More than the Sum of its Parts: Susceptibility to Algorithmic Disadvantage as a Conceptual Framework

Paola Lopez
paola.lopez@univie.ac.at
University of Vienna and University of Bremen
Austria and Germany

ABSTRACT

Algorithmic systems are increasingly being applied in contexts of state action to, in some capacity, mediate the relations between state and individual. Disadvantageous effects, such as potential discriminatory outcomes brought forth by different kinds of biases, have been the locus of severe critique by academic scholarship and political activism. There has been scholarly work conceptualizing biases and types of biases, as well as types of harm. Drawing from Elizabeth Anderson's conceptualization of relational equality, this paper emphasizes the relationality of the encounters between state and individual. This paper introduces "susceptibility to algorithmic disadvantage" as a conceptual framework to address the relational constellation at play. Susceptibility to algorithmic disadvantage has a vertical dimension that addresses the relation between a state actor and an individual and a horizontal dimension that is characterized by intersectional inequalities that prevail in societal contexts. Intersectional feminist scholarship has established that interlocking systems of oppression amount to more than the sum of their single-axis parts. Paralleling this argument, this paper argues that susceptibility to algorithmic disadvantage amounts to more than the sum of the vertical and the horizontal dimension: the dimensions co-constitute and reinforce each other. The proposed framework is applied to four international case studies situated in crucial areas of state action: facial recognition in law enforcement in the USA, biometric identification in social welfare in India, dialect recognition in the asylum system in Germany, and grade prediction in the education system in the UK. Viewed through the lens of the proposed framework, heterogeneous use cases in different locations and areas of state action emerge as similar considering the inquiry into questions of justice, rendering the proposed framework a useful tool for analysis.

CCS CONCEPTS

• **Computing methodologies → Machine learning**; *Philosophical/theoretical foundations of artificial intelligence*; • **Applied computing → Law, social and behavioral sciences**.

ACM Reference Format:
Paola Lopez. 2024. More than the Sum of its Parts: Susceptibility to Algorithmic Disadvantage as a Conceptual Framework. In *The 2024 ACM Conference on Fairness, Accountability, and Transparency (FAccT '24), June 03–06, 2024, Rio de Janeiro, Brazil.* ACM, New York, NY, USA, 11 pages. https://doi.org/10.1145/3630106.3658944

FAccT '24, June 03–06, 2024, Rio de Janeiro, Brazil

ACM ISBN 979-8-4007-0450-5/24/06
https://doi.org/10.1145/3630106.3658944

1 INTRODUCTION

Algorithmic systems are increasingly being applied in contexts of state action. Much scholarly work has tended to algorithmic bias and subsequent discrimination, as well as to invasive practices and harmful malfunctions (see, e.g., [4, 7, 11, 17, 19, 25, 57, 80]). How the state treats an individual is a question pertinent to the inquiry into (in)justice. This paper directs attention to the relational constellation at play between state and individual: Drawing from Elizabeth Anderson's philosophical scholarship on relational equality, this paper introduces the conceptual framework *susceptibility to algorithmic disadvantage* in two dimensions to address said relation. For the two dimensions, I combine philosophical theorizing on vulnerability and intersectional feminist theory.

As case studies, this paper presents four international examples of algorithmic systems deployed in the context of state action, as well as potential emerging disadvantageous effects for individuals. These cases are heterogeneous in several ways: they differ in technological architecture, target group, geographical region, and state action area. However, there is a common thread of injustice that connects these, as well as numerous other cases. The following questions, then, arise: What is it about these cases, and other cases *like* these, that gives rise to injustice? What does *alikeness* of cases *like* these mean? And finally: What do we mean when we speak of injustice? This paper aims to present *susceptibility to algorithmic disadvantage* as a concept for comparing—as in: rendering alike—the state-individual relations and their algorithmic mediation that will serve as the locus for the inquiry into questions of justice. *Susceptibility to algorithmic disadvantage*, this paper argues, is what renders the constellation a particularly unjust one for those that are affected—throughout different areas of state action, different global locations, and different technologies.

Elizabeth Anderson's concept of *relational equality* has been used in the context of FAccT and FAccT-adjacent research to productively critique notions of algorithmic fairness. While [79] has deployed Anderson's relational equality to, firstly, show the shortcomings of only measuring accuracy rates among different demographic groups in the context of pretrial risk assessments and, secondly, propose a modified ("Affirmative") approach, this paper focuses on the common threads of injustice in numerous cases simultaneously, shifting the focus from improving specific systems to grasping the injustice at the core of many systems at once. In [27], the authors draw from relational equality, in that they demonstrate the shortcomings of distributional equality by constructing a case they call "blatantly relationally unfair" in the context of hiring. In [74], the author draws from relational equality to critique existing discourses around legal data governance in the USA and to enrich the efforts to build national legislation guided by equal social relations. This paper has a different scope, in that it focuses on international examples and their common denominator of injustice, and only on algorithmic systems deployed by state actors. Further, this paper, in contrast to [27, 74, 79], considers relations between state and individual and their mediation through algorithmic systems, instead of relations between members of society.

The paper's argument is built as follows: The perspective of relational equality is adapted to describe the state-individual relations and it serves as a starting point for defining what justice and, thus, what injustice looks like. Then, I introduce the framework of *susceptibility to algorithmic disadvantage* that consists of a vertical and a horizontal dimension, drawing from philosophical theorizing on vulnerability (to construct the vertical dimension), as well as intersectional feminist scholarship (for the horizontal dimension). I then parallel the legal intersectional feminist argument of "more than the sum of its parts" to build the same argument for the introduced framework: it is the combination of the vertical and the horizontal dimension that allows us to see injustice better than the single dimensions, tending to the question of *what exactly* renders the application of an algorithmic system unjust. Finally, to put the argument into practice, I apply the susceptibility framework to four heterogeneous international case studies: facial recognition in law enforcement in the USA, biometric identification in social welfare in India, dialect recognition in asylum proceedings in Germany, and grade prediction in the UK. These case studies have been studied independently, and their heterogeneity serves as a proof-of-concept for the case studies' comparability through the proposed framework of *susceptibility to algorithmic disadvantage*.

In total, this paper aims to contribute to the rich scholarship of FAccT a framework that is neither too coarse and simplistic, as simplification and reduction of complexity is one of the causes for algorithmic disadvantage in the first place (see, e.g. [64, 68]), nor too complex, as to lose the common thread of injustice that connects these constellations. I acknowledge the porousness and the limitations of such a claim, and hope for critical engagement, refinement, and dialogue within the FAccT community.

2 ALGORITHMIC SYSTEMS MEDIATING THE RELATIONS BETWEEN STATE AND INDIVIDUAL

In her seminal work "What Is the Point of Equality?" that introduces her theory of democratic equality [3], Elizabeth Anderson defines the democratic state via relations between the state's members and conceptualizes justice via requirements towards said relations. Justice, according to Anderson, is not about the question of how resources are distributed (see also [40, 42, 44]). It is neither about well-being nor about how to compensate for bad luck. Rather, it is the way in which we relate to one another that is the locus of justice: Standing in relations of equality with others is a prerequisite of living a free life (see also [27, 74, 79]). The members of the democratic community, according to Anderson, stand in relations of equality to one another when each member "accepts the obligation to justify their actions by principles acceptable to the other" [3]. Anderson, thus, asserts the importance of *relations* between members of the democratic community.

This paper adapts this conceptualization in two ways: firstly, by including non-citizens in an expanded understanding of the democratic community. It views the state, following Anderson, as the democratic state in the form of "collective self-determination" [3]. In her paper, Anderson, like many scholars who write about democracy, writes mainly about citizens, and she expands her focus globally to include workers in different international locations. She acknowledges the conceptual difficulty of including non-citizens in her conceptualization of the state—when the state is defined as *individuals acting collectively*. This paper argues that, when viewed through the lens of justice, any obligation that a democratic community has vis à vis one of its members who do hold citizenship and can, thus, participate in the democratic community's collective self-determination, it will also have vis à vis an individual without citizenship who encounters, is affected by and, thus, stands in relation with the democratic community. It is especially important, from a justice perspective, to explicitly include non-citizens who happen to find themselves within or in relation to a democratic community.

