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19 Data justice

Abstract: This chapter provides an introductory overview of how data justice is being used as a key concept, framework, and research practice. The overview provides a condensed review of previous research that both informs and makes use of data justice as a research lens. The chapter concludes by highlighting how data justice approaches are particularly relevant for criminology.

Keywords: data, datafication, social justice, AI, automated decision systems

At the Data Justice Lab we use the term *data justice* as a key concept, framework, and practice to research the social justice implications of datafication (see Datafication by Chan), with a particular focus on changing power dynamics. While I am writing this entry, this overview is a condensed version of how we explain our use of the term in the co-authored introduction to our book *Data Justice* (Dencik et al., 2022). Data justice begins from the position that the increasing and widespread collection and use of data across different domains of social and political life is transforming ways of knowing and acting, decision-making processes, critical infrastructure and services, as well as working practices. The datafication of life is happening in ways that entrench and accelerate unjust and oppressive systems and discriminatory practices, while also introducing new power dynamics. For example, automated hiring systems have been found to discriminate on the basis of gender, mental health, disability, and ethnicity (Whitaker et al., 2019, Sánchez-Monedero et al., 2020). Facial recognition systems have been found to discriminate by misidentifying people with darker skin tones and women at rates much higher than white men (Bulamwini and Gebru, 2018). These systems have already led to wrongful arrest and detention. Automated decision-making systems (ADS) are leading to harm as people are falsely flagged as high risk through the use of automated scoring systems in child welfare, policing, sentencing, hiring, credit rating, and housing decision-making (Eubanks, 2018; O'Neil 2016; Redden et al., 2020).

While there are widespread discussions about datafication that promote its contributions to efficiency, security, or economic growth, too often such discussions fail to acknowledge the ways that increasing uses of AI and automated systems are already leading to harm. To prioritize data justice is to recognize that the expansion of data collection and use can and is entrenching and amplifying pre-existing injustices while introducing new power dynamics requiring investigation, critique, and resistance. By using data justice as a framework, the work we have been doing together at the Data Justice Lab stresses the importance of social justice concerns about datafication. Data justice in our work to date has been used as a lens to engage with and advance social justice as well as to challenge injustices related to datafication. Our use of

 https://doi.org/10.1515/9783111062037-020

the term is informed by our collaborations as well as the significant and growing body of work by others.

Overview

Data justice has been informed by work highlighting how already marginalized groups are disproportionately negatively affected by emerging data systems, in ways that amplify and accelerate pre-existing inequality, discrimination, and oppression (Gangadharan et al., 2014; Noble, 2018; Benjamin, 2019; Hoffmann, 2019). It is also informed by media and digital justice work. The term digital justice has been used to link contemporary work to the longer history of media and digital reform (see Digital by Wernimont). As argued by Shade (2023), an early framework for digital justice was created by the Detroit Digital Justice Coalition which brought together community members, researchers, educators, artists, and entrepreneurs to advocate for equitable access to media resources, shared civic participation and decision-making about technologies, common ownership, co-operative models of development, and stresses the need to prioritize healthy communities. Taylor's data justice framework provides a means to account for oppression and different social contexts while highlighting the importance of autonomy and the ability to opt out of data collection (2017). Richard Heeks (2017) provides a framework to assess power and profit asymmetries in datafied applications. Sasha Costanza-Chock's (2018) *Design Justice* work centers on design processes and the conditions and contexts influencing the ways that data infrastructure is developed. This work calls for more participatory design practices that involve communities and building alternative bottom-up infrastructures to empower marginalized communities. For example, DiscoTechs (Discovering Technology Community Fairs) where participants learn things like media making skills, communication tactics, and how to build technology (Costanza-Chock, 2018).

