemptions for confidentiality.²⁸

Some frameworks focus on broader forms of transparency, which include not only the technical components, but also the organisational features of the algorithmic system. The Aotearoa NZ Algorithm Charter requires transparency about the data and processes available, as well as information about how data is collected, stored and secured. The updated UK Data Ethics Framework similarly encourages transparency not only of the algorithmic model, but also on the administrative processes behind the system – including the envisaged benefits, the structure of the project team, the publication of non-personal and non-sensitive data used in the system and an explanation of the working of the system.²⁹

In all mechanisms reviewed, the transparency requirements are subject to exceptions owing to countervailing policy objectives such as trade secrets, system security concerns or privacy.

Most mechanisms do not focus on the form in which information is expected to be made transparent. In general, the expectation is that publishing written documentation online is a suitable form of transparency. In some cases, as in the Algorithm Management and Policy Office reports published in New York,³⁰ the information is merely consolidated in the form of a downloadable document. In some cases, as in France, there has been an active effort to reach out to people who cannot easily access written language, through videos and audio explanations.³¹

One mechanism for publishing relevant information about algorithmic systems that is gaining prominence is the concept of 'algorithm registers'. Registers are consolidated directories providing information about algorithmic systems used by public agencies in different jurisdictions. Some form of an algorithm registry has been implemented in Ontario,³² Amsterdam,³³ Helsinki,³⁴ and in cities in France, including Antibes, Lyon and Nantes.³⁵

27 Chausson, C. (2016). 'France opens the source code of tax and benefits calculators to increase transparency'. European Commission. Available at: <https://joinup.ec.europa.eu/collection/egovernment/document/france-opens-source-code-tax-and-benefits-calculators-increase-transparency>

28 Treasury Board of Canada Secretariat, Government of Canada. (2019). *Directive on Automated Decision-Making*. Available at: <https://www.tbs-sct.gc.ca/pol/doc-eng.aspx?id=32592>

29 UK Government. (2021). Department for Digital, Culture, Media and Sport. Data Ethics Framework. (2021) Available at: <https://www.gov.uk/government/publications/data-ethics-framework>.

30 Thamkittikasem, J., (2020). 'Summary of Agency Compliance Reporting', *New York City Algorithm Policy and Management Office*. Available at: <https://www1.nyc.gov/site/ampo/resources/reports.page>

31 An example of this is the video explanation of a job search engine built by the French Government agency Pole Emploi, see: <https://www.youtube.com/watch?v=AAUNWhmVm2Y>.

32 Ontario. *Data Catalogue*. Available at: <https://data.ontario.ca/group/artificial-intelligence-and-algorithms>

33 City of Amsterdam Algorithm Register Beta. *What is the Algorithm Register?* Available at: <https://algoritmeregister.amsterdam.nl/en/ai-register/>

34 City of Helsinki AI Register. *What is AI Register?* Available at: <https://ai.hel.fi/en/ai-register/>

35 Pénicaut, S. (2021). 'Building Public Algorithm Registers: Lessons Learned from the French Approach'. *Open Government Partnership Blog*. 12 May Available at: <https://www.opengovpartnership.org/stories/building-public-algorithm-registers-lessons-learned-from-the-french-approach/>.

Case study: --- Algorithm registers in Amsterdam, Helsinki and France

While a relatively recent mechanism, algorithm registers (as repositories of information about algorithmic systems, which emphasise public access) are, to varying degrees, documenting the use of algorithmic systems in public agencies in different jurisdictions. Of these, public agencies responsible for algorithm registers in Amsterdam, Helsinki, Nantes, Antibes and Lyon are active and have also described their experiences of implementation.

The white paper published by the governments of Amsterdam and Helsinki on their implementation of algorithm registers indicates that these registers can help structure accountability for the use of algorithmic systems in public agencies, by systematically ensuring public transparency and participation in their development and use.³⁶ Learnings from the implementation of algorithm registers in Nantes and Lyon indicate the importance of involving public agencies in the process of designing these registers. Their implementation has also given rise to questions about the scope of systems and information to include, how to ensure legitimacy for their use, and on prioritising resources to ensure greatest impact.³⁷

The experiences of introducing algorithm registers indicate some of the considerations that should go into constructing mechanisms for public access to information. Primarily, they indicate the importance of designing interventions for specific audiences, who can appropriately understand and respond to the information provided.

They also hold some lessons for the form in which information can be accessed. These registers have mostly arisen as directories for consolidating information about algorithmic systems used across a particular, local jurisdiction. Decentralising and focusing on local governments may ensure that these directories are not too large, unwieldy, or difficult to construct or use. This is a challenge which has arisen, for example, in the context of larger, national directories, such as those being attempted in Chile.³⁸

36 Haataja, M, van de Fliert, L and Rautio, P., (2020). *Public AI Registers: Realising AI transparency and civic participation in government use of AI* Saidot. Available at: <https://ai.hel.fi/wp-content/uploads/White-Paper.pdf>

37 Pénicaud, supra note 34.

38 Consejo para la Transparencia. (2021). *CPLT y la UAI firman convenio para promover transparencia del uso de algoritmos y datos personales en organismos públicos*. Available at: <https://www.consejotransparencia.cl/cplt-y-la-uai-firman-convenio-para-promover-transparencia-del-uso-de-algoritmos-y-datos-personales-en-organismos-publicos/>; Interview with domain expert on algorithmic accountability policy in Chile, on file with the author.

4. Algorithmic impact assessments

Algorithmic impact assessments (AIAs) are an emergent policy mechanism being utilised by public agencies, involving studying the potential use of an algorithmic system in context, and seeking to better understand, categorise and respond to the potential harms or risks posed by the use of these systems.

AIAs may be conducted *prior* to the actual ‘live’ usage of algorithmic systems, or they may be ongoing assessments, concurrent to the use of such systems.³⁹ The goal is to mitigate harmful impacts of a given initiative or deployment, recognising risks and addressing them before implementation.

AIAs draw on the long history of impact assessment frameworks in other domains, such as environment, human rights and Data Protection Impact Assessments (DPIAs).⁴⁰ The latter, in particular, serves as a close precursor to AIAs, given its focus on the fairness and transparency of data-based technologies. In particular, scholars have argued that DPIAs under the EU GDPR can be used as a structural framework for conducting AIAs.⁴¹

It is purported that AIAs provide impacted communities in particular with more involvement in the uses of algorithmic systems by public agencies, and influence over how they respond to potential harms.⁴² In practice, however, most AIAs currently in use have not engaged these communities substantively, and have been applied primarily for internal self-assessment by public agencies. In some cases, for example, under the Canadian Directive on Automated Decision-Making,⁴³ or the New Zealand Algorithm Charter,⁴⁴ the outcomes of AIAs go on to determine the eventual level of regulatory scrutiny applied to particular algorithmic systems.

Theory of change and assumptions

While there is substantial variation in how AIAs are constructed and implemented, in general, they are intended to define and construct a matrix of harms, benefits and risks, in order to evaluate *ex ante* whether the deployment of an algorithmic system is suitable in a particular context, and if not, what measures must be taken by a responsible actor to respond to the possibilities of harm.

-
- 39 Reisman, D., et al. (2018) *Algorithmic Impact Assessment: A Practical Framework for Public Agency Accountability*. AI Now Institute. Available at: <https://ainowinstitute.org/aiareport2018.pdf>.
 - 40 Moss, E., Watkins, E.A., Singh, R., Elish, M.C., and Metcalf, J. (2021). *Assembling Accountability Through Algorithmic Impact Assessment*. Data & Society Research Institute. Available at: <http://datasociety.net/library/assembling-accountability/>.
 - 41 Kaminski, M. E., and Malgieri, G.,(2020) ‘Multi-layered explanations from algorithmic impact assessments in the GDPR.’ *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*. Available at: <https://dl.acm.org/doi/abs/10.1145/3351095.3372875>.
 - 42 Metcalf, Jacob, et al. (2021) ‘Algorithmic impact assessments and accountability: The co-construction of impacts.’ *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*. Available at: <https://dl.acm.org/doi/abs/10.1145/3442188.3445935>
 - 43 Treasury Board of Canada Secretariat, Government of Canada. (2019) *Directive on Automated Decision-Making*. Available at: <https://www.tbs-sct.gc.ca/pol/doc-eng.aspx?id=32592>
 - 44 New Zealand Government. (2020). *Algorithm Charter for Aotearoa New Zealand*. Available at : https://data.govt.nz/assets/data-ethics/algorithm/Algorithm-Charter-2020_Final-English-1.pdf

In doing so, AIAs make visible the subjective choices of particular agencies responsible for the deployment of an algorithmic system, including how they define harms, benefits and risks, and how they assess and choose between alternative policy options related to the deployment of an algorithmic system. They provide information to a range of actors (which may include the agency, oversight bodies, communities affected by the system, or civil society and the public) who can then use these frameworks to assess the credibility and appropriateness of an algorithmic system intended to be used.⁴⁵

A number of the algorithmic accountability policies reviewed in this report rely on some form of an *ex ante* algorithmic impact assessment. These vary in their complexity and the kind of information which is sought to be made legible through the assessment. For example, the Algorithm Charter for Aotearoa New Zealand has a very simple risk matrix assessing only the likelihood and severity of adverse outcomes from automated decision systems.

A more complex AIA model is implemented as a part of the Canadian Directive on Automated Decision-Making, which is composed of 48 risk and 33 mitigation questions, scored along factors including systems design, algorithm, decision type, impact, data use and mitigation mechanisms. Kaminski and Malgieri have argued that DPIAs under the EU GDPR also provide a systematic framework for AIAs when implemented in the context of automated decision-making, although there is limited evidence of them being used in this context.⁴⁶

While the theory of change for AIAs to achieve accountability is rarely made explicit in policies themselves, a series of underlying assumptions become apparent from the ways they are constructed. Firstly, AIAs assume and construct certain predefined categories of ‘impacts’ and ‘harms’ to be measured and assessed. As such, particular attention should be paid to how impacts are defined, and who is defining them (and with which actors in mind).

Secondly, AIAs assume the existence of actors or forums with adequate agency and political power to demand answerability to explain or justify particular choices in the implementation of an algorithmic system, as well as those with the power to enforce identified lapses between the implemented system and its assessment. In some cases, this may be through scrutiny by the general public or by civil society. In others, accountability may be intended through regulatory response enforced by an external body.⁴⁷

In reality, however, most AIAs currently in use do not establish clear links with forums for holding them to account - for example, through politically empowered agencies that can take action against identified harms or risks. In some policies, outcomes of AIAs are tied to particular pre-defined regulatory responses. For example, under the Canadian ADM Directive, a finding of a particular ‘impact level’ through an AIA triggers different levels of scrutiny and governance for those uses.⁴⁸ In the case of the Tamil Nadu Safe and Ethical AI Policy, the AIA is explicitly intended to be applied at the time of procurement, and to be used to reject or recall applications which do not meet a threshold AIA score.⁴⁹

45 Reisman et. al. Supra note 38.

46 Kaminski and Malgieri, Supra note 40.

47 Bovens, M., (2007) ‘Analysing and assessing accountability: A conceptual framework 1.’ *European Law Journal*. Vol. 13 No.4 pp. 447-468. Available at: <https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1468-0386.2007.00378.x>

48 Treasury Board of Canada Secretariat, Government of Canada. (2019). *Directive on Automated Decision Making*. Available at: <https://www.tbs-sct.gc.ca/pol/doc-eng.aspx?id=32592>

49 Government of Tamil Nadu.(2020) *Tamil Nadu Safe and Ethical Artificial Policy 2020*. Available at : <https://elcot.in/sites/default/files/AIPolicy2020.pdf>

In most cases, AIAs are discretionary requirements intended to be a 'self-assessment' by agencies, and are not expressly required to be made publicly available, nor do they have any well-defined consequences after identifying potential impacts. In such cases, AIAs are essentially for 'self-regulation', and used to provide decision-guidance internally to public agencies, without any reference to external actors or forums for enforcing accountability.

Most of the AIA mechanisms reviewed do not establish clear processes for public participation, for ensuring transparency or public access to the outcomes, or clear lines of accountability linking back to the use of algorithmic systems by public agencies. The lack of participation in the development and eventual use of AIAs can substantially hamper their impact and effectiveness, particularly since understanding the impacts of algorithmic systems fundamentally requires taking into consideration the experiences of affected communities.⁵⁰

The lack of transparency and disclosure of AIAs also takes away from a key element that establishes them as a mechanism of wider accountability – the availability of the wider public to deliberate and respond to identified impacts and harms in the use of a potential algorithmic system. Owing to their limited transparency and public participation, most AIAs currently implemented fall substantially short of models for AIAs proposed by experts, such as the AIA for public sector by the AI Now Institute,⁵¹ or the Algorithmic Impact Statement for law enforcement, proposed by Selbst.⁵²

Case study: **Canadian Directive on Automated Decision-Making**

The Canadian Directive on Automated Decision-Making (ADM) is one of the first policies on algorithmic accountability to define and incorporate an Algorithmic Impact Assessment. Under the Directive, an AIA must be conducted by a Federal public agency prior to the 'production' of any ADM system, including at the design stage of a project and immediately prior to the production of a system. These AIAs are required to be updated when there is a change in the functionality or scope of the system, and must be publicly available. At the time of writing, only one AIA was published online and available publicly.⁵³

An AIA under the Directive consists of a number of questions that are framed in relation to policy, ethical and administrative law considerations of ADM system risk areas. The questions involve technical elements of a system, such as the data and the algorithm, as well as organisational elements like consultation and procedures, and to assess impacts along lines of 'economic interests', 'health', 'sustainability' and 'rights' of individuals or communities.

50 Moss, E., Watkins, E.A., Singh, R., Elish, M.C., and Metcalf, J. (2021). *Assembling Accountability Through Algorithmic Impact Assessment*. Data & Society Research Institute. Available at: <http://datasociety.net/library/assembling-accountability/>.