Secondly, this paper adapts Anderson's conceptualization, in that it *lifts* the social relations: the focus lies on the *vertical* relations between state actors and individuals. How the state treats an individual is a substantial question, and state actors, i.e., state agencies, state authorities, and state institutions in the broadest sense, are condensed instances of democratic collective willing and collective self-determination [3]. The relations between an individual and the democratic state—when played out in an encounter between the individual and a state actor—thus emerge as a locus for the inquiry into questions of justice. As Anderson writes, "the fundamental obligation of citizens to one another is to secure the social condition of everyone's freedom" [3]. As this paper understands state actors as condensed instances of the democratic community, our obligations towards one another as individuals play out in the obligations of a state actor towards an individual. Thus, when an individual encounters a state actor, the state actor—as an instance of collective self-determination—recognizes an "obligation to listen respectfully", and the individual does not "need to bow and scrape" before the state actor "as a condition of having their claim heard" [3]. Every individual has the "inalienable right to the social conditions of her freedom"—which translates to everyone's, and in a *lifted* way, every state actor's "unconditional obligation to respect her dignity or moral equality" [3].

It is the qualities of the relations between an individual and a state actor that are examined in this paper: Does the state actor respect an individual's dignity? Does a person need to bow and scrape as a condition of having their claim heard? These are pressing questions in contemporary democracies, and studying them becomes all the more important when algorithmic systems enter the scene. This paper focuses on constellations in which an algorithmic system, in some capacity, is deployed to *mediate* the relations between state and individual. As conceptualized above, the democratic state is viewed as collective willing and collective action. It follows that the algorithmic system in question, in mediating the relations between an individual and the state, by proxy, mediates the relations between one member of the democratic community and others. Hence, the qualities of the mediating functions of algorithmic systems emerge as a locus of interest for the inquiry into the qualities of the relations between an individual and a state actor—which, as has been argued above, are crucial.

3 SUSCEPTIBILITY TO ALGORITHMIC DISADVANTAGE

3.1 The framework

When an algorithmic system is deployed in the context of state action, especially towards individuals in a capacity to severely influence their future endeavors, this can entail disadvantageous effects for the individual. Although disadvantageous effects can be disastrous for every individual who is subject to them, not all individuals suffer from the same extent of distress and harm. For some individuals in some situations, algorithmic disadvantage is especially grave and, as this paper argues, a matter of severe injustice. The question remains how to conceptualize these relational configurations. What does it mean for some people to be *especially* prone to algorithmic exclusion from the democratic promise of justice?

I propose a conceptual framework for the relational constellations at play called *susceptibility to algorithmic disadvantage* which amounts to both a horizontal and a vertical dimension. The vertical dimension addresses the (vertical) relation between a state actor and an individual, and the horizontal dimension the (horizontal) relations between one member of the democratic community and others. Susceptibility to algorithmic disadvantage, that is the claim of this paper, is coarse enough to encompass a wide variety of relational configurations and areas within the context of state action while still being precise enough to account for and render visible the specificities of constellations in which individuals are subject to decisions made or guided by algorithmic systems. Viewed through the lens of susceptibility to algorithmic disadvantage, applications that, at first glance, seem quite different, having differing areas of application, heterogeneous technical architectures, and various global locations, emerge as similar regarding questions of justice. It is people that are susceptible to algorithmic disadvantage who are excluded first from the democratic promise of justice.

Vertical dimension.

The vertical dimension of susceptibility to algorithmic disadvantage describes a situation of severe dependency vis à vis a state actor: an individual is in grave need for something that the state actor is, according to the democratic promise of justice, obligated to provide. This may amount to social welfare, or some kind of protection, caution, or care. In feminist and moral philosophy, the concept of *vulnerability* has been used to describe different aspects and states of dependency. In their taxonomy of vulnerability, Mackenzie et al. differentiate between sources of vulnerability: their notion "situational vulnerability" describes vulnerability that is context-specific, as opposed to "inherent vulnerability" that stems from the human condition itself [45]. The vertical dimension conceptualized in this paper can be described as situational vulnerability towards a state actor. A person who experiences situational vulnerability might depend on a state actor only for a short time, but within this time frame, the state actor exercises power over them. This vertical dimension is perpetually imminent—there is always an imbalance of resources, knowledge, and power between an individual and the state. This imbalance might be actualized by a situation in the life of a person for a temporary time period: unemployment, migration, climate catastrophes, a pandemic, and others. Inhabiting this planet in these times is a vulnerable endeavour. Especially when a person is in a position of situational vulnerability vis à vis a state actor, the way the state actor treats them—in other words, the quality of the relation at play—is highly pertinent with regard to questions of justice. There has been fruitful research bringing the philosophical concept of vulnerability to privacy [14], and to the study of data protection to conceptualize and rethink "vulnerable data subjects" in the context of the European GDPR [47–49]. This paper's scope differs in two ways; firstly, it expands its focus to global examples, with the aim of carving out the common threads of injustice, and secondly, it narrows the focus specifically to state actors deploying algorithmic systems.

Horizontal dimension.

Disadvantageous effects of algorithmic systems are often brought about by power relations that are prevalent within society and that, subsequently, manifest in algorithmic systems [4, 7, 11, 57]. Systems of oppression structured along "axes of power" [18], e.g., gender, race, class, ability, amount to intersectional inequalities that are constituted by and, in turn, constitute our social architecture [12, 38]. The horizontal dimension of *susceptibility to algorithmic disadvantage* aims to describe the social constellation of individuals that are intersectionally disadvantaged, noting that, as Shreya Atrey writes, "intersectionality conceives of 'disadvantage' broadly, including every harm, oppression, powerlessness, subordination, marginalization, deprivation, domination, and violence" [5]. It is important to note that "[s]uch disadvantage is … not personally directed towards … individuals but suffered by individuals because of their membership in a social group" [5]. Thus, according to Sumi Cho, Kimberlé Crenshaw, and Leslie McCall, the focus lies on political and structural inequalities [18]. Following Catharine MacKinnon, this paper focuses on "the forces that create the outcomes, not just their static products" [46]. By "outcomes", MacKinnon means categories, such as race, gender, and class, as well as stereotypes. She writes poignantly: "They are there, but they are not the reason they are there" [46]. Mari Matsuda refers to "a trait, X, which often carries with it a cultural meaning" [50]. This paper does not focus on identities, but on "social location[s] … within intersecting power relations" [20], i.e., on structures that render certain identities, via group membership or supposed group membership, especially prone to disadvantage (see also [22]). These structures infuse algorithmic systems and might bring about disadvantageous effects. Bias in technology design might emerge, for example, from invisibility or hypervisibility of certain groups in machine learning training data (see, e.g., [30, 35, 52, 72]), but should not be reduced to the technical realm [23, 53]. An algorithmic system might function well for many people and, at the same time, systematically malfunction for individuals in positions of intersectional disadvantage.

3.2 More than the sum of its parts

Bringing together both the vertical and the horizontal dimension, susceptibility to algorithmic disadvantage describes relational configurations in which an individual is, firstly, dependent on a state actor and, secondly, in an intra-societal position of marginalization. It is especially those cases in which the overall configuration is *more than the sum of its*—vertical and horizontal—*parts* that are prevalent when it comes to questions of (in)justice. In the following, I recount an argument by intersectional feminist scholarship and, subsequently, parallel the argument and apply it to the framework of susceptibility to algorithmic disadvantage.

