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ALGORITHMIC DECISION-MAKING AND DISCRIMINATION IN DEVELOPING COUNTRIES

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This article seeks to investigate how developing countries can ensure that algorithmic decision-making does not leave protected groups in their jurisdictions exposed to unlawful discrimination that would be almost impossible to prevent or prove. The article shows that universally, longstanding methods used to prevent and prove discrimination will struggle when confronted with algorithmic decision-making. It then argues that while some of the proposed solutions to this issue are promising, they cannot be successfully implemented in a vast majority of developing countries because these countries lack the necessary institutional foundation. The key features of this institutional foundation include: (i) a well-rooted culture of transparency and statistical analysis of the disparities faced by protected groups; (ii) vigilant non-government actors attentive to algorithmic decision-making; and (iii) a reasonably robust and proactive executive branch or an independent office to police discrimination. This article argues that antidiscrimination advocates need to pay special attention to these three issues to ensure that the use of algorithms in developing countries is contemplative and avoidant of proven negative and discriminatory outcomes.

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I. Introduction

A rich body of research arguing that discrimination is wrong for both deontological[1] and teleological[2] reasons explains the motivation this research of many countries around the world that have set out protected characteristics upon which discrimination by both public and private decision-makers is prohibited.[3] Many developing countries have likewise done so through their constitutions and other legislation, but seem to end their commitment there given that detection and action is left to the injured party.[4] That some part of this tenuous situation has held up (with some discrimination suits still being successfully brought before courts) has more to do with the fact that human conduct is what has been at play so far. The use of algorithms to make decisions further complicates the process of identifying and remedying when discrimination has occurred.

While the use of machine-learning algorithms to make hugely consequential predictions and decisions continues to gain ground,[5] questions about how to police the fairness of such decisions and reduce the disparities faced by marginalized people in protected classes abound.[6] The discourse around these questions is burgeoning in developed countries but remains insufficient in developing countries.[7] The gap is particularly eye-catching since the use of algorithms to make decisions is taking root in the developing world nearly as

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[1] In recent years, scholarly output touching on the deontological reasons for determining wrongful discrimination has been rich and outstanding. *See, eg.*, DEBORAH HELLMAN, WHEN IS DISCRIMINATION WRONG? (2008); PHILOSOPHICAL FOUNDATIONS OF DISCRIMINATION LAW (Deborah Hellman & Sophia Moreau, eds., 2013); BENJAMIN EIDELSON, DISCRIMINATION AND DISRESPECT (2015); TARUNABH KHAITAN, A THEORY OF DISCRIMINATION (2015); FOUNDATIONS OF INDIRECT DISCRIMINATION (Hugh Collins & Raunabh Khaitan, eds., 2018).
[2] There is also work that focuses on consequentialist reasons. *See, e.g.*, Richard McAdams, *Economic Theories of Discrimination, in* THE EMPIRE OF DISGUST: PREJUDICE, DISCRIMINATION, AND POLICY IN INDIA AND THE US 369, 374 (Hasan et al. eds., 2019).
[3] *See* KHAITAN, *supra* note 1, at 49–62.
[4] *See* Karen Yeung, *Why Worry About Decision-Making by Machine?*, *in* ALGORITHMIC REGULATION 21, 22 (Karen Yeung & Martin Lodge eds., 2019).
[5] *Id.* at 35–48.
[6] *Id.* at 41–42.
[7] *See* Lindsey Anderson, *Artificial Intelligence in International Development: Avoiding Ethical Pitfalls*, 30 PRINCETON UNIV. J. PUB. & INT'L AFF. (May 20, 2019), https://jpia.princeton.edu/news/artificial-intelligence-international-development-avoiding-ethical-pitfalls.

quickly as it is in the developed world.[8] In any case, global capitalism's history counsels us to expect that people in the developing world will endure aggressive targeting by corporations which profit from selling tools that deploy algorithms in decision-making.[9]

Because of the significant efficiency gaps and low standard of wellbeing developing countries have to contend with[10], these nations readily sympathize with the argument that tools that use algorithmic decision-making should be allowed to freely operate on the basis that the likely benefits outweigh the costs.[11] This claim is powerful, but flawed in seeing people only as a group.[12] Additionally, there is a risk that such tools raise the standards of wellbeing for already-privileged groups of people while expanding inequalities suffered by marginalized people in protected classes.[13] As a result, the 'good' delivered by efficiency is in many cases not good enough.[14]

To further complicate the picture, algorithmic decision-making is creating new challenges for longstanding approaches of preventing and proving direct or indirect discrimination (also referred to hereafter as disparate treatment and disparate impact, respectively). There is now convincing evidence that approaches for preventing discrimination in algorithms which require proof of causation, and *significant* correlation or exclusion of inputs are no longer tenable, meaning that detection of discrimination requires complicated examination of processes.[15] Moreover, while parties that deploy disparate impact algorithms can easily come up with a legal justification for the values and characteristics that the algorithm detects, those individuals that are discriminated against will find it exceedingly

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[8] Several algorithmic tools already operate in countries like Kenya and India, taking part in among others credit-scoring, assignment of housing, school placement and predicative policy. For more information, *see What Determines my Tala Loan?*, TALA BLOG (February 10, 2020), https://tala.co.ke/2020/10/02/what-determines-my-tala-loan/.
[9] *See* Abeba Berhane, *Algorithmic Colonization of Africa*, 17 SCRIPTED 389, 392–93 (2020).
[10] *See* Jona Hoxhaj & Eglantina Hysa, Well-being in Developing Countries 10–11 (2015 https://www.researchgate.net/publication/308112884_Well-being_in_Developing_Countries.
[11] Shakir Mohamed et. al, *Decolonial AI: Decolonial Theory as Sociotechnical Foresight in Artificial Intelligence*, 33 PHIL. & TECH. 1, 13 (2020).
[12] Deborah Hellman, *Measuring Algorithmic Fairness*, 106 VA. L. REV. 811, 842–43 (2020).
[13] *See* Chinmayi Arun, *AI and the Global South: Designing for Other Worlds*, *in* THE OXFORD HANDBOOK OF ETHICS OF AI 589, 600 (Markus Dubber, Frank Pasquale & Sunit Das eds., 2020).
[14] Ben Green, "Good" Isn't Good Enough 2–3 (2019) (NeurIPS Joint Workshop on AI for Soc. Good, Workshop Paper).
[15] Andrea Tsamados et al., *The Ethics of Algorithms: Key Problems and Solutions*, AI & SOC., at 1, 5 (2021).

hard to prove that another approach exists that would achieve the purpose of the algorithm without having a discriminatory impact.[16]

The latest solutions for *ex ante* and *ex post* scrutiny of algorithmic decision-making seem promising but rest on a foundation that necessitates: (i) a well-rooted culture of transparency and statistical analysis of the disparities faced by protected groups[17]; (ii) vigilant non-government actors attentive to algorithmic decision-making[18]; and (iii) reasonably robust and proactive independent or executive branch regulatory policing of discrimination.[19]

This article will show that the current discourse surrounding solutions to algorithmic discrimination is not attuned to the situation in a vast majority of developing countries. These developing countries often lack rich statistical analyses on the disparities faced by protected groups, and struggle with negligible. Furthermore, it is common for civil society groups to show little interest in algorithmic decision-making and the administrative state plays no identifiable role in policing discrimination. This article argues that if these issues are ignored while algorithmic decision-making is allowed to take root in those countries, the result might be a future of increased disparities faced by groups which the individuals and institutions of the country have already marginalized. [20]

Under the assumption that the age of algorithmic decision-making is to result in narrower disparities and less discriminatory conduct suffered by the protected groups in developing countries, I propose that policymakers, lawmakers, researchers, donors, and civic activists need to invest their wealth and efforts on mitigating the discriminatory impact of algorithmic decision-making. In an era where algorithmic tools are primarily designed by "people from the North,"[21] the perspective that this study presents will also point out questions that developers need to consider as they design algorithmic tools.

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[16] *See* Arun, *supra* note 13, at 601.
[17] *See* Tsamados et al., *supra* note 15, at 2, 5, 10.
[18] *See* Laurie Clarke, *Algorithms: The age of self-regulation could be ending*, TECH MONITOR (Feb. 3, 2021), https://techmonitor.ai/ai/algorithms-self-regulation-could-be-ending.
[19] *See* Press Release, Senator Markey, Rep. Matsui Introduce Legislation to Combat Harmful Algorithms and Create New Online Transparency Regime, (May 27, 2021), https://www.markey.senate.gov/news/press-releases/senator-markey-rep-matsui-introduce-legislation-to-combat-harmful-algorithms-and-create-new-online-transparency-regime.
[20] *See* Arun, *supra* note 13, at 603–04 (arguing that vulnerable "southern" populations are particularly at risk).
[21] *Id.* at 601.

This article will touch on discrimination by algorithms used by public and private bodies. Further, the article aims at the substantive rather than procedural goal of anti-discrimination law.[22] It will proceed as follows. Section II will consider unlawful discrimination in algorithmic decision-making, including how it arises and why the longstanding approaches that countries use to prevent and prove discrimination wither when confronted by algorithms. In Section III, the article will review the most promising approaches designed to ameliorate the challenge that algorithmic decision-making poses. This section will also discuss the foundation required for the success of those approaches. Section IV of the article will demonstrate that the foundation required for the successful implementation of the approaches does not exist in a vast majority of developing countries. It will also propose the way forward. Finally, the article concludes in Section V.

