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Algorithms, policing, and race

Insights from decolonial and critical algorithm studies

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Data-driven predictive algorithms are increasingly informing decision-making across Western justice systems. The influence of the technologies spans the earliest stages of the criminal justice process, from the pre-trial and trial phase (during bail and sentencing decision-making) to the later stages when they influence decisions about the intensity of penal interventions. The algorithms are also used by police services to forecast locational crime risks and inform dispatch decisions (Richardson et al., 2019).

Together, the predictive technologies are part of the classificatory algorithms currently labelling individuals and communities as deserving or undeserving in various domains. Examples include social security services (Eubanks, 2018), the health sector (Price, 2019), employment practices (Ajunwa, 2021), and the insurance industry (Tanninen, 2020). The algorithms are, as such, central to the ongoing digital transformation of decision-making across key aspects of social life. Amongst the digital technologies currently proliferating within Western and non-Western jurisdictions are the previously mentioned predictive policing algorithms. They are deployed by some police services for proactive crime control via the identification and surveillance of crime-risk locations or individuals.

This chapter aims to analyze the racial dynamics of the technologies. To this end, it draws on decolonial logics and related perspectives from the multidisciplinary field of critical algorithm studies (CAS), which is part of the broader field of science and technology studies. Insights from both scholarships provide the rationale for the chapter. The insights suggest that, although the technologies reflect liberal race-neutral logics of objectivity and scientific neutrality, they can reproduce historical biases and entrench the 'digitised racialization of risk and crime' (Ugwudike, 2020). Specifically, the studies indicate that the exclusionary contexts of their design and their capacity to reproduce systemic biases can exacerbate harmful racial essentialism. Insights on these issues and possible remedies are required and are provided by this chapter.

Predictive policing algorithms and race neutrality

Predictive policing algorithms are data-driven technologies that observe and draw on patterns in data to forecast either individual risks of offending or locational crime risks. The algorithms form part of what I conceptualise as CrimTech which refers to technologies deployed by justice

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systems for decision making. They rely on various data sources which may include 'big data' – such as linked biometric, health, demographic, geographical, and socioeconomic data – and administrative criminal justice data compiled by justice services (Hannah-Moffat, 2019).

Varieties of technologies exist including those that attempt to assess and predict individual risks of offending (Oswald et al., 2018) or those that are designed to forecast spatio-temporal crime risks (Richardson et al., 2019). Together predictive policing algorithms specifically, have been defined as "data-mining tools that [seek to] predict and pre-empt criminal activity" (Andrejevic, 2017, p. 879). Brayne (2017) notes in an analysis of such algorithms that developers[1] and procurers depict them as scientifically objective technologies that can expedite accurate decision-making which can, in turn, improve systemic efficiency and cost-effectiveness (see also Lavorgna & Ugwudike, 2021). This implies that they are race neutral (Ugwudike, 2020).

The myth of race neutrality

As I have argued elsewhere, underpinning the liberal race-neutral presumption which currently shrouds the design and deployment of predictive policing algorithms and similar technologies are two logics (Ugwudike, 2020). One is the bias elimination fallacy or the belief that excising race from the lexicon of predictive tools automatically eliminates racial bias, rendering them neutral. It is argued that this assumption overlooks the continuing impact of systemic racial bias and structural inequalities in several contemporary Western societies (see, e.g., Murakawa & Beckett, 2010). Studies suggest that, with predictive policing algorithms, for instance, conduits of systemic bias include the reliance on administrative datasets, including crime data that contain records of racially biased arrests that go on to trigger biased algorithmic predictions[2] – the perennial "garbage in, garbage out problem" (see Lum & Isaac, 2016, p. 19). Here, the fundamental source of bias is shielded by ostensibly race-neutral and scientific predictive analytics. Another race-neutral logic is the scientific neutrality fallacy which manifests itself in the view that the quantification of predictive analytics equates to irrefutable scientific objectivity which obviates racially biased decision-making (Ugwudike, 2020). Again, in this case, the presumption of race neutrality appears to be mythical. It merely obscures design processes such as the aforementioned reliance on flawed data that can foment biased predictions. This calls for critical analyses of race-neutral logics.