51 Reisman et. al. Supra note 38.

52 Selbst, A. D., (2017) 'Disparate Impact in Big Data Policing' *Georgia Law Review*. Vol. 52. No. 109. p. 169. Available at: <https://par.nsf.gov/servlets/purl/10074337>

53 There has been some ambiguity about the application of the mandate to conduct AIAs and the scope of automated decision-making that comes under the Canadian AIA. See, for example: Cardoso, T., and Curry, B., (2021) 'National Defence skirted federal rules in using artificial intelligence, privacy commissioner says'. *The Globe and Mail*. 7 Feb. Available at: <https://www.theglobeandmail.com/canada/article-national-defence-skirted-federal-rules-in-using-artificial/>

The AIA does not provide a detailed descriptive account of the use of algorithmic systems, opting instead for a score-based system, where binary positive or negative answers to the questions indicate the ‘impact level’ of a particular system. The results then require the appropriate implementation of accountability mechanisms like peer review, human oversight or explanation.

AIAs are required to be made publicly available, but experts have criticised the AIA for the lack of established mechanisms for engaging affected communities, members of the public or experts to participate in how agencies should respond to identified impacts.⁵⁴

5. Audits and regulatory inspection

Algorithmic auditing refers to a range of practices for inspecting the working of a particular algorithmic system, in order to understand its functioning, and assess it with respect to some predefined normative standard.⁵⁵

While audits are closely related to the Algorithmic Impact Assessments described above, they do have a distinct history of use across different sectors and are generally conducted by a third, second, or first party to the audited organisation.⁵⁶ Third-party audits are conducted by an external party outside of the organisation who assesses the behaviour of a system based solely on its outputs. Second-party audits are conducted by someone hired from outside an organisation who is granted access to the backend of a system along with its outputs. First-party audits are conducted by an internal member of an organisation.⁵⁷ Audits are also typically carried out subsequent to, or concurrent with, the use of a system, while AIAs are generally created prior to, or concurrent with their use.

While audits may be structured in a number of ways, and involve different actors, for the purpose of this report we have examined first- and second-party audits that are either conducted or authorised by government agencies (as opposed to audits conducted, for example, by civil society and media).

A report by the Ada Lovelace Institute and DataKind UK also identifies two kinds of audits relevant to algorithmic systems⁵⁸ – a ‘technical audit’, which examines the technical elements (inputs, outputs, algorithms) to assess reliability, check for discriminatory biases in results, or assess other aspects of the functioning of the algorithmic system, and; a ‘regulatory inspection’, which examines the functioning of an algorithm system, with reference not only to its technical

54 Kaminski et al. (2020). Proposals for ensuring appropriate regulation of artificial intelligence: Comments of Privacy Researchers on Proposals 4 and 5. Available at: <https://tlpc.colorado.edu/wp-content/uploads/2020/03/2020.03.13-Academic-Researchers-Comment-on-ensuring-appropriate-regulation-of-artificial-intelligence-final-1.pdf>

55 Ada Lovelace Institute and DataKind UK. (2020). *Examining the Black Box: Tools for Assessing Algorithmic Systems*. Available at: <https://www.adalovelaceinstitute.org/report/examining-the-black-box-tools-for-assessing-algorithmic-systems>

56 See Moss, E., Watkins, E.A., Singh, R., Elish, M.C., and Metcalf, J. (2021). *Assembling Accountability Through Algorithmic Impact Assessment*. Data & Society Research Institute. Available at: <http://datasociety.net/library/assembling-accountability/>

57 Moss, E., Watkins, E.A., Singh, R., Elish, M.C., and Metcalf, J. (2021). *Assembling Accountability Through Algorithmic Impact Assessment*. Data & Society Research Institute. Available at: <https://datasociety.net/library/assembling-accountability-algorithmic-impact-assessment-for-the-public-interest/>

58 Ada Lovelace Institute and DataKind UK, Supra note 54.

elements, but also with a focus to assess it against some normative standard (for quality assurance, legality, etc.). Similar distinctions have been made in the field of environmental audits, distinguishing between audits which aim at reviewing technical reliability and those that examine wider societal harms.⁵⁹

While audits are an important mechanism for public sector accountability, and in combination with other approaches hold promise for algorithmic systems, they have not been formalised as standard policy mechanisms for public sector use of algorithmic systems. To date, they remain largely ad-hoc exercises conducted under the wider ambit of particular regulatory or administrative agencies.

Theory of change and assumptions

There is a long history of auditing as an accountability mechanism, particularly in the execution of public projects, as well as in use of government finances. In our survey of public-sector auditing approaches, audits are generally *post-facto* mechanisms for accountability, in that they study the actual implementation of particular systems to identify whether they are functioning as intended.

Algorithmic auditing presumes that the auditor is sufficiently empowered and capable of creating an independent account of the functioning of a particular algorithmic system. The outputs of audits, if made public, can make the system more legible to external actors (like regulators or the wider public), and therefore carries the potential to trigger other accountability mechanisms, including through public scrutiny or through regulatory action.⁶⁰

Audits may be used to assess the performance of an algorithmic system as measured against particular standards (performance audits), or to analyse their compliance with particular norms (compliance audits), and provide recommendations for compliance or improving performance on particular metrics.⁶¹ Audits may also be used as mechanisms to understand systematic failures in the use of an algorithmic system, which may inform how algorithmic systems are used in other contexts.

The theory of change behind algorithmic auditing assumes that a particular system is ‘auditable’. The notion of auditability has multiple components. First, that the public agencies or private parties responsible for the system can provide adequate information about it to an independent auditing team or an external party, who is in a position to hold the audited parties to account (which depends on a number of legal, political and organisational factors).⁶² Second, it assumes that auditors can gain insight into the use of the system through available information and

59 Raji, I. D, et al. (2020). ‘Closing the AI accountability gap: defining an end-to-end framework for internal algorithmic auditing.’ *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*. Available at: <https://arxiv.org/abs/2001.00973>

60 Gendron, Y., Cooper, D.J. and Townley, B. (2007). ‘The construction of auditing expertise in measuring government performance’, *Accounting, organizations and society*, Vol. 32, No. 1–2. pp. 101–29. Available at: <https://www.sciencedirect.com/science/article/abs/pii/S0361368206000390>

61 INTOSAI. (2019). Performance Audit Principles. Available at: https://www.intosai.org/fileadmin/downloads/documents/open_access/ISSAI_100_to_400/issai_300/ISSAI_300_en_2019.pdf

62 Bovens, M, and Anchrit Wille, A., (2020). ‘Indexing watchdog accountability powers a framework for assessing the accountability capacity of independent oversight institutions’ *Regulation & Governance*. Vol. 15. No. 3. Available at: <https://onlinelibrary.wiley.com/doi/full/10.1111/rego.12316>

documentation about them.⁶³ Finally, the theory of change behind algorithmic auditing rests on the assumption that a system's behaviour over time is consistent with its behaviour when audited. An audit that assesses an algorithm's behaviour in 'lab settings' or in one particular context may not provide much information about that system's behaviour in a new context or with new data. Audits provide a snapshot of a system's behaviour in time, and so may need to be regularly conducted to assess behaviour changes in new settings.

Algorithmic auditing for the public sector has largely been conducted through ad-hoc exercises, instead of as a part of a systematic policy or regulation on algorithmic accountability. The Draft Guidance on AI Auditing released by the UK Information Commissioner's Office (ICO)⁶⁴ outlines a comprehensive framework to conduct an AI audit within the specific requirements set out under the UK Data Protection Act.

Some algorithmic audits have been conducted as ad-hoc regulatory inspection exercises embedded within broader structures of government accountability, particularly by supreme audit institutions (i.e. independent auditor institutions tasked with auditing government activities). The purposes for which algorithmic systems have been audited in the public sector have varied widely. Some regulatory inspections have focused on quality assurance and to ensure that systems are functioning 'as intended', while others have focused on uncovering broader societal risks emerging from the use of these systems, like risks of discrimination or impact on public trust.

The National Audit Office of Sweden, for example, conducted the first audit of three automated decision-making systems used by the Swedish Government, to understand whether the use of automated decision-making systems was effective and efficient, and if it jeopardised legal certainty in decision-making.⁶⁵ The audit measured the performance of the three systems against efficiency and legal certainty standards required by legislation, and made specific recommendations on apparent shortcomings, including lapses in documentation of automated decision-making systems. The Netherlands Court of Audit also audited prescriptive or predictive algorithms that have a 'substantial impact' on government behaviour, through three exploratory case studies, and documented the process and framework it applies to auditing such systems.⁶⁶

The UK Centre for Data Ethics and Innovation (CDEI), an expert committee established under a government ministry, has also conducted a review into bias in algorithmic decision-making, which included examining biases and discrimination in algorithmic systems used by local governments in the UK.⁶⁷ The UK Treasury conducted a Review of Quality Assurance in

63 Raji, D., et. al., supra note 58.

64 UK Information Commissioner's Office. (2020). *Draft Guidance on the AI Auditing Framework* Available at: <https://ico.org.uk/media/about-the-ico/consultations/2617219/guidance-on-the-ai-auditing-framework-draft-for-consultation.pdf>

65 Swedish National Audit Office (2020). *Automated Decision-Making in Public Administration* Available at: <https://www.riksrevisionen.se/en/audit-reports/audit-reports/2020/automated-decision-making-in-public-administration--effective-and-efficient-but-inadequate-control-and-follow-up.html>

66 Netherlands Court of Audit. (2021). *Understanding algorithms*. Available at: <https://english.rekenkamer.nl/publications/reports/2021/01/26/understanding-algorithms>

67 Centre for Data Ethics and Innovation. (2020). *Review into bias in algorithmic decision-making*. 2020. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/957259/Review_into_bias_in_algorithmic_decision-making.pdf

Modelling in 2013 to assess the quality of business-critical models used in policymaking across government departments, and to ensure that they are fit for purpose.⁶⁸ Similarly, in 2020 the UK Office of Statistics Regulation conducted an audit of statistical-grading algorithms used for exam qualifications, to analyse their quality, as well as their ‘trustworthiness’, and provides recommendations on the broader use of algorithmic systems and models by public agencies.⁶⁹

While there does not appear to be a standard practice for ‘algorithmic auditing’ in the public sector, there is some literature that attempts to integrate learnings across various initiatives. For example, a white paper by Supreme Audit Institutions in Norway, Finland, UK, Netherlands and Germany, makes recommendations for audits of public-sector machine learning projects, which are based on their own experiences in conducting such audits.⁷⁰

Case study: --- Audits of algorithmic systems in Allegheny County

The Allegheny Family Screening Tool (AFST) is an algorithmic system used by the County of Allegheny, Pittsburgh, to identify and predict situations where children may be at risk of maltreatment. The tool has been the subject of intense public scrutiny and criticism, and, perhaps as a consequence, has been subject to technical audits and wider evaluations by both independent actors (third-party auditors) and auditors working with the developers of the system (second-party auditors).⁷¹

A technical audit (referred to as an ‘impact evaluation’) of the AFST was conducted by researchers from Stanford in 2019,⁷² to study the implementation of the AFST since December 2016. The audit examined the performance of the AFST across metrics including accuracy, disparities in accuracy, workload and consistency in outcomes. This audit found that the use of the AFST improved the accuracy of child-welfare referrals, promoted consistency and reduced disparities on these metrics between different racial or ethnic groups.

68 HM Treasury (2013). *Review of quality assurance of Government analytical models: final report* UK Government Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/206946/review_of_qa_of_govt_analytical_models_final_report_040313.pdf

69 Office for Statistics Regulation (2021). *Ensuring statistical models command public confidence*. UK Government. Available at: <https://osr.statisticsauthority.gov.uk/publication/ensuring-statistical-models-command-public-confidence/>

70 Supreme Audit Institutions of Finland, Germany, the Netherlands, Norway and the UK. (2020). *Auditing machine learning algorithms: A white paper for public auditors*. Supreme Audit Institutions of Finland, Germany, the Netherlands, Norway and the UK. Available at: <https://www.auditingalgorithms.net/>

71 See generally: Eubanks, V., (2018). *Automating Inequality: How High-Tech Tools Profile, Police, and Punish the Poor*. New York: St. Martin's Press. and Moss, E., Watkins, E.A., Singh, R., Elish, M.C., and Metcalf, J. (2021). “Assembling Accountability Through Algorithmic Impact Assessment.” Data & Society Research Institute. <http://datasociety.net/library/assembling-accountability/>

72 Goldhaber-Fiebert, J., and Prince, L., (2019). ‘Impact evaluation of a predictive risk modeling tool for Allegheny County’s child welfare office.’ *Pittsburgh: Allegheny County*. (2019). Available at : https://www.alleghenycountyanalytics.us/wp-content/uploads/2019/05/Impact-Evaluation-from-16-ACDHS-26-PredictiveRisk_Package_050119_FINAL-6.pdf

The AFST was subjected to a ‘process evaluation’, which looked into the organisational features of the design and implementation of the tool, including assessing community participation, experiences of public officials and caseworkers using the tools and issues of transparency. The evaluation also provides recommendations on how these parameters can be improved.⁷³

The implementation of the AFST continues to be subject to criticism on various grounds, including on contested definitions of ‘fairness’ and accuracy that were studied by the technical audit.⁷⁴ Both the technical audit and the process evaluation reveal how audits and inspections can provide important visibility on technical and organisational features of an algorithmic system, but its impact ultimately depends on how such audits are constructed, and their ability to build legitimacy and trust among the wider community impacted by an algorithmic system.

6. External/independent oversight bodies

Several jurisdictions rely on independent oversight bodies, which are intended to oversee and direct the use of algorithmic systems by public agencies.⁷⁵ These independent oversight mechanisms are intended to ensure accountability by monitoring the actions of public bodies, and making recommendations, sanctions, or decisions about their use of algorithmic systems.

Oversight mechanisms vary widely in form and function. Some mechanisms rely upon legislative oversight, while others function in advisory capacities without specifically delegated legal powers.

Theory of change and assumptions

Independent oversight mechanisms are generally responsible for monitoring the actions of a public agency and making recommendations, sanctions or decisions about their use of algorithmic systems.