Intersectional feminist scholarship in legal studies, social theory, and philosophy has brought forth the argument that inequalities and systems of oppression cannot be thought of as single-axis phenomena: It is not racism and sexism that are merely additively combined to yield, say, racist sexism (or sexist racism). Rather, the "intersecting oppressions" reinforce and constitute each other [38]. Being affected by the intersection of systems of oppression is more than the sum of its single-axis parts [5, 15, 18, 51, 75, 78]. This argument has been made conceptually, as well as legally. Kimberlé Crenshaw coined the term "intersectionality" and demonstrated in specific legal cases that anti-discrimination law is neither equipped to see nor to adequately respond to intersectional constellations: It can merely see single-axis discrimination, that is, discrimination on the basis of *one* protected feature [21]. Moreover, Crenshaw showed that it is the very togetherness of race and gender as systems of oppression creating a constellation in which the legal position of Black women is invisibilized: In her discussion of the *DeGraffenreid v. General Motors* case, she argues that Black women were denied legal protection against the disadvantage they suffered because the law was not able to conceptually grasp intersectional constellations. As neither discrimination purely on the basis of gender, nor discrimination purely on the basis of race could be proven, the plaintiffs who—as Crenshaw argues—suffered from a disadvantage because they were Black women, were left without legal remedy [21]. The legal protection of Black women against discrimination, in this case, amounts to *less than its individual parts*—in other words, the interlocking constellation of oppression emerges as *more than the sum of its parts.*

Paralleling the intersectionality argument, in the configuration of the vertical and the horizontal dimension of susceptibility to algorithmic disadvantage, we as a society need to pay special attention and caution to cases in which both a dependency on a state actor and an intersectionally marginalized societal positionality converge and co-constitute each other. Put differently: Systematically malfunctioning, invasive, and biased algorithmic systems are always undesirable, but they become unacceptably unjust when the individuals affected are in a position of dependence and the stakes are high. And, conversely: Being vulnerable vis à vis a state actor that deploys an algorithmic system is always uncomfortable, but if the system functions well and in line with the state actor's obligation to fulfill its promise of justice, vulnerability to a certain extent cannot be prevented, as it lies at the core of democratic states that we are ruled by our elected representatives and governed by our institutions—as long as they function well and there are checks and balances, as well as effective protective measures and remedies against disadvantage. However, if great dependency meets systematic, biased malfunctioning, the constellation becomes severely unjust. An algorithmic system, in these situations, can have a myriad of downstream effects.

4 FOUR INTERNATIONAL CASE STUDIES

The following section sets forth four international examples of algorithmic systems that mediate the relations between individual and state by way of shaping the encounters between an individual and a state actor. The case studies are situated in heterogeneous areas of state action: law enforcement, social welfare, the asylum system, and the education system. The cases are international: USA, India, Germany, and UK. The proposed framework is applied to carve out the specificities, and the similarities, of the relational constellations at play in order to find the common threads of relational injustice. On a methodological note, in the exposition of the following case studies, a close reading was conducted on publicly available government and state actors statements and documents. In doing that, I aim to tell the algorithmic systems' stories in the words of the state actors, and subsequently contrast them with points of critique.

4.1 Facial recognition software in law enforcement in the USA

The first case study examines facial recognition technology and its deployment by the Michigan State Police in the United States of America. While Michigan is not special in its practice of deploying facial recognition technology, the reason this subsection focuses on Michigan is the wrongful arrest of Robert Williams that has gained a lot of media attention as one of the the first caused by a false positive result. Thus, while similar policies are in place in numerous other states (see, e.g., [31]), this case study focuses on the policies around facial recognition in Michigan at the time of Williams's arrest as an example. The Michigan State Police has been utilizing facial recognition algorithms since 2001 "to identify subjects without identification on a traffic stop [and to] assist … in a criminal investigation when surveillance video or other suspect images are available" [54]. Both contexts require a probe image available to the respective law enforcement agency that is algorithmically compared to existing images in the underlying database. The Statewide Network of Agency Photos (SNAP) Unit Program is the "central repository for storing the State of Michigan's digital facial images … and associated data for law enforcement access" [62]. The SNAP, managed by the SNAP Unit, combines the facial recognition tool with image data "from local, state, and federal agencies" [62]. The image dataset "contains a copy of images captured by the MDOS [Michigan Department of State]" [62]. According to a study conducted by the Center on Privacy & Technology at Georgetown Law in 2016, the dataset available to the SNAP contains 4 million mugshots and over 40 million photos from driver's licenses and ID cards [31]. Facial recognition algorithms are supposed to enable automated comparison of an unknown person's image to a large number of stored images that "allows for the completion of digital lineups that meet the best practice standards for eyewitness identification" [63]. A comparison with a database of this magnitude without an algorithmic system would require facial examining professionals in law enforcement to manually look through the images. This, according to the Michigan State Police, would result in "lengthy, inefficient, and costly investigations" and, thus, would entail the potential to "put the public at greater risk of victimization" [54].

1. Relations

In the following, the use of facial recognition technology in a criminal investigation is viewed through the lens of relations between individuals and the state, here being represented by law enforcement agencies as state actors. Facial recognition algorithms *establish* a relation in two steps: Firstly, by having one's image submitted into the central facial image database, which is a prerequisite for, secondly, being identified as a candidate for a facial match by the algorithmic system. Obviously, an image of a person can only be suggested as a potential matching result by the facial recognition software if the image is stored in the corresponding database. Thus, there is a preexisting relation between individual and state—which is not necessarily a relation between individual and law enforcement agency, as the majority of the images in the SNAP is taken from Michigan Department of State database that contains driver's license images. However, as the database also contains mugshots, the arrest behaviour of law enforcement agencies in Michigan does play a role in establishing the database. In total, any person with a driver's license and any person who has been arrested is a potential candidate of a facial recognition result. This preexisting, imminent relation through which the individual may be algorithmically seen by a law enforcement agency is a precondition for the particular relation between an individual and a law enforcement agency that is actualized via a facial recognition algorithm match.

2. Vertical dimension

The Michigan State Police uses facial recognition software "to enable detectives to generate investigative leads in criminal investigations" [54]. Thus, the deployment of facial recognition technology creates a relation between an individual and a law enforcement agency in a specific investigation—a relation that is brought about by the algorithmic system when an individual emerges as an "investigative lead" [62]. If the corresponding investigation entails an arrest of the person, then the person must, as we all always must, comply with law enforcement, regardless of whether the arrest is lawful or not. Any arrest and subsequent detention—focal points of a priori legitimate state violence—puts an individual in a position of substantial situational dependency: An arrest bears the potential of disrupting a person's private and professional life, as well as their well-being, and it can entail a significant use of resources. Thus, the relation between an individual and a law enforcement agency established by a facial recognition algorithm brings about a time span of adversity and dependence for the individual.

3. Horizontal dimension

There are severe issues related to racial inequalities in two ways. The first aspect concerns the preexisting relation discussed above: In order to be suggested as a potential candidate by the facial recognition algorithm, one's image has to be available for algorithmic comparison in the underlying database. While the repository of driver's license and ID photos has not been critiqued for enacting racist practices, the arrest practices and, thus, the ensuing assembling practices of mugshots have [13, 36, 37]. Racist police practices result in a high number of arrests of Black individuals, which, subsequently, create image data via the collected mugshots. Having one's image stored in the mugshot database means that an individual is seen a certain way by a law enforcement agency, and thus, by facial recognition algorithms: as a potential criminal—not only in the specific instance of their original arrest, but also in future instances through the lens of facial recognition algorithms. The second aspect concerns the performance of the facial recognition technology per se. Critical scholarship has been researching facial recognition systems and their biases and imbalances extensively (see, e.g., [11, 16, 17, 32]). As for state actors, according to an extensive report on 189 facial recognition algorithms—including algorithms that are deployed by SNAP—conducted by the US National Institute of Standards and Technology (NIST) in 2019, the false positive rate is significantly higher on images of Black individuals: the authors observed an "elevation of false match rates" [33]. The authors abstain from explaining the differences in performance—the scope of their study is restricted to "quantify[ing] differential outcomes between demographics" [33].

