The Flaws of Policies Requiring Human Oversight of Government Algorithms

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Abstract
Policymakers around the world are increasingly considering how to prevent government uses of algorithms from producing injustices. One mechanism that has become a centerpiece of global efforts to regulate government algorithms is to require human oversight of algorithmic decisions. Despite the widespread turn to human oversight, these policies rest on an uninterrogated assumption: that people are able to oversee algorithmic decision-making. In this article, I survey 40 policies that prescribe human oversight of government algorithms and find that they suffer from two significant flaws. First, evidence suggests that people are unable to perform the desired oversight functions. Second, as a result of the first flaw, human oversight policies legitimize government uses of faulty and controversial algorithms without addressing the fundamental issues with these tools. Thus, rather than protect against the potential harms of algorithmic decision-making in government, human oversight policies provide a false sense of security in adopting algorithms and enable vendors and agencies to shirk accountability for algorithmic harms. In light of these flaws, I propose a more stringent approach for determining whether and how to incorporate algorithms into government decision-making. First, policymakers must critically consider whether it is appropriate to use an algorithm at all in a specific context. Second, before deploying an algorithm alongside human oversight, agencies or vendors must conduct preliminary evaluations of whether people can effectively oversee the algorithm.
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1 Introduction

Governments across the world are increasingly turning to automated decision-making systems, often described as algorithms, as tools to make or inform consequential decisions (Calo & Citron, 2021; Eubanks, 2018; Green, 2019; Henley & Booth, 2020). These developments have raised significant debate about when and how governments should adopt algorithms. On the one hand, algorithms bring the promise of making decisions more accurately, fairly, and consistently than public servants (Kleinberg et al., 2018; Kleinberg et al., 2015). On the other hand, the use of algorithms by governments has been a source of numerous injustices (Calo & Citron, 2021; Eubanks, 2018; Green, 2019). The algorithms used in practice tend to be rife with errors and biases, leading to decisions that are based on incorrect information and that exacerbate inequities. Furthermore, making decisions via the rigid, rule-based logic of algorithms violates the principle that government decisions should respond to the circumstances of individual people. In the face of these competing hopes and fears about algorithmic decision-making, many policymakers have explored regulatory approaches that could enable governments to attain the benefits of algorithms while avoiding the risks of algorithms.

One mechanism that has become a centerpiece of global efforts to regulate government algorithms is to require human oversight of the decisions rendered by algorithms. These human oversight policies enable governments to use algorithms as long as a human has some form of oversight or control over the final decision. In other words, algorithms may assist human decision-makers but may not render final judgments on their own. These policies are intended to ensure that a human is in a position to protect against mistaken or biased algorithmic predictions. They are also intended to protect human dignity by keeping a “human in the loop” of automated decision-making (Jones, 2017; Wagner, 2019). In theory, adopting algorithms while ensuring human oversight could enable governments to obtain the best of both worlds: the accuracy, objectivity, and consistency of algorithmic decision-making paired with the individualized and contextual discretion of human decision-making.

Recent legislation suggests that human oversight is able to protect against the most severe harms of government algorithms. In its proposed Artificial Intelligence Act, the European Commission asserted that human oversight (along with other mechanisms) is “strictly necessary to mitigate the risks to fundamental rights and safety posed by AI” (European Commission, 2021). Following this logic, many policies position human oversight as a distinguishing factor that makes government use of algorithms permissible. For instance, the European Union’s General Data Protection Regulation (GDPR) restricts significant decisions “based solely on automated processing” (European Parliament & Council of the European Union, 2016). The Government of Canada

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1 Throughout this paper, “human oversight” refers to human judgment at the moment an algorithm renders a decision about a specific individual. An example of this form of human oversight involves a judge deciding whether to follow an algorithm’s recommendation to release a criminal defendant before trial. The discussion of human oversight in this paper does not pertain to more structural forms of human oversight of algorithms, such as people’s councils (McQuillan, 2018) and public task forces (Richardson, 2019).
mandates that federal agencies may use high-risk AI systems only with human intervention and a human making the final decision (Government of Canada, 2021). Washington State allows state and local agencies to use facial recognition in certain instances, but only if high-impact decisions “are subject to meaningful human review” (Washington State Legislature, 2020).

Despite the emphasis that legislators have placed on human oversight as a mechanism to mitigate the risks of government algorithms, the functional quality of these policies has not been thoroughly interrogated. Policymakers calling for human oversight occasionally invoke values (such as human rights and dignity) as a motivation for these policies, but rarely reference empirical evidence demonstrating that people are able to oversee algorithms as desired. In fact, when policies and policy guidance do reference empirical evidence about human-algorithm interactions, they usually express reservations about the limits of human oversight, particularly related to people over-relying on algorithmic advice (Engstrom et al., 2020; European Commission, 2021; UK Information Commissioner’s Office, 2020).

This lack of affirmative evidence hints at an important challenge facing human oversight policies. Although inserting a “human in the loop” may appear to satisfy legal and philosophical principles, research into sociotechnical systems demonstrates that people and technologies often do not interact as expected (Suchman et al., 1999). Hybrid systems that require collaboration between humans and automated technologies are notoriously difficult to design, implement, and regulate effectively (Bainbridge, 1983; Gray & Suri, 2019; Jones, 2015; Pasquale, 2020; Perrow, 1999). Thus, given that human oversight is being enacted into policies across the world as a central safeguard against the risks of government algorithms, it is vital to ensure that human oversight actually provide the desired protections. If people do not oversee algorithms as intended, human oversight policies would have the perverse effect of alleviating scrutiny of government algorithms without actually addressing the underlying concerns.

This article interrogates the efficacy and impacts of human oversight policies. It proceeds in four parts. The first two parts lay out the context of my analysis. Section 2 provides background on the tensions and challenges raised by the use of algorithms in government decision-making. Section 3 describes the current landscape of human oversight policies. I survey 40 policy documents from across the world that provide some form of official mandate or guidance regarding human oversight of public sector algorithms, finding that these policies prescribe three approaches to human oversight.

Section 4 provides the primary evaluative analysis of the article. In this section, I evaluate the three forms of human oversight prescribed by the documents surveyed in Section 3. To accomplish this evaluation, I draw on the growing body of evidence regarding how people interact with algorithms in experimental settings and how government decision-makers use algorithms in practice. I find that existing human oversight policies suffer from two significant flaws. First, human oversight
policies have a meager basis in empirical evidence: the vast majority of research suggests that people cannot reliably perform any of the desired oversight functions. This first flaw leads to a second flaw: human oversight policies legitimize the use of flawed and unaccountable algorithms in government. Human oversight is being adopted as a remedy for fundamental concerns about the quality and legitimacy of government algorithms yet is unable to actually address the underlying issues that generate these concerns. Thus, rather than protect against the potential harms of algorithmic decision-making in government, human oversight policies create a regulatory loophole that provides a false sense of security in adopting algorithms and enables vendors and agencies to foist accountability for algorithmic harms onto lower-level human operators.

Section 5 provides the primary prescriptive analysis of the article. In this section, I consider how to adapt regulation of government algorithms in light of the two flaws to human oversight policies described in Section 4. It is clear that policymakers must stop relying on human oversight as a remedy for the potential harms of algorithms. However, the correct response is not to simply abandon human oversight, leaving governments to depend on autonomous algorithmic judgments. Nor should regulators prohibit governments from ever using algorithms. Instead, legislators must develop alternative governance approaches that more rigorously address the concerns which motivate the (misguided) turn to human oversight.

Drawing on the lessons from both flaws of human oversight policies, I propose a two-stage approach for determining whether and in what form governments should be permitted to incorporate algorithms into decision-making. A central goal of this approach is to increase the burden placed on agencies to proactively justify their decisions regarding how they use and govern algorithms. First, rather than assume that human oversight can address fundamental concerns about algorithmic decision-making, policymakers should consider whether it is actually appropriate to use an algorithm to make or inform a specific decision. If an algorithm violates fundamental rights, is badly suited to a decision-making process, or is untrustworthy, then governments should not use the algorithm, even with human oversight. The second stage concerns settings where policymakers envision a potential role for algorithms alongside human judgment. Rather than taking for granted that human oversight is effective, policymakers should require that vendors or agencies conduct preliminary evaluations of whether people can collaborate with the algorithm in a desirable manner. If there is not sufficient evidence demonstrating that human oversight is effective and that the algorithm improves human decision-making, then governments should not incorporate the algorithm into human decision-making processes.

Compared to the status quo of blanket rules that enable governments to use algorithms as long as a human provides oversight, this proposed regulatory approach will present more stringent

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2 The precise meaning of “improves” will depend on the context and goals of any specific decision-making process. Common standards of improvement include the accuracy of predictive judgments and the fairness of decisions.
standards for government use of algorithms and will help to prevent human oversight from operating as a superficial salve for the injustices associated with algorithmic decision-making.

2 Discretion, Algorithms, and Decision-Making in Government

The introduction of algorithms into government decision-making has been a source of significant controversy (Angwin et al., 2016; Calo & Citron, 2021; Eubanks, 2018; Green, 2019; Henley & Booth, 2020). Debates about the proper role for algorithms in government are grounded in the competing demands placed on public policy in the settings where algorithms are used. Many of the most consequential and controversial government uses of algorithms take place in street-level bureaucracies such as courts, police departments, schools, welfare agencies, and social service agencies (Lipsky, 2010). Within street-level bureaucracies, street-level bureaucrats—such as judges, police officers, teachers, and social workers—make consequential decisions about how to instantiate public policy with respect to specific individuals (Lipsky, 2010). Examples of algorithms in street-level bureaucracies include judges using risk assessments to inform pretrial and sentencing decisions (Angwin et al., 2016; Wisconsin Supreme Court, 2016), child services workers using predictive models to inform which families to investigate for child neglect and abuse (Eubanks, 2018), and welfare agencies using algorithms to determine eligibility for benefits (Allhutter et al., 2020; Calo & Citron, 2021; Charette, 2018; Henley & Booth, 2020). Policymakers call most strongly for human oversight of algorithms in high-stakes decisions such as these (European Commission, 2021; European Parliament & Council of the European Union, 2016; Government of Canada, 2021).