II. Unlawful Discrimination in Algorithmic Decision-Making

a. How Discrimination in Algorithmic Decision-Making Arises

At its essence, machine learning involves the development of algorithms which enable a computerized system to analyze a dataset and yield functions (also known as rules or models that are deterministic mappings from a set of input values to one or more output values).[23] On the other hand, algorithms can simply be defined as complex processes that a computer follows to reach decisions.[24] In machine learning, an initial algorithm gives the computerized system a function that guides its analysis of complex datasets to find recurring patterns.[25] From the captured patterns, the computerized system creates another algorithm with an updated function, and uses this function to analyze and reach decisions or predictions about similar real-life datasets.[26]

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[22] This is an important caveat because a focus on the procedural goal, or both the procedural and substantive goals, would necessarily force the research into a different direction. For example, procedural justice may demand the omission of any input data which contains protected characteristics and proxies as an end in itself. This study is not concerned with that. It is instead focused on the substantive result of preventing discrimination on the basis of protected characteristics.

[23] JOHN D. KELLEHER, DEEP LEARNING 6–7 (2019).

[24] *See Algorithms and Complexity*, BRITTANICA, https://www.britannica.com/science/computer-science/Algorithms-and-complexity (last visited Oct. 6, 2021).

[25] *See* KELLEHER, s*upra* note 23, at 7.

[26] Jon Kleinberg et al., *Discrimination in the Age of Algorithms*, 10 J. LEGAL ANALYSIS 113, 132 (2019) (referring to the first algorithm as the "trainer" and the second one as the "screener").

The journey to creating—or constantly updating—the algorithm that gives the final prediction or decision is known as "training."[27] In the course of training, the initial algorithm processes a dataset (known as the training dataset) and comes up with the function which best matches the patterns in the dataset.[28] That function is then encoded in the computer as a model[29] to be used by the other algorithm to make inferences out of new datasets. While the model that emerges usually captures patterns, associations, or correlations in a dataset, it does not explain the cause or nature of these links.[30]

It would be naïve and dangerous to believe that algorithms make decisions (inferences) in an objective and bias-free way.[31] So long as any aspect of algorithms' connection of patterns and correlations in the big data they assess is in any manner dependent on human interpretation,[32] they cannot be bias-free. Because existing bias is often the result of long histories of structural injustice, it is difficult to extricate it out of the training datasets fed into machine-learning algorithms, especially since such a move might reduce the accuracy of inferences that an algorithm makes.[33] The bias is of course not always wrong or unlawful—however, the bias becomes unlawful when it reaches a point that the government has prohibited under anti-discrimination law.[34]

Algorithmic discrimination can arise out of one or a combination of the following: modelling, training, and usage. In modelling, consider that large and complex datasets usually present more than one fitting function to an algorithm. To help the algorithm select an exact function, human beings supplement the information provided by the dataset with a series of assumptions about the characteristics of the best function. This is what is known as an inductive bias.[35] For instance, a screening algorithm for employees will be designed in line with human classification of which candidate fits the description of a "good" employee and which one does not. Not only are such inductive biases bound to include

[27] *Id.*
[28] *See What is Training Data?*, APPEN (June 28, 2021), https://appen.com/blog/training-data/.
[29] KELLEHER, *supra* note 23, at 13.
[30] Thomas Nachbar, *Algorithmic Fairness, Algorithmic Discrimination*, 48 FLA. ST. U.L. REV. 509, 521 (2021).
[31] Kleinberg et al., *supra* note 26, at 116.
[32] Naturally, this is nearly always the case since the dataset used to train an algorithm will not only implicitly carry the structural injustices in a society, but it is also often selected and prepared by human beings with biases.
[33] Kleinberg et al., *supra* note 26, at 116
[34] DEBORAH HELLMAN, WHEN IS DISCRIMINATION WRONG? 1–4 (2011).
[35] KELLEHER, *supra* note 23, at 18–19.

some prejudices, but they might also contain sensitive information that reveals protected characteristics[36] or proxies for protected characteristics.[37]

Training machine-learning algorithms comes with similar risks since an algorithm is likely to inherit the prejudices and biases within the datasets used to train them, whether via supervised or unsupervised learning.[38] Even where the training takes place 'online', which is where an algorithm is released into an environment to try out different policies and functions (training and inference are therefore interleaved), there remains the danger that the environment may not be sufficiently representative.[39] Finally, when algorithms are used in environments for which they were not specially modelled and trained, they can have discriminatory consequences. Take for example an algorithm modelled and trained for a setting in country A and then used for a setting in country B without any careful adjustments being made. Such an algorithm could easily discriminate against some protected groups in country B.

The end result is that various problems of discrimination could arise out of an algorithm's decisions and predictions. To begin, algorithms may engage in disparate treatment by actively considering a person's protected characteristics or using proxies to arrive at those characteristics. They may also have a disparate impact on vulnerable protected groups based on some aspect of their modelling, training, and usage. Finally, their decisions may increase disparities in a way that many would deem unfair.[40]

Although human decision-making can also be discriminatory, discrimination by machine-learning algorithms is far more worrisome than human discrimination. Machine-learning algorithms, as Natalia Criado and Jose Such have so starkly observed, "have the potential to discriminate more consistently, systematically and at a larger scale than traditional discriminatory practices."[41] Part of the reason for this is that the efficiency which computational decision-makers offer makes them very attractive, which in turn means that where their use is widespread, any discriminatory effect they have will appear in many identical iterations in rapid succession—essentially discrimination on a 'grand' scale.[42] It is

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[36] NATALIA CRIADO & JOSE SUCH, DIGITAL DISCRIMINATION 85 (Karen Yeung & Martin Lodge eds., 2019).
[37] Anya Prince & Daniel Shwarcz, *Proxy Discrimination in the Age of Artificial Intelligence and Big Data*, 105 IOWA L. REV. 1257, 1273–81 (2020).
[38] CRIADO & SUCH, *supra* note 36, at 86.
[39] *Id.*
[40] Kleinberg et al., *supra* note 26, at 139.
[41] CRIADO & SUCH, *supra* note 36, at 85.
[42] Nachbar, *supra* note 30, at 533.

no wonder algorithmic decision-making is drawing special attention from all those interested in antidiscrimination.

b. Why Longstanding Approaches to Preventing and Proving Discrimination are Inadequate

The challenges that algorithmic decision-making creates for legal analyses are in many ways analogous to those which technologies such as the telegraph, the internet, DNA identification and synthetic biology created when they first appeared on the scene. Surveying responses to the emergence of technologies such as the telegraph, the internet, DNA identification, and synthetic biology, one of the chief lessons Gregory Mandel notes is that often, pre-existing legal categories may no longer apply to new law and technology disputes.[43] This lesson comes to life when one tries to apply longstanding approaches of detecting discrimination onto algorithmic decision-making.

Most approaches to detecting discrimination are designed to find out and prevent direct use of protected characteristics in decision-making and t allowing apparently neutral decisions to have a lopsidedly negative impact on protected groups without acceptable justification.[44] Antidiscrimination law in almost every country still requires that successful litigants prove (at least) some significant correlation[45] between the protected characteristic and the decision made; or between a specific factor/ policy and the lopsidedly negative impact it has on protected groups.[46] For human decisions, this has often been possible to prove even if imperfectly.[47] The same cannot be said of decisions made by algorithms.

The complexity of the manner in which algorithms find patterns, create functions and arrive at inferences makes it difficult for individuals to confidently pinpoint the input or proxy that is causing discrimination or which has any significant correlation to the discrimination.[48] To make matters worse, dynamic self-learning algorithms modify the functions they use regularly.[49] For these reasons, it is no longer possible to point out with any precision which inputs are

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[43] GREGORY MANDEL, LEGAL EVOLUTION IN RESPONSE TO TECHNOLOGICAL CHANGE 227–38 (Roger Brownsword et al. eds., 2017).
[44] Nachbar, *supra* note 30, at 535.
[45] KHAITAN, *supra* note 1, at 169.
[46] *Id.* at 69–71, 166–67.
[47] Kleinberg et al., *supra* note 26, at 130.
[48] Nicole Posner, *The Hidden Dangers of Algorithmic Decision-Making*, TOWARDS DATA SCIENCE (Dec. 1, 2018), https://towardsdatascience.com/the-hidden-dangers-in-algorithmic-decision-making-27722d716a49.
[49] Anupman Chander, *The Racist Algorithm?*, 115 MICH. L. REV. 1023, 1039 (2017).

responsible for some disparate treatment or impact,[50] which is exactly the sort of connection most legal tests require of a litigant attempting to prove discrimination.[51] Under these circumstances, it is nearly impossible for litigants to prove that discrimination has occurred without some change in antidiscrimination law.

