Algorithmic Reproductive Justice

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Reproductive justice is an intersectional feminist framework and movement which argues all people have the right to have a child, to not have a child, to parent in safe and healthy environments, and to own their bodies and control their futures. We identify increasing surveillance, assessing worth, datafication of bodies, monetising inequality and misinformation, and decimating planetary health as forms of structural violence associated with emerging digital technologies. These trends are implicated in the (re)production of inequities, creating barriers to the realisation of reproductive justice. We call for algorithmic reproductive justice, and highlight the potential for both acts of resistance and industry reform to advance that aim.

CCS Concepts: • **Human-centered computing → HCI theory, concepts and models**; • **Social and professional topics →** *Computing profession.*

Additional Key Words and Phrases: Artificial intelligence, AI, fairness, human rights, reproductive rights, reproductive justice, social justice, reproductive coercion, eugenics, algorithmic violence, structural violence

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1 INTRODUCTION

The proliferation of AI technologies as solutions to social problems has required that ethical constructs such as fairness be formally specified in the creation of system rules. Abebe et al. [2] noted this as one of computing's important roles in social change, that is as a 'formalizer': it opens up new opportunities to explore and challenge not just the systems themselves but the premises upon which they are built. This opening up has led to a flourishing technical literature on fairness metrics/implementations [97, 112, 115] and the ensuing critique of such metrics/implementations (e.g. [54, 144, 147]). Notably, there has been a thorough examination of the philosophical underpinnings of varied approaches to AI fairness [69, 97, 99, 103], with a growing concern for the dominance of fairness construed as (distinctly Western [15, 121]) distributive justice [2, 55, 61, 71, 126]. Approaches rooted in social justice [14, 15, 34, 37, 57, 66, 111, 131, 137] have been proposed to sensitise algorithmic fairness to structural inequity. Such work tends to overlap significantly with AI critiques situated within critical theories of race and gender [13, 15, 58, 82, 87] arguing that the operationalisation of such socially constructed categories erases information needed to understand the patterns of difference the AI is rendering as objective fact; and, relatedly, with the growing body of work adopting a feminist approach to AI ethics [38, 58, 71, 75, 87, 121, 126, 127, 135]. Emerging from these epistemological developments is a greater focus on intersectionality[1] in discourses of AI harm [109], a deeper examination of power dynamics within which AI is implicated [8, 106], and a call to engage more/meaningfully with marginalised people and their perspectives [79].

[1]A term coined by Kimberlé Crenshaw [31] to capture the multiplicative effects of experiencing multiple forms of marginalisation. This approach centres the ways other forms of marginalisation intersect with gender to compound inequities, and seeks to empower marginalised people.

This paper builds on and contributes to these efforts, while also attending to the comparative lack of theorisation on the fairness of (non-AI) digital technologies and their infrastructuralisation of data-driven decision-making. We build from work on how structural violence is being (re)produced in the digital sphere (e.g. [150]), and draw explicit attention to the important (but generally overlooked) implications for *reproductive justice* (hereafter RJ). While there is an emerging literature on the utilisation of digital technology as a tool for economic empowerment and activism in the RJ movement (e.g. [62, 146]), there has been a dearth of attention to emerging technologies and the realisation of rights outlined in the RJ framework (discussed in the following section); this invisibility of *digital* reproductive injustices in the RJ community is matched by a neglect in the computing community of the ways emerging digital technologies can and do (re)create reproductive injustices. There is an urgent need for dialogue between these communities. Our aim here is to bring multiple, disparate bodies of research together to show how closely they are related, to highlight how ubiquitous and consequential digital threats to RJ are, and to bring AI ethics and RJ thinkers and activists into more direct conversation. We begin by briefly introducing RJ, followed by an illustrative exploration of how emerging technologies impede RJ. We then discuss the value of adopting a RJ lens above and beyond a broader social justice lens, and we briefly touch on what could be done to address these issues.

2 DIGITAL REPRODUCTIVE INJUSTICES

Conceived in the US in 1994 by Black women, the RJ movement arose in part to address the neglect of intersectional feminist issues in the reproductive rights movement [90, 119, 120]. The reproductive rights movement, focused primarily on access to contraception and abortion, failed to act in solidarity to address the broader range of reproductive coercion faced by marginalised people. The RJ movement, by contrast, focused on this wider spectrum of coercion: Particularly since the turn of the 20th century,[2] the underpinning eugenicist principles of reproductive health governance in the US have sought simultaneously, and often forcibly, to increase the fertility of white, cisgendered, heterosexual, middle-class women without disabilities while reducing the fertility of marginalised groups falling outside of this narrow population [9, 116, 119, 120]. While this differential pattern of structural reproductive pressures on more privileged people (towards fertility) and more marginalised people (against fertility) may appear to be two separate forms of reproductive coercion, in fact they are linked—flipsides of the same eugenic coin.[3] As a framework and a movement, RJ aims to unveil and counteract reproductive inequities to create a world in which all people can realise their core rights as outlined in this framework, *viz.*: the right to have a child, the right to not have a child, the right to parent children with dignity in safe and healthy environments, and the right to own their bodies and control their futures [119, 128].

Repeated acts of structural violence have resulted in the systematic violation of RJ for marginalised people. The most egregious examples include forced sterilisation, systematic abrogation of social protection, selective divestment in institutions (e.g. schools, hospitals) serving marginalised people, child removals, mass incarceration, and barriers to access to contraception and abortion. While a large literature on RJ focuses on the US given its geospatial and historical roots, the movement was purposely grounded in an *international* human rights framework [119]. As founding activist and scholar Loretta Ross [120] explains, the Black women who founded the movement learned from the human

[2]Under slavery, the fertility of Black women was economically valuable to enslavers [73, 119]. The economic benefits of the rape and forced marriage of Black women were structurally reinforced when, in 1662, Virginia overturned the practice of defining the status of a child as free versus enslaved based on the father's status. Children's status thereafter followed that of their mothers. Enslavers using sexual violence to father children could then legally enslave their children [119]. Once the fertility of Black women was no longer profitable for white men, the focus became repression of Black women's fertility.
[3]The same social valuations which determine whose fertility is valued also shape who is assigned dangerous or undesirable work. Where blanket pronatalist mechanisms (e.g. abortion bans) are paired with selectively enforced systems of fertility restriction (e.g. forced sterilisation of marginalised people, removal of marginalised children), the sum result is a eugenic fertility regime. Relegating some people to the most dangerous and/or undesirable socially necessary tasks goes hand in hand with assigning value in a social hierarchy (see [80] for more on the structural functions of marginalisation).

rights claims advanced by women in Global Majority countries. Recent literature [45–47, 67, 89, 92, 134] reflects that reproductive oppression, marginalisation, and violation of the rights articulated by RJ activists and scholars are global phenomena. Below, we outline several ways emerging technologies are compounding social inequities globally, and we consider the implications of this for RJ. We consider not just the current state of development, but also the direction of travel for these technologies. This is not an exhaustive list of potential harms and implications for RJ, but rather an illustrative framing of some of the pressing but under-researched issues at the intersection of digital innovation and RJ.

2.1 Increasing surveillance

From scraping social media to facial recognition software to algorithmic monitoring, emerging digital technologies are being widely used to surveil populations around the world. The supposed benefits of increasing surveillance (e.g. public safety, increased productivity) are used to justify the collection and analysis of big data underpinning these new forms of surveillance. Yet a growing literature has highlighted the significant harms these technologies produce. We add to this literature by considering some of the ways digital technology is creating and perpetuating structural barriers to RJ.

One harm of digital surveillance is in monitoring and detention of immigrants and asylum seekers. In 2009 the UK Border Agency's Human Provenance Pilot Project (now defunct) used DNA testing to make highly dubious claims about the ancestry and origin of asylum seekers to assess whether asylum claims were legitimate [13]. Participation was 'voluntary', but power dynamics between an asylum seeker and a government agency effectively made opting out a non-option. In the US, Immigration and Customs Enforcement (ICE) has used external company Vigilant to sidestep privacy regulations preventing collecting data from sensitive locations; purchasing information from Vigilant enables ICE to act on information which is illegal for them to harvest directly [30]. ICE also offers highly profitable contracts to companies that widen their systems of surveillance, including electronic ankle monitoring systems to surveil people released from detention facilities who remain under state custody [13]. Being scrutinised at borders and detained within them obstructs RJ. For example, Fleming et al. [48] show Latinx people in the US who experienced an immigration raid may delay childbearing due to the financial and psychological impacts of detention, impeding their right to have a child. Family separation and detention also clearly impedes the ability to raise children with dignity in safe and healthy environments, as does hypervigilant monitoring of released detainees through ankle monitoring. For people who can become pregnant who live in areas with limited/no abortion care legally available following the upending of the Roe v. Wade in 2022, any form of monitoring technology creates a unique barrier to the right to not have a child (importantly, incarcerated people who have been released subject to ankle monitoring also experience this barrier to RJ). Nor is state surveillance the only digital surveillance threat to RJ. For instance, people in abusive partnerships have reported abusers using apps for monitoring mobile phones [141] and cars [64] to surveil private communications and whereabouts. RJ activism and scholarship has long highlighted multitudinous harms the monitoring and detention of migrant populations causes (see e.g. [98]), and the structural inequities which ensure that these violations of human rights are disproportionately inflicted upon (multiply) marginalised people (see [48, 119]). What a critical computing perspective adds is how emerging technologies can increase the scope of monitoring, sidestep regulatory barriers, and redefine the very ways that we understand heritage and borders in order to detain and exclude marginalised people.

Discourses on AI ethics have raised concerns regarding the use of emerging technologies to increase the 'objectivity' and efficiency of the criminal justice system in ways that disproportionately negatively impact marginalised people—particularly racially marginalised and migrant populations—through a combination of racially patterned predictive policing [124], misidentification (e.g. as 'criminals') by facial recognition [20, 65, 85],[4] and the use of biased criminal risk assessment algorithms for bail and sentencing determinations [13, 17, 39, 53, 59]. To our knowledge, however, these discourses have not made explicit how these trends threaten RJ, particularly for (multiply) marginalised people, who are more efficiently targeted and drawn into the carceral net [41].