Independent oversight is premised on the oversight body having influence over the conduct of a public agency and its use of algorithmic systems, as well as the existence of adequate power and resources within the oversight body. The formal remit of an oversight body is generally broader than completing an auditing process. External oversight as an accountability mechanism

73 Hornby Zeller Associates Inc., (2018). *Allegheny County Predictive Risk Modeling Tool Implementation: Process Evaluation*. Available at: <https://www.alleghenycounty.us/Human-Services/News-Events/Accomplishments/Allegheny-Family-Screening-Tool.aspx>

74 See, for example: Keddell, E., (2019). ‘Algorithmic justice in child protection: Statistical fairness, social justice and the implications for practice.’ *Social Sciences* Vol. 8. No.10 p. 281. Available at: <https://www.mdpi.com/2076-0760/8/10/281/htm>

75 Borrowing from Bovens, we use the term ‘independent oversight’ to refer to bodies whose primary function is to observe and respond to ‘first order’ tasks of the executive, and are intended to operate with a degree of independence from the conduct of the executive body they are overseeing. See: Bovens, M., and Wille, A., (2020). ‘Indexing watchdog accountability powers a framework for assessing the accountability capacity of independent oversight institutions.’ *Regulation & Governance*. Vol. 15. No. 3. Available at: <https://onlinelibrary.wiley.com/doi/full/10.1111/rego.12316>

emphasises systematic reporting obligations and ongoing deliberation to measure the actions of public agencies against a particular standard of conduct, and is premised on the ability of the oversight body to directly influence the design and use of particular algorithmic systems, either prior to, or concurrent with their use.⁷⁶

Sometimes these bodies are set up to fast-track a deliberative or legislative process, to decide on the appropriate limits on a particular kind of system. For example, facial recognition technology (FRT) moratorium laws in the US have created task forces that are meant to deliberate on whether, and (if so) under what conditions, the moratorium on FRT should be lifted.⁷⁷

Our review indicates varied institutional forms for independent oversight bodies. Some mechanisms are established through legislation, such as the New York Local Law 49, which created an Automated Decision Systems Task Force, or in Community Control of Policy Surveillance (CCOPS) legislation in Seattle and Oakland.⁷⁸ Others are established as a matter of executive policy, and intended to function in an advisory capacity – like the New Zealand Data Ethics Advisory Group⁷⁹ and the West Midlands Police Data Ethics Committee.⁸⁰

The form, function and scope of oversight bodies varies widely. In New York City, for example, the Algorithm Management and Policy Officer is the executive body empowered for oversight, including for ‘receiving, investigating, and addressing any complaints from individuals’ about the use of algorithmic systems by public agencies’.⁸¹ In the Oakland Surveillance Ordinance, control and oversight over surveillance technologies is provided directly to legislative bodies like city councils, as well as to executive bodies like the Privacy Advisory Commission,⁸² who must approve the use of surveillance technologies. Finally, oversight mechanisms may be established in a purely advisory capacity without executive or political authority, as in the West Midlands Police Data Ethics Committee,⁸³ or the New Zealand Data Ethics Advisory Group,⁸⁴ which are intended to provide non-binding guidance on the ongoing use of algorithmic systems by public agencies on issues including human-rights compliance, scientific validity, privacy and ethics.

76 Bovens, M., and Wille, A., (2020).

77 Kak, A., (ed) (2020). *Regulating Biometrics: Global Approaches and Urgent Questions*, AI Now Institute. Available at: <https://ainowinstitute.org/regulatingbiometrics.pdf>

78 ACLU. (2021). *Community Control Over Police Surveillance (CCOPS) model bill*. Available at: <https://www.aclu.org/legal-document/community-control-over-police-surveillance-ccops-model-bill>

79 New Zealand Government (2020). *Data Ethics Advisory Group*, data.govt.nz. Available at: <https://data.govt.nz/leadership/advisory-governance/data-ethics-advisory-group/>

80 West Midlands Police and Crime Commissioner (2021). *Ethics Committee*. Available at: <https://www.westmidlands-pcc.gov.uk/ethics-committee/>

81 Office of the Mayor, City of New York. (2019). *Executive Order No. 50: Establishing An Algorithms Management And Policy Officer*. Available at : <https://www1.nyc.gov/assets/home/downloads/pdf/executive-orders/2019/eo-50.pdf>

82 City of Oakland. *Privacy Advisory Commission*. Oaklandca.gov. Available at: <https://www.oaklandca.gov/boards-commissions/privacy-advisory-board>

83 West Midlands Police and Crime Commissioner. (2021). *Ethics Committee*. Available at: <https://www.westmidlands-pcc.gov.uk/ethics-committee/>

84 New Zealand Government. (2020). *Data Ethics Advisory Group*, data.govt.nz. Available at: <https://data.govt.nz/leadership/advisory-governance/data-ethics-advisory-group/>

Oversight bodies also act as forums where a diversity of expertise and participation can be brought together, which is crucial for the effectiveness of any accountability mechanism. For example, the West Midlands Police Data Ethics Committee has members with expertise in data science, law, human rights, ethics, victimisation and social exclusion, and includes representatives of the community as well as senior police officials. The Washington State Bill S.B. 6280, established a task force for surveillance oversight, with members of government, private retailers, as well as ‘representatives from advocacy organisations that represent consumers or protected classes of communities historically impacted by surveillance technologies including, but not limited to, African American, Hispanic American, Native American, and Asian American communities, religious minorities, protest and activist groups, and other vulnerable communities’.⁸⁵

Case study: --- New York City Automated Decisions Task Force

In 2017, New York City Council passed Bill Int. 1696, establishing an ‘Automated Decision Systems Task Force’ to examine government use of automated decision-making systems and to make recommendations to the mayor and the City Council on a number of specific concerns, including on standards and procedures to be followed in the implementation of automated decision systems (ADS) by public agencies in New York City.

The report of the ADS Task Force was released in November 2019,⁸⁶ and contains a number of recommendations on the ‘responsible use’ of ADS, including building organisational structures for managing ADS use across agencies, improving processes for the public to learn about and engage with ADS use, and implementing management functions like standards for reporting ADS or assessments of ADS for disproportionate impact.

Some of these recommendations were incorporated within Executive Order 50 of 2019, which established an Algorithmic Management and Policy Officer (AMPO)⁸⁷ as a centralised agency for managing ADS use in the city. As of July 2021, the AMPO has managed to publish one compliance report, consolidating some uses of ADS across public agencies, and briefly describing their purpose and function.

The functioning of the ADS Task Force as a forum for algorithmic accountability and oversight has been criticised. A shadow report of the ADS Task Force prepared by civil society, citizen advocacy groups and experts indicates some of the challenges that arose in the functioning of the Task Force.⁸⁸ The report highlights the lack of public outreach and mechanisms for

85 Washington State Legislature. (2020). *SB 6280 – 2019-20: Concerning the use of facial recognition services*. Available at: <https://app.leg.wa.gov/bills/summary?BillNumber=6280&Year=2019&Initiative=false>

86 New York City. *New York City Automated Decision Systems Task Force*. Available at: <https://www1.nyc.gov/site/adstaskforce/index.page>

87 NYC. *Algorithms Management and Policy Officer*. Available at: <https://www1.nyc.gov/site/ampo/index.page>

88 Richardson, R., (ed.) (2019). *‘Confronting Black Boxes: A Shadow Report of the New York City Automated Decision System Task Force’*. AI Now Institute. Available at: <https://ainowinstitute.org/ads-shadow-report-2019.pdf>

incorporating public feedback in the Task Force process, as well as the opacity of the Task Force process more generally. Further, it highlights the lack of information provided to members of the Task Force (particularly, of non-government members) about ADS systems used by city agencies, which prevented the Task Force from fulfilling its mandate.

The experience of the Task Force also raises a number of questions about how external oversight mechanisms should be constructed, including the kinds of expertise and diversity that should be assembled in such mechanisms, and what the scope of these bodies should be. For example, both the Task Force report and the shadow report, describe how a large portion of the Task Force's time was devoted to negotiating and contesting questions about the scope of ADS that should be subject to scrutiny.

7. Human oversight and rights to explanation, hearing and appeal

Some policies require that decisions made with the aid of algorithmic systems adhere to particular procedures, as a means of ensuring fairness and providing forums for individual redress in the case of a biased or erroneous decision. These procedural protections are intended to provide forums for affected individuals or groups to debate or contest particular decisions that affect them. They include providing notice of the decision and a hearing to the affected parties, the duty to provide reasoned decisions and explanations of a decision, the right of affected parties to present evidence and or the right to have 'human intervention' in the decision-making process.

Mechanisms like this, that attempt to ensure accountability by implementing fair processes, have a long history within legal and institutional frameworks for administrative accountability.

Theory of change and assumptions

Rights to hearing and appeal, and the requirements of fair procedure in such hearings, are intended to provide particular forums where the propriety of administrative decisions can be debated and addressed.⁸⁹

Procedural protections like notice, explanations and forums for hearing and appeal are intended to allow affected individuals and groups to contest decisions that do not meet specific legal standards, for example, those that are arbitrary, or which take into account irrelevant information. They are intended to respond to fairness and accountability concerns raised by algorithmic systems that may make impactful decisions without adequately justifying them, or providing the means to meaningfully contest them.⁹⁰ Appeals to human intervention, on the other hand, are intended to introduce human agency into an algorithmic process and identify particular persons as having ultimate responsibility over decisions taken with the use of algorithmic systems.⁹¹

89 Citron, D., (2007). 'Technological due process.' *Washington University Law Review*. Vol. 85 pp. 1249-1313. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1012360

90 Hildebrandt, M., (2019). 'Privacy as Protection of the Incomputable Self: From Agnostic to Agonistic Machine Learning', *Theoretical Inquiries in Law*. Vol. 19. No. 1. Pp.83-121. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3081776

91 Koulu, R., (2020). 'Proceduralizing control and discretion: Human oversight in artificial intelligence policy.' *Maastricht Journal of European and Comparative Law*. Available at: <https://journals.sagepub.com/doi/full/10.1177/1023263X20978649>

Procedural fairness mechanisms assume that the individuals or groups who are provided a forum to contest decisions are in a position to identify deviation from a norm, and to participate in a decision, or force a correction of a wrongly made decision. In practice, this assumption is routinely tested given the lack of information about these systems and the fact that individuals often lack the bargaining power or resources to pursue complaints. Further, appeals to human intervention often assume that merely having a human-in-the-loop is adequate for ensuring accountability of decisions made using algorithmic systems, often without taking into account how algorithmic systems interact with, and influence, humans and organisational structures of decision-making.⁹²

A prominent example of procedural rights as a mechanism for algorithmic accountability are rights found in the EU General Data Protection Regulation (GDPR) relating to automated decision-making. The GDPR requires data processors using automated data processing to provide notice, allow for forms of appeal to human oversight, and in some cases, to provide explanations of the decisions taken using automated processing of data by an algorithmic system.⁹³ These rules have also been enacted through various national legislations, including in the UK and Ireland.⁹⁴

Duties of notice and explanation, as well as human-in-the-loop requirements, can also be found in the Canadian ADM Directive, while the Aotorea New Zealand Algorithm Charter recommends that agencies allow automated decisions to be appealed, and that the role of human oversight in an automated decision is explained.

Case study: --- Due process rights under the GDPR

The EU General Data Protection Regulation (GDPR) incorporates a number of procedural protections for individuals, for decisions taken using automated processing of information. Most prominently Article 22 of the GDPR has rules regarding solely automated decision-making that has ‘legal’ or ‘significant’ effects on individuals, including a right to require human intervention in such decisions. In cases where these exemptions apply, individuals have rights, among others, to ‘obtain human intervention on the part of the controller, to express his or her point of view and to contest the decision.’

Article 15 of the GDPR also incorporates requirements of ‘explanation’ for decisions taken using automated processing of data, which includes access to ‘information about the logic involved, as well as the significance and the envisaged consequences of such processing’.

92 Green, B., and Chen, Y., (2019). ‘The principles and limits of algorithm-in-the-loop decision making.’ *Proceedings of the ACM on Human-Computer Interaction*. Vol. 3. Issue. CSCW pp.1-24. Available at: <https://dl.acm.org/doi/10.1145/3359152>

93 Article 29 Working Party. (2018). Guidelines on Automated individual decision-making and Profiling for the purposes of Regulation 2016/679. Available at: <https://ec.europa.eu/newsroom/article29/items/612053/en>

94 Malgieri, G., (2019). ‘Automated decision-making in the EU Member States: The right to explanation and other “suitable safeguards” in the national legislations.’ *Computer Law & Security Review* Vol. 35 No.5. Available at: <https://www.sciencedirect.com/science/article/pii/S0267364918303753>

There is little available evidence about the practical implementation of these procedural rights. However, scholars have focused on the ambiguity and limited scope of these protections. For one, it is unclear how the reliance on nominal ‘human intervention’ can address accountability issues for decisions taken with the aid of algorithmic systems, and has been criticised as potentially ‘rubber stamping’ algorithmic decision-making. Moreover, there is ambiguity around the possibility and utility of generating ‘explanations’ for algorithmic decision-making, particularly in the context of systems that incorporate machine-learning techniques.

The GDPR example indicates some of the challenges that procedural mechanisms for accountability face in implementation, including the need for a more granular understanding of how algorithmic systems alter the discretion available to the decision-making institutions, and how (if at all) human intervention or oversight in such processes can be incorporated to ensure meaningful accountability.⁹⁵

8. Procurement conditions

Government procurement conditions have been an important area of intervention for transparency and accountability.⁹⁶ Some policies attempt to translate these general rules of transparency and accountability to algorithmic systems. The rules governing the acquisition of algorithmic systems by governments and public agencies are an important point of intervention in ensuring their accountable use.

Development and deployment of many algorithmic systems (or particular components of these systems) in use by governments are outsourced to vendors, either as product purchases or as service and development agreements. This means that private vendors bear substantial responsibility for the design and deployment of these systems. The terms of the contract, which govern the procurement and acquisition of an algorithmic system from a vendor, are crucial.

When governments acquire algorithmic systems from private vendors, particular procurement conditions may be applied that limit the design and development of an algorithmic system (e.g. to ensure that a system considered for procurement is transparent and non-discriminatory).