More than any other government setting, street-level bureaucracies are caught in a dilemma between rule-based and standard-based decision-making. While rules involve clear definitions and consequences, facilitating consistency and predictability, standards permit discretion, facilitating flexibility and sensitivity to the circumstances of specific cases (Solum, 2009). Street-level bureaucrats face an “essential paradox”: they must strive to treat everyone equally by following pre-specified rules, yet also to be responsive to individual cases by exercising discretion; adherence to either of these goals necessarily conflicts with the other (Lipsky, 2010). Furthermore, there is “no ‘objective’ solution” regarding the appropriate balance between rules and discretion (Wilson, 2000).

The extent to which judges and other street-level bureaucrats should be granted discretion over individual cases is thus a source of strenuous and recurring debate (Christie, 1986; Lipsky, 2010). On the one hand, both publics and policymakers often express a strong desire to curb discretion in the interest of objectivity and consistency (Christie, 1986; Lipsky, 2010; Wilson, 2000). Allowing human decision-makers to exercise discretion means relying on the judgment and morality of those individuals, a prospect that causes significant unease (Zacka, 2017). Such discretion raises the specter of biased or arbitrary treatment by unelected agents of the state (Zacka, 2017). The United States is particularly prone to the response of using rules to limit discretion (Wilson, 2000).
On the other hand, there are many reasons to desire discretion in street-level bureaucracies. Discretion enables street-level bureaucrats to reason about public policies laden with ambiguous and conflicting goals based on the particular context at hand (Zacka, 2017). Restricting discretion would entail imposing a rigid, formal logic on the unavoidably ambiguous, uncertain, and unpredictable situations that street-level bureaucrats encounter, preventing them from adapting government decisions to complex or novel situations (Lipsky, 2010; Zacka, 2017). Reducing the decisions of judges, police officers, social workers, and other street-level bureaucrats to a set of pre-specified instructions and rules would violate deeply held social commitments to having decisions be responsive to individuals’ conditions and needs (Lipsky, 2010). Discretion is therefore desirable—both normatively and practically—as it allows decision-makers to strike an appropriate balance between a variety of important values and objectives in light of each individual’s particular circumstances (Lipsky, 2010; Zacka, 2017).

These competing demands on street-level bureaucracies lead to significant debate about the proper role and implementation of algorithms in government. The desire to reduce individual discretion and promote consistency present strong motivations for government agencies to use algorithms. Algorithms bring a promise of accuracy, objectivity, and consistency that is attractive to both policymakers and publics. Evidence suggests that algorithms make policy-relevant predictions more accurately, fairly, and consistently than public servants (Kleinberg et al., 2018; Kleinberg et al., 2015). Thus, in addition to goals such as cutting costs and enhancing efficiency, governments adopt algorithms hoping to attain greater accuracy when making predictive judgments, to replace biased human decisions with “objective” automated ones, and to promote more consistent decision-making (Calo & Citron, 2021; Engstrom et al., 2020; Green, 2019; New Jersey Courts, 2017).³

However, despite these desires for algorithmic accuracy, objectivity, and consistency, the specter of governments making high-stakes decisions with algorithms raises two significant concerns. First, evidence suggests that these algorithms are neither as accurate nor fair as hoped. Algorithms used in settings such as the criminal justice system (Angwin et al., 2016), education (Kolkman, 2020), policing (Fussey & Murray, 2020; Green, 2019), and welfare (Calo & Citron, 2021; Charette, 2018) have suffered from notably high error rates. Many of these and other algorithms used by governments have been shown to be biased against women, minorities, and low-income individuals (Angwin et al., 2016; Buolamwini & Gebru, 2018; Kolkman, 2020; Richardson et al., 2019).

³ These efforts in government also reflect a broader political economic trend toward replacing or undercutting workers with AI systems (Gray & Suri, 2019; Pasquale, 2020). Across domains, however, AI perennially relies on human assistance (Gray & Suri, 2019) and more just outcomes arise when AI is used to complement rather than replace professionals (Pasquale, 2020).
Second, making decisions via the rigid, rule-based logic of algorithms violates the strongly held desire for governments to be responsive to individual circumstances. Unlike street-level bureaucrats, algorithms adhere to predetermined decision rules and are unable to adapt reflexively to novel or marginal circumstances (Alkhatib & Bernstein, 2019). Scholars have thus raised concerns that automation and algorithms significantly reduce opportunities for discretion in street-level bureaucracies and administrative agencies (Bovens & Zouridis, 2002; Buffat, 2015; Calo & Citron, 2021). Automated decision-making also threatens due process, as such systems often levy judgments without providing people with notice or the ability to meaningfully inspect and challenge decisions (Citron, 2008). Although it may be inadvisable to provide individuals with a general right to have decisions about them be made by humans (Huq, 2020), individual justice requires human judgment for decisions that involve ethical and contextual analyses (Binns, 2020). This philosophically grounded notion is matched by human perceptions that decisions made by algorithms are less trustworthy and fair than those made by humans and that being evaluated by algorithms is dehumanizing (Binns et al., 2018; Lee, 2018).

Thus, although algorithms promise certain benefits, algorithmic decision-making raises significant concerns about the unreliability of algorithms and the lack of contextual human discretion in decision-making. Government efforts to adopt algorithms are therefore often met with public skepticism and resistance, as communities reject the prospect of inhuman and inflexible automated systems shaping consequential decisions about their lives. For instance, protests against such tools in recent years have included signs saying “Families over Algorithms” (Scharfenberg, 2018) and chants of “Fuck the algorithm” (Kolkman, 2020).

These concerns motivate the turn to human oversight. By requiring that a human is kept in the decision-making loop, human oversight policies attempt to obtain the benefits of algorithms—accuracy, objectivity, and consistency—while ensuring that a person is in place to correct for any algorithmic errors and biases and to provide individualized judgment for each decision. The rest of this article describes and evaluates these policies.

3 Survey of Human Oversight Policies
This section summarizes how legislation and policy guidance describe the appropriate role for human oversight of algorithms used by governments. To conduct this survey, I collected policy documents related to government uses of algorithms. I considered documents that fall into one of the following three categories: 1) proposed or passed legislation; 2) policy guidance by government or government-appointed bodies; and 3) manuals, policies, and court cases related to two notably controversial and high-stakes risk assessment tools in the U.S. (risk assessments used in criminal justice settings and the Allegheny County Family Screening Tool). I discovered documents by searching for recently passed or proposed legislation related to AI and privacy, reviewing academic literature and news stories regarding AI regulation, and searching for documentation from the vendors and managers of criminal justice risk assessments and the
Allegheny County Family Screening Tool. I reviewed each document to determine whether it discusses human use or oversight of algorithms. This process yielded 40 policy documents that provide some form of official mandate or guidance regarding human oversight of public sector algorithms. These 40 documents are listed in the Appendix (and are all cited at least once in this section).

I analyzed these policy documents to determine how they describe the proper role for humans in government decision-making processes aided by algorithms. I used inductive coding, looking particularly for what each document emphasizes as the central principle guiding human oversight policy. I also looked for any specific mechanisms that these documents provide regarding how to facilitate the desired form of human involvement and oversight in decision-making.

This coding process revealed that policies take three overlapping yet distinct approaches to human oversight. Each approach rests on a central word or phrase that links the documents to a common framework for human oversight. I describe these approaches in order from least to most stringent in terms of the requirements placed on human oversight. The first approach involves restricting decisions that are made “solely” by algorithms. The second approach provides a corollary to the first approach, affirmatively stating the importance of human discretion and oversight. Finally, the third approach provides an extension of the first and second approaches, emphasizing the need for “meaningful” human oversight. Each approach is presented with quotes from the applicable policy documents in order to demonstrate the coherence of these themes.

3.1 Restricting “Solely” Automated Decisions
The first approach to human oversight is to directly prohibit or restrict decisions that are made through “solely” automated means. Nineteen of the 40 reviewed documents take this approach to oversight. All of them are proposed or passed legislation.

The approach of prohibiting solely automated decisions is taken, most notably, by the European Union’s General Data Protection Regulation (GDPR). Article 22 of the GDPR mandates (with several exceptions) that “data subject[s] shall have the right not to be subject to a decision based solely on automated processing, including profiling, which produces legal effects concerning him

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4 Although many of these documents are specifically focused on government uses of algorithms, others provide broader guidance that encompasses—but does not exclusively consider—government settings. As such, much of the analysis that follows also applies to human oversight in non-government settings.

5 Out of these 40 documents, 22 are proposed or passed legislation (category 1), eight provide policy guidance (category 2), and ten are related to the two controversial risk assessment tools (category 3).

6 A significant number of common words and phrases appear across the policy documents following each approach. This pattern is not particularly surprising given the trends in how technology policies develop. Recent privacy laws have developed in part by following the model of prior, high-profile privacy laws such as Europe’s General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA) (Chander et al., 2021; Schwartz, 2019). A similar pattern has been observed in AI ethics, as recent statements of principles share many common elements (Field et al., 2020; Jobin et al., 2019). This pattern simplified the coding process, as many of the policy documents contained identical (or very similar) words and phrases.
or her or similarly significantly affects him or her” (European Parliament & Council of the European Union, 2016). Nine of the EU member states specifically address solely automated decision-making in their national GDPR implementations.⁷

Since the passage of the GDPR, many jurisdictions outside the EU have proposed or passed laws that include GDPR-style restrictions on solely automated decision-making. Policies in Argentina (Republic of Argentina, 2018), Mauritius (Parliament of Mauritius, 2017), Kenya (Republic of Kenya, 2019), and South Africa⁸ (Republic of South Africa, 2013) provide default prohibitions on solely automated decision-making, much like the GDPR. Policies in Bahrain (Kingdom of Bahrain, 2018), Brazil (National Congress of Brazil, 2019), Québec (National Assembly of Québec, 2020), Uganda (The Republic of Uganda, 2019), and the United States (Brown, 2020) do not prohibit any instances of solely automated decision-making, but require protections for the subjects of solely automated decisions.