4. More than the sum of its parts

In 2020, the New York Times reported on the arrest of Robert Williams, after some items were stolen in a luxury boutique in Detroit, a case that "may be the first known account of an American being wrongfully arrested based on a flawed match from a facial recognition software" [37]. Williams's driver's licence picture was among the candidates provided by the SNAP system after a still image from a surveillance camera was submitted to a facial recognition system. Furthermore, there have been severe procedural failings on the part of the Detroit Police Department during the investigation [37]. Racially biased law enforcement practices creating a larger—and in its size racially biased—set of potential matching candidates, together with a statistically significant technological malfunctioning on images of Black individuals, can create a nexus of reinforcement of false positive results in which potential arrests are statistically more probable for Black individuals [36, 39]. Thus, brought about by two facets of racial inequalities, the deployment of facial recognition algorithms carries the potential of creating relations between individuals and law enforcement agencies that are severely disadvantageous to Black individuals who are, thus, systematically excluded from the democratic promise of justice. In algorithmically viewing them as default offenders, the state fails in its unconditional obligation to respect their moral equality.

4.2 Aadhaar in India

This case study focuses on Aadhaar, the world's largest biometric identification system. It is situated in India and was established in 2009, and it provides "single source offline/online identity verification across the country" [60]. Several countries are planning to implement a similar system [65, 67]. When residents enrol in the Aadhaar system, they submit biographical data (including name, address, gender, date of birth), as well as biometric data (ten finger prints, two iris scans, and a facial photograph) to the Unique Identification Authority India (UIDAI) [59]. The enrolled resident is subsequently issued a unique 12-digit identification number (the Unique Identification number, UID, or "Aadhaar number") that is, within the UIDAI's central database, linked to their data. Coupling a person's UID number with aforementioned biometric data is supposed to ensure uniqueness.

Apart from issuing the Aadhaar numbers to residents, the UIDAI also carries out the authentication process. If residents aim to authenticate their identity, e.g., in the process of receiving governmental benefits, they provide their Aadhaar number, as well as biographical information, e.g., their name, and biometrical information via, e.g., an electronic fingerprint or iris scanning device, to the respective government agency who distributes the benefits. The agency, then, sends the combined data to the UIDAI, and the UIDAI authenticates the given information: the Aadhaar platform matches the provided data with the data in the central database and makes an automated decision on whether the resident is, indeed, who they claim to be. The result (yes/no) is then sent back to the agency that has made the authentication request. According to the data dashboard of the UIDAI, the Aadhaar platform has carried out more than 80 billion authentications, including over 60 billion "Fingerprint Authentic[a]tions" and over one billion "Iris Authentications" [58]. According to the UIDAI, the Aadhaar system enables "streamlin[ing] ... [the] delivery mechanism under the welfare schemes", as well as "ensuring that services are delivered to the intended beneficiaries only" [60]. Now that the *Aadhaar (Targeted Delivery of Financial and Other Subsidies, Benefits and Services) Act, 2016* was passed, it is, for most governmental benefits or subsidies, imperative for beneficiaries to be correctly authenticated via Aadhaar number to receive said benefits [59].

1. Relations

If a resident wishes to receive governmental benefits or subsidies that the state is obligated to provide, they, in turn, are obligated to, firstly, enrol in the Aadhaar system of authentication and, secondly, be authenticated correctly at each moment of contact. The Aadhaar platform serves as a lens through which the respective government agency and, thus, the state, views beneficiaries. They are *seen* to the extent that they appear in the Aadhaar system [69]. The relations between an individual and a state actor are mediated by the Aadhaar platform via constituting the individual's personhood before the state in all contexts of application. Aadhaar renders an individual legible before the state. Thus, Aadhaar, whenever deployed, emerges as *constitutive* for the relation between state and individual itself in this situation: A person who is not, or not correctly, recognized by the Aadhaar platform is not recognized by the state in this context. Being correctly recognized by the Aadhaar is a prerequisite for there being a relation between state and individual in the first place. Thus, in order for the state to fulfill its obligations towards the individual, the individual has to subject herself to be rendered intelligible and "machine readable" [70] by the Aadhaar system.

2. Vertical dimension

Individuals who are entitled to governmental subsidies, benefits, or services are in a constellation of situational dependency. If welfare schemes can only be accessed via correct authentication via Aadhaar, then individuals obviously depend on the algorithmic system's functioning. This is especially pertinent for individuals who have very limited resources available to them, which, of course, will correlate with the dependency on welfare schemes itself. The Public Distribution System is a welfare scheme that distributes "[r]ice, wheat, sugar, salt and other cereals" to households below the poverty line, often consisting of "landless agricultural labourers" [56]. Between 2016 and 2017, this distribution system was infrastructurally coupled with an automated authentication procedure via Aadhaar. In order to receive their monthly supplies, beneficiaries have to be authenticated by the Aadhaar platform. Thus, there is a severe degree of dependence of individuals vis à vis the well-functioning of the authentication system. Not being authenticated correctly can lead to not being able to access the benefits one is entitled to.

3. Horizontal dimension

Enrolling properly in the Aadhaar system requires submitting biometric data. This requirement a priori restricts the scope of individuals who can be enrolled properly to individuals whose bodies can provide fingerprint data and iris scans. Thus, there is an expectation of a specific type of human body embedded in the system, a bodily norm for which the system has been built and, in effect, a "dissonance between Aadhaar's imagined enrolee ... and the diversity of its actual enrollees" [69]. There are numerous reasons for a person to not meet the requirement to provide adequate data which, thus, make the enrolment and, subsequently, the authentication processes cumbersome: illness, injury, disability, or illegible fingerprints after years of manual labour, or a lack of physical capacities, and/or financial resources to travel to an enrolment agency [41, 65]. Further, transgender individuals and individuals who do not conform to the gender categories available are subject to discriminatory practices at enrolment, and they face difficulties providing evidence for their gender entry [69]. Also, unhoused individuals cannot provide a home address at enrolment [69]. Structured interviews conducted by [56] resulted in the finding that it is women who have the most difficulties during the authentication procedure, having to re-do the authentication procedure disproportionally more often. One potential reason the authors give is the intersectional convergence of their gender and hard manual domestic and agricultural work.

4. More than the sum of its parts

The most obvious disadvantageous effects arise from an error during the authentication procedure, as mentioned above. Being denied access to resources that a person is entitled to and also depends on, clearly bears the potential to severely worsen their overall situation. There are several claims that Aadhaar-related issues have caused deaths from starvation after individuals and families have been denied their assigned food ration [66, 71]. Thus, the dependency on the technology's correct functioning is augmented by the situational dependency on welfare schemes. A false negative result when submitting fingerprints or an iris scan for authentication can result in a beneficiary not being able to access the respective benefits [41]. Hence, in the cases in which the Aadhaar platform fails to perform properly, the constellation of dependency is, in turn, augmented by the implementation of Aadhaar. Thus, not having a body that conforms to the Aadhaar system's norm jeopardizes any relations to state actors that Aadhaar is deployed to intermediate. Especially when intra-societally marginalized positions coalesce with a severe dependency on welfare schemes, e.g., for basic sustenance, the disadvantageous effects become exponential. The authentication system that promises "progress" and "intangible symbolic value" [70] fails those that are most dependent on its functioning. Any state actor that relies solely on Aadhaar to manage access to resources and does not simultaneously offer feasible and effective alternatives denies them a relation and, thus, fails to fulfill its obligations of care towards said individuals who are, in effect, excluded from the democratic promise of justice.

4.3 Dialect recognition in Germany

This case study focuses on an automated dialect recognition system deployed by the Federal Office for Migration and Refugees in Germany (*Bundesamt für Migration und Flüchtlinge*, in short: BAMF). In asylum proceedings, an asylum seeker's country of origin is a crucial piece of information. Depending on the country, the German state is obligated to provide certain levels of protection and care. The "language and dialect identification assistance system" [28], in short DIAS, was introduced in 2017 to assist case workers in the process of determining countries of origin—the language and, more specifically, dialect a person speaks is supposed to serve as an indicator. According to the BAMF, the "high influx of asylum seekers at EU borders and within member states," together with a "lack of identity documents amongst a large number of asylum seekers" and "concerns about fake and counterfeit passports" [28] render it crucial to reliably determine the country of origin, as it is linked with the question of the asylum seeker's eligibility for different levels of protection.