In almost every country, antidiscrimination law also tries to protect the vulnerable by prohibiting certain distinctions motivated by the consideration of protected characteristics.[52] Such an approach is likewise likely to be pointless when it comes to algorithmic decision-making. Regulation that prescribes for the exclusion of protected characteristics from the input data which algorithmic tools can consider will achieve little from the standpoint of substantive justice since algorithms can still recover the protected information (as it almost certainly remains embedded in the non-excluded data).[53] In that case, protected characteristics would still be used implicitly. It is important to note that there is no exclusionary approach that shows any promise—even if we attempt to go further and eliminate the use of proxies for protected characteristics, algorithms will still analyze the available data in a way that recovers the sensitive aspects.[54]

If the case laid out in the preceding paragraph is not convincing enough, there is yet another reason why exclusionary approaches are undesirable. There is strong evidence to show that insisting on such approaches could lead to increased disparities since algorithms successfully prevented from using protected characteristics will have no choice but to impose one interpretation for both the most privileged and most marginalized groups.[55] The end result would be the loss of opportunities to mitigate the harms of already-biased measurement.[56] Moreover, algorithmic decisions made in such environments would be far more difficult to scrutinize.[57]

An approach focused on ring-fencing the types of input data that algorithms can consider will suffer a fate that is similar to the exclusionary approaches, which should not come as a surprise given that ring-fencing is

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[50] Talia Gillis, *The Input Fallacy*, MINN. L. REV. (forthcoming 2022) (manuscript at 41–66), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3571266.
[51] KHAITAN, *supra* note 1, at 69–71.
[52] *See* Sophia Moreau, *What is Discrimination?* 38 PHIL. & PUB. AFF. 143 (2010).
[53] Gillis, *supra* note 50 (manuscript at 48–49).
[54] *See* Prince & Shwarcz, *supra* note 37, at 1302–04.
[55] Gillis, *supra* note 50 (manuscript at 53–54).
[56] *Id*. (manuscript at 48–52).
[57] Betsy Williams et al., *How Algorithms Discriminate Based on Data They Lack: Challenges, Solutions, and Policy Implications*, 8 J. INFO. POL'Y 78, 82–90 (2018).

fundamentally exclusionary. In fact, approaches tethered to ring-fencing may only serve to make the predictions and decisions of many algorithms less accurate than they can be when a larger size and richer variety of inputs are made available.[58] Such a declined level of correct inferencing would obviously discourage the use of algorithms to make decisions, even when doing so would increase efficiency or increase access to resources for marginalized people.[59]

Once again relying on antidiscrimination law's longstanding interest in policing the factors that may be considered in decision-making, some have urged for legal frameworks that allow or compel designers to alter input data to combat discrimination,[60] a certain kind of input-data-focused affirmative action. This is a flawed approach to the extent that it is founded on the presumption that the problem lies only within the input data. It is also unlikely to be effective because no matter the amount of *ex ante* data-tinkering that takes place, one can never be certain how an algorithm will perform until it is run in a real environment.

Litigants who allege indirect discrimination from algorithmic decision-making face one more understated problem. Once disparate impact is satisfactorily demonstrated, multiple legal frameworks give the liable party an opportunity to offer a justification for the decision that caused the disparate impact.[61] Then the party alleging discrimination must show the existence of an alternative decision which would achieve the justificatory aims of the accused party without that disparate impact.[62] We can safely assume that the party deploying the algorithm will offer justification that hovers around issues of efficiency and expanded opportunity (for both their entity and those they serve).[63] In the face of this reality, what alternative decision can the party alleging discrimination propose? Without access to expert computer scientists and details

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[58] *See* Gillis, *supra* note 50 (manuscript at 61–62).
[59] *See* Kleinberg et al., *supra* note 26, at 120 (describing potential for improved pretrial release outcomes for marginalized groups); Williams et al., *supra* note 57, at 86 (stating "[w]hen data are 'big,' unknown data points are more easily filled in through prediction, imputation, and proxies.").
[60] *See* Ignacio Cofone, *Algorithmic Discrimination is an Information Problem*, 70 HASTINGS L.J. 1389, 1393–94, 1410–24 (2019).
[61] KHAITAN, *supra* note 1, at 75–76 (discussing US, UK, and EU examples of justification for indirect discrimination); *see also* Hugh Collins, *Justice for Foxes: Fundamental Rights and Justification of Indirect Discrimination*, *in* FOUNDATIONS OF INDIRECT DISCRIMINATION LAW 249, 251–55 (Hugh Collins & Tarunabh Khaitan eds., 2018).
[62] Outside the United States, this burden-shifting is known as the proportionality test. *See* KHAITAN, *supra* note 1, at 181 (describing the proportionality test); *see* Collins, *supra* note 61, at 254 (noting potentially legitimate purposes for rules with disparate impact such as "improving the efficiency of the business or the effectiveness of a service"); *see generally* KHAITAN, *supra* note 1, at 124 (describing societal power imbalance dynamics).
[63] *See* KHAITAN, *supra* note 1, at 181 (describing the proportionality test).

about how the algorithm made its decision, the party alleging discrimination faces a remarkably distorted power imbalance.[64]

Is the challenge posed by algorithmic decision-making different from that which human decision-making has always presented? Kleinberg and others have argued that human decision-making features more opacity and algorithms may be less of a challenge to the antidiscrimination project.[65] Although there is some truth in their assertion, there are two reasons why we still need to be concerned with algorithmic decision-making. First, while antidiscrimination law has over time developed tools to assess human decisions, those methods—without modification—fall short when it comes to algorithmic decisions.[66] We therefore have no choice but to grapple with the problem and fashion new approaches. Second, as previously stated in this part, the scale of discrimination that can come from algorithmic decisions dwarfs that which may come from human decision-making.[67] This is enough reason for us to take it very seriously.

III. The Most Promising Proposed Solutions and the Foundation Required for Successful Implementation

a. Major Proposed Solutions

There are two broad frames organizing the most promising proposed solutions: a) measures focused on auditing the software, code, or function and b) measures focused on auditing outcomes. In this part of the article, I will review these solutions. I will then argue that the foundation required to successfully implement them needs to have: i) existing statistical analysis that allows one to examine whether disparities faced by protected groups are increasing or decreasing; ii) a certain degree of transparency to allow review of algorithm design as well as the impact of the decisions they make; iii) a well-resourced, democratically legitimate institution that can vigorously police discrimination and iv) the existence of vigilant civil society groups that devote resources and time to algorithmic decision-making.

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[64] *See* Collins, *supra* note 61, at 254 (noting potentially legitimate purposes for rules with disparate impact such as "improving the efficiency of the business or the effectiveness of a service").
[65] Kleinberg et al., *supra* note 26, at 154.
[66] *See generally* Joshua Kroll et al., *Accountable Algorithms*, 165 U. PA. L. REV. 633 (2017) (discussing the lag in legal accountability for algorithmic decision-making).
[67] CRIADO & SUCH, *supra* note 36, at 85.

1. *Ex Ante* Scrutiny

The goal is to build algorithms in a way that ensures non-discrimination. For two particular reasons, the obstacles to that goal are considerable. First, the question of how much bias counts as discrimination is still highly disputatious.[68] Second, it is difficult to translate policy goals into terms specific enough to be reduced to code,[69] especially in a climate with little agreement about what constitutes discrimination. As a result, one could find some technical tools which protect against one understanding of discrimination yet allow for others.[70] There is no way to test with certainty whether new algorithms contain biases to a degree that would lead them to unlawfully discriminate.[71] Nevertheless, there has been serious progress towards instituting techniques to confirm whether algorithms satisfy non-discrimination norms. Some are automated computational methods designed by computer science researchers and engineers, while others are proposals made by legal scholars.

The standout feature of *ex ante* scrutiny is its reliance on methods which allow stakeholders to ensure algorithms do not discriminate *before letting them run in any environment*.[72] Situations that are amenable to *ex ante* scrutiny are referred to as white box scenarios.[73] Those instances require that: i) the code "can be inspected and comprehended" (for example, a decision tree can illustrate the algorithm's function), or ii) the training data sets that were used are widely available.[74] Recent computer science research proposes two ways to successfully conduct *ex ante* scrutiny of algorithms. The first is a model-checking approach, where "non-discrimination norms are operationalized as formal properties."[75] The second is the mathematical approach, in which "non-discrimination norms are operationalized as mathematical formulas defined over data sets."[76] They offer a promising starting point for effectively responding to our problem.

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[68] *Id.* at 92.
[69] Pauline Kim, *Auditing Algorithms for Discrimination*, 166 U. PA. L. REV. 189, 192 (2017).
[70] *See id.* at 193–94.
[71] CRIADO & SUCH, *supra* note 36, at 92.
[72] *See id.* at 95; Cofone, *supra* note 60, at 1440.
[73] CRIADO & SUCH, *supra* note 36, at 95.
[74] *Id.*
[75] *Id.*
[76] *Id.*

Both approaches can play a key role in assessing the functions which a machine learning algorithm is to use,[77] even though interpretability remains a major problem.[78] The amount of important information that can be extracted from the function will depend on the kind of question asked and the type of algorithm involved. While it would still be impossible to be sure exactly how the algorithm will run in its target environment, these methods would make it possible to examine what Gillis and Spiess refer to as "the facilitation of discriminatory decisions."[79]

Although some claim that transparency offers limited returns[80] and may be unnecessary,[81] the success of methods of *ex ante* scrutiny largely depends on transparency within the process. To some degree, key stakeholders need access to details regarding an algorithm's training data sets or function-creation before it is deployed to make decisions affecting human lives.[82] Such transparency can also be crucial for other *ex ante* strategies such as examining objectives or assessing the inductive bias of an algorithm.[83]

Consider the examination of objectives. According to Kleinberg and others, regulation of algorithms should pay attention to the human choices behind: i) what outcome an algorithm is designed to decide; ii) what inputs are made available to an algorithm; and iii) the training procedure that is used.[84] The authors make the case that transparency is crucial for the scrutiny of these three objectives. According to them, the key is instituting regulation that requires detailed record-keeping by anyone who designs an algorithm, a move which other scholars have likewise called for.[85] Of course, such a move would still be

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[77] *See* Talia Gillis & Jann Spiess, *Big Data and Discrimination*, 86 U. CHI. L. REV. 459, 474 (2019) ("The decision process that led to a certain outcome can theoretically be recovered in the context of algorithmic decision-making.").
[78] *See* Tsamados et al., *supra* note 15, at 41 (describing challenges to interpretability).
[79] Gillis & Spiess, *supra* note 77, at 474.
[80] Kroll et al., *supra* note 66, at 657–59.
[81] Nachbar, *supra* note 30, at 544–48 (arguing that accountability is more important than transparency); *see generally* Kleinberg et al., *supra* note 26, at 152 (discussing the importance of transparency), at 117–18 (providing an example of an algorithmic objective that causes a disparate gender impact, which could be remedied through a different algorithmic objective).
[82] Nachbar, *supra* note 30, at 544–48 (arguing that accountability is more important than transparency).
[83] *See generally* Kleinberg et al., *supra* note 26, at 152 (discussing the importance of transparency).
[84] *Id.*
[85] *Id.* at 152–53; Tsamados et al., *supra* note 15, at 5 (citing Gebru et al., *Datasheets for Datasets*, ARXIV:1803.09010, at 2 (2020), http://arxiv.org/abs/1803.09010).

toothless in the face of the changing relevance of the dataset on which the algorithm is built, and the costs of compliance.[86] Whatever the case, transparency could go some way towards enabling *ex ante* scrutiny of objectives in a manner that prevents discrimination.