All of the policies discussed in this section require that the subjects of any solely automated decisions are granted rights and protections. One of the most emphasized and common safeguards is the right for subjects of solely automated decisions to obtain post hoc human intervention. In other words, after someone has been subject to a solely automated decision, they can request that a human inspect and consider altering that decision. Twelve of the 19 policies discussed in this section explicitly incorporate a right to human intervention.⁹

3.2 Emphasizing Human Discretion

The second approach to human oversight reflects a corollary to the first approach. In these documents, policymakers, algorithm vendors, and courts emphasize that decisions must involve human discretion, which provides protection against the potential perils of automated decisions. Fourteen of the 40 policy documents fall take this approach to oversight. One is passed legislation, three provide policy guidance, and ten relate to criminal justice and child welfare risk assessments.

Several policy documents state that human oversight and discretion are essential for protecting values such as human rights. The Canadian Directive on Automated Decision-Making requires that decisions likely to have “high” or “very high” social impacts “cannot be made without having

⁷ (Malgieri, 2019) provides an overview of how each member state implements Article 22, along with translations of the relevant sections from these laws that are not otherwise available in English. Austria (Austrian Parliament, 2018), Belgium (Belgian Federal Parliament, 2018), France (French Parliament, 2018), and Hungary (Hungarian Parliament, 2018) expand the scope of decisions that are subject to restrictions on solely automated decision-making. France (French Parliament, 2018), Germany (Bundestag, 2019), and the Netherlands (Dutch Parliament, 2018) distinguish the requirements for particular public and private sector settings. Ireland (Houses of the Oireachtas, 2018) and the United Kingdom (U.K. Parliament, 2018) describe detailed procedures that must accompany any permitted solely automated decisions (The UK’s implementation of the GDPR went into effect in 2018, before the UK left the EU). Slovenia (Slovenian Parliament, 2020) calls for ex ante impact assessments.

⁸ South Africa passed the Protection of Personal Information Act in 2013, following the release of the draft GDPR. Most of the provisions (including the section related to automated decision-making) went into effect in 2020.

⁹ The six exceptions are Argentina, Austria, France, Mauritius, Québec, Slovenia, and South Africa.
specific human intervention points during the decision-making process; and the final decision must be made by a human” (Government of Canada, 2021). A discussion paper by the Australian Human Rights Commission proposes that algorithmic decisions “must be […] subject to appropriate human oversight and intervention” (Australian Human Rights Commission, 2019). Multiple reports by the New Zealand Government similarly emphasize the need to “retain” and “preserve” human oversight as core priorities for how governments should adopt and manage algorithms (Statistics New Zealand, 2018, 2020).

All ten of the documents related to controversial risk assessment algorithms in the United States emphasize the importance of human discretion. In the face of significant public scrutiny, these documents present human discretion as a safety valve that limits the influence of automated tools and mitigates the potential harms of mistaken or biased algorithmic predictions. The key mechanism meant to enable human oversight to perform this function is the discretion to override an algorithm’s judgments.

The Allegheny County Department of Human Services, which oversees the Allegheny Country Family Screening Tool (AFST),\(^{10}\) presents human oversight as an essential safeguard for decision-making. In response to concerns about the algorithm fully determining outcomes, the Department stresses that “[s]creening decisions are not in any way ‘dictated’ by the AFST,” as “supervisors have full discretion over call screening decisions” (Allegheny County Department of Human Services, 2019a). The Department further justifies the AFST due to the use of human discretion, claiming that the tool produces “few, if any, unintended adverse effects given workers’ willingness to use their own discretion in the screening decision” (Allegheny County Department of Human Services, 2019b).

Documents related to risk assessments used in criminal justice settings place a similar emphasis on discretion. Northpointe, which developed the COMPAS risk assessment,\(^{11}\) acknowledges that the algorithm can make mistakes and writes that “staff should be encouraged to use their professional judgment and override the computed risk as appropriate” (Northpointe, 2015). Arnold Ventures, which developed the Public Safety Assessment (PSA), strongly emphasizes that “[j]udges are not required to follow the PSA” (Arnold Ventures, 2019). The New Jersey Courts (which adopted the PSA in 2017) writes that the PSA “do[es] not replace judicial discretion” (New Jersey Courts, 2017). Other organizations that create and oversee such tools similarly highlight the importance of professional judgment and the ability of staff to override a risk assessment’s

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\(^{10}\) The AFST is a risk assessment that predicts the likelihood that children will be removed from their home due to child neglect and abuse in the next two years. These predictions are presented to child welfare workers to inform their decisions about which cases to investigate (De-Arteaga et al., 2020; Eubanks, 2018).

\(^{11}\) COMPAS (short for Correctional Offender Management Profiling for Alternative Sanctions) is a risk assessment that predicts the likelihood that criminal defendants will be arrested in the next two years. These predictions are presented to judges to inform their pretrial release and sentencing decisions (Angwin et al., 2016; Northpointe, 2015).
recommendations (Andrews & Bonta, 2001; Steinhart, 2006; Wisconsin Department of Corrections, 2018).

Human discretion also played a central role in two court cases that supported the use of risk assessments in criminal sentencing. In *Malenchik v. State of Indiana* and *State of Wisconsin v. Loomis*, two state supreme courts considered whether it was appropriate for risk assessments to inform sentencing decisions. Both courts argued that as long as judges have discretion regarding how to incorporate algorithmic advice into sentences, then it is acceptable to use risk assessments to inform criminal sentencing. Noting that risk scores are “neither […] intended nor recommended” to replace individualized sentencing decisions, the Indiana Supreme Court stated that it “defer[s] to the sound discernment and discretion of trial judges to give the tools proper consideration and appropriate weight” (Indiana Supreme Court, 2010). Similarly, acknowledging that COMPAS is imperfect, the Wisconsin Supreme Court stated that “courts [should] exercise discretion when assessing a COMPAS risk score with respect to each individual defendant” (Wisconsin Supreme Court, 2016).

3.3 *Requiring “Meaningful” Human Input*

The third approach to human oversight represents an extension of the first and second approaches. Rather than simply calling for human involvement in decision-making, documents taking this third approach recognize that some forms of human involvement can be superficial or inadequate. They therefore emphasize that human input and oversight must be “meaningful.” Seven of the 40 reviewed documents take this approach to oversight. Two are proposed or passed legislation and five provide policy guidance.

Efforts to promote meaningful human input are addressed, first and foremost, at avoiding the pitfalls of restrictions on “solely” automated decisions. The narrow scope of such restrictions makes it possible for institutions to circumvent regulatory obligations by inserting superficial forms of human involvement into the decision-making process (Veale & Edwards, 2018; Wagner, 2019).

Two influential European bodies have emphasized meaningful human input in direct reference to the GDPR. In its guidance related to the GDPR, the Article 29 Data Protection Working Party asserts that “[t]o qualify as human involvement, the controller must ensure that any oversight of the decision is meaningful, rather than just a token gesture” (Article 29 Data Protection Working Party, 2018). The UK Information Commissioner’s Office stresses that “human input needs to be meaningful,” clarifying that “a decision does not fall outside the scope of [GDPR] Article 22 just because a human has ‘rubber-stamped’ it” (UK Information Commissioner’s Office, 2020).

Other policies and policy guidance also emphasize meaningful human oversight of government algorithms. A Washington State law regulating government use of facial recognition requires that
significant decisions concerning individuals “are subject to meaningful human review” (Washington State Legislature, 2020). The European Commission’s High-Level Expert Group on AI lists “human agency and oversight” as the first of “seven key requirements for Trustworthy AI,” describing the importance of “meaningful opportunity for human choice” (High-Level Expert Group on AI, 2019). The European Commission’s proposal for an Artificial Intelligence Act and a report commissioned by the Administrative Conference of the United States similarly stress the need for substantial forms of human oversight that avoid the pitfalls of simplistic forms of human oversight (Engstrom et al., 2020; European Commission, 2021).

Although the policy documents proposing this third approach do not provide precise or detailed definitions of what “meaningful” human involvement entails, these policies collectively propose three central components. First, human decision-makers must be able to disagree with the algorithm’s recommendations. Numerous of these documents emphasize that for human oversight to be meaningful, human reviewers must have the competence and authority to override algorithmic decisions (Article 29 Data Protection Working Party, 2018; European Commission, 2021; High-Level Expert Group on AI, 2019; UK Information Commissioner’s Office, 2020; Washington State Legislature, 2020).

Second, human overseers must understand how the algorithm operates and makes decisions. Policies recommend algorithmic explanations and transparency in support of this goal. Several policy guidance documents suggest explanations of algorithmic decisions as a mechanism to facilitate human understanding (Engstrom et al., 2020; High-Level Expert Group on AI, 2019; UK Information Commissioner’s Office, 2020). Numerous policies and reports also describe the need for transparency in algorithm design so that human decision-makers can interpret the output of algorithmic systems (Engstrom et al., 2020; European Commission, 2021; High-Level Expert Group on AI, 2019; UK Information Commissioner’s Office, 2020; Washington State Legislature, 2020).

Third, human decision-makers must not rely on algorithms and should instead thoroughly consider all of the information relevant to a given decision. Several documents raise concerns about people over-relying on algorithmic recommendations even when granted the ability to make final decisions (Engstrom et al., 2020; European Commission, 2021; High-Level Expert Group on AI, 2020; UK Information Commissioner’s Office, 2020). Two European regulatory agencies further stress that human reviewers must weigh algorithmic assessments alongside additional information and factors (Article 29 Data Protection Working Party, 2018; UK Information Commissioner’s Office, 2020).