Incarceration has long been used to restrict the freedom and rights of Black people [5, 73]. As Dorothy Roberts [116] has shown, this includes active measures to restrict reproductive freedom. Beginning in the 1980's, she explains, US states criminalised reproduction by prosecuting illicit drug use while pregnant. These laws particularly targeted poor Black women, largely through the legal system's selective focus on specific kinds of drugs.[5] Black women's 'associations with public hospitals, welfare agencies, and probation officers' meant 'their drug use is more likely to be detected and reported. These women are already enmeshed in a social welfare structure that makes them vulnerable to state monitoring of every aspect of their lives. . . ' [116, p. 173]. Nor are efforts to criminalise reproduction unique to the US. For example, in El Salvador, an especially restrictive abortion law has meant marginalised women have been prosecuted and imprisoned for seeking abortion care, and also for obstetric emergencies [24]. Healthcare providers, treated as state monitoring agents, are an essential source of data for law enforcement [152]. This surveillance and incarceration of marginalised women has chilling implications in the context of data-driven technologies which pool information from varied sources—frequently without the knowledge of the data's subjects. This is enabled by the expansion of carceral technologies into new spheres of life [12], including digital monitoring of employees. There is disturbing potential for such intimate monitoring (e.g. the number of bathroom breaks taken) to generate data that can feed algorithms that predict pregnancy. Not only are data from these different sources being pooled, enabling different institutions to access a wider array of personal information than they might otherwise have been able to, but they are also being used to make judgments about highly value laden concepts, such as 'risk'[6] [13, 17, 86], moving the needle of what surveillance can accomplish from response to prediction. Predictions about criminalised behaviour such as drug use during pregnancy and seeking abortion care can easily be used to apply racist, classist, and otherwise deeply problematic, structurally violent assumptions to prevent marginalised people from accessing RJ-related services, and to quickly and efficiently punish them for daring to make (often choiceless)[7] choices about their own lives.

We also note the worrying use of criminal risk prediction algorithms on minors, as in Pasco County, Florida's 'intelligence-led policing' [132]. Structural inequities are hard-coded into these models through selection of model features such as parental divorce, prior encounters with police, and mental distress, which are purportedly experienced disproportionately by racially marginalised people and people facing socioeconomic pressures, effectively serving as marginalisation markers. The predicted risk of 'criminality' also tends to be self-fulfilling: it catalyses heightened police scrutiny of children with some low-level (likely spurious) signal of 'criminality', increasing the chances of evidence of criminality being found. The 'at risk' child is ensnared in the carceral net, as are cohabitating family members, who face a higher number of emotionally charged interactions with police—encounters which can be quite literally deadly. The result is lengthy, and reproductively consequential, incarceration of individuals identified as in need of intervention to 'break the cycle' that leads to 'criminal' behaviour.

[4]There is growing resistance to these technologies in marginalised communities. For example, Newham Council in London recently voted to ban the use of facial recognition for police surveillance on the grounds that it violated anti-discimination laws [129].

[5]This is *not* a statement that Black women disproportionately use drugs; numerous studies have shown that notion is false (see e.g. [145]). Rather, group disparities in *type* of drug being used have been systematically leveraged to target racially marginalised people. However, we also note that the criminalisation of and moral posturing about illicit drug use is a marginalising act of structural violence regardless of who is using what, and when.

[6]We identify 'risk' as a value-laden logic that invites greater surveillance and penalties rather than protection.

[7]Ross and Solinger [119] note popular rhetoric about reproduction assumes people are empowered agents, choosing from a 'marketplace' of reproductive options to enact personal preferences. This assumption, they explain, does not align with the reality: People who experience structural barriers do not have the same choices available, and often must make 'choiceless choices'—decisions based on severely structurally constrained options.

Incarceration limits one's ability to control their own body and future, and is a barrier to the rights to have a child and to not have a child. It restricts one's sexual relationships (potentially for the duration of one's reproductive lifespan) and ability to access adequate reproductive healthcare [60]. Coercive contraception and sterilisation programmes have been used both to prevent women from having children once they leave prison and as part of plea deals of women brought up on charges but not sentenced to prison time [60, 116]. Incarcerated people cannot raise children with dignity in safe and healthy environments because they separated from their children and, in many cases, children are placed into the social (foster) care system, or even incarcerated themselves. And, for people released from prison, stigma and discrimination can strongly impact their ability to access basic needs such as housing and employment, which further structurally impairs their ability to provide a safe and healthy environment [60].

2.2 Assessing worth

The highly subjective, value-laden notion of 'worthiness' has long been deployed to ameliorate moral qualms about the stratified distribution of valued resources; the very notion of 'worthiness' is a tool of structural violence. Sometimes this is obvious, such as in the language of 'creditworthiness', and sometimes it is slightly more subtle, buried in narratives around 'deservingness' [80], such as when states decide who should (and who should not) be eligible for social protection schemes [26]. Emerging digital technology is increasingly being used to assess worth [25, 36, 78] and, linked to this, to shape the distribution of resources, with implications for the realisation of RJ.

Digital technology is being used in the context of migration to assess worth. The aforementioned Human Provenance Pilot Project, for example, pushed asylum seekers to subject themselves to genetic surveillance, but it also sought to label them as 'worthy' or 'unworthy' of legal migrant status based on faulty assumptions about ancestry. Digital technology is also implicated at the US border, where the Customs and Border Protection mobile application (CBP One) serves the manifest function of scheduling application appointments to enter the country for migrants waiting in Mexico [32]. A latent function is to effectively create a digital border around the US by using digital technology to restrict access to appointments and screen out individuals assumed to be lacking the basic technological and linguistic proficiency to contribute to the 'productive' economy. Among other concerns, CBP One has been widely criticised for supporting limited languages and requiring a phone and a wifi connection to use [118]. Fluency in preferred languages, ownership of a suitable phone for running the app, relevant technological skills, and access to wifi are all markers of privilege/social status. These factors represent a *relative, context-specific* privilege, but one used as a marker of worthiness for who gets a chance not even at citizenship, but simply at the appointment lottery. This situation is a matter of RJ because it has left large groups of people living liminal and precarious lives on the border, unable to provide a safe and healthy environment for their families, with limited control over their futures, and with limited access to healthcare.

AI's deployment has been critiqued for reinforcing racist, sexist, classist, and otherwise structurally violent forms of employment discrimination in screening job applicants [13, 30, 93]. We argue that these new forms of employment discrimination—forms which are hidden from view, enforcing patterns of discrimination at scale yet claiming to resolve human bias in hiring [114, 122]—have implications for RJ. In an economy that ties the capacity to access basic necessities such as food and housing to participation in waged labour, the inability to access employment due to (algorithmically compounded) discrimination makes it difficult to provide for a child's needs [26, 46]. This is a threat to the right to parent with dignity and the right to have a child; decisions about, if and when to reproduce can be strongly influenced by financial precarity. Because the discrimination embedded in AI employment screening follows the well-worn lines of discrimination seen prior to the use of AI, (multiply) marginalised people are particularly subject to this form of bureaucratic violence. And, linking to the structural violence associated with increasing AI surveillance, AI systems may be especially efficient at discriminating against people who have experienced the violence of the widening carceral net, further compounding the reproductive injustices associated with mass incarceration.

AI is also being deployed in many US states to make decisions about child welfare and removals [19, 41, 72, 123]. A 2018 national child welfare system reform bill expanded data collection in the system, in part with the aim of constructing predictive tools to address systemic problems [35]. Instead, the deployment of AI in this context simultaneously reproduces (and amplifies) biases in the existing decision-making procedures, while also alleviating the moral burden of child welfare decision-making. In a simulation study, Du et al. [35] show (hypothetical) implementation of an automated risk assessment tool *increases* both racial inequities in long-term care and the total number of young people in foster care, directly contradicting reform goals. Utilising AI in child welfare decision-making is also linked to increasing surveillance, as (multiply) marginalised parents are those most likely to be under digital surveillance and to have their children removed from them [41]. The sterilised language of algorithmic risk assessment belies the underlying judgement about the worthiness of parents that underpins the decision to remove a child from their natal home (see for example [50]). The way children's 'vulnerability' and the 'risks' associated with different home environments and parental characteristics are defined are inherently moral judgements developed within the sociocultural value system of a specific, self-preserving social hierarchy; contrary to intentionally reassuring messaging about AI, shifting from a human decision-maker to an algorithm does not suddenly render these judgements neutral. And, where algorithms define risks as 'ever being involved in the criminal legal system' or 'receiving social welfare'—as in the infamous Allegheny Family Screening Tool [41, 50]—some families are 'marked in perpetuity' as 'risky' [50], i.e. as perpetually unworthy of parenthood. Technological decision-making processes in social work assessments can remove social workers' capacity to engage with contextual considerations and operate professional judgement [18]. Even if we accept the (false) premise of 'objectivity' of AI risk assessment, it is still problematic to assume that rigid systems of algorithmic categorisation and mandated action will reduce harm in a system where human traits such as empathy (inherently lacking in AI [36]) are essential for identifying and dismantling harmful practices and structures. While not all human decision-makers are motivated to effect positive change and keep families together, there is a greater likelihood of human decision-makers with this motivation than of AI built to optimise in this way. The system of child removals has been constructed on racist, colonialist, classist, ableist, and otherwise inherently discriminatory assumptions (for more, see [102, 116, 119]). The underpinning assumption of AI risk assessment in this context is that some people are unworthy of parenthood. In strong contrast, RJ asserts that all people are worthy of parenthood, but some people—particularly (multiply) marginalised people—face myriad structural barriers that can prevent them from having children and from parenting those children in safe and healthy environments. Parents cannot raise their children in safe and healthy environments when their children are taken from them, and the deployment of automated decision-making compounds rather than negates this problem.

AI is also being used is to assess financial worthiness. Financial worthiness is often treated as a moral judgement, with credit scores being used as a particularly quick, easy, and ostensibly objective indicator of someone's worthiness and character [78]. Credit scoring algorithms are significantly less accurate for individuals with limited credit histories (or 'thin data') [16], a situation more common for (multiply) marginalised people; so, too, are such individuals' scores more susceptible to the impacts of any single negative datapoint [16]. People experiencing financial precarity, often reflecting complex histories of marginalisation, are less resourced for buffering the instabilities this precarity creates (e.g. ill health, job inflexibility, lack of access to child care and transportation), thus increasing the likelihood of credit-reducing incidents on their record. Additionally, 'fringe alternative data' [136] from people's online behaviours, used for online consumer-credit marketing, creates a trove of intimate data that can be sold to companies to optimise their predictions.