Evaluating the inductive bias used by algorithms could be another concrete goal of *ex ante* scrutiny. As stated earlier in this article, inductive bias refers to a set of assumptions that an algorithm uses to supplement the data it runs to find a function.[87] Frequently, attempts to find one final function using information from the data alone are unsuccessful, leaving the algorithm with what is known as an "ill-posed problem" where it is not possible to select a single best answer using the information available.[88] Collecting more data is almost always not a viable way forward because the "data is not available or is too expensive to collect."[89] So algorithms are fed—and apply to the available data—assumptions about what the most desirable decision or prediction should look like. Obviously, these kinds of assumptions could carry within them discriminatory biases. With some level of transparency, we should be able to scrutinize them for that.

To enable these examples of *ex ante* scrutiny, some scholars have proposed regulation which would require that administrative agencies publish guidelines on software development.[90] Others have argued for a legislative environment that "protect[s] whistle-blowers and allow[s] a public interest cause of action [to] aid in increasing detection of overt misdeeds in designing software."[91] This kind of 'technical accountability'[92] is likely to be of limited usefulness because even the best-calibrated methods can miss some programming flaws.

More concerningly, analyzing source code on its own (static analysis) may tell us nothing about how an algorithm will interact with the environment it is eventually set into[93] while analyzing the code as it runs in its natural field (dynamic testing) still fails to guarantee whether or not a certain outcome—in this case discrimination—will occur.[94] The fact that some jurisdictions have no closed

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[86] *See* Kleinberg et al., *supra* note 26, at 153.
[87] KELLEHER, *supra* note 23, at 18.
[88] *Id.* at 16.
[89] *Id.* at 17–18.
[90] Kroll et al., *supra* note 66, at 701.
[91] Deven Desai & Joshua Kroll, *Trust but Verify: A Guide to Algorithms and the Law*, 31 HARV. J.L. & TECH. 1, 5 (2017).
[92] *Id.* at 10–11.
[93] Kroll et al., *supra* note 66, at 647–48.
[94] *See* Desai & Kroll, *supra* note 91, at 37.

list of protected grounds only makes it more difficult to guarantee successful implementation of any of these solutions.[95] For these reasons, *ex post* scrutiny has increasingly started to seem more promising.

2. *Ex Post* Scrutiny

Ex post scrutiny has become incredibly attractive because, as has been discussed in the preceding part of this article, algorithms are not entirely decipherable even if their code is made easily available. Of course, in other situations algorithm code might be unavailable for reasons touching on the protection of intellectual property. In both scenarios, to know what an algorithm will do, one must run it.[96] *Ex post* scrutiny looks at probing outcomes that result from such runs, asking the key question: how will the algorithm impact protected cognate groups in its decision-making?[97] Underlying this approach is the idea that auditing outputs is useful for detecting some systematic disadvantaging of particular groups on the basis of protected characteristics.

Researchers in the field of computer science are making strides in devising methods that can be used to assess algorithmic output for unlawful discrimination. For example, in 2017 Tramer and others pioneered a tool kit they called FairTest. It combines different methodologies and metrics to find out 'unwarranted association'—strong correlations between the output of a machine learning algorithm and the protected characteristics of a person.[98] If such a method is perfected and widely deployed, it will allow the isolation and real-life testing of algorithms to be an incredibly productive enterprise insofar as preventing discrimination is concerned.[99]

Apart from these technical advances, legal scholars are also proposing ways to prevent algorithmic discrimination starting at the examination of outcomes. In one piece, Gillis and Spiess propose an approach they refer to as "discrimination stress testing" in which an agent picks a hypothetical environment in which the algorithm is designed to run and evaluates the outcome when the algorithm is used.[100] The agent should be attentive to issues like population of

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[95] CRIADO & SUCH, *supra* note 36, 89–90.
[96] Kleinberg et al., *supra* note 26, at 114.
[97] Prince & Schwarcz, *supra* note 37, at 1311.
[98] Florian Tramer et al., *FairTest: Discovering Unwarranted Associations in Data-Driven Applications*, 2017 IEEE EUR. SYMP. SEC. & PRIV. 401, 404–14 (2017).
[99] *See id.* at 402–03.
[100] Gillis & Spiess, *supra* note 77, at 481.

protected groups when selecting the hypothetical environment.[101] Once this is done, the agent can review whether the algorithm will result in increased disparities for protected groups, and finally, whether those disparities are unacceptable.[102] Importantly, the last review requires already existing data on the protected group in question within that environment.

In a more recent article, Gillis develops the idea further.[103] Her proposal takes the following step-by-step route: a) a decision on inputs is taken and a function is generated by an initial algorithm; b) a second algorithm is programmed with that function and thereafter applied to a dataset of people to see the distribution produced; and c) there is an evaluation of the outcome to determine whether the decision made by the second algorithm is discriminatory.[104] Here, Gillis contributes the idea about how to measure the outcome for discrimination asserting that a reviewer needs to be attentive to any absolute disparities or incremental expansion of disparities faced by protected groups. While the former can be noted easily,[105] the latter requires that a baseline of data already exists.[106]

The importance of baseline data comes into sharper focus when one considers the most advanced methods of measuring outcome fairness for decisions made by algorithms. Consider Deborah Hellman's 'error ratio parity' method, which is one of the most carefully constructed ones.[107] It makes the case for reviewers to measure algorithmic fairness using a method in which one compares an algorithm's false positive and false negative rates for the different cognate groups in its environment.[108] Crucially, this method requires a reviewer's constant reference to already-existing baseline data to find out whether an algorithm's decision-making expands or reduces disparities suffered by protected groups.[109]

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[101] *Id.* at 481–84.
[102] *See id.* at 484–87.
[103] Gillis, *supra* note 50 (manuscript at 35–36).
[104] *Id.* (manuscript at 68–69).
[105] *See generally* Mark MacCarthy, *Fairness in algorithmic decision-making*, BROOKINGS (Dec. 6, 2019), https://www.brookings.edu/research/fairness-in-algorithmic-decision-making/ (applying an 80% rule of thumb would allow reviewer to see if the results of an algorithm are discriminatory).
[106] Gillis, *supra* note 50 (manuscript at 74–76).
[107] *See* Hellman, *supra* note 12, at 835–42.
[108] *Id.* at 835–39.
[109] *Id.* at 840–41; *see also* Sandra Wachter et al., *Bias Preservation in machine Learning: The Legality of Fairness Metrics Under EU Non-Discrimination Law*, 123 W. VA. L. REV. 735, 761–64 (2020) (claiming even an algorithm which has no disparate impact and causes no expansion of inequality can still be discriminatory, proposing use of "bias transformation" metrics instead of "bias preservation" metrics to respond to ensure more fairness for protected group).

There is another way of carrying out *ex post* scrutiny of algorithms. It is premised on the claim that the auditing of outcomes will always fall short because there are only a finite number of inputs that can be tested and outcomes which can be observed.[110] This does not mean all *ex post* scrutiny is unreliable. The direction some scholars claim we must take is *ex post* analysis of outcomes which evaluates properties of the software being used.[111] For example, these properties include whether undisclosed elements are recorded or whether the elements are consistent among decision subjects as appropriate (to confirm whether all decisions, for example, result from the same function).[112]

One of the understated attractions of *ex post* scrutiny is its allowance for the possibility of redesigning algorithms to correct for discrimination after the fact.[113] Once an outcome is audited and disparate impact or unacceptable expansion in disparities is flagged (which is not possible for *ex ante* scrutiny), a decision can be made to reject the responsible algorithm and adopt a new one.[114] The only serious contentions against this kind of "tuning"[115] come out of a uniquely American strife regarding the legality of affirmative action.[116] The major issue there can be summed up as the idea that taking into account a person's protected characteristics to fix disparate impact is itself disparate treatment. Thankfully, this is an uncertainty which most other countries across the world have long overcome. Consequently, in most countries one would not need to rely on elaborate legal maneuvers[117] to recreate fair algorithms based on findings from *ex post* scrutiny.