Decolonial perspectives in the field of technology design and development (Adams, 2021; Birhane, 2019; Couldry & Ulises, 2019; Mohammed et al., 2020) and insights from the CAS scholarship or the related field of critical data studies (Barocas & Selbst, 2016; Benjamin, 2019; Boyd & Crawford, 2012; Brayne, 2017; Kitchin & Lauriault, 2014) are particularly useful in this context. They suggest that the race neutrality frame obfuscates the ethical challenges posed by technologies such as predictive policing algorithms and could indeed reproduce and perpetuate historical biases. Race scholars similarly contend that, more broadly, the idealistic race neutrality logic reflects a decontextualized abstract liberalism that ignores the continuing reality of systemic bias in institutional contexts (e.g., Bonilla-Silva, 2015) including justice systems (Murakawa & Beckett, 2010).

Despite allusions to the neutrality and scientific objectivity of predictive policing algorithms, as we shall see later in the chapter, studies have revealed several ethical challenges associated with the algorithms, and racial bias has emerged as a key issue (Ensign et al., 2017; Lum & Isaac, 2016; Richardson et al., 2019). The liberal race-neutral frame ascribed to the technologies obscures this problem and other similar challenges. It presumes that systemic and structural biases have been eradicated with the supposed advent of a post-racial age.[3] From this perspective, digital technologies such as predictive policing algorithms are being designed and deployed in criminal justice settings that are devoid of racial bias. Presumably, the technologies reflect the progressive ideals of a colour-blind, post-racial world. It is in this context that sections of CAS and decolonial perspectives become relevant given their focus on unravelling respectively, historical structures of racial inequality that permeate algorithm design and fuel racially biased predictions, and the enduring legacy of colonial logics that continue to foment systemic bias and broader structural disadvantage.

In the next section, the chapter provides an overview of decolonial logics in the fields of technology design and criminology. After this, the chapter discusses analogous perspectives from CAS and draws on both decolonial logics and CAS to analyze the exclusionary contexts of the bias associated with 'race-neutral' predictive policing algorithms, and how best to develop remedial strategies.

Decolonial logics and critical algorithm studies

A recurring theme traversing decolonial theory is the notion that constructed racial and other hierarchies evident in contemporary social, political, and economic structures, are themselves rooted in enduring legacies of colonialism, refuting claims about the emergence of a race-neutral and post-racial world. Decolonization is thus proposed and is defined by Mohammed et al. (2020) in their analysis of decolonial artificial intelligence (AI) systems as, "the intellectual, political, economic and societal work concerned with the restoration of land and life following the end of historical colonial period" (Mohammed et al., 2020, p. 663; see also Adams, 2021). In the context of technology design and deployment, decolonization challenges the dominance of colonial epistemology and aims to decentre Western influences whilst proposing the amplification of historically marginal, non-Eurocentric voices (e.g., Birhane, 2019).

Decolonial and decolonizing studies arguably have a longer history in criminological scholarship and they similarly advocate epistemological and paradigmatic shifts that can restore and reinstate localized modes of knowledge production (see, for example, Anthony & Sherwood, 2018; Blagg & Anthony, 2019). These should foreground the realities of historically marginalized populations in colonized Black African regions (Agozino, 2018, 2021) and Indigenous communities in "Anglo-settler colonial jurisdictions" from Australia and New Zealand to Canada and the United States (Cunneen & Tauri, 2017, p. 359). Ultimately, the decolonizing mission is to redress the long-standing racially discriminatory effects of colonial power and thought on contemporary knowledge production, social structures, and systems of governance in those locations. It is argued that criminology as a discipline should embrace this decolonizing agenda. Indeed, there have been calls to decolonize criminology via theories and methods that foreground the colonial roots of contemporary racial and other oppressions within and beyond justice systems. A primary contention here is that Western criminological thought continues to ignore or underplay the historical legacy of colonialism and its enduring influence on crime control practices and institutions as well as broader social structures which continue to disadvantage racialized people[4] (Cunneen & Tauri, 2017). This criticism has been extended to the field of Southern Criminology which seeks to amplify perspectives from the Global South.[5] As Agozino (2004) notes, "Criminology is a social science that served colonialism more directly than many other social sciences" (p. 343). From this perspective, the imperialistic, racially divisive logics and relations of colonialism continue to permeate current criminal justice practice, including applications of predictive policing software.