During the process of utilizing DIAS, the BAMF case worker "invites the asylum seeker to verbally describe a specific picture ... as fluently and detailed as possible" and the asylum seeker's speech sample is recorded and analysed. The output of the analysis is a list of possible candidates of dialects and their corresponding probabilities. The system is being used to recognize Iraqi Arabic, Maghrebi Arabic, Levantine Arabic, Gulf Arabic, Egyptian Arabic, Farsi, Dari, and Pashto [10, 43]. According to the BAMF, the report and the dialect probabilities are not to be used as a definite determination of dialect and, thus, country of origin. Rather, the respective case worker is to consider the report "as a clue to the country of origin" [10] and "as one source of information for the overall assessment of the case records to decide the case"—then, against the background of the report, "the plausibility of the asylum seeker's narrative can be tested by targeted questioning" [28].

1. Relations

When an individual seeks asylum in Germany and encounters the BAMF, the individual establishes a relation to the state. This relation, even if it is not a relation between a citizen and the state, as mentioned above, is of importance regarding the question of justice. The individual establishes a relation, hoping for care and protection, which is mediated by the DIAS, as the system plays a role in determining the plausibility of the asylum seeker's "narrative" [28] if documents are not available. In a situation in which the state doubts the individual's narrative, the algorithmic system is supposed to provide a clue "in order to support the verification or falsification of information about the country of origin" [29]. The outcome of the dialect classification, thus, *pre-structures* the future relations between individual and state. The classification of the individual's recorded speech sample emerges as a *quasi-constitutive* building block of the obligation or non-obligation (and its legitimization) by the state.

2. Vertical dimension

The situation in which an asylum seeker encounters the BAMF is characterized by severe dependency: the individual demands certain protection and status—aspects of which impact the course of their life—and their claim is being tested. The individual has no documents or carries documents that are considered not reliable enough, as otherwise their narrative would not be in question, and they entered the state after a cumbersome and often dangerous journey from a place they wished to leave. Hence, having their speech sample analysis fit the proclaimed narrative can be crucial for the asylum seeker. If the asylum seeker's narrative converges with the results of their speech sample analysis, does the asylum seeker receive the protection they aim for, as, depending on the country of origin, the state is obligated to grant the individual a certain protection status. If the outcome of the automated analysis contradicts the asylum seeker's narrative, then there is additional questioning by the case worker. Thus, the DIAS system's output, in a next step, constitutes the degree of dependence of the asylum seeker vis à vis the individual case worker.

3. Horizontal dimension

A pertinent issue that has been widely criticized is the overall unreliability of the dialect recognition system. Language is considered too fluid and dynamic—as how one speaks might change throughout a person's life—to be classified correctly by a machine [9, 43]. Deploying the dialect recognition system towards asylum seekers requires them to adhere to the language standards brought about by the technology in order to be classified correctly. Embedded in the use of the algorithmic system is a conceptualization of a normed individual and their use of language: Within the algorithmic system, a dialect is conceptualized as a collection of language features that are derived from the corresponding training data and thus standardized accordingly. Individuals who speak in a way that differs from the algorithmic description of their supposed dialect might be classified in a way that disrupts their proclaimed narrative and, subsequently, might severely endanger their life.

4. More than the sum of its parts

Critics have argued that the dialect recognition system might be deployed as a de facto automated tool, especially if corresponding case workers have a large workload, or if they are not trained well in assessing the significance of a probability [9]. Furthermore, it is difficult for asylum seekers to contest the algorithmic result, which might lead to misclassification and, therefore, to a rejection of the respective asylum seeker's narrative [8, 9]. Further, since the classification system is applied in situations of uncertainty, the scarcity of identifying documents reinforces the individual's burden of potentially contesting an algorithmic result. This might especially disadvantage individuals who, at the time of seeking asylum in Germany, have already experienced a history of migration and displacement, and thus might have already been subject to severe precarity: Frequent changes of location may impact the way one speaks, as does the situation one finds oneself in when describing a picture and knowing that one's speech is being recorded and analyzed. Due to the gravity of the corresponding decision, this might have severely disadvantageous effects for the asylum seeker: the exclusion from the relation of protection can be life-threatening.

4.4 Prediction of grades in the UK

This case study is situated in the education sector. In March 2020, when the COVID-19 crisis unfolded in the UK, it was decided that students would not take their GCSE and A-level exams—neither in person nor in a digital setting. Students, however, still needed exam grades to apply for higher education or employment positions. Faced with these challenges, Gavin Williamson, at the time Secretary of State for Education, issued a direction to Ofqual, the Office of Qualifications and Examinations Regulation, stating that the students of 2020's cohort should be "issued with calculated results" that should be based on their school's "judgement of their ability" and be "supplemented by a range of other evidence" [77]. Thus, the students would be awarded grades to exams they would never have taken, a "creative solution to these challenges" that would "allow them to progress to further study or employment" in spite of the disruptions caused by COVID-19 [77]. It is common practice for UK schools to estimate and individually predict a student's performance: Predicted grades to final exams are "part of the admissions process" to higher education [73]. However, before 2020, there would be an actual exam that, subsequently, would serve as evidence for the performance of the student. In the past, the actual exam grades were significantly lower than the grades predicted by the schools, as yearly published data by the Universities and College Admissions Service (UCAS) demonstrates [61]. Put differently, "schools … tend to be optimistic when estimating the grades" [61]. In the situation of not conducting exams, relying solely on estimated grades would, therefore, entail "inflationary effects" due to the overall results being "implausibly high", which would "likely undermine the credibility of students' grades" [61]. In order to mitigate this "risk to standards", Ofqual, therefore, was directed to, firstly, standardise the grades across schools, and, secondly, carry out the standardisation in a way so that the "distribution of grades follows a similar profile to that in previous years" [77].

Ofqual developed a model (the Direct Centre Performance model, in short: DCP model) that incorporated several aspects: schools were asked to submit, for every student and every subject, an individually estimated grade (the Centre Assessed Grade, in short: CAG), as well as a ranking of the students' estimated abilities within one subject class. Further, the model takes into account the grade distribution of previous years per school and subject as a tool to standardise, or "adjust" [61], the provided CAGs along the provided student rankings. For small groups of 15 students or less, however, the model would mainly focus on the CAGs due to the lack of methodical robustness of applying distributions to such small groups. This overall approach, as Ofqual argued, would ensure, firstly, fairness to all students across different schools, as some schools might be more optimistic in predicting grades than others, as well as, secondly, a realistic and reliable overall result [61]. After extensive critique and protests, the government decided to refrain from using the CDP model for calculation and, instead, award the CAG grades [6, 76]. In consequence, however, extensive qualitative research in Bangladesh showed that just removing an algorithmic system does not remove its "algorithmic imprint" [24].

1. Relations

Final exam grades affect a student's opportunities in the realms of higher education, as well as in employment. In regulating the conditions of final exams, Ofqual plays an important role in the process of obtaining grades and, thus, determining a student's future opportunities. This is always the case, but was especially pertinent during the time of disruption by COVID-19 beginning in 2020. The DCP model was supposed to provide reliability and stability to this entire generation of students. Thus, the relation between Ofqual and this cohort of students is a different one than in the previous years. The pandemic as a global crisis event established a relation between individual students and the state actor Ofqual that was unpredecented and that came about in this specificity through decisions made by the Secretary of State for Education.

2. Vertical dimension

Faced with the extraordinary circumstances of 2020 and the ensuing uncertainty of how to proceed, the government decided to instruct Ofqual to fabricate grades for all students. Instantly, the degree of dependency of individual students towards Ofqual was augmented to an unforeseen extent: One would not have thought that Ofqual would ever determine students' grades in the absence of actual exam performance. Thus, facilitated by the pandemic and ensuing decisions, the individual student emerges as unprecedently dependent vis à vis the state actor Ofqual. Regarding the CDP model through the lens of dependency, it becomes clear that the students' schools also play a meaningful role in determining their grades and, thus, their future opportunities: schools were asked to submit individually estimated grades in the form of the CAGs, as well as comparative rankings of students. Thus, within this constellation, the position of power is shared between Ofqual and the schools. There is, however, a systematic horizontal difference between two degrees of dependency of students, a difference that is caused by methodological decisions in the development process of the CDP model: As discussed above, in cohorts with 15 students or less, the CAG grade was endowed with greater weight in relation to the previous grade distributions. For larger cohorts, the estimated relative ranking of the students among their peers, as well as past grade distributions were combined to calculate a grade. Thus, in small cohorts, the individual students depend less on Ofqual and more on their respective schools' estimate of their performance which, as discussed above, is more optimistic in general.