As these operate outside of financial regulations on non-discrimination, highly problematic proxies are frequently used to profile people in ways tantamount to 'digital redlining' [136] (see also [104]), leading to concrete—but frequently unrecognised—harms such as psychological distress and loss of autonomy [150]. Cruelly, advertising algorithms use these detailed profiles to microtarget the poor [106, 136] with payday lending, subprime mortgages, and other forms of predation, then seize upon their algorithmically optimised 'failure' to wipe out their wealth (Cathy O'Neil and Safiya Umoja Nobel in [65]). These structural pressures mean people's scores follow them from one automated decision system after the other, reducing life opportunities on the basis of 'objectively' determined moral 'inferiority' [78]. Perversely, difficult-to-repay debt, which further harms credit, can become the only option for survival—a choiceless financial choice. Drawing on interviews in Argentina and Brazil, Cavallero and Gago [21, p. 44] explain 'Debt only comes in to "save us" because we have been violently impoverished, to the point of an induced precarity. Debt becomes unpayable because first there was looting and dispossession.' Creditors actively target marginalised people for whom debt has become necessary for survival. Identifying financially 'unworthy' people *creates* a market of consumers for a product which is has no value except to reinforce the label, creating a feedback loop of demand. For someone whose financial options have been restricted by harmful 'worthiness' labels, the 'right' time to have a child may never arrive, creating a barrier to the right to have a child. The costs of reproductive healthcare (and, even where this is free at the point of care, care-seeking trajectory costs such as transport, child care, and missed work (see [27, 46])) are a significant barrier to the right to not have a child. And, it is difficult to control one's future and provide a safe and healthy environment when 'creditworthiness' and linked spirals of predatory debt render meeting basic needs impossible.

The use of AI to assess financial worthiness can have a particularly chilling effect for people with abusive partners. Leaving an abusive partner can be nearly impossible for people experiencing financial precarity and debt (see for example [21]). While this is not unique to the digital era, AI facilitates information sharing between institutions over a long duration in a way that can be unknown to individuals whose financial records are being impacted and, related to this, can be shared and applied without the benefit of context. For example, a woman in London defaulted on payments for a student overdraft in 2016 because her abusive partner exerted control over her finances, leaving her with no money and severely restricted knowledge of outstanding bills [56]. After she left her partner, he received her statutory maternity pay, creating further financial problems for her. As she established a life away from him, she became aware of the payment she owed and took immediate action, fully settling the debt within three years. However, this left a mark against her credit report which she could not have removed (despite her circumstances), leaving her unable to purchase a home and provide for her son as she wished. AI was used to assess her worth in a way that ignored the structural violence informing her circumstances, with lasting consequences for her right to parent with dignity in a safe and healthy environment. While credit scores pre-dated algorithms, AI has made it easier than ever for different systems to share information; creditworthiness has increasingly become an all-encompassing, inescapable metric for general 'worthiness'.

Another example comes from China's social credit system, which tracks activities such as time use and purchasing history and gives a citizen score ranking that can determine people's access to social resources, including housing and transportation [13]. Given the importance of social and financial resources for being able to raise a child in a safe and healthy environment, a system designed to restrict access to e.g. housing through automated behaviour monitoring is a threat to RJ. Systematically excluding people from basic necessities is also a structurally violent act of reproductive coercion which can lead people to defer childbearing, possibly indefinitely. And, a long global history of reproductive coercion against marginalised people, up to and including forced sterilisation, highlights the very dark potential for such a system to be used to impede the right to have a child by providing technological cover for enforcing harmful notions of who 'should' reproduce.

The very act of assessing worthiness is a form of structural violence which systematically restricts some people's access to basic goods. It is nonsensical to claim that enforcing a social hierarchy in this way is an objective act free from human bias. Nonetheless, this is the widely-touted claim for why AI is better suited for assessing worthiness in a wide variety of systems. Decisions involved in compiling and coding data that are necessary for creating algorithms in the first place are strongly influenced by the human biases of those developing and deploying the systems (e.g. their beliefs regarding the relative trustworthiness of certain groups of people [78]). AI is being used to make assessments about worthiness in a variety of contexts that have far-reaching implications for the realisation of RJ.

2.3 Datafication of bodies

While the collection and analysis of data is certainly nothing new (indeed, datafication has been used historically, for example, to racialise people to legitimise the eugenics movement [140]), *digital datafication* has emerged from the capacity to rapidly collect, store, and analyse a previously unthinkable volume of data through technological advances [94]. The very notion of what counts as data has expanded as technology has evolved to capture an ever growing range of activities in our lives. It is 'the process of translating the flux of life into discrete machine-readable data points' [63]. At the same time, personal control over whether or how one's own data are collected and analysed is often very limited [25, 34], and important context and nuance is lost through the process of abstraction necessary to collect and analyse data at this scale. Increasingly, data are being marketised to facilitate surveillance capitalism, with serious consequences for life chances [29, 150, 151], particularly for marginalised people. While datafication and its nefarious manifestations are nothing new [140], emerging digital technology has dramatically increased the pace and scale of this process.

A range of apps that rely on AI to process and analyse data have emerged with the manifest aim of helping people improve their health. However, their latent function is datafication. Users enter personal details alongside a stream of information specific to the app's aim, directly contributing to their own datafication. Period trackers are one example, offering users the ability to track their menstrual cycles to increase their knowledge of their bodies, plan for menstruation, and even monitor ovulation, with implications for (not) becoming pregnant. Reproductive health experts have raised serious scientific concerns about the data underlying some AI-based fertility trackers (for example [113]), raising questions about efficacy and safety for conception and pregnancy prevention. Where abortion is criminalised, these data can be used to predict potential pregnancies, placing app users in danger if the data (and particularly predictions based on the data) are shared with law enforcement. Following the overturn of Roe v. Wade in the US, experts have warned that apps are not subject to the same data privacy laws as medical providers [10], highlighting a threat to the right to not have a child that this form of datafication can pose. Women who seek criminalised abortion care may be at risk of incarceration (and associated barriers to RJ, as in §2.1). There is also a serious risk that women who seek care for obstetric emergencies could experience accusations of foetal harm [116], possibly up to and including formal charges conflating miscarriage and abortion as seen elsewhere in the world [88]. In short, this form of datafication incentivises and creates efficient pathways for people to share private data, simultaneously placing themselves at risk of greater surveillance while also generating profit for companies that use data as capital.

Extractive AI tools are fueling opportunities across Global Majority countries, from gig economies to prenatal care, for populations previously excluded from technological benefits. One crucial consideration is the implications for RJ in an ostensible zero sum scenario where people are either excluded from AI benefits (like AI assisted prenatal care) or left to the mercies of AI's rampant, uninhibited data gathering potential. In a context where digital technology can serve as bridging capital, including benefits like greater RJ in prenatal care, how can cautions about ethical concerns enhance access to equitable outcomes instead of (re)creating inequity? Scholarship [4, 42] adducing the entrenched role of colonialism nuances these concerns. According to decolonial logics [130], a key starting point for understanding conflicts between the benefits and burdens of AI is the role of deep-rooted inequality [91]. Lutz's [91] characterisation of tensions between exclusion and inclusion emphasises AI as a resource with the potential to bridge existing capital gaps. However, AI exposes how entrenched inequalities reproduce themselves if particular attention is not given to ensure transparency and accountability. Decolonial logics show inequality is historically defined, and AI merely exemplifies a novel way to understand the profile of the usual beneficiaries and the typically neglected (see for example [1]). Prenatal care presents a useful example of this argument, especially in the context of algorithmic RJ: technologies for prenatal care can reach far and wide because they overcome some longstanding structural concerns—for instance ensuring inclusivity for rural dwellers who typically face isolation from material structures and urban dwellers for whom costs of medicines and care are pose barriers. Often the minoritised people for whom such modes of care is presented as inclusive are also those who earn their living through the gig economy, again with AI enabling more access to markets that can be classed as inclusive [142]. However, the scholarship adducing inequality in the distribution of benefits and burdens demands consideration of the unique ways digital benefits can also be burdens [142], pinpointing overt costs of membership for those technologies offering greater equality and the more covert cost of datafication [29]. When the benefits of using AI to, for example, improve birth outcomes are weighed against the harms of datafication, the implications for the realisation of RJ are complex.

As Ruja Benjamin notes [13], AI datafication is being used to compile and analyse genetic data, with the aim of providing a genetic blueprint for intelligence and other socially valued traits for AI-assisted reproductive decision-making. She cites the documentary *DNA Dreams*, a film about how scientists in China are working to identify alleged 'intelligence' alleles. Benjamin explains the scientific team rebutted criticism that this is a eugenic agenda, arguing that rather than selectively promoting the fertility of 'highly intelligent' people and discouraging the fertility of others, the team's goal is simply to enable everyone to have the 'best kids' possible. Benjamin labels this 'Equal Opportunity Eugenics', explaining the very notion of 'best kids' and indeed of 'intelligence' itself are socially defined, highly subjective ideas; the choices scientists are making to define intelligence and correlate this with genetic markers is, contrary to the scientific team's rhetoric, neither a neutral nor an inclusive act. Ultimately, whether selectively encouraging fertility on the basis of a value-laden characteristic or encouraging everyone to make fertility decisions to maximise a specific characteristic, the result is still eugenics. The datafication of intelligence (and other subjective, selectively valued traits) and efforts to select on these traits are rooted in 'a belief that more humans can be like those already deemed superior' [13, p. 117]. The history of eugenics highlights how socially defined and deeply biased ideas about which traits are/should be valued, packaged as objective scientific insight, can be a powerful tool of structural violence used to restrict the right to have a child, to not have a child, and to control one's own body and future.

2.4 Monetising inequality and misinformation

As with the other trends we have highlighted, monetising inequality and misinformation is not new. However, AI is facilitating the spread of misinformation in ways that make it more rapid, voluminous, and targeted, while simultaneously increasing the potential for financial gain from spreading misinformation and stoking inequalities [104].