Insights from CAS reaffirm decolonial logics concerning the enduring emblems of coloniality and repudiate the race neutrality discourse. Scholars in this field contend that data-driven predictive technologies, including predictive policing algorithms, can reproduce historical forms of structural disadvantage (e.g., Benjamin, 2019; Brayne, 2017; Richardson et al., 2019). In this respect, studies have found that where a predictive policing algorithm relies on crime data it can reproduce racial biases embedded in the data via the overprediction of crime risks associated with racialized people (Ensign et al., 2017; Lum & Isaac, 2016). The next sections explore the exclusionary contexts of this adverse outcome and the essentialism it can foment, with specific reference to both decolonial perspectives and CAS.

Exclusionary contexts of algorithmic bias

As I discussed in a previous analysis of digital predictive technologies in justice systems, the race-neutral frame ignores algorithmic biases that can arise from broader structural conditions of technology design (Ugwudike, 2020). A relevant example is unequal access to digital capital, which is a sociological concept that, broadly defined, refers to the resources required for accessing and/or designing and developing technologies (van Dijk, 2005). Insights from CAS and related fields suggest that unequal access to this form of capital in contemporary Western neoliberal societies signifies long-standing power asymmetries and marginalizations rooted in the racial, gender, and other constructed hierarchies. Benjamin (2019), for example, notes that the empowered group invariably comprises White males of relatively high socio-economic status, typically entrepreneurs, researchers, and others. Their digital capital empowers them to infuse their products with unregulated and unchallengeable values in the form of personal choices, ideologies, assumptions, theoretical preferences, and other subjectivities.

In tandem with these insights from CAS, decolonial logics from criminology (e.g., Agozino, 2021) similarly suggest that unequal access to digital and other forms of capital in contemporary times is a reflection of coloniality. The concept of coloniality refers to relics of colonialism or, as Mohammed et al. (2020) put it, "coloniality is what survives colonialism […] coloniality names the continuity of established patterns of power between coloniser and colonised—and the contemporary remnants of these relationships" (p. 663). From a criminological perspective, Dimou (2021) similarly defines coloniality as "long-standing patterns of power that emerged because of colonialism and that are still at play" (p. 431). Dismissing any notions of race neutrality, decolonial discourses in criminology draw attention to how unequal access to capital breeds power imbalance and reproduces adverse outcomes such as the disproportionate vulnerability of historically marginalized populations to higher rates of criminalization compared with other groups (Agozino, 2021).

In the same way, the CAS scholarship suggests that the concentration of digital capital specifically, within historically powerful groups, reproduces colonial power inequalities and has been linked to adverse outcomes for racialized people. As we shall see, studies have shown that the data choices of those equipped with digital capital can produce profound implications in the sense that they can trigger adverse outcomes such as racially biased overprediction (e.g., Lum & Isaac, 2016), despite the depiction of the tools as race neutral.

With their digital capital, the developers are also empowered to construct new forms of knowledge about risk and riskiness whilst racialized people typically lack similar levels of access to digital capital[6] and are, as such, often unable to fully participate in such knowledge production processes. Their lack of digital capital excludes them from design processes (Costanza-Chock, 2018) when potentially harmful choices that inform racially biased predictions and knowledge production about risk and riskiness can be pre-empted and avoided. Perhaps unsurprisingly and contrary to race neutrality logics, they invariably bear the ethical burden of both technology design and deployment (see Barabas, 2020; Taylor, 2017) or the 'ethical debt' (such as racially biased overprediction) that accumulate as technologies are deployed over time (Petrozzino, 2021). Their exclusion is problematic, not least because justice systems are high-stakes domains where access to certain human rights and civil liberties can be withdrawn.

Adverse outcomes: the problem of essentialism

Perspectives from CAS further repudiate the race-neutral logics of bias elimination and scientific objectivity ascribed to predictive policing algorithms in additional ways. Echoing decolonial discourses, sections of CAS argue that the algorithms can reproduce and perpetuate historical forms of knowledge production which consistently label racialized people as intrinsically criminogenic. The roots of this form of essentialism can be traced to the tendency of the algorithms to over-predict or artificially inflate crime risks, as noted by several studies (see Ensign et al., 2017; Lum & Isaac, 2016). Decolonial logics suggest that such overprediction events are instances of coloniality in that they sustain or even worsen racial essentialism, which remains one of the hallmarks of constructed colonial racial hierarchies and knowledge systems.