Outcome scrutiny of the nature discussed in the preceding paragraphs is not as novel as it may seem to some. A close iteration of it, in the form of field experiments, has long been used to test for discrimination in employment and consumer transaction decisions.[118] And as Annette Zimmerman, Elena Di Rosa and Hochan Kim incisively observed, pharmaceutical products have always had

[110] Desai & Kroll, *supra* note 91, at 38–39.
[111] *Id.* at 39.
[112] *Id.* at 40.
[113] Nachbar, *supra* note 30, at 543.
[114] *Id.* at 552.
[115] *See id.* at 543.
[116] *See generally* Kim, *supra* note 69, at 197–202; Kroll et al., *supra* note 66, at 692–95; Nachbar, *supra* note 30, at 538–52.
[117] *See* Nachbar, *supra* note 30, at 552 (proposing that one way to get around the problem is to adopt a legal test that splits the overall decision into: (1) a decision to reject the first algorithm and (2) a decision to redesign a new algorithm, wherein the first decision should be given considerable legal deference, and seldom leads to liability).
[118] Kim, *supra* note 69, at 190.

to go through several rounds of trials and tests before receiving approval for use.[119] It is also similar to 'bank stress testing,' which requires selected banks to report their stability under hypothetical macroeconomic scenarios.[120] With such context in mind, the human rights impact assessments that the United Nations Special Rapporteur for freedom of expression has pressed states and companies to conduct prior to deploying AI systems does not seem too much to ask.[121]

Of course, *ex post* scrutiny of algorithms still has some shortcomings. Dynamic self-learning algorithms constitute a stern test since they change their functions so regularly that it is difficult for any reviewer to keep up.[122] Consider for example the fact that in 2018, the Google algorithm updated over 3,234 times.[123] By the time one outcome review is complete, the algorithm will be using a new function.[124] It is hard to determine how such algorithms can be audited from an outcome-focused perspective. Furthermore, the pervasive disagreements about the outer limits of the discrimination doctrine will continue to dog any efforts to conduct outcome-based scrutiny. Finally, as stated earlier, it is not possible for a reviewer to be entirely certain about the final outcome an algorithm will have. Even the best calibrated test environments can miss some critical aspects of the final environment in which an algorithm is set to run.[125] Although all three are hard problems to solve, there seems to be consensus that *ex post* scrutiny offers the best chances to prevent and prove discrimination in algorithmic decision-making.[126]

b. Foundation Required for Successful Implementation

A few things become have become clear amidst the concern of discrimination in algorithmic decision-making. First, we cannot seriously expect the vast majority of the people who will face algorithmic discrimination to start

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[119] Annette Zimmermann et al., *Technology Can't Fix Algorithmic Injustice*, BOSTON REV. (Jan. 9, 2020), https://bostonreview.net/science-nature-politics/annette-zimmermann-elena-di-rosa-hochan-kim-technology-cant-fix-algorithmic.
[120] Gillis & Spiess, *supra* note 77, at 481.
[121] *See* David Kaye (Special Rapporteur), *Promotion and Protection of the Right to Freedom of Opinion and Expression*, U.N. Doc. A/73/348, at 16–19 (Aug. 29, 2018).
[122] *See* Boris Babic et al., *When Machine Learning Goes Off the Rails*, HARV. BUS. REV. (Jan. 2021), https://hbr.org/2021/01/when-machine-learning-goes-off-the-rails.
[123] *Google Algorithm Update History*, MOZ, https://moz.com/google-algorithm-change, https://perma.cc/S76X-KNWD] (last visited Sept. 20, 2020).
[124] *See* Babic et al., *supra* note 122.
[125] *Id.*
[126] Chris Oxborough et al., *The responsible AI framework,* PWC, https://www.pwc.co.uk/services/risk/insights/accelerating-innovation-through-responsible-ai/responsible-ai-framework.html (last visited Sept. 26, 2021).

and sustain a suit. The knowledge gap between them and the entity using the questionable algorithm will almost always be excessively wide, and their access to necessary resources like computer and data science expertise will be limited.[127] As a result, there is a need for a powerful and capable outside actor that will police the use of algorithms in decision-making to ensure there is no resultant discrimination.[128] Writing in the context of algorithmic discrimination in labor issues, for example, Aislinn Kelly-Lyth notes that: "Absent intervention from a coordinating body with significant technical expertise, an individual is unlikely to realize that they may have been disadvantaged by the employer's use of an algorithm—and even if they do, they will struggle to find any evidence to prove it."[129] The institution in question cannot be the judiciary since judges have to wait for cases to be brought before them. It cannot be a legislative body either since legislatures have neither the staff nor the time to repeatedly carry out the kind of intensive reviews and investigations necessary. The most viable institutions would be new or already-existing independent commissions or regulatory agencies.[130]

Excellent examples of already-existing agencies leading the way can be found in the United States. Consider: i) the Department of Housing and Urban Development taking legal action against Facebook on the claim that its machine-learning algorithms were allowing advertisers to exclude people from seeing certain listings based on protected characteristics[131] ii) the Consumer Financial Protection Bureau assessing Upstart Network's credit-scoring algorithms[132] and iii) the New York State Department of Financial Services opening an

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[127] *Coding in 2016 is like reading in 1816*, PRENDA (Oct. 18, 2016), https://www.prendacodeclub.com/blog/coding-2016-like-reading-1816/.

[128] Christina Curlette et al., *Monitoring the Errors of Discriminative Models with Probabilistic Programming*, SEMANTIC SCHOLAR (2016), at 1, https://www.semanticscholar.org/paper/Monitoring-the-Errors-of-Discriminative-Models-with-Curlette-Schaechtle/94cdfca0d8d5550b51d48fd4a38d019441f8a1de.

[129] *See* Aislinn Kelly-Lyth, *Challenging Biased Hiring Algorithms*, 41 OXFORD J. LEGAL STUD. 899, 921 (2021).

[130] Recently, there has also been an outgrowth of a self-regulatory approach where entities deploying algorithms hire private companies and consultants to audit their algorithms for any discriminatory results. So far, however, the verdict on this approach has been bleak. *See*, *e.g.*, Alfred Ng, *Can Auditing Eliminate Bias from Algorithms*, THE MARKUP (Feb. 23, 2021), https://themarkup.org/ask-the-markup/2021/02/23/can-auditing-eliminate-bias-from-algorithms.

[131] Katie Benner et al., *Facebook Engages in Housing Discrimination with its Ad Practices, U.S. Says*, N.Y. TIMES (Mar. 28, 2019), https://www.nytimes.com/2019/03/28/us/politics/facebook-housing-discrimination.html.

[132] *Consumer Announces First No-Action Letter to Upstart Network*, CONSUMER FIN. PROT. BUREAU (Sept. 14, 2017), https://www.consumerfinance.gov/about-us/newsroom/cfpb-announces-first-no-action-letter-upstart-network/.

investigation into Apple Card's algorithms.[133] Moreover, the Algorithmic Accountability Bill, still under consideration in the United States Congress, empowers the Federal Trade Commission to supervise companies' assessments of their algorithms for inaccurate, unfair, biased or discriminatory decisions.[134]

The idea of existing agencies being given such purview has also taken root in the United Kingdom, where recent analysis has, for instance, proposed a joint role for the Equality and Human Rights Commission and Information Commissioner's office.[135] There is also the possibility that a new agency is set-up to conduct the kind of oversight this article argues is required. A 2017 article by Andrew Tutt argues that the sort of institution which needs to be set up should be the equivalent of "an FDA for algorithms." He argues that while other subject-matter agencies could also work, a central agency would be better because of the complexity, opacity, and dangerousness that algorithms come with.[136] While it is interesting to consider, the debate Tutt brings up is beyond the ambit of this article. I limit myself here to the claim that if we intend to effectively fight discrimination arising from algorithmic decision-making, we need some agency or independent commission to be accorded a primary role in the effort.

Setting standards and vigorously policing the use of algorithms (including starting suits where necessary) would be the key tasks that such regulatory agencies or independent commissions play. Indeed, Gillis and Spiess specifically argue for regulators performing these kinds of tasks when they propose "discrimination stress testing" of algorithms.[137] Similarly, a 2019 report by Brookings proposes the same kind of responsibilities for the selected regulatory agencies.

A different approach would be to require disparate impact assessments for automated decision systems used in the contexts covered by these laws. The

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[133] Neil Vigdor, *Apple Card Investigated After Gender Discrimination Complaints*, N.Y. TIMES (Nov. 10, 2019), https://www.nytimes.com/2019/11/10/business/Apple-credit-card-investigation.html [https://perma.cc/M2VC-5THW]. *See* Linda Lacewell, *Building a fairer and more inclusive financial services industry for everyone*, N.Y. DEP'T FIN. SERVICES (Nov. 10, 2019), https://medium.com/@nydfs/building-a-fairer-and-more-inclusive-financial-services-industry-for-everyone-917183dae954 (it is important to note, however, that this investigation was opened only after an Apple Card user wrote a 'thread' on Twitter—joined by others—alleging that the credit limit Apple's algorithms gave him was disproportionately higher than what they gave his wife).
[134] Algorithmic Accountability Act, H.R. 2231, 116th Cong. § 1108 (2019).
[135] Kelly-Lyth, *supra* note 129, at 921–23.
[136] Andrew Tutt, *An FDA for Algorithms*, 69 ADMIN. L. REV. 83, 111–18 (2017).
[137] Gillis & Spiess, *supra* note 77, at 481–87.

assessments should be provided to the appropriate regulatory agency charged with enforcing the anti-discrimination laws and to the public. Each agency could also be assigned the responsibility to conduct its own disparate impact assessment, and to have new authority, if necessary, to obtain data from developers and companies for this purpose. Agencies could also be authorized to work with outside researchers to conduct these assessments, and to approve certain researchers to receive data from developers and companies to conduct these assessments.[138]

Having an outside actor to police algorithmic discrimination is crucial because the affected parties—especially in developing countries—will almost certainly not have the capacity to realize when an algorithm has discriminated against them. The best institution, such an actor, can be a regulatory agency or an independent commission/office.[139]

The second thing that becomes clear is that having non-governmental actors with the resources and capacity to investigate discrimination in decisions made by algorithms can make an incredible difference in ensuring fairness. When such groups publish their findings, it makes communities more alert to the risks of algorithms making decisions.[140] This in turn leads to more caution and scrutiny, which is surely a desirable development in the context of algorithmic decision-making.[141] Often, governments will also decide to focus on the issue because of the attention drawn to it by the groups this article has in mind.[142]

In countries where this has happened, the groups tend to be civil society groups or news organizations.[143] With regards to algorithmic decision-making in particular, ProPublica has for example, been at forefront of investigations that have illuminated possible discriminatory conduct.[144] Some of their findings have come from simply testing a tool (like Facebook's advertising portal),[145] others have involved the intricate study of risk algorithm data carrying decision

[138] MacCarthy, *supra* note 105.
[139] *Id.*
[140] *Id.*
[141] *Id.*
[142] *See* Julia Angwin & Terry Parris, *Facebook Lets Advertisers Exclude Users by Race*, PROPUBLICA (Oct. 28, 2016), https://www.propublica.org/article/facebook-lets-advertisers-exclude-users-by-race (discussing Facebook's housing ads in the United States that allows advertisers to exclude users by race).
[143] *Id.*
[144] *Id.*
[145] *Id.*

outcomes[146] and their most famous one yet involved a rigorous, detailed analysis of ten thousand criminal defendants' algorithmically predicted recidivism rates with their actual rates over a two-year period.[147]

The work of UK non-profit Foxglove also gives us a model for reimagining the role that civil society needs to play in policing discrimination where algorithmic decision-making is involved.[148] In collaboration with the Joint Council for the Welfare of Immigrants, the group filed a suit against UK's Home Department claiming that an algorithm used to make VISA decisions was discriminatory.[149] Before the case was heard and determined, the Home Office decided to discontinue the use of the streaming tool,[150] a clear win for the claimants. Of particular interest to this study is how the suit was developed. It appears that use of the tool only came to light when a group of lawyers were shown the streaming process during a visit to a VISA processing center.[151] The suit also seems to have relied significantly on (a) information disclosed by the Home Department during pre-action correspondence[152] and (b) statistical data that was already available.[153] This brings us to the third prong of the foundation.