Inequities in access to assisted reproductive technology (ART) have long been a barrier to the right to have a child, with the most marginalised people both within and across national boundaries having the least access [7, 9, 44, 51, 138]. AI is now being developed in the selection and analysis of sperm cells and oocytes, the evaluation of embryo quality for decisions about transfer and implantation, and predictions of the probability of success for in vitro fertilisation (IVF) [117]. As Rolfes et al. explain, the application of AI in this context has introduced a strong potential for compounding disparities by charging a premium for AI-assisted ART, which could provide more effective ART treatments and more successful outcomes with less need for repeated invasive procedures. This is likely to be particularly the case when AI-assisted ART is not widely available, potentially leading to a widening of the care gap between privileged and marginalised people who experience infertility and even raising costs across the sector, creating further barriers to the right to have a child for marginalised people.

We have already touched upon one of the mechanisms by which search algorithms monetise inequality, namely through targeted advertising that bets on people's failure (§2.2). To this we add the following: An analysis from February 2023 has shown that nearly half of adverts returned by Google UK when users were searching for abortion-related phrases such as 'NHS abortion advice' (National Health Service) were advertisements for anti-abortion groups [33]. For users who see the search platform as a tool for efficiently navigating the Internet (rather than as a business that makes its money from advertising revenue), the relevance and accuracy of results returned and the relationship of these characteristics to the potential for revenue generation may be extremely opaque.[8]

2.5 Decimating planetary health

Since the term was coined in 2013, a growing body of work has focused on planetary health—that is, how human activity has impacted complex and interconnected ecological systems, and how the devastating effects of natural resource depletion and the climate crisis in turn threaten human health around the globe [149]. While popular excitement over possible technosolutions to the climate crisis abound, significantly less attention is given to the planetary harms inherent in the profligacy and extractive ethos of emerging digital technologies. Linked to these planetary costs are very real human costs, both in terms of harms to the people who depend on effected ecosystems and harms to the people who are doing the dangerous extractive labour.

For example, minerals such as lithium, dysprosium, and cobalt are essential for manufacturing processor chips, computer displays, batteries, and other technology components [30, 40]. Both the physical activity of mining itself and the environmental degradation linked to it carry serious health consequences for miners and for communities surrounding mines—disproportionately for marginalised people and communities in Global Majority countries. The high demand for minerals underpinning the industry, and the structural violence linked to the extraction of these resources, is a threat to RJ. Where child labour is used, mining is a direct threat to the ability to raise children in safe and healthy environments; mining poses both short-and long-term threats to children's health [107].[9] The pollution from nearby mining activities can also create health hazards such as mercury and lead contamination, which negatively impacts human health and child development [52, 110]. And, the ill health of parents who work in mines can also pose a risk to children, e.g. by reducing household income when wage earners become ill and through health risks such as transmission of tuberculosis, which is a common health problem in mining communities [108]. Because mining also carries a high risk of death, people who are undertaking this dangerous form of labour experience a risk to all of their

[8]This is despite Google's protestations that this is not an issue because the word 'Ad' appears in bold before the links in question; links to valid, regulated abortion providers were also labelled as adverts [33]; simply labelling an advert as such is not a sufficient cue as to the validity of the linked information.
[9]Although risks of injury and toxic exposures are very real in extractive industries, children can, as empowered actors, choose to work to contribute to their household economy. Simply withdrawing an important source of income without attending to broader structural constraints and investing in livelihood alternatives is not a useful solution [101, 105]. Viewed through a RJ lens, uptake of precarious and/or dangerous work may be considered in many circumstances a choiceless choice, and removing (rather than broadening) already constrained choices is an inadequate solution.

rights under the RJ framework. Moreover, where demand for natural resources increases conflict, communities face an increased risk of food and water insecurity, displacement, injury, and death, all of which are barriers to RJ [43, 46].

More broadly, despite the key role of digitalisation in (inter-)governmental climate strategy (e.g. [28]), at present digital technologies pose a material threat to the realisation of climate targets [76]. While often mistaken as directly reducing carbon emissions, the efficiencies emerging digital technologies deliver instead promote the desire to do more (for cheaper), creating rebound effects that offset efficiency gains; meanwhile, the impulse to find new ways to capitalise on datafication further drives the growth of emissions by data centres that store these limitless troves, and by the computational intensity of AI processing this data [49, 81]. In short, the AI industry is a massive contributor to the climate crisis and its sequelae. Because of the inextricable links between climate justice and RJ, the substantial and direct role digital technologies play in compounding the climate crisis is a pressing matter for RJ. Put simply, no one can live in a safe and healthy environment, no one can have the children that they want to have, and no one can have control over their future on a planet that cannot sustain life.

3 DISCUSSION

3.1 Why Reproductive Justice?

The issues outlined above have been raised by scholars applying a social justice lens to critique AI. So what is gained by exploring these issues through a RJ lens? First, this lens lifts the veil on additional dimensions of systemic harms. In 2004, cardiologist Nanette Wenger critiqued medical science for taking a 'bikini approach' [148]—a narrow focus of women's health as being about breasts and reproductive systems, neglecting the rest of the body. By framing the reproductive harms of emerging digital technology as stemming mainly (or solely) from technologies focusing on women's reproductive systems (e.g. menstrual trackers), computing risks a similarly problematic approach. RJ offers a useful lens for seeing the reproductive coercion embedded in a broader, more subtle range of emerging technologies. Applying the explicitly intersectional feminist lens of RJ reveals the potential, and already realised, forms of reproductive coercion being fostered by digital technologies. Explicit attention to algorithmic RJ is essential for achieving 'strong intersectional fairness in AI' [83]. Our paper seeks to be a bridge for bringing AI ethics and RJ activists and scholars into conversation; visiting the intersection of these two fields highlights how digital technologies are putting a thumb on the RJ scale—a form of digital gatekeeping that enforces broader sociocultural notions of who can and 'should' reproduce. The specific harms of RJ are linked to but *not subsumed by* broader forces of marginalisation, yet people with a particular stake in RJ are not brought into discussions about fairness, accountability, and transparency. RJ principles align well with an Ubuntu-inspired relational ethics model which extends beyond principles of fairness and trust, requiring AI ethics to contend with community good, respect for others, and safeguarding humanity as well [6]. Examining emerging social justice issues in AI and related digital technologies through the RJ lens will help to give the reproductive implications of these technologies the attention that they deserve. Second, and relatedly, being rooted in international human rights, a RJ framing may afford strategic advantage in terms of global solidarity. It grounds discussions of AI harm within international fora such as the United Nations, which is in the early stages of grappling with the threat AI poses to human rights and what unified international action against these threats might look like. Critiquing digital technology through RJ opens the door to cooperation with groups fighting for RJ around the globe.

Third, this lens clarifies AI's disturbing potential for alignment with eugenics. Extant critiques have identified similarities between AI classifications and the physiognomy/phrenology historically used to legimitise eugenics [30, 58], but we suggest the connection to eugenics is also more direct. Dan McQuillan is perhaps most bold in calling out the eugenic tendencies of AI. He warns [96] AI is entangled with a) problematic notions of intelligence that have always legitimised racialised social hierarchies, and b) the instinct to optimise intelligence, which led to overt eugenics; but he also argues AI is deployed in ways that grant/deny opportunities to individuals in ways that racially stratify mortality. As we have noted, premature deaths related to deployment of AI technologies have implications for people's freedom to reproduce. But whereas McQuillan writes, 'It wouldn't be necessary for AI-driven eugenics to be implemented by anything as crude as forced sterilization: it could simply operate as infrastructural filtering at scale' [96, p.92], we assert eugenic pressures exerted by emerging technologies go beyond filtering of opportunity (distributive injustice).

Fourth, our discussion of implications for RJ has revealed the interconnected nature of digital reproductive harm, with multiple violent processes converging on the most marginalised people around the globe. For example, as Cavallero and Gago [21] point out, the debt crisis that is disproportionately affecting families and marginalised people in Argentina and Brazil is rooted in transnational processes of structural adjustment: Global Majority countries that have experienced centuries of colonial extraction to generate capital for Global Minority countries are now experiencing another wave of extraction in which social protection systems are being dismantled to pay for state debt.This is an act of neocolonialism, with structural adjustment effectively asking countries to foot the bill for their own exploitation. Families and marginalised people being forced into debt and precarity to line the pockets of financiers in Global Minority countries. Thus seemingly local experiences of debt and its sequelae are rooted in global processes of extraction. We add to their incisive analysis that the opaque introduction of AI and its quiet ubiquity can supercharge harmful processes, including the structural violence of debt, by providing a veneer of objectivity while breaking down boundaries between systems of oppression.

Finally, because RJ draws attention to how history animates current inequities, algorithmic RJ elucidates the role of (neo)colonialism in creating the infrastructure for our deeply inequitable digital world. Digital technologies did not spring forth from nowhere; a tendency to look towards exciting new directions without considering historical context can mask the underpinning analog inequities on which the foundations of our digital world are built. Indeed, the Silicon Valley motto of 'move fast and break things' misses the myriad ways things are, in fact, already broken. Consideration of the historical context of technological advances at a global scale highlights how historical harms are replicated by this ethos. RJ invites us to consider the historical roots of inequities, how inequities are maintained in the current system, and how they can be best redressed. For instance, we noted the duality between AI's potential for bridging capital, with the potential to combat socioeconomic inequity globally, and the probabilities for merely reproducing said inequities [96]. Indeed, this view of AI as actual (rather than mere abstract) technologies offering real-life capital for populations historically marginalised and systematically excluded from the benefits of emerging technology globally allows insight through the concrete lens of RJ. We are particularly concerned about algorithmic harm landing disproportionately in parts of the world where digital technology represents significant bridging capital, and therefore the choice to push back against technology's more insidious effects can ultimately be a choiceless choice between the very real harms of using versus not using a given technology. What can be regarded as an 'uncritical' welcome of these technologies can also be understood in regards to how historically structured inequitable arrangements, including access to digital technologies, distorts rather than actualises agency. Concerns with uncritical acceptance cannot be divorced from the representation of AI as a social good [143]. This insight adds renewed urgency to calls to develop AI ethics that transcends a narrow, privileged, colonialist perspective [125, 139]. There is a clear need for research that expands our (currently woefully inadequate) understanding of lived experiences of digitally-implicated harm and the barriers they pose to reproductive (and other forms of) justice; RJ provides a toolkit for informing this research, and links discussions about digital inequities to an activist community with extensive expertise in addressing inequities.