The negative construction of Black and Indigenous populations as inherently deviant and a 'social problem' (Agozino, 2018) has long been described as a feature of coloniality which is embedded, not only in criminological thought but also more broadly in contemporary social structures and institutional practices. Overprediction of crime risks in cases involving racialized people can exacerbate such essentialism. It can normalize the demonization of racialized people whilst sustaining and validating racially inequitable policies and power structures entrenched in the legacy of colonialism.

Overprediction stems partly from the unrepresentative data on which the technologies rely for crime forecasts, data which, as already noted, can include administrative records of racially biased decision-making. Unfortunately, studies suggest that the algorithms cannot detect problems such as those that call for a nuanced analysis of crime data and other criminal justice datasets (see generally, Fair Trial and EDRi, 2022). Instead, the technologies interpret the data as race-neutral proxies for crime. In reality, however, well-documented discriminatory practices such as "over-searching" and "over-patrolling" (Vomfell & Stewart, 2021, p. 566; see also, Shiner et al., 2018) do find their way into such data and can partly explain the over-representation of racialized people in criminal justice statistics across justice systems where predictive technologies are deployed (Australian Bureau of Statistics, 2018; Bureau of Justice Statistics, 2018; Canadian Centre for Justice Statistics, 2019; Ministry of Justice, 2019). Their over-representation draws attention to the disadvantage racialized people experience in justice systems. It also contributes to algorithmic overprediction.

Criminologists have theorized the adverse experiences of racialized people in justice systems, invoking themes relevant to decolonial logics. Examples include the disempowering effects of coloniality and the associated colonial epistemologies that continue to foster the exercise of power, sovereignty, and control over racialized people in contemporary institutions and wider society (Dimou, 2021). Meanwhile, empirical research from the field of CAS continues to reveal how such overrepresentation foments the ethical problem of algorithmic overprediction of crime risks.

It is worth acknowledging that developer-led studies have alluded to the race neutrality and accuracy of predictive policing technologies (e.g., Brantingham et al., 2018; Mohler et al., 2015). Independent studies, on the other hand, suggest otherwise. Lum and Isaac's (2016) study, for example, investigated the effects of using a predictive policing algorithm that relies on crime data from a Police Department in the US for locational crime forecasts. They found that, because the crime data had been artificially inflated by excessive police presence in locations heavily populated by Black people, it triggered an algorithmic self-reinforcing feedback loop whereby the algorithm repeatedly targeted those locations for high crime-risk predictions (overprediction), encouraging even more policing in those areas and heightening exposure to unwarranted criminalization (see also Browne, 2015).

Lum and Isaac (2016) concluded that "allowing a predictive policing algorithm to allocate police resources would result in the disproportionate policing of low-income communities and communities of colour" (p. 18). Ensign et al. (2017) arrived at similar conclusions. Their analysis of the same algorithm relied on police data from Lum and Isaac's (2016) study and uncovered similar algorithmic feedback loops (see also Chapman et al., 2022; Richardson et al., 2019). These studies and others from the field of CAS demonstrate the links between unrepresentative crime data and algorithmic risk inflation which disadvantages Black and Indigenous people and can reproduce and entrench notions of Black riskiness and criminality. As already noted, decolonial logics suggest that such contemporary instances of essentialism are emblems of coloniality.

CAS scholars similarly recognize the embeddedness of this essentialism in historical structures and oppressive racial, class, and gender relations. Benjamin (2019), for example, acknowledges that technologies such as predictive policing algorithms which rely on flawed "data that have been produced through histories of exclusion and discrimination" (p. 10) can reproduce long-standing racial ideologies. Of particular relevance here are deeply entrenched views and beliefs that essentialize racialized people as the immanently risky other. This form of essentialism poses profound implications. For instance, decolonial discourses suggest that colonial constructions of racial difference continue to fuel the criminalization of racialized people and their sustained overrepresentation in prisons across Western jurisdictions (Jackson, 1988; Tauri, 2016).

The CAS scholarship is similarly unravelling the historical roots of the ethical issues associated with algorithms deployed in justice systems (Benjamin, 2019) and other domains such as welfare allocation services (Eubanks, 2018), internet platforms (Noble, 2018), and other domains. In synergy with decolonial perspectives on the persistence of coloniality despite allusions to race neutrality, the scholarship is providing useful insights into how historical and long-standing inequalities along racial, gender, and socioeconomic lines are also being played out in these settings disadvantaging Black and Indigenous populations. It is thus not surprising that Couldry and Ulises (2019) point to a "decolonial turn" (p. 1) in critical studies of data and technology.