12 In this respect, documents calling for meaningful human oversight overlap with the documents described in Section 3.2, many of which explicitly state that humans must be able to override an algorithm’s judgments.
4 Two Flaws with Human Oversight Policies

In this section, I evaluate the efficacy of human oversight policies and argue that they suffer from two flaws. First, drawing on recent empirical evidence about how people interact with algorithms in government and other settings, I consider whether people are capable of providing the types of oversight that policies call for. Despite the hopes of policymakers, the vast majority of evidence suggests that people cannot provide the envisioned protections against algorithmic errors, biases, and inflexibility. Second, I consider the implications of these limits to human oversight. Ungrounded assumptions of effective human oversight promote a false sense of security in adopting algorithms and shift accountability for algorithmic harms from vendors and policymakers to frontline operators who typically have little agency or power.

4.1 Flaw 1: Human Oversight Policies Have a Meager Basis in Empirical Evidence

The first flaw of human oversight policies is that they have little basis in empirical evidence. The vast majority of research suggests that people are unable to provide reliable oversight of algorithms. The underlying problem here is a mismatch of skills and responsibilities: algorithms have been adopted for their superior prediction abilities relative to humans, yet then those same humans have been tasked with judging the quality of algorithmic predictions. Asking people to monitor automated systems that were adopted to improve upon human performance creates “an impossible task” for the human monitor (Bainbridge, 1983).

To show the empirical limits of human oversight policies, I will return to the three forms of human oversight introduced in Section 3 and describe why each is highly unlikely to provide the desired protections against algorithmic errors, biases, and inflexibility.

4.1.1 Restrictions on “Solely” Automated Decisions Provide Superficial Protection

Policies that restrict “solely” automated decisions have the clearest flaws: they provide protection for a limited number of cases and are susceptible to avoidance through superficial human involvement. It is uncommon for public sector algorithms—particularly in high-stakes settings such as criminal justice and child welfare—to operate without human involvement and without a human making the final decision. Policies restricting “solely” automated decisions are therefore unlikely to apply in the cases that have generated the most public scrutiny and outcry. Furthermore, the narrow scope of “solely” automated decisions creates flimsy and easily avoidable protections. At least by the letter of these laws, any nominal form of human involvement is sufficient to avoid the protections placed on solely automated decisions. Provisions like the GDPR’s Article 22 thus may create an incentive to introduce superficial human oversight of algorithms (i.e., “rubber stamping” automated decisions) as a way to bypass restrictions (Veale & Edwards, 2018; Wagner, 2019).\(^\text{13}\)

\(^{13}\) This type of superficial human oversight would represent an example of “skeuomorphic humanity,” providing the impression that a human is making decisions when that is not actually the case (Brennan-Marquez et al., 2019).
In addition, the right to post hoc human intervention fails to provide robust protections against the harms of solely automated decisions. Procedurally, the right to human intervention puts the onus on individuals to request human review after they have already been harmed by a decision. Many people will have neither the means nor knowledge to take advantage of this right. Even when people do request human intervention, it can be slow and onerous to obtain remedies, allowing the harm of a flawed automated decision to manifest (Calo & Citron, 2021). Substantively, human intervention is unlikely to produce better decisions in most settings. This form of human intervention amounts to the ability of a human reviewer to override an automated decision. As the next section will describe, people are bad at evaluating the quality of algorithmic judgments, leading them to typically override algorithms in detrimental ways.

4.1.2 Human Discretion Does Not Improve Outcomes

Even when human oversight moves beyond “rubber stamp” approaches, such that people are granted agency to use discretion and make final decisions, human oversight is unlikely to provide protections against the harms of algorithmic decision-making.

Across a wide range of domains, automated decision-support systems tend to alter human decision-making in unexpected and harmful ways. Numerous studies have demonstrated that humans (including experts) are susceptible to “automation bias”—i.e., deferring to automated systems without exercising the level of independent judgment that they would without an automated aid (Parasuraman & Manzey, 2010; Skitka et al., 1999). Automation bias can involve omission errors—failing to take action because the automated system did not provide an alert—and commission errors—following the advice of an automated system even though it is incorrect and there is contradicting evidence (Parasuraman & Manzey, 2010; Skitka et al., 1999). Furthermore, automating certain parts of human tasks can make the remaining tasks more difficult and cause human skills to deteriorate (Bainbridge, 1983). As a result, automated systems may simply lead to different types of errors rather than reducing overall errors as intended (Skitka et al., 1999). Automation can also create a diminished sense of control, responsibility, and moral agency among human operators (Berberian et al., 2012; Cummings, 2006).

Similar issues arise when people collaborate with algorithms to make predictions. A significant body of research demonstrates that people are bad at judging the quality of algorithmic outputs and determining whether and how to override those outputs. People struggle to evaluate the accuracy of algorithmic predictions (Goodwin & Fildes, 1999; Green & Chen, 2019a, 2019b; Lai & Tan, 2019; Springer et al., 2017), leading them to discount accurate algorithmic recommendations and to rely on bad algorithmic recommendations (Dietvorst et al., 2015; Goodwin & Fildes, 1999; Lim & O’Connor, 1995; Springer et al., 2017; Yeomans et al., 2017). This means that even though algorithmic advice can improve the accuracy of human predictions, people’s judgments about when and how to diverge from algorithmic recommendations are typically incorrect (Green & Chen, 2019a, 2019b; Grgić-Hlača et al., 2019; Lai & Tan, 2019).
People have also been shown to exhibit racial biases when incorporating algorithmic advice into their predictions (Green & Chen, 2019a, 2019b). Furthermore, although an evaluation of the Allegheny Family Screening Tool found that staff were able to override many algorithmic errors (De-Arteaga et al., 2020), other evidence shows that algorithmic errors reduce the quality of expert judgments (Kiani et al., 2020).

The use of algorithms in policing and the criminal justice system exemplifies the limits of human oversight and discretion in practice. Police have been shown to follow incorrect advice from algorithms, even when tasked with overseeing an algorithm and under no mandate to follow its advice. For instance, police in London “overwhelmingly overestimated the credibility” of a live facial recognition system, judging computer-generated matches to be correct at three times the actual rate of accuracy (Fussey & Murray, 2020). Such behavior led to the first known case of arrest due to faulty facial recognition in the United States, when the Detroit Police Department arrested a man due solely to a facial recognition match that was clearly incorrect (Hill, 2020).

In contrast, judges across the United States regularly deviate from algorithmic advice, but typically in detrimental ways. Reports from several U.S. jurisdictions show that judges frequently override release recommendations in order to detain defendants, leading to inflated detention rates (Human Rights Watch, 2017; Sheriff’s Justice Institute, 2016; Steinhart, 2006; Stevenson, 2018; Stevenson & Doleac, 2021). Furthermore, judges often make more punitive decisions regarding Black defendants than white defendants who have the same risk score, causing the introduction of risk assessments to exacerbate racial disparities in pretrial detention (Albright, 2019; Cowgill, 2018; Stevenson & Doleac, 2021). Thus, rather than enable decision-makers to identify and correct algorithmic biases, human discretion can enable decision-makers to inject new forms of inconsistency and bias into decisions.

4.1.3 Even “Meaningful” Human Oversight Does Not Improve Outcomes
Finally, policies mandating “meaningful” human oversight are also unlikely to deliver on their promises. Such policies face two major issues. First is a definitional issue: although the policy documents reviewed suggest three core components of meaningful human oversight, none propose a straightforward definition of meaningful oversight. Although policies agree that a human operator rubber stamping algorithmic decisions clearly does not constitute meaningful oversight, they do not provide any standard for evaluating how meaningful any form of human oversight is. As a general matter, this could be appropriate: many policies rely on standards whose meaning depends on contextual judgments (Lipsky, 2010; Solum, 2009; Zacka, 2017). However, for any definition of meaningful oversight to be desirable, at least some components of meaningful oversight must improve outcomes. Indeed, the second issue with mandating meaningful human oversight is the inherent imprecision of this principle means that there is no consensus regarding what it actually entails (Crotof, 2016).

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14 In the related context of autonomous weapon systems, “meaningful human control” has gained widespread support as a governance principle, yet the “inherent imprecision” of this principle means that there is no consensus regarding what it actually entails (Crotof, 2016).
oversight is a functional issue: the three components described as central to meaningful human oversight are either unlikely to improve decision-making or are very difficult to achieve. This means that proposals for meaningful human oversight of public sector algorithms sound reassuring but do not actually provide any benefits.

The first requirement of meaningful human oversight is that humans must be allowed to override algorithmic recommendations. This is already the case in most of the high-stakes settings in which algorithms are used, such as the criminal justice system. Yet as described in Section 4.1.2, both laypeople and public servants cannot reliably evaluate the quality of algorithmic advice and tend to override algorithms in detrimental ways. Thus, although this proposed component of meaningful human oversight is satisfied in many instances, most evidence suggests that it does not improve outcomes.

The second requirement of meaningful human oversight is that human overseers must understand the algorithm’s operations and outputs. This goal is meant to be facilitated by algorithmic explanations and transparency. As with the first requirement, despite the broad support for this idea, evidence suggests that algorithmic explanations and transparency do not actually improve human oversight. Studies have found that explanations do not improve people’s ability to make use of algorithmic predictions (Bansal, Wu, et al., 2021; Green & Chen, 2019b). In fact, explanations can have the harmful effect of prompting people to place greater trust in algorithmic recommendations even when the recommendations are incorrect (Bansal, Wu, et al., 2021; Jacobs et al., 2021) or when the explanations have no basis in the algorithm’s actual functioning (Lai & Tan, 2019). Algorithmic transparency similarly reduces people’s ability to detect and correct model errors (Poursabzi-Sangdeh et al., 2021). Based on this evidence, the proposed remedies of explanations and transparency appear to hinder—rather than improve—people’s ability to identify algorithmic mistakes and make effective use of algorithmic recommendations.