3.2 Doing better

We have raised significant concerns regarding the application of AI in domains including criminal justice, social care, and AI-assisted reproductive decision-making. That said, our critique is not so much of particular emergent/AI system(s) as it is of the extractive ethos driving various interlinked technologies [29] which, *in combination*, obstruct RJ. Meaningfully controlling one's future requires meaningful control of one's data, including real opportunities to reject data-driven systems. Consent regimes are demonstrably inadequate protections for almost everyone [68, 77], but (multiply) marginalised people have even less power to exert choice under heightened surveillance, and often face strong incentives to demonstrate compliance with agencies demanding their data [41]. Moreover, the consequences of the failures of consent regimes is far from evenly distributed across society. Our analysis underscores the importance of real solutions to the perennial challenge of privacy in the age of surveillance capitalism [150, 151]—solutions which are anticipatory (see [23] for more) rather than exclusively, and glacially, reactive. Echoing Ruha Benjamin, we propose that solutions in this space focus on the power dynamics of *visibility*, i.e. empowering people to make the choice of when and to whom to be visible—a stark contrast to the way digital technologies currently make marginalised people visible when they want to avoid the gaze and invisible when they want to be seen [13, p. 68]. Focusing on the two sides of this visibility problem should help curtail structurally violent surveillance, consumer profiling, and datafication while also revealing people's real experiences of all forms of injustice.

Relatedly, our analysis emphasises meaningfully engaging with marginalised people throughout the entire design pipeline. A growing literature emphasises the importance of methodologies that support genuine dialogue [74, 96], *actually listening* to marginalised voices [13, 34, 58, 80, 84, 95]. However, involving marginalised people does not necessarily constitute meaningful engagement unless their participation is both genuinely valued and *on their own terms*; there is important work to be done in co-design of the engagement methodologies themselves [79] to avoid repeating patterns of harmful extractivism within participatory approaches to AI ethics (see [70]). Concern with epistemic inclusivity is identified in decolonial scholarship as indicative of both Eurocentric and androcentric control of knowledge development, rationalising the marginalisation of colonised communities from power [4]. Fannon [42], for instance, draws a parallel between the ability to control one's narrative and access to resources key to one's transformation. Epistemic colonialism applies not only to methodologies, but also to the Eurocentric and individualistic ethical principles used in AI decision-making [6]. Scholars assess such concerns from a decolonial perspective, citing the need for greater epistemic inclusion [3, 29, 100]. Cave's [22] exploration of AI as constitutive of a value laden history draws attention to the role of knowledge development processes in how inequity is reproduced. This includes historic shaping of 'scientific' knowledge like eugenics as legitimate; Cave exhorts the need to resist AI's capacity to reproduce and rationalise such harms with critical analyses adducing ethics. Couldry and Mejias [29] meanwhile, in defining data colonialism as 'the predatory extractive practices of historical colonialism with the abstract quantification methods of computing' also encourage epistemic equality. This is likely to ensure that the way technologies are conceptualised include the voices and values systems of those historically marginalised from knowledge development and resources.

Finally, given the wide-ranging corrosive effects of data profiteering, realising RJ will require a radical culture change in our relationship with data. The continuously growing carbon footprint of the world's data-driven systems threatens all of our rights. This demands computing respond proportionally to the existential threat of the climate crisis [81]. Efforts to incorporate renewable energy, offset emissions, and increase efficiency are not enough; we must also seriously constrain consumption. This means limiting data collection, even deleting existing data, and resisting the temptation to throw computing—particularly AI—at every problem. The climate impacts of AI have been underappreciated within

AI ethics policy and research, with little to no attention to this matter at preeminent conferences in the field (notable exception: [11]), and this urgently needs to change.

We have outlined some of the (potential) barriers to the realisation of rights that emerging technology presents. It is also essential to recognise the potential for technologies to be reshaped, co-opted, and reimagined as tools for liberation. For example, when asked about predictive models in child welfare systems, stakeholders (e.g. care leavers, parents) identified the potential for digital technologies to be used in solidarity with families to prevent child removals and counteract child welfare agencies [133]. We caution against viewing people who are marginalised by technology as passive and powerless. Waiting for industry and regulators to resolve the structural violence embedded in emerging technology promises to be too little, too late. History has shown that social progress is often driven not by unprompted acts of benevolence at the top of the social hierarchy, but by the active unveiling of obfuscated structural violence and resistance to this violence. Scholars and activists with expertise in and toolkits for resistance of forms of structural violence embedded in emerging technology can both gain momentum from and add momentum to the RJ movement.

4 CONCLUSION

Our aim is not to claim digital technologies can only result in reproductive coercion and harm; there are many ways that AI can be deployed to improve lives if designed and deployed equitably, with the voices of marginalised non/users being centred in this process. Nor was our aim to give a comprehensive accounting of all of the multitudinous harms caused by migrant detention, incarceration, employment discrimination, child removals, and the many other structurally violent processes that we have mentioned as examples in this paper; RJ activists and scholars have already done this with far greater breadth and depth then we can hope to achieve here. We have merely skimmed the surface. Rather, we wish to add four complementary points to the already rich RJ literature. First, the barriers to RJ we've explored are not unique to the digital realm. However, emerging digital technologies are reproducing and amplifying existing barriers in ways that need explicit scrutiny. Second, that false narratives of objectivity are sometimes deployed to obfuscate the structural violent ways technology is being developed and deployed is one reason links between technology and RJ merit further attention. While technology itself does not inherently aim to reproduce and amplify structural violence, it is created for and by human beings, and is therefore subject to the same potential biases of any other human-created system. Claims that technology will be a panacea for biased social systems because technology is free from human bias are, simply put, false. Third, digital technologies are not a substitute for strong and equitable social systems. AI may be useful in many contexts for improving efficiency and cutting costs. However, the gaping holes in the social safety net created by decades of neoliberal divestment in systems that support people to have and raise families cannot be patched with a technological quick fix (see [26] for more). Fourth, there are some highly concerning trends in emerging technologies which have important implications for RJ. These include (but are not limited to) increasing surveillance, assessing worth, datafication of bodies, monetising inequality and misinformation, and decimating planetary health. Both because of the harms (potentially) amplified by emerging digital technologies, and because of the power of activism that seeks to resist this harm, we have sought to highlight the potential for mutual learning and solidarity RJ and computing scholars and activists.

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REFERENCES

[1] Rediet Abebe, Kehinde Aruleba, Abeba Birhane, Sara Kingsley, George Obaido, Sekou L Remy, and Swathi Sadagopan. 2021. Narratives and counternarratives on data sharing in Africa. In *Proceedings of the 2021 ACM conference on fairness, accountability, and transparency*. 329–341.

[2] Rediet Abebe, Solon Barocas, Jon Kleinberg, Karen Levy, Manish Raghavan, and David G Robinson. 2020. Roles for computing in social change. In *Proceedings of the 2020 conference on fairness, accountability, and transparency*. 252–260.

[3] Rachel Adams. 2021. Can artificial intelligence be decolonized? *Interdisciplinary Science Reviews* 46, 1-2 (2021), 176–197.

[4] Biko Agozino and Stephen Pfohl. 2003. *Counter-colonial criminology: A critique of imperialist reason*. Pluto Press.

[5] Michelle Alexander. 2010. *The New Jim Crow: Mass Incarceration in the Age of Colourblindness*. The New Press.

[6] Lameck Mbangula Amugongo, Nicola J. Bidwell, and Caitlin C. Corrigan. 2023. Invigorating Ubuntu Ethics in AI for Healthcare: Enabling Equitable Care. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency* (Chicago, IL, USA) *(FAccT '23)*. Association for Computing Machinery, New York, NY, USA, 583–592. https://doi.org/10.1145/3593013.3594024

[7] Obehi A Asemota and Peter Klatsky. 2015. Access to infertility care in the developing world: the family promotion gap. In *Seminars in reproductive medicine*, Vol. 33. Thieme Medical Publishers, 017–022.

[8] Chelsea Barabas, Colin Doyle, JB Rubinovitz, and Karthik Dinakar. 2020. Studying up: Reorienting the Study of Algorithmic Fairness around Issues of Power. In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency* (Barcelona, Spain) *(FAT* '20)*. Association for Computing Machinery, New York, NY, USA, 167–176. https://doi.org/10.1145/3351095.3372859

[9] Liberty Barnes and Jasmine Fledderjohann. 2020. Reproductive justice for the invisible infertile: A critical examination of reproductive surveillance and stratification. *Sociology Compass* 14, 2 (2020), e12745.

[10] Laura Belmonte. 2023. Can Human Rights Survive Technology? *Diplomatic History* 47, 1 (2023), 1–18.

[11] Emily M Bender, Timnit Gebru, Angelina McMillan-Major, and Shmargaret Shmitchell. 2021. On the dangers of stochastic parrots: Can language models be too big?. In *Proceedings of the 2021 ACM conference on fairness, accountability, and transparency*. 610–623.

[12] Ruha Benjamin. 2019. *Captivating technology: Race, carceral technoscience, and liberatory imagination in everyday life*. Duke University Press.

[13] Ruha Benjamin. 2020. *Race after technology: Abolitionist tools for the new jim code*. Oxford University Press.

[14] Cynthia L Bennett and Os Keyes. 2020. What is the point of fairness? Disability, AI and the complexity of justice. *ACM SIGACCESS Accessibility and Computing* 125 (2020), 1–1.

[15] Abeba Birhane, Elayne Ruane, Thomas Laurent, Matthew S. Brown, Johnathan Flowers, Anthony Ventresque, and Christopher L. Dancy. 2022. The forgotten margins of AI ethics. In *2022 ACM Conference on Fairness, Accountability, and Transparency*. 948–958.

[16] Laura Blattner and Scott Nelson. 2021. How costly is noise? Data and disparities in consumer credit. *arXiv preprint arXiv:2105.07554* (2021).