Conceptions of data justice are informed by mobilization and resistance to datafied injustice. Given the lack of transparency and accountability surrounding much corporate and government uses of AI and automated decision-making systems (ADS), the work by grassroots groups, civil society organizations, and journalists to investigate, challenge, and advocate for more just societies and practices influences how we both understand and operationalize data justice. As just a few examples, the Center for Media Justice in the United States has created a Data Justice Lab in relation to Data for Black Lives to bridge research, data, and movement work. The Detroit Digital Justice Coalition have developed guidelines for equitable data practices. The American/Canadian Environmental Data Governance Initiative has developed an environmental justice framework. The Indigenous Data Sovereignty movement, made up of the alliance of groups all over the world, asserts Indigenous ownership about the collection and use of data by and about Indigenous peoples and lands. This movement builds on long-standing struggles against the extraction and exploitation of Indigenous peoples, their knowledge systems, customs, and lands (Kukutai and Taylor, 2016; Lewis,

2020). Data Justice is also being shaped by the growing platform co-operatism movement, which is challenging the monopolistic and extractive nature of platform capitalism.

The empirical research investigations we have done together at the Data Justice Lab informs our use of the term and has involved bringing together concerns about social justice, tech justice, and political mobilization (Dencik et al., 2016) and researching how datafication is changing state citizen relations and governance (Hintz et al., 2019; Redden, 2018). This work has also involved researching where and how people are already being negatively affected by data practices as well as learning from the people who are trying to redress and prevent data harms (Redden et al., 2017, 2020). Foregrounding the politics of data and attending to contexts has involved recognizing the importance of reparation and challenging cognitive injustices that fail to recognize non-mainstream and non-Western ways of knowing (Milan and Treré, 2019; Treré, 2019).

Prioritizing social justice in our research is based on recognition that the way technology is developed and used is not inevitable or neutral, but that technologies are embedded within social actors and forces and a particular political economy. Further, we share the view that technologies should be viewed as 'sites of struggle,' and that with any application there will be competing values, politics, and visions informing people's ideas about if and how technologies should be deployed (Eubanks, 2018). Attending to where such struggles are taking place reinforces the important fact that our datafied present and future are not predetermined, but that we have important work to do together to determine the kinds of datafied worlds we want to live in. Prioritizing social justice in this work involves recognizing our shared interdependence with each other and our environments.

Approaches to data justice are informed by long-standing concerns about the social justice implications of the nature of information and communication technologies. This work stresses the importance of understanding the way in which systems of measurement and evaluation, like the map and the census, provide a means through which people and territory have been surveyed and regulated (Kitchin, 2014; Hacking, 2007; Isin and Ruppert, 2019). There is a long history of states consolidating power through their uses of data and technology (Milner and Traub, 2021). Data then, about the world, has real-world impact as people use it to justify or make decisions. Information power, as argued by Hoffmann, is central to other forms of power (2020). For example, categorizations of people as deserving or undeserving has long been used as a way to justify or deny people's access to services or opportunities (see Categorization and Sorting by Franko). With AI and automation such processes of categorization and value are being embedded in infrastructure design and code. Data justice approaches are often informed by previous work outlining how data systems are part of longer histories and embedded in contexts where there is already a lot of structural and systemic violence and inequality. AI and ADS systems can intensify and accelerate this inequality because they incorporate classification and bureaucratic regimes that have been developed in ways that provide security to some but lead to greater vulnerability for

many (Spade, 2011). Key work in surveillance studies has detailed the technological shifts that enable increasing corporate and government surveillance and the need to be alert to how this contributes to social sorting and normalizing cultures of surveillance (Lyon, 2015, 2002; Gandy, 1993). This work stresses the importance of attending to datafication beyond concerns about how it enables privacy infringements, to concerns about the violations of human rights, new modes of subjectification, accelerated discrimination, pre-emption of due process in decision-making, and shifts in the ways governments come to know about and engage with people and social issues.