The third requirement of meaningful human oversight is that decision-makers must avoid relying on algorithms and instead consider all of the relevant information. Although this goal is appealing, evidence suggests that it is difficult (if not impossible) to achieve in practice. Studies have found that automation bias persists even after training and explicit instructions to verify an automated system (Parasuraman & Manzey, 2010). Furthermore, even when people do not rely entirely on automation, an algorithm can still significantly alter how people make decisions. Experimental studies suggest that risk assessments increase the weight that judges, law students, and laypeople place on risk relative to other considerations when making simulated pretrial and sentencing decisions (Green & Chen, 2021; Skeem et al., 2019; Starr, 2014). These results mean that it is not sufficient for an algorithm merely to improve the accuracy of human predictions, as an algorithm’s effects on decision-making processes can counteract the potential benefits of enhanced predictions (Green & Chen, 2021). Thus, while it is desirable that decision-makers presented with algorithms balance the algorithm’s advice with other information and factors, evidence suggests that people
typically defer to automated tools and increase their attention to the factors emphasized by algorithms.

4.2 Flaw 2: Human Oversight Policies Legitimize Flawed and Unaccountable Algorithms in Government

The second flaw of human oversight policies follows from the first: because human oversight mechanisms are ineffective, human oversight policies legitimize flawed and unaccountable algorithms in government without mitigating the issues with these tools. The issue is not that human oversight is harmful in and of itself. Instead, the issue is that human oversight is unable to produce the benefits that motivate its adoption. The resulting mismatch between expectations and reality means that human oversight reduces scrutiny of government algorithms without reliably reducing the harms of these systems.

This second flaw has two dimensions. First, human oversight provisions conceal foundational concerns about algorithmic decision-making, providing policymakers and publics with a false sense of security that even flawed algorithms are safe to use in high-stakes arenas. Second, human oversight provisions shift accountability for algorithmic harms from agency leaders who determine the structure of algorithmic systems to frontline human operators who are relatively powerless. All told, human oversight policies effectively create a loophole that allows governments to adopt flawed algorithms and to shirk accountability for the harms that result.

4.2.1 The Assumption of Effective Human Oversight Provides a False Sense of Security in Adopting Algorithms

Human oversight policies cover up fundamental concerns about the use of algorithms in government decision-making. In response to community activism and media exposés, vendors and policymakers increasingly acknowledge that government algorithms can be error-prone and biased and that relying on algorithms for high-stakes decisions can be unjust. In many cases, these concerns undercut the reasoning for adopting algorithms in government. However, rather than prohibit certain applications of algorithms, policymakers present human oversight as the salve that enables governments to obtain the benefits of algorithms without incurring the associated harms. Under this approach, human oversight plays a central role in enabling governments to employ high-stakes algorithms. Were any of the proposed forms of human oversight effective, then perhaps this remedy would be appropriate to mitigate the risks of government algorithms. But given the failures of existing human oversight mechanisms, such regulations divert attention from fundamental concerns about algorithms and justify the inappropriate integration of algorithms into government decision-making.

15 The “rubber stamp” loophole set up by prohibitions on “solely” automated decisions has proven relatively easy to identify (Veale & Edwards, 2018; Wagner, 2019), prompting some regulators developing legislation to drop calls for GDPR-style restrictions on solely automated decisions (Office of the Privacy Commissioner of Canada, 2020). However, the limits of the other two approaches to human oversight are more subtle and consequential, as these forms of oversight have intuitive appeal and are increasingly common.
Two examples demonstrate how human oversight provides false comfort in the face of concerns that undermine the logic for algorithmic decision-making in government. The first example involves the assertion that humans should regularly override algorithmic decisions. The developers and managers of risk assessment tools for sentencing and child welfare point to human overrides as an important safeguard against imperfect predictions and as evidence that the algorithms are not replacing human judgment (Allegheny County Department of Human Services, 2019a; Northpointe, 2015; Wisconsin Department of Corrections, 2018). Similarly, multiple policy guidance documents calling for meaningful human oversight warn that, if humans agree with the algorithm too often, then decisions should be considered solely automated (Article 29 Data Protection Working Party, 2018; UK Information Commissioner’s Office, 2020). In other words, for human oversight to be meaningful, decision-makers must routinely disagree with the automated system (Veale & Edwards, 2018; Wagner, 2019).

At first glance, these calls for overrides appear prudent. Policymakers are right to be concerned about the perils of solely automated decision-making. If a human decision-maker rarely overrides an algorithmic decision, then the decision-making process would be nearly solely automated, potentially violating due process and human dignity and subjecting people to mistaken and biased judgments. Allowing humans to disagree with algorithms seems to provide an avenue for injecting discretion and error-correction into decisions. The problem, however, is that human overrides cannot actually remedy the concerns that motivate overrides. Policies calling for overrides therefore provide the appearance of quality control—legitimizing the use of flawed and controversial algorithms—but do not actually address the underlying issues.

Consider the two scenarios in which overrides of automated decisions appear particularly desirable. One reason to call for human overrides is because of a lack of trust in an algorithm to make accurate and fair decisions. Although human overrides seem reassuring in the face of doubts about the quality of algorithmic judgments, this remedy is unlikely to be effective: substantial evidence demonstrates that humans tend to override algorithms in detrimental rather than beneficial ways (Green & Chen, 2019a, 2019b; Grgić-Hlača et al., 2019; Lai & Tan, 2019).

A second reason to call for human overrides is because an algorithm fails to account for considerations that are essential to a given decision. For instance, pretrial risk assessments do not consider the full range of factors that judges must balance (Green & Chen, 2021). In such cases, human overrides seem to improve decisions by incorporating considerations that the algorithm omits. However, although human overrides provide reassurances in the face of concerns about myopic algorithms, they are unable to address the underlying concerns. People cannot reliably balance an algorithm’s advice with other important factors, as they often over-rely on automated advice (Parasuraman & Manzey, 2010; Skitka et al., 1999) and place greater weight on the factors that algorithms emphasize (Green & Chen, 2021; Skeem et al., 2019; Starr, 2014).
Thus, when proponents of criminal justice and child welfare risk assessments call for human overrides, they deflect criticism of these controversial tools but fail to mitigate the underlying concerns. Human oversight cannot address concerns about inaccurate, unfair, and myopic algorithms. More structural reforms are necessary. If an algorithm is so flawed that policymakers do not trust it to make decisions without a significant number of human overrides, then the appropriate remedy is to improve the algorithm. If the algorithm cannot be sufficiently improved, then the appropriate remedy is to stop using the algorithm. Similarly, if an algorithm ignores criteria that must be considered when making a given decision, then the appropriate remedy is to alter the algorithm so that it accounts for all relevant criteria. If this is not feasible, then the appropriate remedy is to stop using the algorithm.

The false sense of security provided by human oversight can also be seen in *State v. Loomis*. In this case, the Wisconsin Supreme Court ruled that courts could use the COMPAS risk assessment to inform sentencing as long as decisions involved judicial oversight and discretion (Wisconsin Supreme Court, 2016). Although the Wisconsin Supreme Court was right to recognize the perils of relying on COMPAS to determine sentences, its reliance on human oversight to alleviate these concerns was misplaced.

Consider the two central worries that prompted the Wisconsin Supreme Court to call for human oversight. First, concerned about the errors and biases of risk assessments, the Court pointed to judges’ discretion to ignore these tools. Most notably, the Court mandated that COMPAS be accompanied by a list of concerns that have been raised about the tool (Wisconsin Supreme Court, 2016). Although it seems reassuring to prompt judges to use discretion when considering risk assessments, doing so leaves judges with conflicting guidance: on the one hand the court hailed risk assessments for their ability to provide reliable and accurate predictions, while on the other hand the court warned that risk assessments can be laden with errors and biases. Furthermore, discretion is unlikely to be an effective remedy, as evidence demonstrates that judges often use their discretion to ignore risk assessments in punitive and racially biased ways (Albright, 2019; Cowgill, 2018; Human Rights Watch, 2017; Sheriff’s Justice Institute, 2016; Steinhart, 2006; Stevenson, 2018; Stevenson & Doleac, 2021).

Second, concerned about risk assessments violating due process, the Court attempted to limit the extent to which judges could rely on these tools. The Court asserted that judges may use risk assessments to inform—but not determine—particular aspects of sentences, defending the use of COMPAS in the case being reviewed because the risk assessment had no discernable impact on the final outcome. Even as it praised the ability of risk assessments to promote better outcomes, the Court affirmed Loomis’ sentence on the grounds that the circuit court “would have imposed

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16 The Indiana Supreme Court followed similar reasoning when justifying risk assessment tools in *Malenchik v. State* (Indiana Supreme Court, 2010).
the same sentence regardless of whether it considered the COMPAS risk scores” (Wisconsin Supreme Court, 2016). Although it seems reassuring to assert that judges cannot rely on risk assessments, this reasoning again leaves judges with conflicting guidance. On the one hand, if risk assessments can be used only to inform outcomes that would have been reached independently, then there is no functional reason to use such tools at all. On the other hand, if risk assessments are to improve outcomes as the Court intends, then such tools must influence sentencing decisions. Furthermore, it is unlikely that judges will limit their consideration of risk assessments as the Court envisions. Evidence suggests that judges and other people often defer to automated advice and change their decision-making processes due to algorithms, yet do not recognize that these behaviors are occurring (Green & Chen, 2021; Parasuraman & Manzey, 2010; Skeem et al., 2019; Starr, 2014).