[17] Sarah Brayne. 2017. Big data surveillance: The case of policing. *American sociological review* 82, 5 (2017), 977–1008.

[18] Karen Broadhurst, David Wastell, Sue White, Christopher Hall, Sue Peckover, Kellie Thompson, Andrew Pithouse, and Dolores Davey. 2010. Performing 'initial assessment': identifying the latent conditions for error at the front-door of local authority children's services. *British journal of social work* 40, 2 (2010), 352–370.

[19] Anna Brown, Alexandra Chouldechova, Emily Putnam-Hornstein, Andrew Tobin, and Rhema Vaithianathan. 2019. Toward algorithmic accountability in public services: A qualitative study of affected community perspectives on algorithmic decision-making in child welfare services. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–12.

[20] Joy Buolamwini and Timnit Gebru. 2018. Gender shades: Intersectional accuracy disparities in commercial gender classification. In *Conference on fairness, accountability and transparency*. PMLR, 77–91.

[21] Luci Cavallero and Verónica Gago. 2021. *A feminist reading of debt*. Pluto Press London.

[22] Stephen Cave. 2020. The problem with intelligence: its value-laden history and the future of AI. In *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society*. 29–35.

[23] Alan Chan, Rebecca Salganik, Alva Markelius, Chris Pang, Nitarshan Rajkumar, Dmitrii Krasheninnikov, Lauro Langosco, Zhonghao He, Yawen Duan, Micah Carroll, Michelle Lin, Alex Mayhew, Katherine Collins, Maryam Molamohammadi, John Burden, Wanru Zhao, Shalaleh Rismani, Konstantinos Voudouris, Umang Bhatt, Adrian Weller, David Krueger, and Tegan Maharaj. 2023. Harms from Increasingly Agentic Algorithmic Systems. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency* (Chicago, IL, USA) *(FAccT '23)*. Association for Computing Machinery, New York, NY, USA, 651–666. https://doi.org/10.1145/3593013.3594033

[24] Ethics Citizen's Coalition for the Decriminalization of Abortion on Grounds of Health and El Salvador Fetal Anomaly. 2014. From hospital to jail: the impact on women of El Salvador's total criminalization of abortion. *Reproductive Health Matters* (2014), 52–60.

[25] Danielle Keats Citron and Frank Pasquale. 2014. The scored society: Due process for automated predictions. *Wash. L. Rev.* 89 (2014), 1.

[26] Amy Clair, Jasmine Fledderjohann, and Bran Knowles. 2021. *A Watershed Moment for Social Policy and Human Rights?: Where Next for the UK Post-COVID*. Policy Press.

[27] Ernestina Coast, Alison H Norris, Ann M Moore, and Emily Freeman. 2018. Trajectories of women's abortion-related care: a conceptual framework. *Social Science & Medicine* 200 (2018), 199–210.

[28] European Commission. n.d.. A European Green Deal. https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en.

[29] Nick Couldry and Ulises A Mejias. 2019. Data colonialism: Rethinking big data's relation to the contemporary subject. *Television & New Media* 20, 4 (2019), 336–349.

[30] Kate Crawford. 2021. *The atlas of AI: Power, politics, and the planetary costs of artificial intelligence.* Yale University Press.

[31] K Crenshaw. [n. d.]. University of Chicago Legal Forum; 1989. *Demarginalizing the intersection of race and sex: A black feminist critique of antidiscrimination doctrine, feminist theory and antiracist politics* 139 ([n. d.]).

[32] US Customs and Border Protection. 2023. CBP One Mobile Application. https://www.cbp.gov/about/mobile-apps-directory/cbpone

[33] Shanti Das. 2023. Google adverts direct pregnant women to services run by UK anti-abortion groups. *The Guardian* (2023). https://www.theguardian.com/world/2023/feb/25/google-adverts-direct-pregnant-women-anti-abortion-groups?CMP=Share_AndroidApp_Other

[34] Lina Dencik, Fieke Jansen, and Philippa Metcalfe. 2018. A conceptual framework for approaching social justice in an age of datafication. *DATAJUSTICE project* 30 (2018).

[35] Yuhao Du, Stefania Ionescu, Melanie Sage, and Kenneth Joseph. 2022. A Data-Driven Simulation of the New York State Foster Care System. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency* (Seoul, Republic of Korea) *(FAccT '22)*. Association for Computing Machinery, New York, NY, USA, 1028–1038. https://doi.org/10.1145/3531146.3533165

[36] Jason R D'Cruz, William Kidder, and Kush R Varshney. 2022. The Empathy Gap: Why AI Can Forecast Behavior But Cannot Assess Trustworthiness. *AAAI 2022 Fall Symposium Series, Thinking Fast and Slow and Other Cognitive Theories in AI* (2022).

[37] Elizabeth Edenberg and Alexandra Wood. 2023. Disambiguating Algorithmic Bias: From Neutrality to Justice. In *Proceedings of the 2023 AAAI/ACM Conference on AI, Ethics, and Society* (, Montréal, QC, Canada,) *(AIES '23)*. Association for Computing Machinery, New York, NY, USA, 691–704. https://doi.org/10.1145/3600211.3604695

[38] Upol Ehsan, Ranjit Singh, Jacob Metcalf, and Mark Riedl. 2022. The algorithmic imprint. In *2022 ACM Conference on Fairness, Accountability, and Transparency*. 1305–1317.

[39] Danielle Ensign, Sorelle A Friedler, Scott Neville, Carlos Scheidegger, and Suresh Venkatasubramanian. 2018. Runaway feedback loops in predictive policing. In *Conference on fairness, accountability and transparency*. PMLR, 160–171.

[40] Nathan Ensmenger. 2021. *The cloud is a factory.* The MIT Press Cambridge, MA.

[41] Virginia Eubanks. 2018. *Automating inequality: How high-tech tools profile, police, and punish the poor.* St. Martin's Press.

[42] Frantz Fanon. 2008. *Black skin, white masks.* Grove press.

[43] FAO, IFAD, UNICEF, WFP, and WHO. 2022. The State of Food Security and Nutrition in the World 2022: Repurposing food and agricultural policies to make healthy diets more affordable. https://www.fao.org/3/cc0639en/online/cc0639en.html. *The State of the World Report Series* (2022).

[44] Jasmine Fledderjohann. 2022. Self-reported fertility impairments and help-seeking strategies among young women in Malawi. *Global public health* 17, 9 (2022), 2139–2155.

[45] Jasmine Fledderjohann and Liberty Walther Barnes. 2018. Reimagining infertility: a critical examination of fertility norms, geopolitics and survey bias. *Health policy and planning* 33, 1 (2018), 34–40.

[46] Jasmine Fledderjohann, Sophie Patterson, and Maureen Owino. 2023. Food Insecurity: A Barrier to Reproductive Justice Globally. *International Journal of Sexual Health* 35, 2 (2023), 296–311.

[47] Jasmine Fledderjohann and Celia Roberts. 2018. Missing men, missing infertility: The enactment of sex/gender in surveys in low-and middle-income countries. *Population horizons* 15, 2 (2018), 66–87.

[48] Paul J Fleming, William D Lopez, Charo Ledon, Mikel Llanes, Adreanne Waller, Melanie Harner, Ramiro Martinez, and Daniel J Kruger. 2019. 'I'm going to look for you and take your kids': Reproductive justice in the context of immigration enforcement. *PloS one* 14, 6 (2019), e0217898.

[49] Charlotte Freitag, Mike Berners-Lee, Kelly Widdicks, Bran Knowles, Gordon S Blair, and Adrian Friday. 2021. The real climate and transformative impact of ICT: A critique of estimates, trends, and regulations. *Patterns* 2, 9 (2021), 100340.

[50] Marissa Gerchick, Tobi Jegede, Tarak Shah, Ana Gutierrez, Sophie Beiers, Noam Shemtov, Kath Xu, Anjana Samant, and Aaron Horowitz. 2023. The Devil is in the Details: Interrogating Values Embedded in the Allegheny Family Screening Tool. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency* (Chicago, IL, USA) *(FAccT '23)*. Association for Computing Machinery, New York, NY, USA, 1292–1310. https://doi.org/10.1145/3593013.3594081

[51] Jessica D Gipson, Marta J Bornstein, and Michelle J Hindin. 2020. Infertility: a continually neglected component of sexual and reproductive health and rights. *Bulletin of the World Health Organization* 98, 7 (2020), 505.

[52] Philippe Grandjean, Roberta F White, Anne Nielsen, David Cleary, and Elisabeth C de Oliveira Santos. 1999. Methylmercury neurotoxicity in Amazonian children downstream from gold mining. *Environmental health perspectives* 107, 7 (1999), 587–591.

[53] Ben Green. 2020. The false promise of risk assessments: epistemic reform and the limits of fairness. In *Proceedings of the 2020 conference on fairness, accountability, and transparency*. 594–606.

[54] Ben Green. 2022. Escaping the impossibility of fairness: From formal to substantive algorithmic fairness. *Philosophy & Technology* 35, 4 (2022), 90.

[55] Daniel Greene, Anna Lauren Hoffmann, and Luke Stark. 2019. Better, nicer, clearer, fairer: A critical assessment of the movement for ethical artificial intelligence and machine learning. In *Proceedings of the 52nd Hawaii International Conference on System Sciences*.

[56] The Guardian. 2020. What's at the heart of a credit score that can ruin a life. https://www.theguardian.com/money/2020/jan/08/credit-score-default-agencies-report.

[57] Seeda Gurses, Sita Gangadharan, and Suresh Venkatasubramanian. 2019. Critiquing and rethinking accountability, fairness, and transparency. *Our Data Bodies Project US* 15 (2019).

[58] Alex Hanna, Emily Denton, Andrew Smart, and Jamila Smith-Loud. 2020. Towards a critical race methodology in algorithmic fairness. In *Proceedings of the 2020 conference on fairness, accountability, and transparency*. 501–512.

[59] Karen Hao. 2019. AI is sending people to jail—and getting it wrong. *MIT Technology Review* (2019). https://www.technologyreview.com/2019/01/21/137783/algorithms-criminal-justice-ai/

[60] Crystal M Hayes, Carolyn Sufrin, and Jamila B Perritt. 2020. Reproductive justice disrupted: Mass incarceration as a driver of reproductive oppression. *American journal of public health* 110, S1 (2020), S21–S24.