While procurement is generally considered a mechanism to promote public management goals – including competition and efficiency – there is a growing recognition of its utility in leveraging procurement mechanisms to ensure transparency and accountability in algorithmic systems, particularly considering that these systems play a crucial role in policymaking and decision-making by public agencies.⁹⁷

95 Edwards, L., and Veale, M. (2017). ‘Slave to the algorithm: Why a right to an explanation is probably not the remedy you are looking for.’ *Duke Law & Technology Review* Vol. 18. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2972855

96 Open Government Partnership. *Open Contracting and Public Procurement*. Available at: <https://www.opengovpartnership.org/policy-area/open-contracting/>

97 Mulligan, D. K., and Bamberger, K. A., (2019). ‘Procurement as policy: Administrative process for machine learning.’ *Berkeley Technology Law Journal* vol. 34 p. 773. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3464203

Theory of change and assumptions

Procurement conditions intend to establish contractual responsibility and liability for an algorithmic system with the vendor who is responsible for its development. Establishing contractual pre-conditions for acquiring algorithmic systems ensures that systems that do not comply with specific conditions of transparency or fairness are not acquired or used by governments, or that, if a vendor fails to meet contractual conditions, they are subject to contractual liability.

Procurement conditions also allow for interventions in the design of algorithmic systems, as well as during their use.⁹⁸ Evidently, procurement conditions are only applicable where a public agency acquires algorithmic systems through a standard procurement process (usually involving open tendering) and may not be applicable in cases where systems are acquired through other means, including those which are internally developed within government, or procured through direct purchases or gifts.

Our review indicates that procurement conditions are increasingly sought to be leveraged by governments to ensure algorithmic accountability. The UK Government has developed extensive guidance on leveraging government procurement mechanisms for artificial intelligence used by public agencies in the UK, including suggestions for ensuring transparency of algorithmic decisions, and fairness in data processing.⁹⁹

The City of Amsterdam requires that procurement of algorithmic systems by public agencies in the city incorporates certain standard clauses in its procurement conditions.¹⁰⁰ These include conditions for transparency, including the right of government auditors or agencies to examine the underlying data and models; conditions for the vendor to assess algorithmic systems for bias, and risk management strategies to be complied with by the vendor. Similar considerations for procurement are also included in the Tamil Nadu Safe and Ethical AI Policy.¹⁰¹

Procurement is also leveraged for accountability in the AI source list of the Government of Canada – a list of authorised vendors from whom procurement is expedited. A condition for inclusion in the AI source list is ‘demonstrated competence in AI ethics’.¹⁰²

98 World Economic Forum. (2020). *AI Government Procurement Guidelines*. Available at: <https://www.weforum.org/reports/ai-procurement-in-a-box/ai-government-procurement-guidelines>

99 UK Government. (2020). *Guidelines for AI Procurement*. Available at: <https://www.gov.uk/government/publications/guidelines-for-ai-procurement>

100 Municipality Amsterdam. (2020). *Standard Clauses for Municipalities for Fair Use of Algorithmic Systems*. Available at: <https://www.amsterdam.nl/innovatie/>

101 Government of Tamil Nadu. (2020). *Safe and Ethical AI Policy*. Available at: <https://elcot.in/sites/default/files/AIPolicy2020.pdf>

102 Government of Canada. (2015). *AI Source List*, Public Services and Procurement Canada. Available at: <https://buyandsell.gc.ca/procurement-data/tender-notice/PW-EE-017-34526>

Case study: --- Standard clauses for the procurement of algorithmic systems

The City of Amsterdam in 2020 published and adopted the 'Standard Clauses for Municipalities for Fair Use of Algorithmic Systems' (Standard Clauses).¹⁰³ This document is legally mandated for the procurement of algorithmic systems by public agencies in Amsterdam, and establishes contractual terms between the public agency and an external contractor providing the system. The scope and application of the Standard Clauses have been further explained through an explanatory memorandum.

The Standard Clauses establish conditions to be followed for the procurement of any algorithmic system, whether the procurement is through a service or development agreement or as a purchase. These conditions include, among other things: reviews of 'data quality' to ensure the avoidance of distortions, inaccuracies and biases; establishing that the rights to the data used or collected through the use of the algorithmic system will lie with the municipality; quality assurance about compliance of the algorithmic system with laws, and assurances of accuracy; transparency into the functioning of the algorithmic system, including a mandate to make the working of the system auditable and explainable to the municipality or to an external auditor; and risk identification and management requirements for the contractor.

The Standard Clauses are a novel experiment in using project management tools available under government procurement systems to ensure accountability in the design and functioning of algorithmic systems procured from non-government vendors. They establish mechanisms for transparency and demarcate responsibilities for the functioning of algorithmic systems between public agencies and contractors, which are notable areas of opacity and failures of accountability in the use of algorithmic systems.

¹⁰³ City of Amsterdam. (2020). *Standard Clauses for Municipalities for Fair Use of Algorithmic Systems*. Available at: <https://www.amsterdam.nl/innovatie/digitalisering-technologie/contractual-terms-for-algorithms/>

Learning from the first wave of algorithmic accountability policy implementation

In this section we describe, based on findings from our literature review and interviews with domain experts and officials responsible for implementing the policies, some of the factors that determine whether algorithmic accountability policies meet their stated objectives. It also explores how policymakers can be attendant and responsive to these factors, and design policy interventions that are suitable to their particular contexts.

The design and implementation of algorithmic accountability policies is heavily dependent on social and political contexts, which vary widely and include systemic factors such as political will, effective legal institutions and the rule of law. Context determines both the forms of algorithmic accountability policies that emerge in different jurisdictions, as well as how they are implemented and what their effect is.

This section identifies six lessons, which will help to shape the effective deployment and implementation of algorithmic accountability policies:

1. Clear institutional incentives and binding legal frameworks can support consistent and effective implementation of accountability mechanisms, supported by reputational pressure from media coverage and civil society activism.
2. Algorithmic accountability policies need to clearly define the objects of governance as well as establish shared terminologies across government departments.
3. Setting the appropriate scope of policy application supports their adoption. Existing approaches for determining scope such as risk-based tiering will need to evolve to prevent under- and over-inclusive application.
4. Policy mechanisms that focus on transparency must be detailed and audience appropriate to underpin accountability.
5. Public participation supports policies that meet the needs of affected communities. Policies should prioritise public participation as a core policy goal, supported by appropriate resources and formal public engagement strategies.
6. Policies benefit from institutional coordination across sectors and levels of governance to create consistency in application and leverage diverse expertise.

1. Clear institutional incentives and binding legal frameworks can support the consistent and effective enforcement of accountability mechanisms, supported by reputational pressure from media coverage and civil society activism

Algorithmic accountability policies have been implemented across a number of institutional and legal contexts. Some policy frameworks are implemented through direct legislative mandates, as in the case of transparency requirements under the French Digital Republic Bill,¹⁰⁴ or the city-level legislation in various US cities, which has established oversight mechanisms for algorithmic systems, including in New York,¹⁰⁵ San Francisco,¹⁰⁶ Oakland¹⁰⁷ and Seattle.¹⁰⁸ Other policies have been implemented through executive orders and delegated legislation – including the Canadian Directive on Automated Decision-Making, and the New York Executive Order establishing the Algorithms Management and Policy Officer.

In many cases, there is no clear legal framework for the implementation of policy mechanisms, and as such, they are intended to be implemented through less formal or non-binding incentive structures, including voluntary commitments (as in New Zealand's Algorithm Charter)¹⁰⁹ or as non-binding guidance (as in the UK Government's Guidance on AI in the Public Sector,¹¹⁰ and the Data Ethics Framework,¹¹¹ among others).

Legal frameworks

The use of a legal framework to implement a policy can be a crucial factor influencing the degree of adoption of these policies within public agencies. Existing policies fall within a spectrum of legal backing – from entirely voluntary, to those with specific authorising legislation.

104 Government of France. (2016). *The Digital Republic bill - Overview*. Available at: <https://www.republique-numerique.fr/pages/in-english>

105 Office of the Mayor, City of New York. (2019). *Executive Order No. 50 November 19, 2019 Establishing An Algorithms Management And Policy Officer*. Available at: <https://www1.nyc.gov/assets/home/downloads/pdf/executive-orders/2019/eo-50.pdf>

106 San Francisco Board of Supervisors. (2019). *Acquisition of Surveillance Technology Ordinance*. Available at: <https://www.sanfranciscopolice.org/your-sfpd/policies/19b-surveillance-technology-policies>

107 City of Oakland, California. (2021). *Code Of Ordinances*. Available at: https://library.municode.com/ca/oakland/codes/code_of_ordinances?nodeid=tit9pupemowe_ch9.64reacus_sute

108 Seattle, Wash., Mun. Code §§14.18.020(A). 2017.

109 New Zealand Government. (2020). *Algorithm Charter for Aotearoa New Zealand*. Available at: https://data.govt.nz/assets/data-ethics/algorithm/Algorithm-Charter-2020_Final-English-1.pdf

110 Office for Artificial Intelligence. (2021). *A guide to using artificial intelligence in the public sector*. UK Government. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/979892/A_guide_to_using_AI_in_the_public_sector__Print_version_.pdf

111 Central Digital and Data Office. (2021). *Data Ethics Framework*. UK Government. Available at: <https://www.gov.uk/government/publications/data-ethics-framework>

Legal frameworks on their own are neither necessary nor sufficient determinants for the implementation of policy mechanisms – the effectiveness of legal frameworks depends on a number of factors, including political will and cultural norms. Some public official respondents indicated that adversarial approaches, including legal sanctions for non-compliance with algorithmic accountability policy, can be a disincentive to innovation within agencies, and may also require additional resources for establishing mechanisms for monitoring and enforcement. Additionally, particularly at this early stage of the development and use of algorithmic accountability policy, mechanisms that are intended to be non-mandatory statements of principles or values can provide important points of convergence on which to base subsequent legal or regulatory frameworks.

These caveats aside, in general, establishing algorithmic accountability policy through formal legal frameworks can provide important incentives for implementation, including the potential of judicial or legislative review and oversight. Policy mechanisms that are adopted through legislation have a clearer and more certain path to institutionalisation, such as in the cases of local Surveillance Technology ordinance in Oakland, USA, or the Automated Decisions Task Force law in New York City, USA.¹¹²

As one public official respondent described, implementing algorithmic accountability policy through legislation, whether primary or secondary, ensures that the policy is ‘on the agenda’ of government agencies. Embedding mechanisms within existing state institutions and systematically implementing them, for example within budget agendas or oversight mechanisms, can provide important incentives for the implementation of algorithmic accountability initiatives. Outlining potential consequences or sanctions in cases of non-compliance, as has been included within Canada’s Directive on Automated Decision-Making, can also provide clarity on incentives for the implementation of policy measures by public agencies.¹¹³

An empowering legal mandate is also crucial for external oversight bodies or auditors to access information that is required to assess and evaluate an algorithmic system. For example, the New York ADS Task Force was not empowered to survey or inspect algorithmic systems that they are supposed to oversee, and this severely limited its ability to effectively perform its mandate.¹¹⁴ One respondent from the Government of France also noted that the presence of a ministerial mandate for regulatory inspection of an algorithmic system used by a public agency was instrumental in gaining access to, and ensuring the effective implementation of the auditor’s mandate.

When developing legal frameworks, an important consideration is the extent to which they leverage existing mechanisms of administrative accountability, such as existing rules governing administrative conduct in a jurisdiction.

Scholarship on administrative use of algorithmic systems has focused on the relevance of administrative procedural frameworks (such as requirements of notice and a hearing, or limits on administrative discretion by requiring irrelevant evidence to be discarded), in establishing algorithmic accountability for administrative agencies, through protecting

112 New York City Council. (2018). *Automated decision systems used by agencies*. Available at: <https://legistar.council.nyc.gov/LegislationDetail.aspx?ID=3137815&GUID=437A6A6D-62E1-47E2-9C42-461253F9C6D0>

113 Government of Canada. (2019) *Directive on Automated Decision-Making* Available at: <https://www.tbs-sct.gc.ca/pol/doc-eng.aspx?id=32592>.

114 Richardson, R (ed.). (2019). *Confronting Black Boxes: A Shadow Report of the New York City Automated Decision System Task Force*. AI Now Institute. Available at: <https://ainowinstitute.org/ads-shadow-report-2019.pdf>

individual interests and establishing public legitimacy of administrative decisions.¹¹⁵ Principles of administrative accountability such as due process and limits on administrative discretion are well-established and embedded within institutional frameworks, which can be leveraged in policies for the accountability of algorithmic systems. However, most policy frameworks have been conspicuously silent on how established principles and structures of administrative accountability could be applied to the use of algorithmic systems.¹¹⁶

Only a few of the policies we surveyed leverage existing administrative frameworks for accountability in this way. These include Canada's ADM Directive, which is linked to its Management Accountability Framework,¹¹⁷ and the Australian Ombudsman's guidance on administrative law and automated decision-making, which is one of the first examples of policy documents on algorithmic decision-making and stems from a comprehensive report by the Australian Administrative Review Council in 2004.¹¹⁸

Internal incentives

Respondents pointed to other important internal incentives, beyond legal frameworks, as factors in implementation. Several public officials interviewed noted that reputational challenges (like critical media coverage or public protest) from concerns or failures around algorithmic systems were a key driver for the implementation of accountability policies.

In the case of the Governments of Canada and the Netherlands, for example, respondents noted that the adoption of accountability policies is often triggered by particular instances of increased media scrutiny over government use of algorithmic systems.

Some respondents also noted that public officials and agencies are driven by the desire for effective and accountable delivery of services to the general public. Such cultural norms of professionalism for public agencies, whose legitimacy depends on public trust, distinguish them from the incentives of private actors who depend on incentives like profit making.