3. Horizontal dimension

According to media reports, the grades of students at public schools located in socio-economically disadvantaged areas were disproportionally often adjusted down from the predicted CAG grades, and, thus, negatively affected, by the CDP model [1, 2, 26]. The data published by Ofqual shows that the increase of A and A* grades (the two best grades), compared to the year 2019, is highest for "independent", i.e., private, schools [55, 61]. Viewed from the perspective of an individual student who, obviously, prefers being awarded good grades over bad grades, it is an advantage to be enrolled in a private school and, thus, in comparison, a disadvantage to be enrolled in a public school. The model related reason might be twofold: firstly, the past years' grade distributions that are reported to be higher in private schools and, thus, passed on to the grade calculation, and secondly, the difference in calculating students' grades, a difference that is derived from the differing degrees to which the three factors, i.e., the CAG, the student rankings, and the past grade distributions, are considered in the grade calculation. As discussed above, for small cohorts of 15 students or less, the emphasis is placed on the predicted CAG grades which are overall significantly more optimistic than previous years' grade distributions. According to critics of the CDP model, small cohorts are more common in private schools than in public schools (see, e.g., [34]). Hence, built into the

CDP model architecture, is a systematic difference between private schools and public schools—a difference that results in disproportionately optimistic calculated grades for private school students: The exception rule for small cohorts benefits students in private schools that can be assumed to be socio-economically privileged. In contrast, schools "with large cohorts … are seeing their lowest grade profile ever, particularly at the higher grades, A to C", as stated by the Association of Colleges chief executive, David Hughes [55].

4. More than the sum of its parts
Potential disadvantageous effects of deploying the CDP model towards individual students are obvious, assuming that it can be considered beneficial for a student to be awarded a good grade and disadvantageous to obtain a bad grade. The planned issuing of calculated grades is an instance of increased dependency of an individual student vis à vis the state. The pandemic that causes this exceptional dependence also causes an economic crisis and, thus, amplifies the adversities that students face when they finish school, rendering their grades especially important for educational success and economic security. This dependency plays out disadvantageously for students in public schools, compared to students in private schools. As discussed above, the reason given for building and implementing the CDP model for the calculation of grades is the aim for an overall appearance of reliability of the grades, as opposed to "inflationary effects" of the CAG grades and the ensuing "undermin[ing] [of] the credibility of students' grades" [61]. The issued grades are supposed to be credible and reliable. This, of course, can only be a fictitious aim, as every single awarded grade would be calculated and, thus, fabricated by the CDP model. Credibility, then, is supposed to be established by ensuring a similar distribution compared to previous years [77]. Hence, the credibility of disproportionally good grades for some students is stabilized by the disproportionate amount of low grades of others, in the sense that the overall grade distribution can appear credible: the state fails to respect each student's moral equality, in that privileged students' disproportionately good grades rely on and are, technically explicitly, sustained by disadvantaged students' disproportionately bad grades.

5 CONCLUSION

The way one looks at a phenomenon impacts the way this phenomenon is accepted, contested, and regulated. The framework *susceptibility to algorithmic disadvantage*, as a way to look at algorithmic systems, can inform philosophically well-grounded policy and regulation, as well as activist opposition and contestation. *Susceptibility to algorithmic disadvantage* weaves together common threads of injustice in the relational mediation by algorithmic systems between individuals and state actors. As was shown in the case studies, a wide range of algorithmic systems—diverse in their area of application, technological architecture, as well as in their global location—can be assessed with regard to the framework. This paper tends to the question of what it means for people to be *especially* prone to being excluded from the democratic promise of justice. Considering the ways a state actor treats an individual, especially an individual in a severely dependent and intersectionally marginalized position, we as a society must call for caution in the development and implementation of algorithmic systems, especially when it comes to the invisibilization of individuals that are susceptible to algorithmic disadvantage. The algorithmic erosion of the democratic promise of justice towards individuals, as this paper has shown, systematically excludes those that are susceptible to algorithmic disadvantage, and as this is a global issue, this calls for global efforts against algorithmic injustice.

REFERENCES

[1] Richard Adams and Niamh McIntyre. 2020. England A-level downgrades hit pupils from disadvantaged areas hardest. *The Guardian* (Aug. 2020). https://www.theguardian.com/education/2020/aug/13/england-a-level-downgrades-hit-pupils-from-disadvantaged-areas-hardest
[2] Richard Adams, Sally Weale, and Caelainn Barr. 2020. A-level results: almost 40% of teacher assessments in England downgraded. *The Guardian* (Aug. 2020). https://www.theguardian.com/education/2020/aug/13/almost-40-of-english-students-have-a-level-results-downgraded
[3] Elizabeth S. Anderson. 1999. What Is the Point of Equality? *Ethics* 109, 2 (Jan. 1999), 287–337. https://doi.org/10.1086/233897
[4] Julia Angwin, Jeff Larson, Surya Mattu, and Lauren Kirchner. 2016. Machine Bias. *ProPublica* (2016). https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing
[5] Shreya Atrey. 2019. *Intersectional Discrimination* (1 ed.). Oxford University Press. https://doi.org/10.1093/oso/9780198848950.001.0001
[6] Garfield Benjamin. 2022. #FuckTheAlgorithm: algorithmic imaginaries and political resistance. In *2022 ACM Conference on Fairness, Accountability, and Transparency*. ACM, Seoul Republic of Korea, 46–57. https://doi.org/10.1145/3531146.3533072
[7] Ruha Benjamin. 2019. Assessing risk, automating racism. *Science* 366, 6464 (Oct. 2019), 421–422. https://doi.org/10.1126/science.aaz3873
[8] Anna Biselli. 2019. Bloß nicht verzetteln: Das BAMF und seine IT-Projekte. *Netzpolitik.org* (2019). https://netzpolitik.org/2019/bloss-nicht-verzetteln-das-bamf-und-seine-it-projekte/
[9] Anna Biselli. 2022. BAMF weitet automatische Sprachanalyse aus. *Netzpolitik.org* (Sept. 2022). https://netzpolitik.org/2022/asylverfahren-bamf-weitet-automatische-sprachanalyse-aus/
[10] Deutscher Bundestag. 2022. Antwort der Bundesregierung auf die Kleine Anfrage der Abgeordneten Clara Bünger, Nicole Gohlke, Gökay Akbulut, weiterer Abgeordneter und der Fraktion DIE LINKE. – Drucksache 20/3133 – Einsatz von Dialekterkennungssoftware im Bundesamt für Migration und Flüchtlinge. https://dserver.bundestag.de/btd/20/032/2003238.pdf
[11] Joy Buolamwini and Timnit Gebru. 2018. Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification. *Proceedings of Machine Learning Research* 81 (2018), 1–15.
[12] Judith Butler. 1997. *The Psychic Life of Power: Theories in Subjection*. Stanford University Press.
[13] Paul Butler. 2017. *Chokehold: policing black men*. New Press, New York.
[14] Ryan Calo. 2017. Privacy, Vulnerability, and Affordance. *DePaul Law Review* 66, 2 (2017), 591–604.
[15] Anna Carastathis. 2014. The Concept of Intersectionality in Feminist Theory: The Concept of Intersectionality in Feminist Theory. *Philosophy Compass* 9, 5 (May 2014), 304–314. https://doi.org/10.1111/phc3.12129
[16] Jacqueline G. Cavazos, P. Jonathon Phillips, Carlos D. Castillo, and Alice J. O'Toole. 2021. Accuracy Comparison Across Face Recognition Algorithms: Where Are We on Measuring Race Bias? *IEEE Transactions on Biometrics, Behavior, and Identity Science* 3, 1 (2021), 101–111. https://doi.org/10.1109/TBIOM.2020.3027269
[17] Valeriia Cherepanova, Steven Reich, Samuel Dooley, Hossein Souri, John Dickerson, Micah Goldblum, and Tom Goldstein. 2023. A Deep Dive into Dataset Imbalance and Bias in Face Identification. In *Proceedings of the 2023 AAAI/ACM Conference on AI, Ethics, and Society* (Montr\'{e}al QC Canada). ACM, 229–247. https://doi.org/10.1145/3600211.3604691
[18] Sumi Cho, Kimberlé Williams Crenshaw, and Leslie McCall. 2013. Toward a Field of Intersectionality Studies: Theory, Applications, and Praxis. *Signs: Journal of Women in Culture and Society* 38, 4 (June 2013), 785–810. https://doi.org/10.1086/669608
[19] Alexandra Chouldechova. 2017. Fair Prediction with Disparate Impact: A Study of Bias in Recidivism Prediction Instruments. *Big Data* 5, 2 (June 2017), 153–163. https://doi.org/10.1089/big.2016.0047
[20] Patricia Hill Collins. 2019. *Intersectionality as Critical Social Theory*. Duke University Press. https://doi.org/10.1515/9781478007098
[21] Kimberlé Crenshaw. 1989. Demarginalizing the Intersection of Race and Sex: A Black Feminist Critique of Antidiscrimination Doctrine, Feminist Theory and Antiracist Politics. *University of Chicago Legal Forum* 1989, 1 (1989), 139–167.