By calling for judicial discretion, the Wisconsin Supreme Court alleviated its concerns about sentencing risk assessments without actually mitigating the harms associated with these tools. The foundational issue troubling the Court was the low quality of risk assessments and the conflict between risk assessments and due process. Judicial discretion cannot address these concerns. Rather than pointing to human oversight, the Court should have placed greater scrutiny on the algorithm’s quality and on whether it is appropriate for an algorithm to alter a defendant’s sentence. If the Court was not comfortable with the accuracy and fairness of risk assessments, then it should not have allowed these tools to be presented to judges until their quality improves. Similarly, if the Court was not comfortable with algorithms altering sentences, then it should not have allowed algorithms to be incorporated into sentencing adjudications at all. All told, if the Court would not allow the use of COMPAS without human oversight, then there is scant evidence supporting its decision to allow the use of COMPAS with human oversight.

4.2.2 Relying on Human Oversight Diminishes Responsibility and Accountability for Institutional Decision-Makers

By appearing to address foundational concerns about government algorithms, human oversight policies shift responsibility for algorithmic systems from agency leaders and technology vendors to human operators. Human oversight policies position frontline human operators as the scapegoats for government algorithms, even though algorithmic errors and injustices are typically due to factors over which frontline human overseers have minimal agency, such as the system design and

\[\text{17}\] Such reasoning reflects an element of contradictory and circular logic that underlies human oversight policies. The respective motivations for algorithmic and human judgments are directly opposed. On the one hand, algorithms are attractive because they promise consistency and objectivity. On the other hand, human oversight is attractive because it promises to counteract algorithmic consistency and objectivity with human flexibility and discretion. Thus we see algorithms being introduced to improve upon the cognitive limits and biases of humans, and then those same humans presented as the essential backstop overseeing algorithmic limits and biases. Facilitating desirable combinations of human and algorithmic decision-making will ultimately require developing policies that grapple with the inherent tensions between these modes of judgment and that consider the appropriate role for each in light of the tradeoffs. One starting point for such an approach is to take lessons from how the law combines rule-like and standard-like decision criteria in other domains (Strandburg, 2021).
the political goals motivating implementation. The emphasis on human oversight thus allows vendors and governments to have it both ways: they can promote an algorithm by proclaiming how its capabilities exceed those of humans, while simultaneously defending the algorithm and those responsible for it from scrutiny by pointing to the protection (supposedly) provided by human oversight. When something goes well, governments and vendors can hail the benefits provided by the algorithm. When something goes wrong, governments and vendors can blame and punish the individuals operating the system.

A notable instance of this convenient finger-pointing occurred in the aftermath of a Black man in Detroit being wrongfully arrested following an incorrect match by a Detroit Police Department (DPD) facial recognition system (Hill, 2020). Representatives from each of the three technology companies that produced the system immediately blamed the mistaken arrest on human operators following an inappropriate investigation process (Hill, 2020). Appearing the following year on the national news program 60 Minutes, the Detroit Police Chief similarly blamed “[s]loppy, sloppy investigative work” for the incident (CBS News, 2021). Noting that the detective and commanding officer have since been disciplined, the Detroit Police Chief added, “it wasn’t facial recognition that failed. What failed was a horrible investigation” (CBS News, 2021).

Although the operators surely could have followed a more thorough investigative process in this particular case, placing blame on the operators obscures the role of other actors—particularly the technology vendors and police chief—responsible for the system-level decisions that led to this arrest. It is DPD leadership and the technology vendors who chose to implement a shoddily-tested investigative technology known to have low accuracy when evaluating Black faces (Buolamwini & Gebru, 2018; Hill, 2020) in the U.S. city with the largest share of Black residents, against the opposition of many Black residents (Campbell, 2019). In fact, the Detroit Police Chief himself admitted that the DPD’s facial recognition system is incorrect 96% percent of the time, and DPD data demonstrates that the system is used almost exclusively to investigate Black suspects (Koebler, 2020). No form of human oversight could make it appropriate for DPD to use a facial recognition system that violates civil liberties, is incorrect in the vast majority of cases, and is used to surveil Detroit’s Black population. Instead, these harms can be remedied only by banning police facial recognition altogether (Hartzog & Selinger, 2018; Stark, 2019), as several jurisdictions across the United States have recently done (Hill, 2021) and many civil society organizations have called for (Amnesty International, 2021; European Digital Rights, 2021; Fight For The Future, 2021). Thus, although the human operators were the most proximate to the wrongful arrest, the

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18 This phenomenon matches the long-standing pattern of human operators being blamed for breakdowns in technical systems, even though the harms of these systems are typically structured by the decisions of more powerful institutional actors (Elish, 2019; Perrow, 1999).

19 For instance, the Austrian Public Employment Service hails the objectivity and precision of its algorithm that informs which job seekers will receive government assistance, yet simultaneously legitimizes the algorithm in the face of acknowledged limitations by describing it as a mere “second opinion” (Allhutter et al., 2020).
police chief and vendors are more substantively responsible for the incident and are the ones who should be held accountable.

5 An Alternative to Human Oversight Policies
This study has shown that policies mandating human oversight for government algorithms are flawed in two ways. First, human oversight is unable to provide the desired protections. In turn, human oversight policies legitimize flawed and unaccountable algorithms in government without remedying the issues with these tools. These findings demonstrate that policymakers must stop relying on human oversight as a central mechanism for protecting against the harms of government algorithms.

If legislators cannot depend on human oversight, then how should they regulate government algorithms? The answer is certainly not to simply remove human oversight from existing systems, allowing algorithms to operate autonomously. However, it is also imprudent to entirely abandon algorithms, relying solely on human judgment for all decisions. Instead, drawing on the lessons from the two flaws of human oversight policies, it is necessary to develop an alternative strategy for determining whether (and in what form) to incorporate algorithms into government decision-making.

In this section, I propose a two-stage approach to the evaluation, implementation, and governance of public sector algorithms. This approach is oriented around addressing the two flaws of human oversight policies. First, rather than crafting blanket rules that enable governments to use algorithms as long as a human provides oversight, policymakers must place far greater scrutiny on whether an algorithm is even appropriate to use in a given context. Second, rather than assuming that people can oversee algorithms effectively, policymakers must empirically evaluate whether the proposed forms of human oversight can actually function as desired. A central principle guiding this proposal is to increase the burden placed on agencies to affirmatively justify both their decisions to adopt algorithms and their proposed mechanisms for governing those algorithms.

5.1 Stage 1: Determining Whether an Algorithm is Suitable for a Decision
The first stage in determining the appropriate role for algorithms in governments is to evaluate whether a given algorithm is suitable for the proposed decision. This stage is intended to address the second flaw of human oversight policies, which is that they legitimate the use of algorithms despite flaws suggesting that these tools should not be used at all. Before government agencies incorporate algorithms into decision-making procedures, they must affirmatively justify that the proposed application does not violate human dignity, the decision is amenable to algorithmic augmentation, and the algorithm is trustworthy. There must also be mechanisms for holding institutional decision-makers accountable for these decisions.
Determining whether an algorithm is appropriate for a decision requires considering three components. Policymakers must first consider “red lines” that mark unacceptable uses of algorithms. Applications such as facial recognition and predictive policing violate fundamental notions of justice and human rights (Hartzog & Selinger, 2018; Richardson et al., 2019; Stark, 2019; Stop LAPD Spying Coalition, 2018). The issues with these algorithms cannot be remedied by increased accuracy or more reliable human oversight. Instead, it is necessary to ban these applications of algorithms outright. In recognition of these dangers, numerous jurisdictions across the U.S. have recently placed bans or moratoria on police use of facial recognition and predictive policing algorithms (Hill, 2021; Ibarra, 2020; Stein, 2020). Similarly, many academics and civil society organizations across Europe and North America have argued that red lines are necessary for regulating AI (European Digital Rights, 2021).

If an algorithm is not prohibited by a red line, policymakers should then consider whether it can be appropriately integrated into a given decision. Making this determination involves two dimensions of analysis: one focused on the decision and one focused on the algorithm. The first dimension of analysis is the extent to which the decision in question is amenable to algorithmic decision-making. As with decision-support systems in other domains (Cummings, 2006), the appropriate role for algorithms depends on the extent to which human discretion is essential to making the decision. Because algorithms make decisions according to predetermined rules, the more that a decision requires individualized human discretion, the less appropriate it is for algorithms to play a role in decision-making. While it may be appropriate to automate decisions guided by predetermined rules, decisions guided by standards require human discretion and cannot be adequately made by algorithms (Citron, 2008). Discretion is particularly desirable for decisions that require determining the appropriate application of ambiguous and conflicting goals in individual cases that are difficult to classify in advance (Binns, 2020; Zacka, 2017). This analysis suggests that it may be appropriate for governments to adopt machine learning algorithms for pure prediction problems, but not for decisions that involve balancing predictions with other factors.

The second dimension of analysis is the extent to which the algorithm in question is trustworthy, relative to the stakes of the decision at hand. The more that the algorithm is trustworthy, the more appropriate it is to have the tool influence decisions. Trust in an algorithm depends on several factors. First and foremost, it is essential that the algorithm has been rigorously evaluated for the task at hand and that those tests demonstrate that the algorithm makes predictions accurately and fairly. Transparency into the algorithm’s source code, training data, and development process are necessary for understanding how the algorithm works and how to interpret evaluations of the algorithm. An additional prerequisite is that the outcome of interest can be measured with reasonable accuracy and validity, as low-quality data and bad proxy variables present a significant limit on an algorithm’s reliability (Jacobs & Wallach, 2021). Finally, trust is relative to the stakes

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20 Policymakers should also consider additional factors at this stage, such as whether the algorithm in question actually represents a desirable approach to reform (Green, 2020).
of the decision: decisions that involve higher stakes associated with erroneous predictions require a higher standard for trusting algorithms. Some of these principles for evaluating the trustworthiness of an algorithm are already incorporated into the requirements for algorithmic impact assessments (Brown, 2020; California Legislature, 2021; Government of Canada, 2021). These principles suggest that it may be appropriate for governments to adopt algorithms which have passed rigorous and transparent evaluations, but not algorithms which have known flaws or are hidden from public scrutiny.