Mitigations and solutions rooted in a confluence of decolonial and critical algorithm studies logics

Mitigations and remedies have been proffered to address the biases and other ethical challenges associated with predictive policing algorithms and other data-driven predictive technologies applied in justice systems. Commonly cited mitigations include debiasing datasets (Johndrow & Lum, 2019), conducting internal and external audits (Brown et al., 2021; Jobin et al., 2019; Mittelstadt, 2019; Raji et al., 2020) and developing explainability and transparency techniques (Parent et al., 2020; Ugwudike, 2022; Zeng et al., 2015).

In this section, I demonstrate how synergies between decolonial and CAS logics can contribute to ongoing efforts to avoid or at least remediate ethical challenges by embedding decolonial thought in technology design. Invocations by criminological scholars and others to decolonize technology design are gathering momentum in light of emerging evidence of ethical issues.

Mohammed et al. (2020) argue that AI communities should consider integrating a decolonial approach into technical practice. This, in their view, is useful for understanding how best to bring AI research and design in line with ethical ideals whilst foregrounding vulnerable groups typically affected by the effects of technological advances. Cave and Dihal (2020) contend that decolonizing AI should involve the dismantling of colonial power structures and the underpinning systems of oppression that continue to permeate technology design and outputs, entrenching injustices (see also Cave, 2020). Primarily, any emblems of coloniality embedded in design processes should be excised. Examples include data practices and any other design features that can reproduce and entrench historical racial, gender, and other biases, fuelling broader disparate impact and other ethical problems (Barocas & Selbst, 2016; Benjamin, 2019; Buolamwini & Gebru, 2018; Hagendorf, 2020).

Decolonization strategies should also involve efforts to uncover historically entrenched, systemic biases and foreground the typically marginalized voices of racialized and other disadvantaged communities. Below I outline several concepts emerging from the field of CAS which are useful for considering how to develop these decolonial ideals and design decolonized, ethical technologies.

Data justice: dismantling data colonialism

Data justice is a concept emerging from CAS scholarship (e.g., Dencik et al., 2016; Taylor, 2017) that can advance decolonial ideals. The concept has been framed in several ways by different disciplines. But fundamentally, it emphasizes the importance of ensuring that those who collect the digital data that are used for algorithm design should ensure that such data are collected and used fairly. This is particularly crucial as societies continue to advance towards datafication, which involves the transformation of key aspects of social life and human activity into data. In the design of predictive policing algorithms, for example, decolonial logics can remind developers that histories of discrimination mean that administrative data are likely to be far from race neutral.

Unlike dominant liberal frames which depict such data as objective crime records, decolonial logics suggest that they can be imbued with historical forms of racial bias and can, as such, potentially generate biased predictions, just as several studies have shown (Chapman et al., 2022; Ensign et al., 2017; Lum & Isaac, 2016). Therefore, care should be taken when selecting data for predictive algorithms. Data justice requires that the way the people are made visible and represented in the datasets used for predictive policing and other similar algorithms does not expose them to bias or any other harmful outcomes (Taylor, 2017).

Data justice can also help dismantle data colonialism (Couldry & Ulises, 2019; Ricaurte, 2019), which is a concept from the CAS scholarship that alerts us to the historical and enduring nature of personal data as a means of pervasive marginalization and exploitative capitalist extraction and accumulation. Theorizations of this problem feature in the decolonial literature (Mohammed et al., 2020). Data colonialism inspires epistemologies that can foment exclusion and the negation of other worlds and forms of *knowledge* (Ricaurte, 2019). Understanding data colonialism and how to reverse the problem is important in contemporary applications of data which reconstitute human experiences and attributes as data points and uncritically posit them as objective reflections of reality as well as useful *knowledge* production tools (Adams, 2021).

Developers equipped with digital capital in the form of financial and other resources such as digital skills and competencies currently dominate such applications of data. They design technologies that draw on the data they select to define risk classifications in justice systems. The classifications are then depicted by the developers as statistically backed, race-neutral 'truths' about crime risks. In the case of predictive policing algorithms, their outputs are fundamental to prevailing knowledge of crime patterns across geographical locations. The knowledge generated from the technologies can determine levels of police dispatch and surveillance. But studies show that when they rely on potentially biased data, they can expose already overpoliced communities to disproportionately high levels of policing and risks of criminalization, reproducing historical biases and inequalities.