It is apparent is that there needs to be a certain level of public record transparency and disclosure to defeat the enforcement gap that algorithmic discrimination often entails.[154] This claim is buttressed by existing cases of impactful algorithmic scrutiny. Consider for instance how, as discussed in the preceding paragraph, Foxglove was able to make its case against the UK government's VISA streaming tool. Consider what as well allowed ProPublica to

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[146] Jeff Larson et al., *How We Examined Racial Discrimination in Auto Insurance Prices*, PROPUBLICA (Apr. 5, 2017), https://www.propublica.org/article/minority-neighborhoods-higher-car-insurance-premiums-methodology.
[147] Jeff Larson et al., *How We Analyzed the COMPAS Recidivism Algorithm*, PROPUBLICA (May 23, 2016), https://www.propublica.org/article/how-we-analyzed-the-compas-recidivism-algorithm [https://perma.cc/8MY6-84RH].
[148] *Update: papers filed for judicial review of Home Office's VISA algorithm*, FOXGLOVE (Jun. 22, 2020), https://www.foxglove.org.uk/2020/06/22/update-papers-filed-for-judicial-review-of-the-home-offices-visa-algorithm/ [https://perma.cc/J9PJ-MH76].
[149] *Id.*
[150] *We won! Home Office to stop using racist visa algorithm*, JOINT COUNCIL FOR WELFARE OF IMMIGRANTS, https://www.jcwi.org.uk/news/we-won-home-office-to-stop-using-racist-visa-algorithm [https://perma.cc/5CBG-WAPR] (last visited Oct. 10, 2021).
[151] Helen Warrell, *Home Office Under Fire for Using Secretive Visa Algorithm*, FIN. TIMES (June 9, 2019), https://www.ft.com/content/0206dd56-87b0-11e9-a028-86cea8523dc2.
[152] *See* R (Joint Council for the Welfare of Immigrants) v. Secretary of State for the Home Department [2019] EWCH (Admin) 452 [9], [11], [25] (Eng.).
[153] *Id.* at [27].
[154] Kelly-Lyth, *supra* note 129, at 903, 927.

critically assess COMPAS's recidivism algorithm. The data analyzed was acquired through public record requests and specifically Broward County's records because the state "had strong open record laws."[155] Without strong public record transparency, such investigations would not be possible. This would deal a hammer blow to any efforts to scrutinize algorithmic decision-making because, as has been observed by others, statistical evidence is set to assume special prominence in any attempts to prove algorithmic discrimination.[156]

Transparency around how algorithms have been trained and what rules or models they are using will also be an important factor. Although there are intellectual property issues likely at play,[157] it would be difficult to carry out any impactful *ex ante* scrutiny of algorithms without having access to some level of data about how exactly they have been designed to work.

IV. Implementing the Most Promising Proposed Solutions in Developing Countries

To assess whether developing countries have the foundation necessary to implement the most promising proposed solutions, I looked into the situation in the following case studies: Kenya, India, Nigeria, South Africa, and the Philippines. The details of my findings are in the annexure at the end of this article.[158] In this part, I will summarize those findings and thereafter propose a strategy for moving forward.

On the policing of discrimination, this article found that all the countries have some law that prohibits discrimination. Even though some have a more comprehensive legal framework than others, it makes little difference at the end of the day. Additionally, all the countries studied have some sort of independent office set up to specifically protect people's human rights. Nonetheless, there is no evidence that any of these independent offices proactively polices discrimination issues in their societies. In all the countries, it is left to the injured party to approach an adjudicator. Furthermore, in all the countries studied, executive agencies do not play any role in policing discrimination, and this has always been the case.

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[155] Larson et al., *supra* note 146.
[156] *See* Sandra Watcher et al., *supra* note 109, at 744, 778.
[157] CHRISTOPH WINTER ET AL., LEGAL PRIORITIES PROJECT, LEGAL PRIORITIES RESEARCH: A RESEARCH AGENDA 50 (Jan. 2021), https://www.legalpriorities.org/research_agenda.pdf.
[158] *See infra* Section VI.

As expected, all the countries examined have countless non-government actors. Still, there is no evidence that any of those actors is especially attentive to algorithmic decision-making. Finally, while all the countries have a legal framework that requires a laudable degree of public record transparency, it remains rare and difficult for people to get the public records they seek. Private entities are also not mandated to release any information that touches on how their tools work. These countries therefore struggle when it comes to the three elements of the foundation I staked out. Because of matching governance inefficiencies and socio-economic conditions, I expect that the same will be true for a vast majority of developing countries.

Given this situation, this article proposes a few steps going forward. First, developing countries generally need to take discrimination on grounds of protected characteristics more seriously and move past hollow commitments towards verifiable action. It is very important for antidiscrimination advocates in developing countries to ground the idea that discrimination is a public concern that needs to be acted on by government.

Second, there need to be regular sophisticated statistical analyses that examine where protected groups stand in the areas where algorithms are to be deployed, for example credit-scoring. This can be made a legal for a country's bureau of statistics and all private entities which use algorithms, for example. Open-record transparency also needs to progress from being only a legal norm on paper to being affected in everyday life. Furthermore, developing countries should consider mandating that private entities make transparent crucial details about how some tools—especially algorithmic ones—are built to work. For example, their training data or the functions and rules that they are use.

Third, there needs to be a reimagination of the role that the administrative state plays in policing discrimination. This article argues that it would be best for the administrative state to take up the role in developing countries since they have the capacity and resources to proactively police discrimination. Independent human rights commissions and offices would not be the most appropriate option because those offices are rarely sufficiently resourced in these countries. Finally, it may be necessary to revisit the burdens placed on litigants when it comes to proving discrimination. In particular, the proportionality test-aligned requirement that asks a litigant to propose a non-discriminatory alternative that still achieves the goals set out is extremely onerous and may need to be reconsidered for cases where algorithms are involved in the decision-making. Finally, developing countries ought to explore the possibility of requiring that entities prove domestic context has been considered in the design of an algorithm expected to run in their communities. As Chinmayi Arun notes, 'the technology and capital that drives AI firmly rests in Northern hands'[159] and this could lead to algorithms running in unexpected ways that cause discrimination in developing countries.

V. Conclusion

This article has discussed the unique problems that algorithms pose for the legal framework that has always been used to prevent and prove discrimination. It has also showed why the solutions currently being mooted will struggle in developing countries, which lack the foundation necessary for successful implementation of the proposals. The situation is only made more concerning when we realize that continuous use of algorithmic tools can easily build a widespread belief that algorithms are infallible.[160]

In response, this article has staked out three foundational points that antidiscrimination advocates in developing countries need to pay special attention to if they are to ensure the existence of methods to guarantee that free and blind use of algorithms does not become the norm. As Martha Minow has argued, incautious deployment of algorithms in society can devalue personhood and leave people subordinate to processes.[161] The stakes are overwhelming, and we have no choice but to confront the challenge.

There are other issues at play which we must grapple with. First, too many developing countries have made hollow commitments to antidiscrimination while endless forms of discrimination are allowed to thrive completely unchecked in their societies. This will need to be courageously addressed. Second, these countries must consider whether there is a need to prioritize antidiscrimination for some protected grounds over others, if only because resources are limited and productivity just as important. Both issues were beyond the scope of this article, but it is hoped that future researchers will have more to say about them.

[159] Arun, *supra* note 13, at 604.
[160] Desai & Kroll, *supra* note 91, at 4.
[161] U.S. Dep't of State, Comm'n on Unalienable Rights Minutes 7 (2020).

VI. Annexure

a. Use of algorithms in making impactful decisions

Country	**Use of algorithms in decision making**
Kenya	At the moment, algorithmic decision making in Kenya mainly features in credit scoring. Tala, a microloan company, uses algorithms to determine loan eligibility. The smartphone app collects data on applicants to assess credit risk. Some of the data includes, frequent contacts, social media interactions and movement and routine habits, for example, whether bills are paid on time. Tala offers this instant credit scoring method as an alternative way for those who lack a credit history. Tala claims that it does not factor gender, race, ethnicity, religion, national origin, sexual orientation, disability, medical history or political opinion into its decisions.[162] However, the risk with its system is that those with less digital infrastructure or lack of a digital footprint, might face unfair discrimination by the algorithm that captures data more available in urban populations. Branch, like Tala, uses algorithms to assess loan eligibility by examining, for example, amount of money in one's mobile money wallet and other loans one has. It considers social features such as social media interaction as less useful than financial data. Another credit scoring platform similar to Tala and Branch is Saida.