[61] Jonathan Herington. 2020. Measuring fairness in an unfair World. In *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society*. 286–292.

[62] Leandra H Hernández and Sarah De Los Santos Upton. 2021. Reproductive Justice and Activism Online. *Networked Feminisms: Activist Assemblies and Digital Practices* (2021), 187.

[63] Mireille Hildebrandt. 2014. Location Data, Purpose Binding and Contextual Integrity: What's the Message? *Protection of Information and the Right to Privacy-A New Equilibrium?* (2014), 31–62.

[64] Kashmir Hill. 2023. Your Car Is Tracking You. Abusive Partners May Be, Too. *The New York Times* (Dec. 2023). https://www.nytimes.com/2023/12/31/technology/car-trackers-gps-abuse.html

[65] Sabine Hoffman and Shalini Kantayya. 2020. Coded Bias. 7th Empire Media.

[66] Anna Lauren Hoffmann. 2019. Where fairness fails: data, algorithms, and the limits of antidiscrimination discourse. *Information, Communication & Society* 22, 7 (2019), 900–915.

[67] Julian Honkasalo. 2018. Unfit for parenthood? Compulsory sterilization and transgender reproductive justice in Finland. *Journal of International Women's Studies* 20, 1 (2018), 40–52.

[68] Gordon Hull. 2015. Successful failure: what Foucault can teach us about privacy self-management in a world of Facebook and big data. *Ethics and Information Technology* 17 (2015), 89–101.

[69] Abigail Z. Jacobs and Hanna Wallach. 2021. Measurement and Fairness. In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* (Virtual Event, Canada) *(FAccT '21)*. Association for Computing Machinery, New York, NY, USA, 375–385. https://doi.org/10.1145/3442188.3445901

[70] Jeffrey A Juarez and Kyle D Brown. 2008. Extracting or empowering? A critique of participatory methods for marginalized populations. *Landscape Journal* 27, 2 (2008), 190–204.

[71] Atoosa Kasirzadeh. 2022. Algorithmic Fairness and Structural Injustice: Insights from Feminist Political Philosophy. *arXiv preprint arXiv:2206.00945* (2022).

[72] Emily Keddell. 2019. Algorithmic justice in child protection: Statistical fairness, social justice and the implications for practice. *Social Sciences* 8, 10 (2019), 281.

[73] Ibram X Kendi. 2016. *Stamped from the beginning: The definitive history of racist ideas in America.* Hachette UK.

[74] Helen Kennedy. 2020. Should more public trust in data-driven systems be the goal? https://www.adalovelaceinstitute.org/blog/should-more-public-trust-in-data-driven-systems-be-the-goal/.

[75] Goda Klumbytė, Claude Draude, and Alex S Taylor. 2022. Critical tools for machine learning: Working with intersectional critical concepts in machine learning systems design. In *2022 ACM Conference on Fairness, Accountability, and Transparency*. 1528–1541.

[76] Bran Knowles. 2021. *ACM TechBrief: Computing and Climate Change.* Technical Report. Association for Computing Machinery.

[77] Bran Knowles and Stacey Conchie. 2023. Un-Paradoxing Privacy: Considering Hopeful Trust. *ACM Transactions on Computer-Human Interaction* (2023).

[78] Bran Knowles, Jason D'Cruz, J.T. Richards, and K.R. Varshney. [n. d.]. Humble AI. *Communications of the ACM, volume=66, number=9, year=2023* ([n. d.]).

[79] Bran Knowles, Jasmine Fledderjohann, John T. Richards, and Kush R. Varshney. 2023. Trustworthy AI and the Logics of Intersectional Resistance. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency* (Chicago, IL, USA) *(FAccT '23)*. Association for Computing Machinery, New York, NY, USA, 172–182. https://doi.org/10.1145/3593013.3593986

[80] Bran Knowles, Jasmine Fledderjohann, John T Richards, and Kush R Varshney. 2023. Trustworthy AI and the Logics of Intersectional Resistance. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency*. 172–182.

[81] Bran Knowles, Kelly Widdicks, Gordon Blair, Mike Berners-Lee, and Adrian Friday. 2022. Our house is on fire: The climate emergency and computing's responsibility. *Commun. ACM* 65, 6 (2022), 38–40.

[82] 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*. 485–494.

[83] Youjin Kong. 2022. Are "Intersectionally Fair" AI Algorithms Really Fair to Women of Color? A Philosophical Analysis. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency* (Seoul, Republic of Korea) *(FAccT '22)*. Association for Computing Machinery, New York, NY, USA, 485–494. https://doi.org/10.1145/3531146.3533114

[84] PM Krafft, Meg Young, Michael Katell, Jennifer E Lee, Shankar Narayan, Micah Epstein, Dharma Dailey, Bernease Herman, Aaron Tam, Vivian Guetler, et al. 2021. An action-oriented AI policy toolkit for technology audits by community advocates and activists. In *Proceedings of the 2021 ACM conference on fairness, accountability, and transparency*. 772–781.

[85] Joshua A Kroll. 2022. *ACM TechBrief: Facial Recognition.* Technical Report. Association for Computing Machinery.

[86] Sarah Lamdan. 2022. The Quiet Invasion of 'Big Information'. *WIRED* (2022). https://www.wired.com/story/big-information-relx-privacy-surveillance-data/

[87] Susan Leavy, Eugenia Siapera, and Barry O'Sullivan. 2021. Ethical data curation for AI: An approach based on feminist epistemology and critical theories of race. In *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society*. 695–703.

[88] Robin Levinson-King. 2021. US women are being jailed for having miscarriages. *The BBC* (2021). https://www.bbc.co.uk/news/world-us-canada-59214544

[89] Gwyneth Lonergan. 2012. Reproductive justice and migrant women in Great Britain. *Women: A Cultural Review* 23, 1 (2012), 26–45.

[90] Zakiya Luna and Kristin Luker. 2013. Reproductive justice. *Annual Review of Law and Social Science* 9 (2013), 327–352.

[91] Christoph Lutz. 2019. Digital inequalities in the age of artificial intelligence and big data. *Human Behavior and Emerging Technologies* 1, 2 (2019), 141–148.

[92] Catriona Ida Macleod, Sian Beynon-Jones, and Merran Toerien. 2017. Articulating reproductive justice through reparative justice: case studies of abortion in Great Britain and South Africa. *Culture, Health & Sexuality* 19, 5 (2017), 601–615.

[93] Paul Marks. 2022. Algorithmic hiring needs a human face. *Commun. ACM* 65, 3 (2022), 17–19.

[94] Viktor Mayer-Schönberger and Kenneth Cukier. 2013. *Big data: A revolution that will transform how we live, work, and think*. Houghton Mifflin Harcourt.

[95] Charlton D McIlwain. 2020. Computerize the race problem? Why we must plan for a just AI future. In *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society*. 4–4.

[96] Dan McQuillan. 2022. *Resisting AI: an anti-fascist approach to artificial intelligence*. Policy Press.

[97] Ninareh Mehrabi, Fred Morstatter, Nripsuta Saxena, Kristina Lerman, and Aram Galstyan. 2021. A survey on bias and fairness in machine learning. *ACM Computing Surveys (CSUR)* 54, 6 (2021), 1–35.

[98] Ariella J Messing, Rachel E Fabi, and Joanne D Rosen. 2020. Reproductive injustice at the US border. *American Journal of Public Health* 110, 3 (2020), 339–344.

[99] Shira Mitchell, Eric Potash, Solon Barocas, Alexander D'Amour, and Kristian Lum. 2021. Algorithmic fairness: Choices, assumptions, and definitions. *Annual Review of Statistics and Its Application* 8 (2021), 141–163.

[100] Shakir Mohamed, Marie-Therese Png, and William Isaac. 2020. Decolonial AI: Decolonial theory as sociotechnical foresight in artificial intelligence. *Philosophy & Technology* 33 (2020), 659–684.

[101] Virginia Morrow. 2013. Whose values? Young people's aspirations and experiences of schooling in Andhra Pradesh, India. *Children & Society* 27, 4 (2013), 258–269.

[102] Sara C Motta. 2016. Decolonizing Australia's body politics: Contesting the coloniality of violence of child removal. *Journal of Resistance Studies* 2, 2 (2016), 100–133.

[103] Arvind Naranayan. [n. d.]. *Fairness Definitions and Their Politics*. Youtube. https://www.youtube.com/watch?v=jIXIuYdnyyk

[104] Safiya Umoja Noble. 2018. *Algorithms of oppression*. New York University Press.

[105] Samuel Okyere. 2022. Moral economies and child labour in artisanal gold mining in Ghana. In *International Child Protection: Towards Politics and Participation*. Springer, 29–55.

[106] Cathy O'Neil. 2017. *Weapons of math destruction: How big data increases inequality and threatens democracy*. Crown.

[107] International Labour Organization. 2019. Child labour in mining and global supply chains. https://www.ilo.org/wcmsp5/groups/public/---asia/---ro-bangkok/---ilo-manila/documents/publication/wcms_720743.pdf.

[108] Katrina F Ortblad, Joshua A Salomon, Till Bärnighausen, and Rifat Atun. 2015. Stopping tuberculosis: a biosocial model for sustainable development. *The Lancet* 386, 10010 (2015), 2354–2362.

[109] Anaelia Ovalle, Arjun Subramonian, Vagrant Gautam, Gilbert Gee, and Kai-Wei Chang. 2023. Factoring the Matrix of Domination: A Critical Review and Reimagination of Intersectionality in AI Fairness. In *Proceedings of the 2023 AAAI/ACM Conference on AI, Ethics, and Society* (, Montréal, QC, Canada,) *(AIES '23)*. Association for Computing Machinery, New York, NY, USA, 496–511. https://doi.org/10.1145/3600211.3604705

[110] Monica Maria Bastos Paoliello, Eduardo Mello De Capitani, Fernanda Gonçalves Da Cunha, Tiemi Matsuo, Maria de Fátima Carvalho, Alice Sakuma, and Bernardino Ribeiro Figueiredo. 2002. Exposure of children to lead and cadmium from a mining area of Brazil. *Environmental Research* 88, 2 (2002), 120–128.