What this suggests is that in justice systems, it is important to recognize that the way communities are represented or made visible in data can influence the way they are treated. If, as decolonial logics suggest, racialized communities are more vulnerable to historical biases and discrimination, these can permeate criminal justice activity and records, and become amplified by predictive algorithms that rely on such records (Lum & Isaac, 2016), regardless of their facile race neutrality.

Design justice: amplifying marginal voices for broader representation

Design justice (Costanza-Chock, 2018) is another useful conceptual tool from CAS that implicitly reflects decolonial logics and is useful for considering how to mitigate the capacity of AI to reproduce historical biases and other ethical challenges. It refers to practical strategies for ensuring that disempowered communities that are typically most affected by algorithmic harms, such as the overprediction of risk, are empowered to participate in key design considerations.

The concept evokes themes associated with the broader notion of data sovereignty (Kukutai & Taylor, 2016; Walter & Suina, 2019). It explains how design processes that centre the methods and knowledge, and perceptions of users, including typically underrepresented groups, can help democratize technology design. This can achieve additional aims of public acceptability and trustworthiness which could be vital for the sustainability of new and emerging technologies. The concept of design justice focuses attention on tools and strategies for reversing historical power asymmetries associated with contemporary technology design and fuelled by uneven access to digital capital (see Van Dijk, 2005).

In sum, data justice and design justice are concepts that echo decolonial sentiments about the importance of foregrounding the voices and contributions of historically marginalized groups in an effort to dismantle entrenched structural dynamics that can permeate technology design and trigger discriminatory outcomes. By highlighting these issues, both concepts reflect decolonial logics and refocus our attention on the structural contexts in which technologies are designed, and on the importance of structural transformation.

Conclusions

Decolonial logics and the CAS scholarship inspire the critical analysis of technologies and their societal impact. Such analysis reveals links between the historical legacy of colonialism and the contemporary racialization of social problems, including crime. Predictive policing technologies may reflect liberalism's idealistic, race-neutral ideology. But decolonial logics and the CAS scholarship suggest that contemporary structural conditions displaying features of coloniality (Mohammed et al., 2020) continue to foment predictions that can reproduce racial ideologies and biases experienced by structurally disadvantaged communities, particularly Black and Indigenous people.

More specifically, studies have shown that such algorithms can reproduce the biased assumption that low-income locations heavily populated by racialized people are the areas most exposed to crime risk. Similar algorithmic assumptions linking race to crime and risk have been found to affect Indigenous First Nations people in Australia (Allan et al., 2019; Shepherd et al., 2014) and Canada (Cardoso, 2020), and can fuel discriminatory geographical profiling and overpolicing. Decolonial and CAS perspectives suggest that developers should remain alert to these problems and the potential of long-held biases to permeate some of the tools they deploy during technology design. The tools include the datasets they select and their theoretical choices (Ugwudike, 2020).

Embedding insights from decolonial and CAS perspectives that highlight the capacity of historical biases to permeate technology design can reorient AI design decisions away from the narrow choices, assumptions, and ideologies of a few developers empowered by their access to digital capital. Further, concepts from CAS such as design justice and data justice, both of which reflect core decolonial aims of dismantling relics of coloniality, such as the enduring marginalization of historically disadvantaged groups (see, e.g., Mohammed et al., 2020), provide useful insights on how best to democratize technology design.

The concepts suggest that democratization should involve opening up design decisions and processes to a wider population, including historically marginalized populations who, as studies suggest, are most affected by the risks and harms of predictive technologies. This may require resource investment to redistribute digital capital and promote digital literacy. Such investment is required to expand the pool of individuals and communities able to participate in building representative and trustworthy technologies for the future.

Notes

1 In this chapter, the term 'developers' refers broadly to those who design and develop data-driven technologies.
2 Rovastos et al. (2020) define algorithmic bias as "the systematic, repeatable behaviour of an algorithm that leads to the unfair treatment of a certain group" (Rovastos et al., 2020, p. 69).
3 See, Goldberg (2015) and Vickerman (2013) for critical analyses of the post-racial discourse.
4 In this chapter, the terms 'racialized communities' or 'racialized minorities' refer to Black and Indigenous communities.
5 See Anthony et al. (2021) for a critique of Southern Criminology.
6 For a UK example showing racial differences in levels of access, see House of Commons Science and Technology Committee (2016).

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