Respondents also noted that while public agencies want to be seen as modernising and innovating in the artificial intelligence and technology sector, reputational concerns have spurred an institutional focus on 'responsible innovation' and encouraged publication of information about how agencies were implementing policy commitments.¹¹⁹

115 Citron, D., (2007). 'Technological due process.' *Washington University Law Review*. Vol. 85 pp. 1249-1313. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1012360

116 For example, see Freeman Engstrom, D., et. al. (2020). *Government by Algorithm: Artificial Intelligence in Federal Administrative Agencies*. Available at: <https://law.stanford.edu/education/only-at-sls/law-policy-lab/practicums-2018-2019/administering-by-algorithm-artificial-intelligence-in-the-regulatory-state/acus-report-for-administering-by-algorithm-artificial-intelligence-in-the-regulatory-state/>

117 Government of Canada. *Management Accountability Framework*. Available at: <https://www.canada.ca/en/treasury-board-secretariat/services/management-accountability-framework.html>

118 Administrative Review Council (Australia). (2004). 'Automated Assistance in Administrative Decision Making: Report to the Attorney-General'. *Australian Government*. Available at: <https://www.ag.gov.au/legal-system/publications/report-46-automated-assistance-administrative-decision-making-2004>

119 For an account of how reputational factors influence public administration management and accountability, see: Busuioac, M. and Lodge, M. (2017). 'Reputation and accountability relationships: Managing accountability expectations through reputation.' *Public Administration Review* Vol. 77 No.1pp. 91-100. Available at: <https://onlinelibrary.wiley.com/doi/10.1111/puar.12612>

2. Algorithmic accountability policies need to clearly define the objects of governance as well as establish shared terminologies across government departments

There is substantial ambiguity in identifying the appropriate object of governance for algorithmic accountability policies. There is often no standard practice or shared vocabulary for defining technologies that should be the focus of policy interventions. Policy interventions reviewed identify a number of closely related technologies and technology-mediated systems as the subject of accountability measures, including ‘artificial intelligence’,¹²⁰ ‘algorithm’,¹²¹ ‘automated decision-making’¹²² and occasionally ‘data science’ or ‘data analytics’.¹²³

Definitional ambiguity is a challenge both at the stage of designing policy (as was evident in the New York City ADS Task Force’s lack of consensus on a definition of ADS),¹²⁴ and in its implementation, particularly when its implementation requires the interpretation of policy at a decentralised level by disparate public agencies. Various respondents noted that the lack of standardisation and clarity in definition as an obstacle in interpreting and implementing policy requirements – it can be hard for agencies to know with confidence which technologies or systems policies refer to. This was also noted in the UK CDEI’s review of bias in algorithmic systems,¹²⁵ and the New Zealand Government in their consultations on the Algorithm Charter with public agencies.¹²⁶

Some policies adopt a broad definition, focusing not only on specific technological thresholds, but on their function and impact in a particular context. For example, the City of Amsterdam’s Standard Clauses for the procurement of algorithms and the New Zealand Algorithm Charter have explicitly adopted a definition that would be inclusive of even relatively simple algorithmic processes.

Since most algorithmic systems are applied in the context of government decision-making of various kinds, certain definitions focus on the relationship between algorithms and the decision-making process at play i.e. whether they ‘automate, aid, or replace’ human decision-making. Such definitions have been adopted in the Canadian Directive on ADM, as well as in the GDPR and its national implementations.

120 E.g. Uruguay’s AI Strategy for Digital Government.

121 E.g. Algorithm Charter for Aotearoa New Zealand. 2020.

122 E.g. General Data Protection Regulation. 2016.

123 E.g. UK Data Ethics Framework. 2021.

124 See Richardson, *supra* note 112.

125 Centre for Data Ethics and Innovation. (2020). *Review into bias in algorithmic decision-making*. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/957259/Review_into_bias_in_algorithmic_decision-making.pdf

126 New Zealand Government. (2020). *Algorithm Charter for Aotearoa New Zealand*. Available at: https://data.govt.nz/assets/data-ethics/algorithm/Algorithm-Charter-2020_Final-English-1.pdf

Adopting broad definitions, particularly in an area where new accountability concerns are constantly being unearthed, can also ensure much-needed dynamism in the application of policy mechanisms. A respondent from the French Government, for example, noted that the application of a technology-agnostic definition assisted their department in the application of policy mandates to a broad range of algorithms which are of concern.

Recognising the need to have a definition which captures the breadth of technological systems, and incorporates a contextual understanding of their use, Richardson outlines the following definition of an ‘automated decision system’ for use and adaptation across policy contexts:

“Automated Decision Systems” are any systems, software, or process that use computation to aid or replace government decisions, judgments, and/or policy implementation that impact opportunities, access, liberties, rights, and/or safety. Automated Decisions Systems can involve predicting, classifying, optimizing, identifying, and/or recommending.¹²⁷

3. Setting the appropriate scope of policy application supports their adoption. Existing approaches for determining scope such as risk-based tiering will need to evolve to prevent under- and over-inclusive application

Another area of ambiguity is the scope of the systems that policies should apply to. Closely tied to the former question of defining the object, it also considers how to prioritise the application of policies to ensure maximum impact, and identifies the degree of scrutiny which should be applied to different algorithmic systems.

A common concern voiced by public officials is the risk of overburdening public agencies by placing mundane or routine algorithmic processes which do not appear to have significant social impacts under review. Respondents from the Governments of Canada and New Zealand noted that limiting the scope of application of the policy, at least initially, helped encourage its adoption within public agencies who may otherwise be hesitant to expend substantial resources on compliance. During the consultations on appropriate scope of regulation conducted during the framing of the algorithm charter in Aotearoa New Zealand, public agencies ‘suggest that a widened scope would have high compliance costs, and ultimately lead to potential delays in delivering analytic work and reduced transparency as the public could find it difficult to determine which algorithms have the greatest impact on decisions affecting them.’¹²⁸

In this section we describe the various factors that are used to determine whether and when a particular system should be subject to policy scrutiny.

127 Richardson, R., (2021). ‘Defining and Demystifying Automated Decision Systems’ *Maryland Law Review*. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3811708

128 New Zealand Government. (2020). *Consultation and submissions summary: draft algorithm charter*. Available at: <https://www.data.govt.nz/docs/sub-summary-algorithm-charter/>

Degree of human oversight

Some policies attempt to narrow the scope of application by excluding algorithmic systems which have some level of human oversight. For example, the EU GDPR attempts to limit its intervention to ‘solely’ automated decision-making systems, as opposed to systems where there is a ‘human-in-the-loop’ who makes the ultimate decision. A respondent from the Canadian Government also indicated that there continues to be ambiguity about the Directive on Automated Decision-Making applying only to automated systems which make decisions without any human input. This is despite the definition including systems which ‘assist’ in human judgement. The Canadian Department of National Defence, for example, has stated that it does not need to comply with the Directive for its use of an automated hiring tool, because the tool did not make the ‘final decisions’.¹²⁹

As noted previously, focusing only on nominal or notional human oversight ignores the complex interactions between algorithmic systems and human decision-makers using such systems. This includes the different ways in which the decisions of humans may be influenced by the outcomes of algorithmic processes. Moreover, it risks diverting responsibility for complex algorithmic systems away from structural concerns, and towards symbolic human agents, who act as ‘moral crumple zones’ for blameworthiness.¹³⁰

Taken together, this means that the scope of the policy intervention should be broad enough to cover decisions aided or influenced by algorithmic or automated decision-making technologies, and that nominal human oversight should not be considered a replacement for meaningful and systemic accountability. Future iterations of policies should also seek to resolve these definitional ambiguities by specifically bringing attention to ways in which human decision-making is mediated through algorithmic systems, including through guidance documents or supplementary interpretive texts.

Individual versus group-level decisions

Some policies also limit their scope of application to ‘decisions’ that impact individuals, as in the GDPR or the Canadian Directive on ADM. Various scholars have noted the limitations of individual-focused accountability regimes.¹³¹ Firstly, measuring, or accounting for impacts at the individual level can ignore systematic harms and discrimination that impact particular groups

129 Cardoso, T., and Curry, B., (2021). ‘National Defence skirted federal rules in using artificial intelligence, privacy commissioner says’. *The Globe and Mail*. Available at: <https://www.theglobeandmail.com/canada/article-national-defence-skirted-federal-rules-in-using-artificial/>

130 Elish, M. C., (2019). ‘Moral crumple zones: Cautionary tales in human-robot interaction.’ *Engaging Science, Technology, and Society*. Vol.5 pp. 40-60. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2848825

131 Taylor, L., (2016). ‘Safety in Numbers? Group Privacy and Big Data Analytics in the Developing World’ in *Group Privacy: the challenges of new data technologies*, Eds. Taylor, L. van der Sloot, B., Floridi, L., Springer: 2017. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2848825

or classes, even where decisions are not made concerning identified individuals. Secondly, algorithmic systems contribute to important policymaking processes in ways that can impact values of public transparency and the accountability of democratic processes in policymaking, for example, by obscuring the data or logic that informs policies.

Our review indicates that policymakers are cognisant of the limitations of individual-focused policy mechanisms, and of the need to consider both group-level impact, as well as wider societal consequences when algorithms are used in policymaking. In fact, a number of policies do identify group harms and impacts as a policy focus – including the New Zealand Algorithm Charter and the UK Data Ethics Framework.

As a respondent from Canada noted, the Directive on ADM's limited focus on ADM affecting only individual legal persons prevented the operation of the policy in other, potentially concerning, uses of ADM, including to make policy choices affecting particular groups. There are, however, a number of policies that do identify group harms and impacts as a policy focus – including the New Zealand Algorithm Charter and the UK Data Ethics Framework. The Algorithm Assessment Report of the New Zealand Government flags the limitations of focusing only on individual impact, and recommends that the scope is expanded to include algorithms utilised in policymaking.¹³²

Governments should consider how the scope of algorithmic accountability policies could be expanded beyond individual impact, to cover collective harms to specific groups, as well as broader societal consequences of administrative decisions. This should include the implementation of broader structural mechanisms like system audits, inspections and oversight that take into account systematic effects of these technologies, apart from rights-based regimes for individuals and groups.

Risk-based tiered approach

The perceived risk or impact of an algorithmic system is also an increasingly prominent factor used to determine the application of policy mechanisms. Some contexts, like law enforcement and criminal justice, are widely accepted as high-risk areas. This is reflected in policy priorities in various jurisdictions – for example, policy mechanisms that focus on the use of algorithmic systems in law enforcement contexts (as in the West Midlands Police Data Ethics Board,¹³³ or on legislation on law enforcement use of facial recognition technologies), or legislation that regulates the use of pre-trial risk assessment scores by the judiciary (as in the Idaho Criminal Procedure Code).¹³⁴ However, there is no clear accepted standard for assessing the risk posed by the use of algorithmic systems more generally, across contexts in which public agencies operate.

132 New Zealand Government. (2020). *Algorithm Assessment Report*. Available at: <https://www.data.govt.nz/toolkit/data-ethics/government-algorithm-transparency-and-accountability/algorithm-assessment-report/>

133 West Midlands Police and Crime Commissioner. (2021). *Ethics Committee*, Available at: <https://www.westmidlands-pcc.gov.uk/ethics-committee/>

134 Idaho Judiciary, Rule and Administration Committee. (2019). *House Bill No. 118. Legislature of the State of Idaho*. Available at: <https://legislature.idaho.gov/wp-content/uploads/sessioninfo/2019/legislation/H0118E2.pdf>

Some jurisdictions have attempted to navigate this challenge by adopting a tiered approach towards the implementation of policy obligations. For example, both Canada and Aotearoa New Zealand require an initial 'risk assessment', the results of which determine the different kinds of obligations which would apply. A risk-based approach, especially at an early or intermediate level of implementation, may help balance the resource limitations of public agencies and oversight bodies with the urgent needs for governing and regulating potentially harmful forms of automated decision-making. Impact assessment or risk assessment frameworks, as utilised in Canada, can be a useful method for agencies to identify, and appropriately mitigate for potential risks and impacts, as a first step to the application of more specific regulation.

Despite its intuitive appeal in narrowing the scope of policy application, binary or rigid risk tiering might also result in an over- or under-inclusive scope. Understandings of risk should be appropriate to the specific societal, political and institutional contexts within which an algorithmic system is being deployed. For example, certain 'high-risk' contexts might already deploy institutionalised forms of accountability that are responsive to their particular contexts. In other instances, what might otherwise be perceived as a 'low-risk' use-case might exist in a context of less scrutiny or institutional accountability.

However, 'risks' and harms are ultimately contextual, and in many circumstances defy measurement. This means that regulatory design must balance risk-based approaches with uncertainty-based approaches towards threats caused by algorithmic systems. These demand greater precaution and recognition of systematic and diffuse harms that might arise in the use of algorithmic systems, but may be difficult to quantify and manage in risk-based approaches.¹³⁵

Appropriate stage of intervention

Another concern regarding the scope of application of policy mechanisms is identifying the appropriate stage at which to intervene. Alan Turing Institute research notes that 'Human error, prejudice, and misjudgement can enter into the innovation lifecycle and create biases at any point in the project delivery process from the preliminary stages of data extraction, collection, and pre-processing to the critical phases of problem formulation, model building, and implementation.'¹³⁶

Various respondents from governments echoed a related concern around their limited ability to effectively intervene in the design of the algorithmic systems, as opposed to only in their use. As public agencies are increasingly relying on private vendors to provide different components of an algorithmic system, respondents were apprehensive of becoming 'rule-takers' for technologies. They were concerned agendas and rules for issues like transparency and bias are in practice determined by private companies, with little visibility or points of intervention provided to governments.

135 Cohen, J. E., (2016). 'The regulatory state in the information age.' *Theoretical Inquiries in Law* vol.17no.2 pp.369-414. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2714072

136 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*. Available at: <https://www.turing.ac.uk/research/publications/understanding-artificial-intelligence-ethics-and-safety>

This cautions policymakers to be attendant to issues of coordination between public and private sectors, and to questions of governance and design of algorithmic technologies, particularly those which establish the agendas for the development of these technologies within the private sector, for example, through participation within standard-setting institutions.

An emerging method through which public agencies can meaningfully intervene at the stage of the design of an algorithmic system is through procurement laws and conditions, such as with the standard terms of contract established by the City of Amsterdam, or Canada's AI Procurement Source List. They attempt to ensure that systems being embedded within public agencies adhere to particular standards of accountability and transparency, as defined by the contractual conditions through which a government agency purchases an algorithmic system.