[162] TALA, *supra* note 8.

	FarmDrive is an alternative credit scoring platform for smallholder farmers. It uses mobile phones, alternative data, and machine learning to bridge the data gap between financial institutions and the loan applicants (the farmers) which usually prevents financial institutions from lending to creditworthy smallholder farmers. The Kenyan Government also recently released a statement explaining that it intends to use algorithms to make decisions on who to assign new housing units to.[163]
India	Private entities in India use algorithms to score creditworthiness. Tala and Branch have operations in India and just as in Kenya, they use their algorithms in a similar fashion to assess loan eligibility of borrowers based on collected data. SalaryDost, another lending platform, uses similar algorithms to profile its customers by analyzing the applicant's smartphone metadata to gain understanding of the applicant's behavior. This information is used to make decisions with the credit risk of each borrower in mind. Other than that, police in India have been using an algorithmic tool called Crime Mapping, Analytics and Predictive System for predictive policing in places like Delhi, Punjab, Uttar Pradesh and Rajasthan. Facial recognition tools have also been used regularly.[164]

[163] KENYA AFFORDABLE HOUSING PROGRAMME, *Development Framework Guidelines* (Oct. 2018), https://www.housingandurban.go.ke/wp-content/uploads/2018/11/Development-Framework-Guidelines-Release-Version.pdf.

[164] Ramachandran Murugesan, *Predictive policing in India: Deterring crime or discriminating minorities*, LSE HUMAN RIGHTS BLOG (Apr. 16, 2021), https://blogs.lse.ac.uk/humanrights/2021/04/16/predictive-policing-in-india-deterring-crime-or-discriminating-minorities/ [https://perma.cc/75W2-NPU9].

	Algorithms have also been used in India's education sector in predicting school dropouts. Microsoft, through Azure Machine learning, processes data comprising of "student performance, school infrastructure and teacher skills" to find patterns among school dropouts. The government the directs schemes and programs to those areas based on that information. Over 10,000 schools in Andhra use this algorithm to predict dropouts.
Nigeria	Like Kenya and India, credit scoring is tied to algorithmic decision-making in Nigeria. Branch uses algorithms to assess loan eligibility by examining, for example, amount of money in one's mobile money wallet and other loans one has. It considers social features such as social media interaction as less useful than financial data. Other online lending platforms like Branch include, Paylater, Palmcredit, QuickCheck, Aella Credit, KiaKia and FairMoney.
South Africa	Cmore is a portal that uses internal and external data to "conduct surveillance, defense and policing operations."[165] Internal date includes information by patrol units from the Cmore Mobile app, for example, communication within the units and feedback from surveillance; while external data is derived from outside sources like drones or other sensors.[166] Cmore uses this information to perform predictive analytics in security to "allegedly prevent future crimes".[167] Cmore uses

[165] Michael Kwet, *Cmore: South Africa's New Smart Policing Surveillance Engine*, COUNTERPUNCH (Jan. 27, 2017), https://www.counterpunch.org/2017/01/27/cmore-south-africas-new-smart-policing-surveillance-engine/.
[166] *Id.*
[167] *Id.*

	these features in partnership with the South African police to prevent crimes such as theft, illicit drugs, and public protest.[168]
The Philippines	Algorithmic decision-making in the Philippines is also applied in credit scoring mobile applications to determine loan eligibility of borrowers by analyzing data accessible to the app on the borrowers' mobile phones. This decision-making method bears inherent biases as discussed earlier. The credit scoring mobile apps in the Philippines are Tala and Lenddo. Suggestions on use of algorithms to predict decisions of courts exist.[169] Decisions from courts can be analyzed and predictions made on how similar cases might be determined in future. This suggestion is meant to help lower courts reduce the backlog of cases.[170]

b. Proactive executive agency or independent commission policing of discrimination

Country	**Legal Framework**	**Policing of discrimination**
Kenya	Antidiscrimination law is found in the Constitution,[171] Employment Act (preventing discriminatory hiring processes)[172], Persons with Disabilities Act (protecting	Executive agencies do not participate in any issues to do with discrimination. While several human rights commissions exist, there is no evidence that any of them

[168] *Id.*
[169] M. B. L. Virtucio et al., *Predicting Decisions of the Philippine Supreme Court Using Natural Language Processing and Machine Learning,* IEEE 42 ANNUAL COMPUTER SOFTWARE AND APPLICATIONS CONFERENCE (COMPSAC) 130 (2018).
[170] *See id.* at 135.
[171] CONSTITUTION art. 27 (2010) (Kenya).
[172] The Employment Act (2007) Cap. 226 § 5 (Kenya).

	persons with disability from discrimination) [173] and the National Cohesion and Integration Act (prohibiting ethnic, racial and religious discrimination).[174]	proactively investigates issues to do with discrimination. When rights are infringed upon, for example freedom from discrimination, one is empowered to institute court proceedings. [175] Hence, the Judiciary comes in to settle discrimination disputes. In particular, the Employment and Labor Relations Court handles matters on discrimination arising in the workplace. There is no individual complaints procedure for victims of discrimination under either the Persons with Disabilities Act or the Employment Act, both of which provide for discrimination to be a criminal offence.
India	Antidiscrimination law can be found in the Constitution, The Persons with Disabilities (Equal Opportunities, Protection of Rights and Full	Policing of discrimination in India is mainly carried out by an independent commission (lacking enforcement powers) and the court system.

[173] The Persons with Disabilities Act (2002) Cap. 133 (Kenya).
[174] The National Cohesion and Integration Act, No. 12 (2008) (Kenya).
[175] CONSTITUTION art. 22 (2010) (Kenya).

	Participation) Act (protecting against discrimination on the ground of disability), Equal Remuneration Act, Maternity Benefit Act (protecting against on the ground of maternity status), Hindu Succession Act, Transgender Persons (Protection of Rights) Act (protecting transgender persons against discrimination) and Scheduled Caste and Scheduled Tribe (Prevention of Atrocities) Act. Article 14, 15, 16, 17 and 18 of Constitution of India also promote equality of all citizens and prohibits discrimination.[176]	The Protection of Human Rights Act creates a National Human Rights Commission.[177] The powers of the commission include, to investigate human rights violations,[178] but there is evidence that it proactively investigates touching on discrimination. Executive agencies do not directly participate in any issues to do with discrimination.
Nigeria	Anti-discrimination law in Nigeria has its foundation in the Constitution, the Discrimination Against Persons with Disabilities	Policing of discrimination is supposed to be done by the Human Rights Commission (which lacks implementation powers) and by the court system.

176 India Const. art. 14–18.
177 The Protection of Human Rights Act, 1994, § 3 (India).
178 *Id.* at § 12.

	(Prohibition) Act (prohibiting discrimination on the ground of disability)[179] and the HIV and AIDS Anti-Discrimination Act.[180]	The executive is not involved in policing discrimination. The National Human Rights Commission exists but it faces major challenges with regards to its independence and effectiveness.[181]

[179] Discrimination Against Persons with Disabilities (Prohibition) Act (2019), § 1 (Nigeria).
[180] HIV and AIDS (Anti-Discrimination) Act (2014), § 1 (Nigeria).
[181] Abuja Ameh Ochojila & Lagos Silver Nwokoro, *Stakeholders examine National Human Rights Commission's struggles on its mandate*, THE GUARDIAN (July 13, 2021), https://guardian.ng/features/law/stakeholders-examine-national-human-rights-commissions-struggles-on-its-mandate/.

South Africa	The law against discrimination can be found in the Constitution, the Promotion of Equality and Prevention of Unfair Discrimination Act and the Employment Equity Act. Section 9 of the Constitution also entitles everyone to equality before the law.[182] The Employment Equity Act purposes to create equity in the workplace not only by treating everyone equally but also by accommodating differences.[183]	The administrative state plays an insignificant role in policing discrimination. Further, policing of discrimination by independent commissions such as the South African Human Rights Commission is not vigorous enough because they lack adequate enforcement powers[184]. Equality Courts [185] determine discrimination cases lodged by affected parties, interested parties, commissions or for public interest. Equality Courts offer relief in the form of, among others, declaratory orders, interim orders, damages, preventing unfair discriminatory practices or ordering for an unconditional apology.[186]
The Philippines	Article II Section 14 of the Constitution provides for	The executive branch is not directly involved in policing

[182] S. AFR. CONST., 1996.
[183] Employment Equity Act 55 of 1998 § 6 (S. Afr.).
[184] John C. Mubangizi, *A comparative discussion of the South African and Ugandan Human Rights Commissions*, 48 COMPAR. & INT'L L.J. 124, 141 (2015).
[185] Promotion of Equality and Prevention of Unfair Discrimination Act 4 of 2000 § 16 (S. Afr.).
[186] *Id.* at § 21.

	equality of men and women before the law, [187] while Article III Section 1 guarantees equal protection of the law to all persons.[188]	discrimination. The Commission on Human Rights is supposed to do so, but there is no evidence that it usually does.

c. Vigilant non-government actors attentive to algorithmic decision-making

Country	**Attention of civil society groups towards algorithmic decision-making**
Kenya	There is no evidence of non-government groups being attentive to algorithmic decision-making.
India	The National Institution for Transforming India (NITI Aayog) is a government think tank that maps out strategies, policies, and programs for the Indian government to foster development. It designed an AI strategy for India. NITI in their strategy acknowledges that algorithmic decision-making bears shortcomings because they are subject to human judgement and limitations including inherent biases and discrimination.[189] NITI suggests that at first a "reactive approach" to reduce bias will be undertaken before AI can achieve complete neutrality despite bias.[190]

[187] CONST., (1987), art. II, § 14 (Phil.).
[188] *Id.* at art. III, § 1.
[189] *See generally* EUROPEAN COMMISSION'S DIRECTORATE-GENERAL FOR COMMUNICATIONS NETWORKS, CONTENT AND TECHNOLOGY, *State of the Art Report: Algorithmic Decision Making* (2018), https://actuary.eu/wp-content/uploads/2019/02/AlgoAware-State-of-the-Art-Report.pdf [https://perma.cc/C8BA-9VXE].
[190] *Id.* at 100.