Considering both discretion and trust in tandem can inform the appropriate role for an algorithm within a particular decision. Each dimension yields a general principle regarding algorithmic decision-making. The more that the decision requires discretion, the less appropriate it is to incorporate an algorithm into that decision. Similarly, the less that the algorithm is trustworthy, the less appropriate it is to incorporate that algorithm into a decision.

These two principles combine, as summarized in Table 1. In quadrants 2 and 3, these principles suggest relatively single-mode decision-making processes. If there is a high need for human discretion and low trust in the algorithm, then governments should rely solely on human decision-making. Conversely, if there is a low need for human discretion and high trust in the algorithm, then governments should rely primarily on algorithmic decision-making. It may be appropriate to incorporate human oversight in a relatively supervisory role, but too much human involvement in quadrant 3 may in fact diminish the quality of decisions.

In quadrants 1 and 4, these principles suggest potentially hybrid decision-making processes. If there is low trust in the algorithm and a low need for discretion, or high trust in the algorithm and a high need for discretion, the arguments for human versus algorithmic decision-making cut against one another. Although we should not turn to solely algorithmic decision-making in these scenarios, it is possible that incorporating the algorithm into human decision-making could improve outcomes. The default in both of these scenarios should be to retain solely human decision-making. Judgments about whether (and in what form) to incorporate an algorithm should depend on case-by-case empirical evaluations of how the algorithm alters human decision-making.

In sum, quadrants 1, 3, and 4 all involve a presumed or potential role for algorithms in decision-making. In these scenarios, decisions about whether and how to combine human and algorithmic judgment must be subject to the results of empirical evaluations regarding how people interact with the algorithm in the given setting. This is the focus of the next stage of analysis, as discussed in Section 5.2.

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21 Relying on solely human decision-making does not mean relying on unchecked discretion. There are many existing mechanisms that constrain—without eliminating—the discretion of street-level bureaucrats (Lipsky, 2010).
Table 1
Summary of roles for human and algorithmic decision-making, based on the need for discretion within the given decision and the trust in the algorithm.\(^{22}\)

| (Relative) Trust in Algorithm | Need for Discretion                                      |
|------------------------------|----------------------------------------------------------|
| Low                          | 1) Primarily or solely human decision-making, with algorithms involved to the extent that rigorous research demonstrates benefits. |
| High                         | 2) Solely human decision-making.                         |
|                              | 3) Primarily or solely algorithmic decision-making.      |
|                              | 4) Primarily or solely human decision-making, with algorithms involved to the extent that rigorous research demonstrates benefits. |

The burden should fall on agencies to demonstrate—prior to adopting an algorithm—that the system is not prohibited by red lines, that it is appropriate for an algorithm to make or inform the decision in question, and that the algorithm is trustworthy. For instance, in order to receive approval to adopt an algorithm (at least above a certain threshold of high-impact decisions), agencies could be required to produce a written report analyzing the proposed algorithmic application across these three considerations. This approach would follow along the lines of surveillance oversight ordinances that have been passed in recent years. For instance, per the Surveillance Technology Ordinance passed in Cambridge, Massachusetts in 2018, before municipal departments can use surveillance technologies, they must provide the City Council with reports describing the technology and its proposed uses and governance (City of Cambridge, 2018). These reports must be made publicly available and be discussed at a City Council meeting open to the public, at which the City Council will decide whether to approve the use of the surveillance technology (City of Cambridge, 2018).

In addition to promoting a more stringent standard regarding whether an algorithm is appropriate to use, this reporting requirement would also support greater democratic participation and accountability in decisions regarding whether to adopt algorithms. First, requiring agencies to face public hearings regarding their proposed applications of algorithms would provide the public with important opportunities to weigh in regarding the decisions driving the adoption of algorithms.

\(^{22}\) Of course, many scenarios will not fit neatly into this 2x2 grid. Table 1 can therefore be seen as identifying poles of a two-dimensional spectrum. For instance, as we move from low-discretion to high-discretion decisions, the threshold for trust in an algorithm in order to consider using it increases accordingly.
The legislative developments of recent years demonstrate the importance of public input into government decisions about algorithmic decision-making. For instance, recent facial recognition and predictive policing bans in the United States were the result of concerted advocacy in each jurisdiction (Hill, 2021; Miller, 2020). In Europe, advocates and companies have jockeyed over the proper role for red lines. Industry representatives removed red lines from the High-Level Expert Group on AI’s ethics guidelines, against the desires of academic members of the Group (Metzinger, 2019). And even though a coalition of 62 civil society organizations preemptively called for the European Commission’s AI Act proposal to include red lines (European Digital Rights, 2021), the proposed Act merely restricts most “high-risk AI systems” (European Commission, 2021).

Second, requiring agencies to justify their choices to adopt algorithms would shift accountability for algorithmic harms toward institutional leaders. Whereas human oversight policies direct attention to human operators, starting with an analysis of an algorithm’s suitability directs attention to actors such as government agencies (especially if agencies are required to produce a publicly available written report laying out their reasoning). This proposed burden would compel agency leaders to justify their choice to implement an algorithm in a given context, making it more difficult for them to direct blame at human operators when the algorithm produces harms. The terms of debate after algorithmic harms arise would move upstream, from whether human operators exercised appropriate oversight to whether a given algorithm should have been adopted in the first place.

5.2 Stage 2: Evaluating and Monitoring Human-Algorithm Collaborations
When the first stage of analysis suggests that there might be a role for algorithms in collaboration with humans (i.e., quadrants 1, 3, and 4 in Table 1), policymakers must then turn to the second stage of analysis. This stage involves determining whether and in what form to combine human and algorithmic judgments. This stage is intended to address the first flaw of human oversight policies, in which human oversight is presented as a safeguard against algorithmic harms despite minimal empirical evidence that it actually provides reliable protections. Unless an algorithm is intended to operate autonomously, it is not enough to show that the algorithm is reliable on its own. Instead, there must be evidence suggesting that people can oversee the algorithm’s functioning and that incorporating the algorithm into decision-making will improve outcomes.

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23 The coalition’s open letter highlighted five categories of AI particularly deserving of red lines: biometric mass surveillance, border and migration control, social scoring systems, predictive policing, and risk assessments in the criminal justice system (European Digital Rights, 2021).

24 This should apply even in many cases in which human operators may appear to be at fault for failing to provide proper oversight. If agency leaders choose to implement a flawed or unjust algorithm without any evidence that staff can provide the desired form of oversight, then they should not be permitted to foist blame on staff for failing to do a task that never should have been expected of them. Human operators should not be completely immune from accountability, but their accountability should be tempered in light of whether the algorithm in question is appropriate for the agency to be using at all and whether people can be reasonably expected to provide the desired forms of oversight.
These evaluations must precede any decision to adopt algorithms in a manner that involves human-algorithm collaborations.

This second stage of analysis involves shifting the burden onto agencies to affirmatively demonstrate that people can effectively oversee an algorithm. Currently, policies calling for human oversight rarely point to empirical evidence or make empirical claims, reflecting the implicit assumption that human oversight is effective. Given the empirical evidence demonstrating the limits of human oversight, however, the default assumption should be that human oversight is likely to be ineffective, unless proven otherwise. The burden should therefore fall on those proposing human oversight of algorithms to provide affirmative evidence that this mechanism improves outcomes and acts a remedy for concerns about algorithmic decision-making.

This burden to evaluate human oversight builds on the emerging trend in AI regulation toward requiring proactive assessments of an algorithm’s performance and behavior. Several recent bills mandate that agencies or vendors must conduct algorithm impact assessments prior to any public sector implementation of an automated decision system (Brown, 2020; California Legislature, 2021; Government of Canada, 2021). Similarly, the EU AI Act requires providers of high-risk AI systems to conduct an ex ante assessment ensuring that their system conforms to the Act’s rules (European Commission, 2021). These requirements represent a burden placed on vendors and agencies, reflecting knowledge of the limits and harms that government algorithms often generate. Although none of these pre-deployment assessments consider the quality of human oversight, legislators should extend these assessments to incorporate evaluations of human-algorithm collaborations.

The central method for assessing human oversight is to conduct experimental evaluations of human-algorithm collaborations before implementing an algorithm in practice. These proactive evaluations of human oversight should progress in two stages. First, in order to uncover breakdowns in human-algorithm collaboration and experiment with potential remedies, vendors should study how laypeople use the algorithm in a lab setting. Although these experiments would be with laypeople, they can shed light on some behaviors of experts in practice and can be conducted in a quick, low-stakes manner on platforms such as Amazon Mechanical Turk (Green & Chen, 2021). These initial experiments would provide a baseline of evidence regarding how people interact with the algorithm. Second, once preliminary evidence suggests that people can collaborate effectively with the algorithm, vendors and governments should study how practitioners use the algorithm in a lab setting. These experiments can test the mechanisms identified as most effective with laypeople and determine the likely effects of implementing the algorithm. An algorithm should be incorporated into practice only when these precursory

25 Strictly speaking, it is possible to skip the first stage and start with the second stage. However, it will generally be beneficial begin with the first stage. Compared to studies with experts, studies with laypeople can be conducted more quickly and with more participants, enhancing the ability to study human-algorithm collaborations and to identify
evaluations suggest that adopting the algorithm will improve human decision-making and that people are able to perform the desired oversight functions.

Even after an algorithm is adopted in practice, human interactions with it must be subject to ongoing monitoring. Persistent monitoring is particularly important in light of evidence that judicial uses of algorithms can shift over time (Stevenson, 2018) and that street-level bureaucrats’ responses to algorithms depend on highly localized details of institutional implementation (Brayne & Christin, 2020). As with the proactive evaluations, this monitoring can be accomplished by extending recently proposed post hoc evaluation mechanisms (Brown, 2020; European Commission, 2021) to incorporate human interactions and oversight. Agencies should be required to collect information about human interactions with algorithms, for instance by tracking overrides of algorithmic decisions to check for racial disparities (Steinhart, 2006). Furthermore, given that automation can reduce its users’ sense of control, responsibility, and moral agency (Berberian et al., 2012; Cummings, 2006), it is also important to continuously monitor whether the algorithm distorts or erodes the moral agency of decision-makers. Evaluations should ensure that algorithms complement rather than diminish the work of government staff (Pasquale, 2020).