4. Policy mechanisms that focus on transparency must be detailed and audience appropriate to underpin accountability

Transparency is a key focus of the policy mechanisms we reviewed. The central questions that arise in the implementation of transparency of algorithmic systems are 'transparency of what' and 'transparency to whom'.

Transparency concerns arise both around the specific decisions made about particular individuals or groups, as well as more general concerns around how the use of algorithmic systems is contributing to the function of particular public agencies, including policymaking and administrative functions. Policy mechanisms focused on meaningful transparency are fundamental in shaping the possibilities for intervention both internally within government accountability mechanisms, as well as externally through civic participation and advocacy.

There is a lack of standard practice about the kinds of information that should be documented in the creation of algorithmic systems, with a view to ensuring fairness and transparency.¹³⁷ Information considered crucial to the accountability function of transparency mechanisms, may simply not be documented. The implementation of algorithmic accountability mechanisms is likely to be fundamental in shaping documentation practices which can enable effective transparency going forward.

Our review indicates two important factors shaping the implementation of policies intended to provide meaningful transparency at this early stage:

1. Agencies must **balance transparency requirements against perceived trade-offs** of competing policy goals favouring confidentiality.
2. **Practical limitations to meaningful transparency**, specifically around what kinds of information to release, and how.

¹³⁷ Raji, I. D, et al. (2020). 'Closing the AI accountability gap: defining an end-to-end framework for internal algorithmic auditing.' *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*. Available at: <https://arxiv.org/abs/2001.00973>

1. Balancing transparency against perceived trade-offs of competing policy goals

These competing policy objectives include concerns around privacy in underlying data systems (as noted in the UK Data Ethics Framework),¹³⁸ concerns about protecting business critical intellectual property, particularly trade secrets and copyrighted information held by private vendors, (as provided for in the Canadian ADM Directive,¹³⁹ as well as the Amsterdam Standard Clauses for Municipalities)¹⁴⁰ or, in particular contexts, concerns about state security.

A recurrent concern raised by public official respondents relates to how transparency of the functioning of algorithmic systems might allow the system to be gamed by adversaries or bad actors, particularly in systems designed to identify fraud or patterns of behaviour, and through sophisticated adversarial attacks intended to fool machine-learning systems.¹⁴¹ In most cases, these exemptions are broadly worded and do not provide meaningful information about how public officials should negotiate trade-offs between transparency and confidentiality.

There needs to be particular challenge to broad and unsubstantiated claims of security risks arising from public disclosures. During deliberations for the (now enacted) New York City POST Act, experts made depositions before the City Council that the public disclosures about surveillance systems demanded by the Act would provide valuable insights to the public but were far from sufficiently detailed for someone to game the system and threaten public safety.¹⁴²

Transparency mechanisms should be designed keeping in mind the potential challenges posed by countervailing policy objectives requiring confidentiality, and trade-offs between transparency and other objectives should be negotiated when deciding to use an algorithmic system. This includes agreeing acceptable thresholds for risk of systems being gamed or security being compromised, and resolving questions about transparency and the ownership of underlying intellectual property. The Standard Clauses for Procurement of Fair Algorithms,¹⁴³ in Amsterdam City, for example, include a requirement to make the algorithmic system available for independent audit, as well as for information about explainability to be publicly disclosed.

138 Central Digital and Data Office. (2021). *Data Ethics Framework*. UK Government. Available at: <https://www.gov.uk/government/publications/data-ethics-framework>

139 Government of Canada. (2019). *Directive on Automated Decision-Making*, Available at: <https://www.tbs-sct.gc.ca/pol/doc-eng.aspx?id=32592>

140 Municipality Amsterdam. (2020). *Standard Clauses for Municipalities for Fair Use of Algorithmic Systems*. Available at: <https://www.amsterdam.nl/innovatie/>

141 Freeman Engstrom, D., et. al. (2020). *Government by Algorithm: Artificial Intelligence in Federal Administrative Agencies*. Stanford Law School. Available at: <https://www-cdn.law.stanford.edu/wp-content/uploads/2020/02/ACUS-AI-Report.pdf>; Veale, M., Van Kleek, M., and Binns, R., (2018). 'Fairness and accountability design needs for algorithmic support in high-stakes public sector decision-making.' *Proceedings of the 2018 CHI conference on human factors in computing systems*. Available at: <https://arxiv.org/pdf/1802.01029.pdf>

142 Fried, G., (2019). 'Creating Comprehensive Reporting and Oversight of NYPD Surveillance Technologies'. *AI Now Institute*. Available at: <https://ainowinstitute.org/ainow-genevieve-fried-testimony-nyc-hearing-postact.pdf>

143 Municipality Amsterdam. (2020). *Standard Clauses for Municipalities for Fair Use of Algorithmic Systems*. Available at: <https://www.amsterdam.nl/innovatie/>

2. Practical limitations to meaningful transparency

These limitations arise both due to the sheer volume of information and documentation that might exist around a particular algorithmic system and its development, as well as, at the other end of the spectrum, the frequent complete lack of documentation appropriate for being made available to the public.¹⁴⁴ As one respondent noted, in the case where the creation of an algorithmic system was meticulously documented, the intended audience (the public agency using the system) found the information unusable due to its volume and its highly technical language.

This speaks not only to the need to develop internal capacity to better understand the functioning of algorithmic systems, but also to the need to design policies for transparency keeping in mind particular audiences and how information can be made usable by them. In the context of the Amsterdam City Algorithmic Register, one respondent noted that considerations of the intended audience were central to the design of the register. In that case, information in the register was specifically curated towards civil society actors and other critical expert audiences, who might be able to better understand the information provided and would be able to filter information for the use of the general public.

In other policies, such as those that seek to implement a 'right to explanation' for automated decisions, (for example in the Canadian ADM Directive, or under the GDPR) the design of transparency mechanisms will differ substantially, for example, by focusing on providing the logic and parameters on which specific decisions are being made, to affected individuals or groups.

One important focus of policies aimed at ensuring transparency, has been on the publication of the source code of algorithmic systems. Underlying source code can be an important mechanism for the technical transparency of algorithmic systems, and in general, is accepted as a best practice. In France, the Etalab has published detailed guidance on when and how public agencies should publish source code, which is maintained in an open, public directory.¹⁴⁵

At the same time, publishing source code is a very limited aspect of transparency, and may potentially distract from other important disclosures. In particular, transparency-by-design requires looking more holistically at the design and use of an algorithmic system, including its intended goals and the choices made concerning data use, model selection, etc.

Scholarship has focused on how certain standardised documentation processes can promote transparency by design. This includes work on dataset documentation to describe its motivations, composition, collection process, recommended uses, etc.,¹⁴⁶ and documenting choices made in the selection of algorithmic models, such as providing explicit benchmarks for model performance across socio-cultural domains.¹⁴⁷

144 Ananny, M., and Crawford, K., (2016). 'Seeing without knowing: Limitations of the transparency ideal and its application to algorithmic accountability.' *New Media & Society* vol. 20 no.3 pp. 973-989. Available at: <https://journals.sagepub.com/doi/abs/10.1177/1461444816676645?journalCode=nmsa>

145 Etalab. *Overview of the guide*. Available at: <https://guide-juridique-logiciel-libre.etalab.gouv.fr/>

146 Gebru, Timnit, et al. (2018). 'Datasheets for datasets'. *Cornell University*. Available at: <https://arxiv.org/abs/1803.09010>

147 Mitchell, M., et al. (2019). 'Model cards for model reporting.' *Proceedings of the conference on fairness, accountability, and transparency*. Available at: <https://arxiv.org/abs/1810.03993>

Other forms of transparency focus on the decision-making by public agencies, including documenting the perceived public benefit and the purposes of using an algorithmic system (as provided for in the UK Data Ethics Framework).

A related but under-considered issue of meaningful transparency concerns the preservation and archiving of algorithmic systems for historical research, oversight or audits. In general, few transparency mechanisms focus specifically on how to maintain the integrity of archived automated decision-systems, particularly those that change constantly as a result of new forms of data or changes to the software code or models. Focusing on documentation standards should also be accompanied by appropriate practices for archiving such systems for historical research.¹⁴⁸

The form in which information is conveyed is also crucial to its contribution to meaningful transparency. One respondent noted efforts from France regarding making information about algorithmic systems available through sources like video explanations or illustrations, as opposed to written forms which many affected people or users might not be familiar or comfortable with. Additionally, respondents noted the necessity of interactive and/or re-usable forms of information disclosure.

These challenges in transparency also affect the manner in which algorithmic accountability policies are implemented and conveyed to different audiences. Opacity in the course of implementation of policy mechanisms can be a barrier to supply-side accountability (for example, within internal reporting mechanisms) and demand-side accountability, by failing to give adequate information about the implementation of the policies. In part, this can be attributed to the relative recency of these interventions in various jurisdictions, and that few instruments explicitly require public disclosure about the implementation of accountability measures.

In the context of Data Protection Impact Assessments (DPIAs) conducted under the GDPR, commentators have critiqued the lack of mechanisms and requirements for mandatory disclosures to the public as a major obstacle in ensuring their effectiveness.¹⁴⁹ Review mechanisms and mandatory public reporting obligations can play a role in increasing transparency around the implementation of algorithmic accountability policy, such as with the Canadian Government's Directive on ADM, which requires the mandatory publication of Algorithmic Impact Assessments by agencies in an open directory.

148 de Ree, M., (2020). 'How Can We Make Our Algorithm As Fair As Possible.' CBS. Available at: <https://www.cbs.nl/en-gb/corporate/2020/49/how-can-we-make-our-algorithms-as-fair-as-possible->

149 Kaminski, M. E., and Gianclaudio, M., (2020) 'Multi-layered explanations from algorithmic impact assessments in the GDPR.' *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*. Available at: <https://dl.acm.org/doi/abs/10.1145/3351095.3372875>

5. Public participation supports policies that meet the needs of affected communities. Policies should prioritise public participation as a core policy goal, supported by appropriate resources and formal public engagement strategies

The challenge of meaningful transparency is closely related to issues around meaningful public engagement and civic participation in the governance of algorithmic systems.

Few policy interventions have meaningfully attempted to ensure public participation, either from the general public or from persons directly affected by an algorithmic system (including public officials or affected communities). Scholarship in the field of transparency and accountability initiatives suggests that participatory governance is ‘more likely to generate state responsiveness to citizens’ demands because in such circumstances citizens have a higher incentives and capacity for engagement and have interfaces with the relevant institutions via their prior participation.’¹⁵⁰

The lack of avenues for public participation in framing the agenda of the New York City ADS Task Force was one of the major critiques raised in the shadow report on the Task Force, which substantially contributed to its eventual ineffectiveness in responding to the perceived needs of citizens, and to civil society critiques. Proponents of public participation, especially of affected communities, argue it is not only useful for improving processes and principles, but is crucial to designing policies in ways that meet the identified needs of affected communities, and in incorporating contextual perspectives that expertise-driven policy objectives may not meet.¹⁵¹ Meaningful participation and engagement – with the public, with affected communities and with experts within public agencies and externally – is crucial to ‘upstreaming’ expertise to those responsible for the deployment and use of algorithmic systems.

However, respondents from various public agencies noted the need for greater public participation as a demand-side intervention as an obstacle to effective implementation of algorithmic accountability policies. In the context of Algorithmic Impact Assessments, Metcalf et al., state that ‘regulatory agencies do not have adequate access to the types of grounded research, technical expertise, or entrée to affected communities to ensure that any list of impacts it stipulates is adequate to the potential harms people may experience.’¹⁵²

Considerations for public engagement and consultation should also keep in mind the forums in which participation is being sought, and what kind of actors or stakeholders are engaging with the process. Processes for public participation in the context of algorithms requires assembling diverse expertise, including specifically affected communities, technical expertise and advocacy

150 McGee, R., and Gaventa, J., (2011) ‘Shifting power? Assessing the impact of transparency and accountability initiatives.’ *IDS Working Papers* vol. 2011 no.383 (pp.1-39. Available at: <https://onlinelibrary.wiley.com/doi/abs/10.1111/j.2040-0209.2011.00383.2.x>

151 See, for e.g. Richardson, supra note 112; Metcalf, et. al., supra note 41.

152 Metcalf, J, et al (2021). ‘Algorithmic impact assessments and accountability: The co-construction of impacts.’ *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*. Available at: <https://dl.acm.org/doi/abs/10.1145/3442188.3445935>

groups, along with private firms and government agencies. Apart from public engagement, it is important to consult and seek the participation from agencies and public officials likely to use the proposed accountability mechanisms, as the New Zealand Government did in its consultations on the Algorithm Charter.¹⁵³

A minority of the reviewed policy mechanisms had adopted clear and formal public engagement strategies, leveraged public participation forums or included public participation as a policy goal. Notably, the New Zealand Algorithm Charter conducted extensive public consultations, including with public agencies likely to use the policy, which Government respondents noted drew from broader commitments to principles for Maori Data Sovereignty. The Charter's principles also urge implementing agencies towards 'Identifying and actively engaging with people, communities and groups who have an interest in algorithms, and consulting with those impacted by their use.' The Oakland Surveillance and Community Safety Ordinance requires extensive public hearings and consultation provided through existing forums for public outreach (such as public council hearings). Public-facing algorithm registers, including those in Amsterdam, Helsinki and Nantes also explicitly seek civic participation through feedback mechanisms embedded in the registers.

Meaningful public engagement and participatory governance requires not only the provision of formal channels and forums for engagement, but also requires policymakers to consider how various actors with varying resources may be able to contribute within those forums. This means providing educational resources and appropriate time to provide meaningful feedback, and for feedback to be considered and responded to. Summaries of responses received during consultation should be prepared and publicly released along with responses.