Data justice and criminology

Data justice is particularly relevant to criminology because many new AI and ADS applications are being used across criminal justice systems, an area where there are already high levels of inequality. For example, previous research documents inequality, systemic and structural racism in criminal justice systems in the United States, Canada, Australia, New Zealand, the United Kingdom, and Europe (see list below). This makes the use of technologies that could intensify and accelerate inequality and discrimination dangerous. Investigations of AI and ADS use in policing and child welfare have detailed how some of the most highly weighted variables in the systems analyzed, such as postal codes or whether or not a person receives benefits, are proxies for ethnicity or poverty and can lead to a disproportionate targeting and impact on already marginalized communities (Eubanks, 2018; O'Neil, 2016). These issues are leading to increasing challenges to uses of predictive systems for policing. For example, in April 2020 the Los Angeles Police Department announced they would stop using PredPol, this after having also stopped using a system called Laser (Redden et al., 2022). While the LAPD said they stopped the use of both in connection with COVID-19 financial constraints, representatives from the Stop LAPD Spying Coalition that had been investigating these systems, their impact, as well as challenging police use of the systems view the announcements as a response to years of community mobilization and organization. The internal audit by the Office of the Inspector General pointed to a number of issues including lack of oversight, inconsistency, and racial profiling. A civilian oversight panel questioned the effectiveness of the LAPD's systems. Stop LAPD's investigations raised significant concerns about the targeting of already marginalized people, particularly the unhoused (Redden et al., 2020).

Predictive technologies are also being used to risk assess the likelihood of a defendant re-offending and these scores are informing decision-making about sentencing and bail (see Sentencing and Risk Assessments by Ugwudike). In the United States, investigators working for ProPublica compared the risk scores assigned to 7,000 people and checked to see how many went on to be charged with a new crime. They found that the risk scores were unreliable and biased. The system was much more likely to falsely flag Black defendants as future criminals than white defendants. The system was also wrongly labeling white defendants as low risk more often than Black defendants (Ang-

win et al., 2016). The bias and errors produced in these kinds of systems are connected to the systemic biases embedded in the data being drawn upon to develop the systems (Lum and Isaac, 2016). Further, there is a growing body of work detailing how AI and ADS systems may violate people's rights, in ways that affect social rights, rights to due process and a fair trial, to the protection of personal data, and to privacy (see Privacy and Data Protection by Bygrave). Our research into cancelled systems demonstrates that systems are being legally challenged in multiple countries on different legal bases (Redden et al., 2022). For example, automated systems have been successfully challenged in different countries for different reasons including failed automation, not ensuring individual determination, a lack of due process, violating Europe's General Data Protection Regulation, being non-compliant with the European Convention of Human Rights and in contravention of the constitutional right to privacy (Redden et al., 2022: 18). This work also identified cities across the United States making the decision to pre-emptively ban uses of facial recognition technologies because of concerns about rights, discriminatory impact, and harm. These efforts are often connected to critical media coverage and civil society and community mobilization.

Conclusion

In our work at the Data Justice Lab we approach data justice as a research agenda that enables us to bring together the key social justice issues that come from our work. However, what data justice means is continually being shaped and developed. In this sense we do not understand data justice as an idea with a predefined end goal, or as an abstract ideal that can have universal applications or fixed practices associated with it (Dencik et al., 2022). In our Data Justice work at the Lab, we plan to continue to use it as a means of employing systematic analysis to understand the social justice implications of the increasing uses of data, AI, and automated decision-making systems. We see our approach with data justice as an avenue through which we can ask questions about how society is organized and the role technology has within it, so that we can also ask questions about how things could be otherwise to enable flourishing for everyone.

Suggested reading

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Research documenting inequality, systemic and structural racism in AI and automated decision-making systems applications

US

https://www.sentencingproject.org/publications/un-report-on-racial-disparities/; https://www.ohchr.org/EN/NewsEvents/Pages/systemic_racism.aspx

CA

https://www.canada.ca/en/department-justice/news/2021/06/addressingsystemic-racism-against-indigenous-peoples-in-the-justice-system-government-of-canada-investments-andinitiatives.html

AU

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UK

https://warwick.ac.uk/services/sg/si/diversity/advance_he_-_understanding_racism_report.pdf

EU

https://www.europarl.europa.eu/RegData/etudes/BRIE/2021/690525/EPRS_BRI(2021)690525_EN.pdf

NZ

https://www.hrc.co.nz/news/migrant-newzealanders-experience-fear-loss-culture-and-identity-due-racism/

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