[22] Kimberlé Crenshaw. 2016. On Intersectionality. Keynote at the Women of the World Festival 2016. (2016). https://www.youtube.com/watch?v=-DW4HLgYPlA

[23] Claude Draude, Goda Klumbyte, Phillip Lücking, and Pat Treusch. 2019. Situated Algorithms: A Sociotechnical Systemic Approach to Bias. *Online Information Review* 44, 2 (2019), 325–342. https://doi.org/10.1108/OIR-10-2018-0332

[24] Upol Ehsan, Ranjit Singh, Jacob Metcalf, and Mark Riedl. 2022. The Algorithmic Imprint. In *2022 ACM Conference on Fairness, Accountability, and Transparency* (Seoul Republic of Korea). ACM, 1305–1317. https://doi.org/10.1145/3531146.3533186

[25] Virginia Eubanks. 2017. *Automating inequality: how high-tech tools profile, police, and punish the poor.* St. Martin's Press, New York.

[26] Donna Ferguson and Michael Savage. 2020. Controversial exams algorithm to set 97% of GCSE results. *The Guardian* (Aug. 2020). https://www.theguardian.com/education/2020/aug/15/controversial-exams-algorithm-to-set-97-of-gcse-results

[27] Benjamin Fish and Luke Stark. 2022. It's Not Fairness, and It's Not Fair: The Failure of Distributional Equality and the Promise of Relational Equality in Complete-Information Hiring Games. In *Equity and Access in Algorithms, Mechanisms, and Optimization* (Arlington VA USA). ACM, 1–15. https://doi.org/10.1145/3551624.3555296

[28] Federal Office for Migration and Refugees. 2020. Conference "Digitalisation of the asylum procedure and integrated identity management" on October 7 2020. Session I: Language recognition and name transcription. https://migrationnetwork.un.org/sites/g/files/tmzbdl416/files/docs/cdr_slides_tks_dias_common_language_analysis.pdf

[29] Federal Office for Migration and Refugees. 2022. Overview of the digitisation initiatives. https://www.bamf-digitalisierungsagenda.de/wp-content/uploads/2022/02/220216_Digitisation_initiatives_barrierefrei.pdf

[30] Batya Friedman and Helen Nissenbaum. 1996. Bias in computer systems. *ACM Transactions on Information Systems* 14, 3 (July 1996), 330–347. https://doi.org/10.1145/230538.230561

[31] Clare Garvie, Alvaro Bedoya, and Jonathan Frankle. 2016. The Perpetual Line-up. Unregulated Police Face Recognition in America. *https://www.perpetuallineup.org/* (Oct. 2016). https://www.perpetuallineup.org/

[32] Stefan Glüge, Mohammadreza Amirian, Dandolo Flumini, and Thilo Stadelmann. 2020. How (Not) to Measure Bias in Face Recognition Networks. In *Artificial Neural Networks in Pattern Recognition*, Frank-Peter Schilling and Thilo Stadelmann (Eds.). Vol. 12294. Springer International Publishing, 125–137. https://doi.org/10.1007/978-3-030-58309-5_10

[33] Patrick Grother, Mei Ngan, and Kayee Hanaoka. 2019. Face recognition vendor test part 3: demographic effects. https://doi.org/10.6028/NIST.IR.8280

[34] Timandra Harkness. 2020. How Ofqual failed the algorithm test. https://unherd.com/2020/08/how-ofqual-failed-the-algorithm-test/

[35] Mireille Hildebrandt. 2019. The Issue of Bias. The Framing Powers of Ml. *SSRN Electronic Journal* (2019). https://doi.org/10.2139/ssrn.3497597

[36] Kashmir Hill. 2020. Another Arrest, and Jail Time, Due to a Bad Facial Recognition Match. *The New York Times* (Dec. 2020). https://www.nytimes.com/2020/12/29/technology/facial-recognition-misidentify-jail.html

[37] Kashmir Hill. 2020. Wrongfully Accused by an Algorithm. *The New York Times* (June 2020). https://www.nytimes.com/2020/06/24/technology/facial-recognition-arrest.html

[38] Patricia Hill Collins. 2014. *Black feminist thought: knowledge, consciousness, and the politics of empowerment.* Routledge, New York, NY, USA.

[39] Khari Johnson. 2022. How Wrongful Arrests Based on AI Derailed 3 Men's Lives. *Wired* (March 2022). https://www.wired.com/story/wrongful-arrests-ai-derailed-3-mens-lives/

[40] Atoosa Kasirzadeh. 2022. Algorithmic Fairness and Structural Injustice: Insights from Feminist Political Philosophy. In *Proceedings of the 2022 AAAI/ACM Conference on AI, Ethics, and Society* (Oxford United Kingdom). ACM, 349–356. https://doi.org/10.1145/3514094.3534188

[41] Reetika Khera. 2019. Aadhaar Failures: A Tragedy of Errors. *EPW Engage* 54, 14 (April 2019). https://www.epw.in/engage/article/aadhaar-failures-food-services-welfare

[42] Youjin Kong. 2022. Are "Intersectionally Fair" AI Algorithms Really Fair to Women of Color? A Philosophical Analysis. In *2022 ACM Conference on Fairness, Accountability, and Transparency* (Seoul Republic of Korea). ACM, 485–494. https://doi.org/10.1145/3531146.3533114

[43] Josephine Lulamae. 2022. The BAMF's controversial dialect recognition software: new languages and an EU pilot project. https://algorithmwatch.org/en/bamf-dialect-recognition/

[44] Alan Lundgard. 2020. Measuring Justice in Machine Learning. In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency* (Barcelona Spain). ACM, 680–680. https://doi.org/10.1145/3351095.3372838

[45] Catriona Mackenzie, Wendy Rogers, and Susan Dodds (Eds.). 2014. *Vulnerability: new essays in ethics and feminist philosophy.* Oxford University Press, New York.

[46] Catharine A. MacKinnon. 2013. Intersectionality as Method: A Note. *Signs: Journal of Women in Culture and Society* 38, 4 (2013), 1019–1030. https://doi.org/10.1086/669570

[47] Gianclaudio Malgieri. 2023. *Vulnerability and Data Protection Law* (first edition ed.). Oxford University Press.