These efforts to evaluate human-algorithm collaborations in specific government settings will be bolstered by research in computer science and related fields. There is growing academic interest regarding how humans make decisions with algorithmic support and whether there are mechanisms that reliably improve human-algorithm collaborations. With sustained research, it may be possible to discover design interventions that improve the quality of human oversight and human-algorithm collaborations.  

Recent work has found that algorithmic accuracy does not always lead to the optimal outcomes (Bansal, Nushi, et al., 2021; Elmalech et al., 2015; Green & Chen, 2021; McCradden, 2021), demonstrating the necessity to take an “algorithm-in-the-loop” approach that considers the design and structure of human-algorithm collaborations rather than focusing only on optimizing algorithm performance (Green & Chen, 2019a). One promising direction along these lines is to explore novel approaches for integrating algorithms into human decision-making processes, such as adding greater structure to human-algorithm collaborations (Strandburg, 2021) and providing decision support tools rather than specific recommendations (Yang et al., 2019). For instance, cognitive forcing functions (e.g., prompting people to make a preliminary decision before being shown the algorithm’s suggestion) can improve human-algorithm collaborations (Buçinca et al., 2021; Green & Chen, 2019b). Future research should also evaluate mechanisms that have been implemented in practice, such as providing training to human operators (Allegheny County Department of Human Services, 2019a) and requiring written justification and supervisor approval for any overrides (Allegheny County Department of Human Services, 2019a; Steinhart, 2006).

strategies for improving them (Green & Chen, 2021). As we gain a deeper scientific understanding of human-algorithm collaborations, it may become more feasible to start with the second stage.

Alternatively, research could uncover fundamental limits to human oversight of algorithms.
6 Conclusion

This study evaluated the global policy trend toward requiring human oversight of algorithms used by governments. By considering human oversight policies in light of research on human-algorithm interactions, I found that these policies suffer from two significant flaws. First, the vast majority of evidence suggests that people are unable to adequately provide any of the envisioned forms of oversight. Second, the incorrect assumption of effective human oversight legitimizes the use of flawed and unaccountable algorithms in government. Thus, rather than enabling governments to attain the benefits of algorithms without incurring the associated risks, human oversight policies justify the inappropriate integration of algorithms into government decision-making and hinder accountability for institutional decision-makers such as agency leaders. In light of these findings, I proposed an alternative approach for determining whether and how to incorporate algorithms into government decision-making. First, governments must determine whether it is actually appropriate to employ an algorithm within a specific context. Second, in settings where they envision a potential role for algorithms alongside human judgment, governments or vendors must perform preliminary evaluations of whether people can collaborate with the algorithm as desired. This proposed process will increase the burden on agencies to justify their decisions to adopt algorithms, helping to ensure that human oversight no longer operates as a superficial salve for fundamental concerns about algorithmic decision-making in government.

As governments adopt algorithms to make or inform consequential decisions, regulation is necessary to ensure that they avoid producing injustices and violating fundamental legal principles. It is not enough merely to enact regulations, however: policymakers must ensure that their regulations actually provide the desired protections and benefits. Relying on intuitively appealing but ineffective regulation could lead to the worst of both worlds: the underlying problem persists, yet the presence of the regulation leads to the perception that the problem has been solved. Efforts to regulate government algorithms must therefore be particularly attentive to the social contexts in which algorithms are embedded and to empirical evidence about how algorithms influence human decision-making. By taking a more sociotechnical and evidence-based regulatory approach, policymakers will facilitate more democratic and equitable decisions regarding how governments use algorithms.

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8 Appendix: Summary of Human Oversight Policies

This table summarizes the 40 policy documents that I reviewed as part of this study. Document Classification refers to the type of policy document (1 = proposed or passed legislation; 2 = policy guidance by government or government-appointed bodies; 3 = manuals, policies, and court cases related to risk assessments used in the US criminal justice settings and the Allegheny County Family Screening Tool). Approach to Human Oversight refers to how each policy presents the appropriate role for human oversight (1 = restricting solely automated decisions; 2 = emphasizing human discretion; 3 = requiring meaningful human input).

| Author/Publisher | Title                                                                 | Year | Document Classification | Approach to Human Oversight |
|------------------|----------------------------------------------------------------------|------|-------------------------|-----------------------------|
| Austrian Parliament | Datenschutzgesetz (Data Protection Act)                           | 2018 | 1                       | 1                           |
| Belgian Federal Parliament | Loi relative à la protection des personnes physiques à l'égard des traitements de données à caractère personnel (Law on the Protection of Natural Persons with regard to the Processing of Personal Data) | 2018 | 1                       | 1                           |
| Bundestag (German Parliament) | Federal Data Protection Act (BDSG)                             | 2019 | 1                       | 1                           |
| Dutch Parliament | Uitvoeringswet Algemene verordening gegevensbescherming (Implementation Act General Data Protection Regulation) | 2018 | 1                       | 1                           |
| European Parliament and the Council of the European Union | General Data Protection Regulation (GDPR) | 2016 | 1                       | 1                           |
| French Parliament | French Data Protection Act                                      | 2018 | 1                       | 1                           |
| Houses of the Oireachtas (Irish Parliament) | Data Protection Act 2018                                      | 2018 | 1                       | 1                           |
| Hungarian Parliament | Data Protection Act                                           | 2018 | 1                       | 1                           |
| Kingdom of Bahrain | Personal Data Protection Law                                    | 2018 | 1                       | 1                           |
| National Assembly of Québec | Bill 64: An Act to modernize legislative provisions as regards the protection of personal information | 2020 | 1                       | 1                           |
| National Congress of Brazil | General Data Protection Law                                    | 2019 | 1                       | 1                           |
| Parliament of Mauritius | The Data Protection Act 2017                                   | 2017 | 1                       | 1                           |
| Republic of Argentina | Ley De Protección De Los Datos Personales (Personal Data Protection Law) | 2018 | 1                       | 1                           |
| Country/Region                  | Legislation/Document                                                                 | Year  | Section | Note |
|--------------------------------|--------------------------------------------------------------------------------------|-------|---------|------|
| Republic of Kenya              | The Data Protection Act, 2019                                                        | 2019  | 1       | 1    |
| Republic of South Africa       | Protection of Personal Information Act                                               | 2013  | 1       | 1    |
| Republic of Uganda             | The Data Protection and Privacy Act, 2019                                             | 2019  | 1       | 1    |
| Senator Sherrod Brown          | Data Accountability and Transparency Act of 2020                                      | 2020  | 1       | 1    |
| Slovenian Parliament           | Zakon o varstvu osebnih podatkov na področju obravnavanja kaznivih dejanj (Personal Data Protection Act in the field of dealing with criminal offenses) | 2020  | 1       | 1    |
| UK Parliament                  | Data Protection Act 2018                                                               | 2018  | 1       | 1    |
| Allegheny County Department of Human Services | Frequently-Asked Questions                                                            | 2019  | 3       | 2    |
| Allegheny County Department of Human Services | Ethical Analysis: Predictive Risk Models at Call Screening for Allegheny County   | 2019  | 3       | 2    |
| Annie E. Casey Foundation      | Juvenile Detention Risk Assessment: A Practice Guide for Juvenile Detention Reform   | 2006  | 3       | 2    |
| Arnold Ventures                | Public Safety Assessment FAQs (“PSA 101”)                                            | 2019  | 3       | 2    |
| Australian Human Rights Commission | Human Rights and Technology: Discussion Paper                                      | 2019  | 2       | 2    |
| Government of Canada           | Directive on Automated Decision-Making                                                | 2021  | 1       | 2    |
| Indiana Supreme Court          | Malenchik v. State                                                                   | 2010  | 3       | 2    |
| Multi-Health Systems Inc.      | The Level of Service Inventory-Revised Manual                                        | 2001  | 3       | 2    |
| New Jersey Courts              | One Year Criminal Justice Reform Report to the Governor and the Legislature          | 2017  | 3       | 2    |
| Northpointe                    | Practitioner’s Guide to COMPAS Core                                                  | 2015  | 3       | 2    |
| Statistics New Zealand         | Algorithm Assessment Report                                                          | 2018  | 2       | 2    |
| Statistics New Zealand         | Algorithm Charter for Aotearoa New Zealand                                          | 2020  | 2       | 2    |
| Wisconsin Dept of Corrections  | Electronic Case Reference Manual                                                     | 2018  | 3       | 2    |
| Wisconsin Supreme Court        | Wisconsin v. Loomis                                                                  | 2016  | 3       | 2    |
| Administrative Conference of the United States | Government by Algorithm: Artificial Intelligence in Federal Administrative Agencies | 2020  | 2       | 3    |
| **Article 29 Data Protection Working Party** | Guidelines on Automated individual decision-making and Profiling for the purposes of Regulation 2016/679 | 2018 | 2 | 3 |
| **European Commission** | Proposal for a Regulation laying down harmonised rules on artificial intelligence (Artificial Intelligence Act) | 2021 | 1 | 3 |
| **High-Level Expert Group on AI** | Ethics Guidelines for Trustworthy AI | 2019 | 2 | 3 |
| **High-Level Expert Group on AI** | Assessment List for Trustworthy Artificial Intelligence | 2020 | 2 | 3 |
| **UK Information Commissioner’s Office** | Guidance on the AI Auditing Framework | 2020 | 2 | 3 |
| **Washington State Legislature** | SB 6280 - 2019-20: Concerning the use of facial recognition services | 2020 | 1 | 3 |