	There are no outside groups with a focus on monitoring algorithmic decision-making in India.
Nigeria	There is no evidence of a non-government group that is attentive to algorithmic decision-making.
South Africa	There is no evidence of a non-government group that is attentive to algorithmic decision-making.
The Philippines	There is no evidence of a non-government group that is attentive to algorithmic decision-making.

d. A well-rooted culture of transparency

Country	**Legal Framework on Transparency and Access to Information**	**Public record transparency**
Kenya	Transparency is a national value binding all state actors.[191] The Constitution calls for transparency from Parliament,[192] financial institutions,[193] the public service[194] and the national police[195] in particular. The Constitution accords citizens the right of access to information held by the state or necessary in	In 2016, Transparency International Kenya, through the County Governance Status Report, revealed that Kenya was yet to adopt open budgetary processes. Information on the county governments was difficult to access and

[191] CONSTITUTION art. 10 (2010) (Kenya).
[192] *Id.* at art. 230.
[193] *Id.*
[194] *Id.* at art. 232.
[195] *Id.* at art. 242.

	the protection of their rights.[196] The Access to Information Act that puts into practice access to information.[197]	services were delivered poorly.[198] Further, public offices fail to respond to requests of access to information[199] within the statutory given framework of 21 days.[200] Most of these requests are either ignored or receive negative responses after a very long time.[201]
India	The right of access to information is provided in the Right to Information Act.[202] The objective of the Act is to promote transparency by providing practical measures for the fulfillment of the right.	Although India has set up an e-government in the hope that people and business will be able to access government information at any time,[203] there is no proof of any culture of public record transparency.

[196] *Id.* at art. 35.
[197] Access to Information Act, No. 31 (2016) KENYA GAZETTE SUPPLEMENT NO. 152.
[198] TRANSPARENCY INTERNATIONAL KENYA, *The Kenya County Governance Status Report* (2016), https://tikenya.org/wp-content/uploads/2017/06/county-governance-status-report.pdf.
[199] Vincent Ng'ethe, *GUIDE: How to use your right to government information in Kenya*, AFR. CHECK (July 23, 2018), https://africacheck.org/factsheets/guide-how-to-use-your-right-to-government-information-in-kenya/ [https://perma.cc/5DU7-Y3SL].
[200] Access to Information Act, *supra* note 197, at § 9(1).
[201] *See* Ng'ethe, *supra* note 199.
[202] Right to Information Act, 2005 (India).
[203] M. Alshehri & S. Drew, *Implementation of e-Government: Advantages and Challenges*, INT'L J. ELEC. BUS. 79, 81 (2011).

Nigeria	The right to access information is guaranteed by the Freedom of Information Act.[204]	Prior to the Act, access to information was not established and transparency was absent in public administration. In fact, request for information was met with claims of the classified nature of information which was protected by the Official Secrets Act.[205] One may request for the information even without showing specific interest in that information.[206] As of 2020, responses to requests for information from government are low, and sometimes the requests are ignored altogether.[207] Even when courts give judgments in favor of

[204] Freedom of Information Act 2011 (Nigeria).
[205] Felicia Segun, *The Law of Freedom of Information in Nigeria*, https://digitalrightslawyers.org/wpcontent/uploads/2021/01/WIG_April2012_Segun_Nigeria.pdf (last visited Jan. 25, 2022).
[206] Freedom of Information Act 2011, *supra* note 204, at § 1(2).
[207] *Why We Have Not Given Up on Processes: Making FOI Requests in Nigeria,* PARADIGM INITIATIVE (May 11, 2020), https://paradigmhq.org/making-foi-requests-in-nigeria/ [perma.cc/U8RT-BWTP].

		applicants, enforcement of these judgments against the government is difficult.[208]
South Africa	The Constitution mandates that transparency be present in public administration and that information is accessible.[209] Transparency also binds the various legislative bodies in the processes they undertake,[210] for example, the budgetary process.[211] The right of access to information held by the state or information necessary in protecting one's right is given to every person.[212] This right is put into effect by the Promotion of Access to Information Act.[213]	Responses to requests for information range from full disclosure to silence.[214] Some of the requests for information are ignored.[215] Sometimes the government believes that the information they provide may be used against them, leading to any request for information to be rejected or not considered at all.[216] When a request for information is not responded to one cannot know the reasons that led to the non-response.[217] There is no central office or agency that has been established to deal with

[208] *Id.*
[209] S. AFR. CONST., 1996 §195.
[210] *Id.* at §§ 57, 70, 116.
[211] *Id.* at § 215.
[212] *Id.* at § 32.
[213] Promotion of Access to Information Act 2 of 2000 (S. Afr.).
[214] D. Marais et al., *The role of Access to Information in Enabling Transparency and Public Participation in Governance: A case study of Access to Policy Consultation Records in South Africa,* 9 AFR. J. PUB. AFF. 36, 44.
[215] *Id.* at 39.
[216] *Id.*
[217] *Id.* at 45.

		requests for information. [218] Therefore, enforcement of transparency and access to information laws is insufficient.
The Philippines	South Africans have a right to information that concerns the public and access to official state decisions, records, and documents is to be granted to the citizens. [219] Additionally, the state is mandated to adopt a policy of "full disclosure" on matters of public interest.[220] The Executive Order No. 2 of 2016 (Freedom of Information Order) gives effect to the right.[221]	Requests for access to information vary in responses depending on the agency or public office involved.[222] Some entities are more forthcoming with information when they trust that the release of that information will lead to reforms.[223] For the Supreme Court, when the correct procedure in requesting access to information is followed and if the information requested is not confidential, requests for

[218] Obotsamang Maropo, The Lack of Accountability and Transparency in Local Government in South Africa (2014) (Master's thesis, University of the Free State) (on file with on KovsieScholar, University of the Free State).
[219] CONST., (1987), art. III, § 7 (Phil.).
[220] *Id.* at art. II, § 28.
[221] Office of the President, Operationalizing in the Executive Branch the People's Constitutional Right to Information and the State Policies to Full Public Disclosure and Transparency in the Public Service and Providing Guidelines, Exec. Ord. No. 2 (July 23, 2016) (Phil.), https://www.officialgazette.gov.ph/2016/07/23/executive-order-no-02-s-2016/.
[222] Alexander Furnas, *Transparency Case Study: Public Procurement in the Philippines,* SUNLIGHT FOUND. (Oct. 7, 2013, 5:56 PM), https://sunlightfoundation.com/2013/10/07/case-study-public-procurement-in-the-philippines/ [perma.cc/4QFJ-JDPE].
[223] *Id.*

		information yield a grant of access to the information without many impediments.[224]

e. Regularly released statistical analyses touching on the disparities faced by protected groups

Country	Available statistics of disparities faced by protected groups
Kenya	Reports and statistics analyzing disparities faced by protected groups are not systematic but rather one-time analyses. The reports do not contain a record of whether the disparities are increasing or decreasing. The existing statistics state that inequalities exist, and some offer specific figures (percentages) on the disparities which is not comprehensive enough.
Nigeria	With a few exceptions,[225] reports and statistics analyzing disparities faced by protected groups are not systematic but rather one-time analyses.
South Africa	The focus of existing analyses is on gender[226] and race.[227] These are only two of the protected characteristics under South African antidiscrimination law.

[224] *See* Merceidez Ragaza, *Philippines: The right to know – Freedom of information in the Supreme Court*, IN-HOUSE CMTY. (Feb. 8, 2019), https://www.inhousecommunity.com/article/right-know-freedom-information-supreme-court/ [perma.cc/E9X3-D6EL].

[225] *Gender in Nigeria Report 2012: Improving the Lives of Girls and Women in Nigeria*, BRITISH COUNCIL NIGERIA (2012), https://reliefweb.int/report/nigeria/gender-nigeria-report-2012-improving-lives-girls-and-women-nigeria.

[226] *Women and Men in South Africa,* CTR. STAT. (1998), http://www.statssa.gov.za/publications/WomenAndMen/WomenAndMen1995.pdf [https://perma.cc/2R7X-U9MR].

[227] *Gender Series Volume IV: Economic Empowerment 2001–2017 Report,* STAT. S. AFR. (Sept. 27, 2018), http://www.statssa.gov.za/?p=11591 [perma.cc/9PS7-V3HT].

The Philippines	The statistics authority releases fact sheets on women and men (indicating any disparities that could be present) each year.[228] The fact sheets contain categories including, health, education, economic participation, employment, among others. However, these fact sheets do not comprehensively analyze the disparities faced by protected classes. Statistics on ethnic inequalities are frequently published analyzing the progress of the inequalities across the years.[229] They indicate among others the levels of schooling, literacy and access to services.

228 *PSA Issues Updates on Women and Men in the Philippines*, PHIL. STAT. AUTH. (Mar. 9, 2021), https://psa.gov.ph/gender-stat [perma.cc/3KRV-87JA].

229 *See generally* Celia M. Reyes, Christian D. Mina, & Ronina D. Asis, *Inequality of Opportunities Among Ethnic Groups in the Philippines* (Phil. Inst. Dev. Stud. Discussion Paper Series No. 2017-42 3, 2017), https://pidswebs.pids.gov.ph/CDN/PUBLICATIONS/pidsdps1742.pdf [perma.cc/7ZH6-ATXB].