[48] Gianclaudio Malgieri and Gloria González Fuster. 2021. The Vulnerable Data Subject: A Gendered Data Subject? *SSRN Electronic Journal* (2021). https://doi.org/10.2139/ssrn.3913249

[49] Gianclaudio Malgieri and Jędrzej Niklas. 2020. Vulnerable Data Subjects. *Computer Law & Security Review* 37 (2020), 105415. https://doi.org/10.1016/j.clsr.2020.105415

[50] Mari J. Matsuda. 1991. Beside My Sister, Facing the Enemy: Legal Theory out of Coalition. *Stanford Law Review* 43, 6 (1991), 1183. https://doi.org/10.2307/1229035 jstor:1229035

[51] Leslie McCall. 2005. The Complexity of Intersectionality. *Signs: Journal of Women in Culture and Society* 30, 3 (March 2005), 1771–1800. https://doi.org/10.1086/426800

[52] Ninareh Mehrabi, Fred Morstatter, Nripsuta Saxena, Kristina Lerman, and Aram Galstyan. 2021. A Survey on Bias and Fairness in Machine Learning. *Comput. Surveys* 54, 6 (2021), 1–35. https://doi.org/10.1145/3457607

[53] Milagros Miceli, Julian Posada, and Tianling Yang. 2022. Studying Up Machine Learning Data: Why Talk About Bias When We Mean Power? *Proceedings of the ACM on Human-Computer Interaction* 6 (2022), 1–14. Issue GROUP. https://doi.org/10.1145/3492853

[54] Biometrics & Identification Division Michigan State Police. 2022. Facial Recognition – Frequently Asked Questions. https://www.michigan.gov/-/media/Project/Websites/msp/bid/Facial_Recognition_FAQ.pdf?rev=1e09deedc197419e9e9d0b3a1fc57a7f

[55] Aamna Mohdin. 2020. Downgraded A-level students urged to join possible legal action. *The Guardian* (Aug. 2020). https://www.theguardian.com/education/2020/aug/13/downgraded-a-level-students-urged-to-join-possible-legal-action

[56] Nikita Nagaraj and Amit Prakash. 2021-10-06. Digital Biometric Authentication and Citizens' Right to Food: Neglect of the 'Local' in India's Aadhaar-enabled Public Distribution System. In *14th International Conference on Theory and Practice of Electronic Governance* (Athens Greece). ACM, 338–345. https://doi.org/10.1145/3494193.3494239

[57] Ziad Obermeyer and Sendhil Mullainathan. 2019. Dissecting Racial Bias in an Algorithm that Guides Health Decisions for 70 Million People. In *Proceedings of the Conference on Fairness, Accountability, and Transparency - FAT* '19*. ACM Press, Atlanta, GA, USA, 89–89. https://doi.org/10.1145/3287560.3287593

[58] Unique Identification Authority of India. 2022. Aadhaar Dashboard. https://uidai.gov.in/aadhaar_dashboard/

[59] Unique Identification Authority of India. 2022. Aadhaar Myth Busters. https://uidai.gov.in/en/my-aadhaar/about-your-aadhaar/aadhaar-myth-busters.html

[60] Unique Identification Authority of India. 2022. Usage of Aadhaar. https://uidai.gov.in/en/my-aadhaar/about-your-aadhaar/usage-of-aadhaar.html

[61] Ofqual. 2020. Awarding GCSE, AS, A level, advanced extension awards and extended project qualifications in summer 2020: interim report. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/909368/6656-1_Awarding_GCSE__AS__A_level__advanced_extension_awards_and_extended_project_qualifications_in_summer_2020_-_interim_report.pdf

[62] Michigan State Police. 2022. MICHIGAN STATE POLICE STATEWIDE NETWORK OF AGENCY PHOTOS (SNAP) ACCEPTABLE USE POLICY. https://www.michigan.gov/-/media/Project/Websites/msp/bid/SNAP_Acceptable_Use_Policy.pdf?rev=6fb89c2e1052458ba0e72a120cd276e9

[63] Michigan State Police. 2022. Statewide Network of Agency Photos (SNAP) Unit. https://www.michigan.gov/msp/divisions/bid/dais/statewide-network-of-agency-photos-snap#:~:text=The%20Statewide%20Network%20of%20Agency,data%20for%20law%20enforcement%20access.

[64] Inioluwa Deborah Raji, I. Elizabeth Kumar, Aaron Horowitz, and Andrew Selbst. 2022. The Fallacy of AI Functionality. In *2022 ACM Conference on Fairness, Accountability, and Transparency* (Seoul Republic of Korea). ACM, 959–972. https://doi.org/10.1145/3531146.3533158

[65] UN Special Rapporteur. 2019. Report of the Special Rapporteur on extreme poverty and human rights. https://undocs.org/A/74/493

[66] Rebecca Ratcliffe. 2019. How a glitch in India's biometric welfare system can be lethal. *The Guardian* (Oct. 2019). https://www.theguardian.com/technology/2019/oct/16/glitch-india-biometric-welfare-system-starvation

[67] Vallari Sanzgiri. 2022. Six countries take up IIIT-B's Aadhaar-like digital identity programme. https://www.medianama.com/2022/07/223-six-countries-take-up-iiit-bs-aadhaar-like-digital-identity-programme/

[68] Andrew D. Selbst, Danah Boyd, Sorelle A. Friedler, Suresh Venkatasubramanian, and Janet Vertesi. 2019. Fairness and Abstraction in Sociotechnical Systems. In *Proceedings of the Conference on Fairness, Accountability, and Transparency* (Atlanta GA USA). ACM, 59–68. https://doi.org/10.1145/3287560.3287598

[69] Ranjit Singh and Steven Jackson. 2021. Seeing Like an Infrastructure: Low-resolution Citizens and the Aadhaar Identification Project. *Proceedings of the ACM on Human-Computer Interaction* 5 (2021), 1–26. Issue CSCW2. https://doi.org/10.1145/3476056

[70] Janaki Srinivasan and Aditya Johri. 2013. Creating Machine Readable Men: Legitimizing the ' *Aadhaar* ' Mega e-Infrastructure Project in India. In *Proceedings of the Sixth International Conference on Information and Communication Technologies and Development: Full Papers - Volume 1* (Cape Town South Africa). ACM, 101–112. https://doi.org/10.1145/2516604.2516625

[71] The Wire Staff. 2018. Of 42 'Hunger-Related' Deaths Since 2017, 25 'Linked to Aadhaar Issues'. *The Wire* (Sept. 2018). https://thewire.in/rights/of-42-hunger-related-deaths-since-2017-25-linked-to-aadhaar-issues

[72] Harini Suresh and John V. Guttag. 2020. A Framework for Understanding Unintended Consequences of Machine Learning. *arXiv:1901.10002 [cs, stat]* (Feb. 2020). http://arxiv.org/abs/1901.10002 arXiv: 1901.10002.

[73] UCAS. 2022. Predicted grades – what you need to know for entry this year. https://www.ucas.com/advisers/managing-applications/predicted-grades-what-you-need-know-entry-year

[74] Salomé Viljoen. 2021. A Relational Theory of Data Governance. *The Yale Law Journal* 131, 2 (2021), 573–654.

[75] Sylvia Walby, Jo Armstrong, and Sofia Strid. 2012. Intersectionality: Multiple Inequalities in Social Theory. *Sociology* 46, 2 (April 2012), 224–240. https://doi.org/10.1177/0038038511416164

[76] Sally Weale and Heather Stewart. 2020. A-level and GCSE results in England to be based on teacher assessments in U-turn. *The Guardian* (Aug. 2020). https://www.theguardian.com/education/2020/aug/17/a-levels-gcse-results-england-based-teacher-assessments-government-u-turn

[77] Gavin Williamson. 2020. DIRECTION UNDER S 129(6) OF THE APPRENTICESHIPS, SKILLS, CHILDREN AND LEARNING ACT 2009, 31 March 2020. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/877611/Letter_from_Secretary_of_State_for_Education_to_Sally_Collier.pdf

[78] Nira Yuval-Davis. 2006. Intersectionality and Feminist Politics. *European Journal of Women's Studies* 13, 3 (Aug. 2006), 193–209. https://doi.org/10.1177/1350506806065752

[79] Marilyn Zhang. 2022. Affirmative Algorithms: Relational Equality as Algorithmic Fairness. In *2022 ACM Conference on Fairness, Accountability, and Transparency*. ACM, Seoul Republic of Korea, 495–507. https://doi.org/10.1145/3531146.3533115

[80] Shoshana Zuboff. 2019. *The age of surveillance capitalism: the fight for a human future at the new frontier of power* (first edition ed.). PublicAffairs, New York.