[111] Seeta Peña Gangadharan and Jędrzej Niklas. 2019. Decentering technology in discourse on discrimination. *Information, Communication & Society* 22, 7 (2019), 882–899.

[112] Dana Pessach and Erez Shmueli. 2022. A review on fairness in machine learning. *ACM Computing Surveys (CSUR)* 55, 3 (2022), 1–44.

[113] Chelsea B Polis. 2018. Published analysis of contraceptive effectiveness of Daysy and DaysyView app is fatally flawed. *Reproductive Health* 15, 1 (2018), 1–5.

[114] Manish Raghavan, Solon Barocas, Jon Kleinberg, and Karen Levy. 2020. Mitigating bias in algorithmic hiring: Evaluating claims and practices. In *Proceedings of the 2020 conference on fairness, accountability, and transparency*. 469–481.

[115] Brianna Richardson and Juan E Gilbert. 2021. A framework for fairness: a systematic review of existing fair AI solutions. *arXiv preprint arXiv:2112.05700* (2021).

[116] Dorothy Roberts. 1997. *Killing the Black Body: Race, Reproduction, and the Meaning of Liberty*. Pantheon Books.

[117] Vasilija Rolfes, Uta Bittner, Helene Gerhards, Jan-Steffen Krüssel, Tanja Fehm, Robert Ranisch, and Heiner Fangerau. 2023. Artificial Intelligence in Reproductive Medicine–An Ethical Perspective. *Geburtshilfe und Frauenheilkunde* 83, 01 (2023), 106–115.
[118] Joel Rose and Marisa Peñaloza. 2023. Migrants are frustrated with the border app, even after its latest overhaul. *NPR* (May 2023). https://www.npr.org/2023/05/12/1175948642/migrants-are-frustrated-with-the-asylum-claim-app-even-after-the-latest-overhaul
[119] Loretta Ross and Rickie Solinger. 2017. *Reproductive Justice: An Introduction.* University of California Press.
[120] Loretta J Ross. 2017. Reproductive justice as intersectional feminist activism. *Souls* 19, 3 (2017), 286–314.
[121] Nithya Sambasivan, Erin Arnesen, Ben Hutchinson, Tulsee Doshi, and Vinodkumar Prabhakaran. 2021. Re-imagining algorithmic fairness in india and beyond. In *Proceedings of the 2021 ACM conference on fairness, accountability, and transparency.* 315–328.
[122] Javier Sánchez-Monedero, Lina Dencik, and Lilian Edwards. 2020. What does it mean to'solve'the problem of discrimination in hiring? Social, technical and legal perspectives from the UK on automated hiring systems. In *Proceedings of the 2020 conference on fairness, accountability, and transparency.* 458–468.
[123] Devansh Saxena, Karla Badillo-Urquiola, Pamela J Wisniewski, and Shion Guha. 2020. A human-centered review of algorithms used within the us child welfare system. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems.* 1–15.
[124] R Joshua Scannell. 2019. This is not Minority Report: Predictive policing and population racism. *Captivating technology: Race, carceral technoscience, and liberatory imagination in everyday life* (2019), 107–29.
[125] Nandana Sengupta, Vidya Subramanian, Anwesh Mukhopadhyay, and Arul George Scaria. 2023. A Global South perspective for ethical algorithms and the State. *Nature Machine Intelligence* (2023), 1–3.
[126] William Seymour, Max Van Kleek, Reuben Binns, and Dave Murray-Rust. 2022. Respect as a Lens for the Design of AI Systems. In *Proceedings of the 2022 AAAI/ACM Conference on AI, Ethics, and Society.* 641–652.
[127] Anastasia Siapka. 2022. Towards a Feminist Metaethics of AI. In *Proceedings of the 2022 AAAI/ACM Conference on AI, Ethics, and Society.* 665–674.
[128] SisterSong. 2023. Visioning New Futures for Reproductive Justice. https://www.sistersong.net/visioningnewfuturesforrj.
[129] Sebastian Klovig Skelton. 2023. Newham Council rejects use of live facial-recognition tech by police. *ComputerWeekly.com* (2023). https://www.computerweekly.com/news/252529364/Newham-Council-rejects-use-of-live-facial-recognition-tech-by-police
[130] Linda Tuhiwai Smith. 2021. *Decolonizing methodologies: Research and indigenous peoples.* Bloomsbury Publishing.
[131] Wonyoung So, Pranay Lohia, Rakesh Pimplikar, A.E. Hosoi, and Catherine D'Ignazio. 2022. Beyond Fairness: Reparative Algorithms to Address Historical Injustices of Housing Discrimination in the US. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency* (Seoul, Republic of Korea) *(FAccT '22)*. Association for Computing Machinery, New York, NY, USA, 988–1004. https://doi.org/10.1145/3531146.3533160
[132] Olivia Solon and Cyrus Farivar. 2021. Predictive policing strategies for children face pushback. https://www.nbcnews.com/tech/tech-news/predictive-policing-strategies-children-face-pushback-n1269674.
[133] Logan Stapleton, Min Hun Lee, Diana Qing, Marya Wright, Alexandra Chouldechova, Ken Holstein, Zhiwei Steven Wu, and Haiyi Zhu. 2022. Imagining New Futures beyond Predictive Systems in Child Welfare: A Qualitative Study with Impacted Stakeholders. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency* (Seoul, Republic of Korea) *(FAccT '22)*. Association for Computing Machinery, New York, NY, USA, 1162–1177. https://doi.org/10.1145/3531146.3533177
[134] Alexandra Minna Stern. 2016. Zika and reproductive justice. *Cadernos de saude publica* 32 (2016).
[135] Harini Suresh, Rajiv Movva, Amelia Lee Dogan, Rahul Bhargava, Isadora Cruxen, Ángeles Martinez Cuba, Guilia Taurino, Wonyoung So, and Catherine D'Ignazio. 2022. Towards Intersectional Feminist and Participatory ML: A Case Study in Supporting Feminicide Counterdata Collection. In *2022 ACM Conference on Fairness, Accountability, and Transparency*. 667–678.
[136] Astra Taylor and Jathan Sadowski. 2015. How Companies Turn Your Facebook Activity Into a Credit Score. https://www.thenation.com/article/archive/how-companies-turn-your-facebook-activity-credit-score/
[137] Linnet Taylor. 2017. What is data justice? The case for connecting digital rights and freedoms globally. *Big Data & Society* 4, 2 (2017), 2053951717736335.
[138] Marie Thoma, Jasmine Fledderjohann, Carie Cox, and Rudolph Kantum Adageba. 2021. Biological and social aspects of human infertility: a global perspective. In *Oxford research encyclopedia of global public health.*
[139] Eugenio V. Garcia. 2021. The International Governance of AI: Where Is the Global South? https://thegoodai.co/2021/01/28/the-international-governance-of-ai-where-is-the-global-south/
[140] Ana Valdivia and Martina Tazzioli. 2023. Datafication Genealogies beyond Algorithmic Fairness: Making Up Racialised Subjects. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency* (Chicago, IL, USA) *(FAccT '23)*. Association for Computing Machinery, New York, NY, USA, 840–850. https://doi.org/10.1145/3593013.3594047
[141] Jennifer Valentino-DeVries. 2018. Hundreds of Apps Can Empower Stalkers to Track Their Victims. *The New York Times* (May 2018). https://www.nytimes.com/2018/05/19/technology/phone-apps-stalking.html
[142] Niels Van Doorn and Adam Badger. 2020. Platform capitalism's hidden abode: producing data assets in the gig economy. *Antipode* 52, 5 (2020), 1475–1495.
[143] João Viera Magalhães and Nick Couldry. 2021. Giving by taking away: Big tech, data colonialism and the reconfiguration of social good. *International Journal of Communication* 15 (2021), 343–362.

[144] Sandra Wachter, Brent Mittelstadt, and Chris Russell. 2021. Why fairness cannot be automated: Bridging the gap between EU non-discrimination law and AI. *Computer Law & Security Review* 41 (2021), 105567.

[145] John M Wallace Jr, Jerald G Bachman, Patrick M O'Malley, Lloyd D Johnston, John E Schulenberg, and Shauna M Cooper. 2002. Tobacco, alcohol, and illicit drug use: racial and ethnic differences among US high school seniors, 1976-2000. *Public health reports* 117, Suppl 1 (2002), S67.

[146] Hua Wang. 2021. Chinese women's reproductive justice and social media. *Technical Communication Quarterly* 30, 3 (2021), 285–297.

[147] Lindsay Weinberg. 2022. Rethinking fairness: an interdisciplinary survey of critiques of hegemonic ML fairness approaches. *Journal of Artificial Intelligence Research* 74 (2022), 75–109.

[148] Nanette K. Wenger. 2004. You've Come a Long Way, Baby*. *Circulation* 109, 5 (Feb. 2004), 558–560. https://doi.org/10.1161/01.CIR.0000117292.19349.D0

[149] Sarah Whitmee, Andy Haines, Chris Beyrer, Frederick Boltz, Anthony G Capon, Braulio Ferreira de Souza Dias, Alex Ezeh, Howard Frumkin, Peng Gong, Peter Head, et al. 2015. Safeguarding human health in the Anthropocene epoch: report of The Rockefeller Foundation–Lancet Commission on planetary health. *The lancet* 386, 10007 (2015), 1973–2028.

[150] Yuxi Wu, Sydney Bice, W. Keith Edwards, and Sauvik Das. 2023. The Slow Violence of Surveillance Capitalism: How Online Behavioral Advertising Harms People. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency* (Chicago, IL, USA) *(FAccT '23)*. Association for Computing Machinery, New York, NY, USA, 1826–1837. https://doi.org/10.1145/3593013.3594119

[151] Shoshana Zuboff. 2019. *The age of surveillance capitalism: The fight for a human future at the new frontier of power: Barack Obama's books of 2019*. Profile books.

[152] Alyson Zureick, Amber Khan, Angeline Chen, and Astrid Reyes. 2018. Physicians' challenges under El Salvador's criminal abortion prohibition. *International Journal of Gynecology & Obstetrics* 143, 1 (2018), 121–126.