In general, there is substantial opportunity for policymakers to leverage existing forms and forums for public participation in policymaking, including, for example, notice and comment mechanisms, or public-hearing processes, which are well established administrative processes used in most jurisdictions. Policymakers can draw from a wealth of scholarship on civic participation in algorithmic governance and efforts by civil society groups to provide guidance on how these forums might be constructed and deployed, for example, the work of the Data Justice Lab, which surveyed forums for public participation like mini publics, community oversight, or participatory budgeting.¹⁵⁴

153 See: New Zealand Government. (2020). *Consultations and submissions summary: draft algorithm charter*. Data.govt.nz. Available at: <https://data.govt.nz/docs/sub-summary-algorithm-charter/>

154 Data Justice Lab. (2021). *Advancing civic participation in algorithmic decision-making*. Available at: https://datajusticelab.org/wp-content/uploads/2021/06/PublicSectorToolkit_english.pdf; see also, Pallett, H., Burall, S., Chilvers, J. and Price, C. (2021). 'Public Engagement with Algorithms in Public Services' *3S Research Group Briefing Note*. Available at: <https://uea3s.files.wordpress.com/2019/10/public-engagement-with-algorithms-in-public-services.pdf>

6. Policies benefit from institutional coordination across sectors and levels of governance to create consistency in application and leverage diverse expertise

There are a broad range of institutional contexts in which public agencies tasked with the implementation of algorithmic accountability policies operate. These include agencies or offices specifically created and tasked for the purpose of implementing algorithmic accountability policies (as in the Algorithms Management and Policy Officer in New York), agencies tasked with data protection legislation (as in the UK Information Commissioner's Office AI Auditing Framework) and in open data, census and statistics organisations (as in New Zealand's Statistics Office responsible for the Algorithm Charter and Data Stewardship, or France's Etalab).

Several kinds of interventions do not emerge from an explicit policy focus on algorithms, instead taking place as part of, or alongside, more general accountability and transparency mechanisms of specific administrative agencies. For example, audits of automated decision-making in Sweden,¹⁵⁵ or the Algorithmic Impact Assessment conducted for the Allegheny County Child Risk Assessment Tool,¹⁵⁶ or the CDEI's assessment of algorithmic discrimination with respect to the UK's Public Sector Equality Duty,¹⁵⁷ which were ad-hoc exercises tied to standards of accountability of public administration not necessarily specific to algorithmic systems. It is important for such interventions to be part of broader and long-term policy focus on algorithmic accountability, as well as for accountability policies to incorporate learnings from these examples.

Policymakers should carefully consider how institutional agendas and capacities might shape the design or implementation of policy objectives, particularly when agencies have leeway in determining the shape and form of policy implementation. For example, the institutional priorities of an agency tasked primarily with enabling government innovation may be different from the priorities of an agency tasked with overseeing privacy or fundamental rights concerns.¹⁵⁸ Therefore policymakers must take into account the institutional context of the implementing executive agency, including the budget and resources provided to the implementing agency, as well as their ability to fulfil mandates for coordinating policy objectives for algorithmic systems used across government agencies.

155 Swedish National Audit Office. (2020). *Automated Decision-Making in Public Administration*. Available at: <https://www.riksrevisionen.se/en/audit-reports/audit-reports/2020/automated-decision-making-in-public-administration---effective-and-efficient-but-inadequate-control-and-follow-up.html>

156 Goldhaber-Fiebert, J., and Prince, L., (2019). *Impact evaluation of a predictive risk modeling tool for Allegheny County's child welfare office*. Pittsburgh: Allegheny County. Available at: https://www.alleghenycountyanalytics.us/wp-content/uploads/2019/05/Impact-Evaluation-from-16-ACDHS-26-PredictiveRisk_Package_050119_FINAL-6.pdf

157 Centre for Data Ethics and Innovation. (2020). *Review into bias in algorithmic decision-making*. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/957259/Review_into_bias_in_algorithmic_decision-making.pdf

158 For theoretical accounts of how institutional contexts affect policy implementation, see Cerna, L., (2013). 'The nature of policy change and implementation: A review of different theoretical approaches' *Organisation for Economic Cooperation and Development*. pp. 492-502. Available at: <https://www.oecd.org/education/ceri/The%20Nature%20of%20Policy%20Change%20and%20Implementation.pdf>

Algorithmic systems can be ‘complex systems’, consisting of various interrelated components operating in dynamic environments. One challenge to the governance of algorithmic systems arises due to this complexity involved in their design and deployment, which requires ‘multi-level’ governance. Various government or non-government agencies might be involved in the design and deployment of a single algorithmic system, which can make the attribution of responsibility and effective coordination between agencies challenging. This problem of ‘many hands’ arises not only in the attribution of legal liability, but also in the need to effectively coordinate responsibility for the implementation of algorithmic accountability policy between different individuals and organisations who may have contributed to certain components of a system.

Contending with this challenge requires building internal institutional capacity and expertise within public agencies that use algorithmic systems, as well as leveraging co-ordination between public agencies who may have expertise on particular areas implicated in the implementation of policy mechanisms. A respondent from the Government of Canada, for example, noted how the implementation of an Algorithmic Impact Assessment questionnaire required coordination from various specialised actors from within institutions, including not only IT departments, but also legal and data protection expertise.

In particular, there is a substantial scope for leveraging existing institutional capacities in agencies tasked with the implementation of data protection law and policy, human rights and administrative law and procedure, to participate in the implementation of algorithmic accountability policy. Algorithmic accountability mechanisms could consider leveraging established mechanisms, including, for example, Data Protection Impact Assessments and surveillance oversight mechanisms, in an effort to establish coordination between relevant administrative agencies and practice, as has been suggested by various scholars.¹⁵⁹

A related challenge for public agencies is to negotiate between the adoption of global principles while considering the local contexts in which they will be applied. As Solow-Niederman and Choi note,¹⁶⁰ algorithmic accountability policy choices must account for the interactions between actors at a global level, and the institutional contexts and local needs and discretions of agencies. Establishing broad, global norms and principles for the governance of algorithmic systems, can conflict with local requirements of tailoring regulatory conditions appropriately to particular contexts. For example, features or information about individuals or communities that contribute to potential discrimination can differ widely across local contexts.

However, allowing for increased discretion at the local level in how global policy commitments are achieved can conflict with requirements of consistency and may also affect mechanisms for transparency and oversight. This speaks to the need for policymakers to be cognisant of potential local-global conflicts in the operation of algorithmic accountability policies, and account for such conflicts by implementing forms of federated accountability, which might include forms of local oversight and particular consideration to local contexts in the reviews and audits of algorithmic systems.

159 Young, M., Katell, M., and Krafft, P.M., (2019). ‘Municipal surveillance regulation and algorithmic accountability.’ *Big Data & Society* 6.2 . Available at: <https://journals.sagepub.com/doi/full/10.1177/2053951719868492>

160 Solow-Niederman, A., Choi, Y., and Van den Broeck, G., (2019). ‘The Institutional Life of Algorithmic Risk Assessment.’ *Berkeley Technology Law Journal*. vol.34 p.705. Available at: <http://starai.cs.ucla.edu/papers/Solow-NiedermanBTLR19.pdf>

Multi-level governance also poses concerns about how knowledge of policy mechanisms is received across government agencies at different levels. The lack of knowledge and comprehension of algorithmic accountability policies across different public agencies as a barrier to their implementation was noted by several respondents in our study. According to Domagala, in her study of public agencies in the UK on the Data Ethics Framework, the lack of awareness was the most prominent obstacle in promoting data ethics tools and practices, with more than a third of surveyed respondents lacking awareness of data ethics policies and guidelines.¹⁶¹

Similarly, a respondent noted that agencies are often apprised of accountability policies only after there are widely publicised failures of algorithmic systems. Mechanisms for collecting and disseminating information to agencies are therefore crucial considerations for the implementation of these systems. Respondents noted a number of mechanisms for communicating policy objectives – including conducting workshops and sessions with public agencies, communicating efforts through professional networks or at conferences, etc. As an intermediate policy goal, jurisdictions could consider focusing on the implementation of the policy mechanisms within particular agencies and documenting the process of implementation, which might provide valuable guidance for other agencies as examples of best practices and challenges that might arise in the course of implementation.

Finally, as noted by various respondents, the increasing participation of private actors in different areas of the use of algorithmic systems in the public sector poses problems for coordination, and ultimately for accountability. This is owing to limitations in visibility of the design of technologies by the private sector, as well as the lack of appropriate mechanisms for public-private coordination or intervention into the design of private technologies by governments. As suggested by Kaminski, resolving these questions requires ‘collaborative governance’ approaches which establish systematic and accountable interfaces, through which governance and coordination can be structured between private and public actors at various stages of the lifecycle of the design and use of algorithmic technologies.¹⁶²

161 Domagala, N. (2020). ‘Data ethics in practice: challenges and opportunities for a data ethics policy function in the public sector’ Presented at the Data for Policy 2020, Zenodo. Available at: <https://zenodo.org/record/3967224>

162 Kaminski, M. E., (2018). ‘Binary Governance: Lessons from the GDPR’s approach to algorithmic accountability.’ *Southern California Law Review*, vol. 92. pp.1529-1616. Available at: https://southerncalifornialawreview.com/wp-content/uploads/2019/12/92_6_Kaminski.pdf

Conclusions and priorities for future research

This study is one of the few comparative and cross-jurisdictional studies about the implementation of algorithmic accountability policies, an emerging area of law, policy and regulation intended to respond to growing recognition and concerns about the social consequences of algorithmic systems and data-based decision making.

As our mapping of algorithmic accountability policy indicates, most of these policies have emerged very recently (largely from 2019 onwards), and discussions about algorithmic accountability policy, as well as their implementation, have been concentrated in a few jurisdictions. This research, therefore, draws from this current narrow pool of evidence – acknowledging that the landscape of algorithmic accountability could look very different as recognition of the challenges posed by algorithmic systems in the public sector grows.

Our review of publicly available literature, as well as insights gathered from interviews and workshops with policy implementers and civil society, indicates that evidence about the impact and effectiveness of algorithmic accountability policies is currently limited. This is not surprising for a nascent field, but creates an opportunity for policymakers to integrate practices that enable policy monitoring and evaluation early on.

Despite the limitations of research in an emergent area of policy, our research nonetheless indicates some of the challenges and key areas that should guide the design and implementation of these policies as they develop, as well as pointing to broader considerations for the policymaking process:

For policymakers

- **Systematic and effective transparency around assumptions and objectives behind policy mechanisms:** The mapping of algorithmic accountability policies (Section 1) indicates that these policies encompass a range of mechanisms and practices that vary widely even as they are described in similar terms. Many of these mechanisms are based on untested claims and assumptions, or unarticulated theories of change, which complicates any assessment of their effectiveness of impact in achieving ‘algorithmic accountability’.

There is a need for a more rigorous articulation of the short-term, intermediate and long-term goals of algorithmic accountability policies, as a first step towards assessing their implementation and effectiveness. This is especially important for those policies that are not subject to a rigorous legislative process that would generally surface these objectives. Regulators could consider, for example, systematising practices like regulatory impact assessments and periodic reviews of policies, as a way of offering relevant actors (including government agencies, civil society, affected communities) clear insight into the assumptions and objectives underlying particular policy mechanisms.

This insight needs to be communicated in a systematic and timely manner, such that there are opportunities for the lively community of researchers, advocates and activists working in this field to contest and inform policy implementation.

- **Strategic engagement with sectoral agencies:** This research has surfaced the value of institutional coordination for enabling implementation of various algorithmic accountability policies. Governing legal frameworks can define the objects of governance and provide a legislative grounding for accountability practices. However, policymakers and agencies that implement accountability mechanisms must still do the work of studying the impacts of these mechanisms within different sectors and levels of government.

Agencies in charge of policy mechanisms related to algorithmic accountability should strive to get buy-in from other sectoral ministries at different stages of implementation. This could be through a formal coordination mandate derived out of a legal or policy framework, or through informal inter-agency working groups, strategically timed agency consultations or other similar initiatives designed around the implementation of the policy intervention at hand.

- **Timely and ongoing engagement with affected communities and civil society:** Our analysis highlights substantial scope for improving transparency and public participation as design principles for algorithmic accountability policy. National and local governments have piloted participatory approaches across several other policy areas, including budgets, audits, contracting and public monitoring of public services, which could provide ideas and tools for policy interventions governing algorithms.¹⁶³ Further, platforms such as the national or local OGP action plan process can also be used to co-create with civil society and relevant citizen groups.

Policymakers should consider the societal and civic consequences of algorithmic systems, informed by perspectives of affected communities, that draw from civil society and forums for civic participation or efforts to 'co-design' for algorithmic accountability.

- **Leverage peer-to-peer learning networks and global principles:** This survey of algorithmic accountability policy recognises that it is in a nascent and unstable state of implementation. In being the first study of its kind to bring together this breadth of evidence, it has highlighted gaps in knowledge sharing and opportunities for further international collaboration.

Governments and regulators would benefit from collaborating and sharing best practices and challenges that arise in policy implementation in their particular contexts, as, for example, the Informal Network on Open Algorithms convened by the Open Government Partnership attempts to do. This also brings to light the importance of international standards and practices on the transparency and accountability of algorithmic systems, including technical standards established by bodies like the IEEE,¹⁶⁴ or through human rights frameworks at the regional or international level.¹⁶⁵

163 Examples of public participation interventions across policy areas: <https://www.opengovpartnership.org/policy-area/public-participation/>

164 For e.g. See Institute of Electrical and Electronics Engineers. (2017). *Standard for Algorithmic Bias Considerations (P0003)*, Available at: https://standards.ieee.org/news/2017/ieee_p7003.html

165 For e.g. See McGregor, L., Murray, D., and Ng, V., (2019). 'International human rights law as a framework for algorithmic accountability.' *International & Comparative Law Quarterly* 68.2. pp. 309-343. Available at: <https://www.cambridge.org/core/journals/international-and-comparative-law-quarterly/article/international-human-rights-law-as-a-framework-for-algorithmic-accountability/1D6D0A456B-36BA7512A6AFF17F16E9B6>

For the research community

This study also draws from and builds on diverse scholarship that studies algorithmic systems with a view to promoting fairness, accountability and transparency in their design and use, particularly in the public sector. Our review of literature in this field indicates that the evidence base for algorithmic accountability research in the public sector could be strengthened, and that future research should prioritise the following areas of study:

- **Further study and trials of algorithmic accountability approaches in practice:** A review of the literature indicates that most accounts of accountability for the use of algorithmic systems in the public sector are descriptive or theoretical, while there are few empirical studies examining the actual impact and effectiveness of policy measures towards ‘accountability’ in particular contexts.

While it is important to identify what accountability looks like for the public sector’s use of algorithmic systems, there is a need for greater empirical insight into whether and how algorithmic accountability policy measures are actually influencing the use of algorithmic systems in the public sector, and to what extent they are achieving their goals. Research in this area should examine the largely untested assumptions on which algorithmic accountability policies are based, and interrogate and explicate their theories of change.

- **Continuous evaluation of algorithmic accountability policies:** This review highlights that the implementation of algorithmic accountability policies is relatively recent and nascent. Most of the mechanisms this paper covers have yet to demonstrate their efficacy. In order to make more nuanced and grounded assertions about the value and limitations of these mechanisms, there must be continuous evaluation to understand the extent to which theoretical accounts of accountability mechanisms compare with the implementation of policies in practice, and revisit and evolve assumptions about algorithmic accountability.

Studies on algorithmic accountability should engage more actively with the studies of transparency and accountability in public administration, particularly as many policies explicitly draw from accountability initiatives in different fields, such as Environmental Impact Assessments, or financial auditing, and yet others are embedded within existing frameworks for administrative accountability, such as notice, explanation and hearing requirements for administrative decisions.

- **Widening research contexts to be more inclusive of diverse regional and institutional experiences:** As noted previously, countries in the Global North, particularly in the EU, Canada and the USA, have been at the forefront of implementing these policies, as well as the focus of the research agenda on the subject. Inevitably, emerging and nascent accountability policies borrow from these approaches, but there has not been much consideration into how useful these approaches may be in the starkly different social, political, legal and organisational contexts of Global South regions.

Research should also focus on the extent to which concepts and methods of ‘algorithmic accountability’ for the public sector can apply across contexts, including where there might be greater resource constraints and different conditions for citizen and civil society participation. This will also involve stocktaking on the foundational legal or policy frameworks that might be required for the effective implementation of algorithmic accountability policies, such as data protection and privacy legislation, and specific principles of public sector accountability in administrative law.

Select bibliography

1. World Economic Forum. (2020). *AI government procurement guidelines*. Available at: <https://www.weforum.org/reports/ai-procurement-in-a-box/ai-government-procurement-guidelines>
2. Administrative Review Council (Australia). (2004). 'Automated Assistance in Administrative Decision Making: Report to the Attorney-General'. *Australian Government*. Available at: <https://www.ag.gov.au/legal-system/publications/report-46-automated-assistance-administrative-decision-making-2004>
3. Ada Lovelace Institute and DataKind UK. (2020). *Examining the Black Box: Tools for Assessing Algorithmic Systems*. London: Ada Lovelace Institute. Available at: <https://www.adalovelaceinstitute.org/report/examining-the-black-box-tools-for-assessing-algorithmic-systems/>
4. Open Government Partnership. Open Algorithm Blog Series. Available at: <https://www.opengovpartnership.org/topic/open-algorithms-blog-series/>
5. European Union Agency for Fundamental Rights. (2020). *Getting the future right artificial intelligence and fundamental rights*. Available at: https://fra.europa.eu/sites/default/files/fra_uploads/fra-2020-artificial-intelligence_en.pdf
6. HM Treasury. (2013). *Review of quality assurance of Government analytical models*. UK Government. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/206946/review_of_qa_of_govt_analytical_models_final_report_040313.pdf
7. Alkhatib, A., and Bernstein, M. (2019). 'Street-Level Algorithms: A Theory at the Gaps Between Policy and Decisions.' *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, ACM, pp. 1–13. doi:10.1145/3290605.3300760.
8. Ananny, M., and Crawford, K. (2018). 'Seeing without knowing: Limitations of the transparency ideal and its application to algorithmic accountability.' *New Media & Society* Vol 20. No 3 pp. 973-989. Available at: <https://journals.sagepub.com/doi/abs/10.1177/1461444816676645?journalCode=nmsa>
9. Bovens, M., (2007). 'Analysing and Assessing Public Accountability. A Conceptual Framework.' *European Law Journal* Vol.13 No4 pp. 447–468. Available at: <https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1468-0386.2007.00378.x>
10. Brathwaite, C. (2020). *Artificial Intelligence & The Caribbean: A Discussion Paper on (Potential) Applications & Ethical Considerations*. in En C. Aguerre, (Ed.). *Inteligencia Artificial en América Latina y el Caribe. Ética, Gobernanza y Políticas*. Buenos Aires: CETyS Universidad de San Andrés.
11. Castillo, C., et. al. (2020). *Algorithmic Impact Assessment of the predictive system for risk of homelessness developed for the Allegheny County*. Eticas Research and Consulting. Available at: <https://www.alleghenycountyanalytics.us/wp-content/uploads/2020/08/Eticas-assessment.pdf>
12. Daly, A., et. al. (2019). 'Artificial Intelligence, Governance and Ethics: Global Perspectives.' *The Chinese University of Hong Kong Faculty of Law Research Paper* No. 2019-15.. Available at: <https://ssrn.com/abstract=3414805>

13. Danaher, J., et al. (2017). 'Algorithmic Governance: Developing a Research Agenda through the Power of Collective Intelligence.' *Big Data & Society*, Vol. 4, no. 2, Available at: <https://journals.sagepub.com/doi/full/10.1177/2053951717726554>
14. Freeman Engstrom, D., and Ho, D. E. (2020). 'Algorithmic Accountability in the Administrative State.' *Yale Journal on Regulation*, Vol. 37 p. 55. Available at: <https://reglab.stanford.edu/publications/algorithmic-accountability-in-the-administrative-state/>
15. Floridi, L. (2020). 'Artificial Intelligence as a Public Service: Learning from Amsterdam and Helsinki.' *Philosophy & Technology*, vol. 33, no. 4, pp. 541–46. Available at: <https://link.springer.com/article/10.1007/s13347-020-00434-3>
16. Galdon Clavell, G., et al. (2020). 'Auditing Algorithms: On Lessons Learned and the Risks of Data Minimization.' *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society*, ACM.pp. 265–71. Available at: <https://dl.acm.org/doi/10.1145/3375627.3375852>
17. Gaventa, J., and McGee, R. (2013). 'The impact of transparency and accountability initiatives.' *Development Policy Review* Vol. 31. Available at: https://assets.publishing.service.gov.uk/media/57a08aabed915d622c00084b/60827_DPRGaventaMcGee_Preprint.pdf
18. Jobin, A., Ienca, M. & Vayena, E. (2019). 'The global landscape of AI ethics guidelines'. *Nature Machine Intelligence*. Vol. 1, pp. 389–399. Available at: <https://www.nature.com/articles/s42256-019-0088-2>
19. Kaminski, M. E., and Malgieri, G. (2020). 'Algorithmic Impact Assessments under the GDPR: Producing Multi-Layered Explanations.' *International Data Privacy Law*. Available at: <https://dl.acm.org/doi/abs/10.1145/3351095.3372875>
20. Katell, M., et al. (2020). 'Toward Situated Interventions for Algorithmic Equity: Lessons from the Field.' *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, ACM. Available at: <https://people.csail.mit.edu/pkrafft/papers/critplat-toolkit-lessons.pdf>
21. Kemper, J., and Kolkman, D., (2019). 'Transparent to whom? No algorithmic accountability without a critical audience.' *Information, Communication & Society* Vol. 22. No. 14 pp. 2081-2096. Available at: <https://www.tandfonline.com/doi/full/10.1080/1369118X.2018.1477967>
22. Lee, M. K., et al. (2019). 'WeBuildAI: Participatory Framework for Algorithmic Governance.' *Proceedings of the ACM on Human-Computer Interaction*, vol. 3, no. CSCW, pp. 1–35. Available at: <https://dl.acm.org/doi/pdf/10.1145/3359283>
23. Metcalf, J, et al. (2021). 'Algorithmic Impact Assessments and Accountability: The Co-Construction of Impacts.' *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*. Pp.735-746. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3736261
24. Mitchell, M, et al. (2019). 'Model Cards for Model Reporting.' *Proceedings of the Conference on Fairness, Accountability, and Transparency*, pp. 220–29. Available at: <http://arxiv.org/abs/1810.03993>
25. Moss, E., et al. (2021). 'Governing with Algorithmic Impact Assessments: Six Observations.' *AAAI / ACM Conference on Artificial Intelligence, Ethics, and Society (AIES)*. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3584818

26. Ortolano, L., and Shepherd, A. (1995). 'Environmental impact assessment: Challenges and opportunities.' *Impact Assessment*, vol. 13, no. 1, pp. 3–30. Available at: https://www.academia.edu/3283927/ENVIRONMENTAL_IMPACT_ASSESSMENT_CHALLENGES_AND_OPPORTUNITIES
27. Raji, I. D., et al. (2020). 'Closing the AI Accountability Gap: Defining an End-to-End Framework for Internal Algorithmic Auditing.' *Computers and Society*. Available at: <http://arxiv.org/abs/2001.00973>
28. Reisman, D., et al. (2018). *Algorithmic Impact Assessment: A Practical Framework for Public Agency Accountability*. AI Now Institute. Available at: <https://ainowinstitute.org/aiareport2018.pdf>
29. Report of the European Commission High Level Expert Group on Artificial Intelligence. Available at: <https://digital-strategy.ec.europa.eu/en/policies/expert-group-ai>
30. Schiff, D.I, et al. (2021). 'AI ethics in the public, private, and NGO sectors: a review of a global document collection.' *IEEE Transactions on Technology and Society*. Available at: <https://montrealetics.ai/ai-ethics-in-the-public-private-and-ngo-sectors-a-review-of-a-global-document-collection/>
31. Schiff, D., et al. (2021). 'Explaining the Principles to Practices Gap in AI.' *IEEE Technology and Society Magazine*. Vol. 40 No.2 pp. 81-94. Available at: <https://www.semanticscholar.org/paper/Explaining-the-Principles-to-Practices-Gap-in-AI-Schiff-Rakova/0fe8b8f1caf1fff85c50442281753b5b7cc7fd89>
32. Solow-Niederman, A., Choi, Y., and van den Broeck, G. (2019). 'The Institutional Life of Algorithmic Risk Assessment.' *Berkeley Technology Law Journal*. Vol. 34 p. 705. Available at: <http://starai.cs.ucla.edu/papers/Solow-NiedermanBTLR19.pdf>
33. Veale, M., et al. (2018). 'Fairness and Accountability Design Needs for Algorithmic Support in High-Stakes Public Sector Decision-Making.' *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, pp. 1–14. Available at: <https://doi.org/10.1145/3173574.3174014>.
34. Wieringa, M. (2020). 'What to account for when accounting for algorithms: A systematic literature review on algorithmic accountability.' *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*. Available at: <https://dl.acm.org/doi/abs/10.1145/3351095.3372833>
35. Yeung, K., and Lodge, M. (2019). eds. *Algorithmic regulation*. Oxford: Oxford University Press.
36. Yeung, K. (2018). 'A study of the implications of advanced digital technologies (including AI systems) for the concept of responsibility within a human rights framework.' *MSI-AUT*. Vol 5. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3286027
37. Young, M., et al. (2019). 'Municipal Surveillance Regulation and Algorithmic Accountability.' *Big Data & Society*, Vol. 6, no. 2, Available at: <https://journals.sagepub.com/doi/full/10.1177/2053951719868492>

Project team

Project Leads: Tonu Basu is the Deputy Director of Thematic Policy Areas at the Open Government Partnership, Jenny Brennan is a Senior Researcher at the Ada Lovelace Institute and Amba Kak is the Director of Global Policy & Programs at the AI Now Institute at New York University.

Lead Researcher: Divij Joshi is a lawyer and researcher interested in the social, political and regulatory implications of emerging technologies and their intersections with human values.

About the partners



For the **Ada Lovelace Institute (Ada)**, this research forms part of their wider work on algorithm accountability and the public sector use of algorithms. It builds on existing work on tools for assessing algorithmic systems, mechanisms for meaningful transparency on use of algorithms in the public sector, and active research with UK local authorities and government bodies seeking to implement algorithmic tools, auditing methods and transparency mechanisms.



For the **AI Now Institute**, law and policy mechanisms are a key pathway toward ensuring that algorithmic systems are accountable to the communities and contexts they are meant to serve. This research builds upon a wider body of work including their framework for Algorithmic Impact Assessments (AIA) and the Algorithmic Accountability Toolkit. In the spirit of proactive engagement with the policy process, alongside a broad civil society coalition, they also published the Shadow Report to the New York City Automated Decision Systems (ADS) Task Force to detail accountability mechanisms for various sectors of the city government.



For the **Open Government Partnership (OGP)**, a multi stakeholder partnership of 78 countries and 76 local jurisdictions, transparency, accountability and participation are key approaches to better policy making. OGP members work with civil society and other key actors in their countries to co-create and implement OGP action plans with concrete policy commitments, which are then independently monitored for ambition and completion through the OGP's Independent Reporting Mechanism. While several OGP countries are implementing their digital transformation agenda through their engagement in OGP, a growing number of OGP members are also using their OGP action plans to implement policies that govern public sector use of digital technologies. Among these, accountability of automated decision-making systems and algorithms has seen increasing interest. OGP convenes an informal network on Open Algorithms with implementing governments, mobilising a cross-country coalition of those working on algorithmic accountability.

Acknowledgements

This project was made possible due to the efforts and contributions of a number of people. We would like to thank the interviewees, as well as the participants at the workshops and discussions organised by the Open Government Partnership for participating in this study and lending their time and experience to this report—in particular the Governments of Canada, France, New Zealand, Netherlands, and the UK.

We would also like to thank Paula Pérez, José Perez Escotto, Joseph Foti, Helen Turek, Alan Wu, Imogen Parker, Andrew Strait, Octavia Reeve, Hannah Kitcher, Meredith Whittaker, Alejandro Calcaño, and Luke Strathmann for their feedback and assistance on this project.