A Primer on Data and Social Justice

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Contents

Abstract

Communities around the world are impacted differently by the collection and use of data, and the deployment of data-driven artificial intelligence and machine learning systems. The opportunities and harms associated with these processes are extremely unevenly distributed—both within and amongst countries. Data and data driven processes can create and exacerbate social and economic injustice, including through breaches of personal privacy, but also to communities through bias, discrimination, misrepresentation, invisibilisation, as well as the dispossession of data as a resource. This primer provides a high-level but practicable starting point for stakeholders wishing to familiarise themselves with the social justice underpinnings of the concept of data justice. It is complemented by another primer which goes into depth on the critical economic aspects of data justice and a policy brief which can be used to advance the principle across diverse contexts.

Introduction

Data has come to play a central role in our day-to-day lives, increasingly shaping societies and fuelling economies. Communities around the world are impacted differently by the collection and use of data, and the deployment of data-driven artificial intelligence and machine learning (AI/ML) systems. The opportunities and harms associated with these processes are extremely unevenly distributed—both within and amongst countries.

Dominant approaches to regulating data have been rooted in cultural and legal norms from Europe and North America, and have largely not been reflective of pluralistic experiences and perspectives. These have focused chiefly on data protection which is equated with individual property rights and privacy. While policy discourse is beginning to look beyond privacy in the European Union, for the most part current frameworks remain insufficient to ensure just outcomes for diverse communities impacted by data collection and use, especially communities who are marginalised or vulnerable (Birhane & Cummins, 2019). The growing dominance of data, big data analytics, the Internet of Things, and algorithms in the context of the global crisis precipitated by COVID-19, has highlighted the need for 1) data to be regulated in the collective interest or for common good, 2) the development of skills and infrastructure outside of the existing dominant countries to ensure that individual countries can effectively manage their own data sovereignty.

While data governance literature and practice has predominantly been concerned with individualised rights and risks, there is a strong need for progressive policy to realise collective social and economic data rights. This encompasses areas such as data availability, accessibility, usability, and integrity; as well as the distribution of ownership of data assets, skills and infrastructure, and value produced and rents extracted through data-driven systems (OECD, 2019).

The ownership of large data stores and the ability to utilise them in data-driven systems is highly concentrated geographically and economically. The vast majority of the world's digital data and innovation capabilities now rests with a handful of monopolistic platform companies in two main regions, with 90% of the market capitalization value of the 70 largest platforms concentrated in China and the United States. By comparison Europe accounts for 4% and Latin America and Africa together account for 1% (UNCTAD, 2019). Regulation (Singh and Gurumurthy, 2021:1), education and investment is needed to disrupt this status quo, which disadvantages already marginalised communities around the world, as well as exacerbating inequalities between countries. Disadvantaged communities and countries are unable to share equitably in the benefits of data-driven innovation, experience the extraction of their data and knowledge as a resource, and experience further marginalisation through social biases and discrimination encoded in and reproduced by data-driven systems.

The Sustainable Development Goals (SDGs) provide a guiding framework for the work of GPAI and the wider project within which this primer has been developed. The use of data in equitable and just ways is identified as a pathway for advancing the SDGs. The primer provides an overview of the emerging concept of data justice as a guiding principle for redressing the inequalities in opportunities and mitigating the differential risks for marginalised, excluded and discriminated people and communities. It explores how the principles of data justice could be integrated into the governance and regulation of data.

This is done by drawing on an integrated literature review, as well as three comprehensive guidelines to data justice developed for impacted communities, developers and policymakers by The Alan Turing Institute for the Global Partnership on Artificial Intelligence Data Governance Working Group (Alan Turing Institute, 2022a; 2022b; 2022c; 2022d).[1] This primer distils the key insights from this substantive work and other literature and reports to provide a high-level but practicable starting point for stakeholders wishing to advance data justice across diverse contexts. It is complemented by another primer which goes into depth on the critical economic aspects of data justice.

The following section briefly defines the key concepts of data and AI/ML. The primer goes on to outline the limitations of current policy approaches to regulating data and AI/ML. Then it introduces and discusses data justice as a guiding principle for policy-making, before offering a reflection on taking data justice forward in a brief conclusion.

[1] This project was undertaken in collaboration with twelve partner organisations from across Africa, Asia, Oceania and the Americas. Summaries and feedback provided by these organisations framed the direction and insights of the research which informed this primer. A list of these "Policy Pilot Partner" organisations is provided in Appendix 1

Key Concepts

Data

When discussing data-driven systems, especially in the context of AI, the term data is usually used to mean digital data (GPAI Data Governance Working Group, 2020). Digital data is any information represented digitally. In this primer data is also used to mean digital data.

It is useful to think of data as raw material which represents and abstracts information about the world, and forms the building blocks of knowledge and intelligence (Kitchin, 2014).

There are many possible types and forms of data. Data can be descriptive (qualitative) or measured (quantitative). It can be structured (organised for a specific purpose) or unstructured (general and varied—for example all the video content hosted on YouTube).

An important category of data is personal data. Personal data is data which relates to an individual, or can be used (on its own or in combination with other data) to identify an individual.[2] Although this has been the focus of data governance to date, non-personal data makes up a significant portion of data flows and is used in ways that affect people and communities.

Data can be collected in many ways, including through online surveys, polls, web-scraping tools, and cookies. Most of the time, those online are unlikely to be aware of the data we are producing through our activities and if or how it is being collected. Those not online are also often unwitting data subjects, as data from their offline activities such as use of government services may be gathered, stored and used online.

Artificial Intelligence and Machine Learning (AI/ML)

When data is accumulated in large quantities and aggregated, it can be used in modelling systems—which transform the raw material of data into an output through complex computational processes (algorithms).

Machines can be trained with large datasets to perform tasks such as classification, prediction and recommendation.[3] This process is often called machine learning (ML), and the resultant systems which perform these functions previously reserved for humans, are called artificial intelligence (AI).

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[2] For a definition of personal data used in legislation see the European Union's General Data Protection Regulation (2016: Art. 4(1)).

[3] Classification systems organise data (such as photos of animals) into categories (such as photos of cats and photos of dogs). Prediction systems use past data to predict a future outcome, for instance, using information about your past purchases with a specific retailer to predict what you might buy in the future. Recommendation systems use past data to recommend new things you might be interested in (such as musical artists) based on your past preferences or behaviour.

Limitations of current policy approaches

With more and more data being accumulated, and rapid advances in computational capabilities, the data-innovation cycle is accelerating, faster than our understanding of its social and economic consequences.

Regulatory frameworks—such as the European Union's General Data Protection Regulation (GDPR)—have been developed to protect people from harms associated with the collection and use of data, and the deployment of AI/ML. However, most current frameworks apply a narrow conception of rights, which is poorly equipped to protect communities affected by the range of potential injustices arising from data practices and systems. At the same time, they have applied these policy prescriptions in a broad and general way, overlooking contextual specificities and not providing sufficient guidance on implementation. With both this narrow understanding of data rights, and overly general approach to rights realisation, they are unlikely to prevent AI/ML from reproducing and exacerbating structural inequality.

This section discusses some of the key limitations of these frameworks in advancing just outcomes. These include the fact that they are dominated by the perspectives and priorities of a few regions, their lack of specific and contextualised guidance for implementation in different places, their narrow conception of data governance as protecting personal rights, and their insufficient sensitivity to the overwhelming power that comes with the ability to collect large data stores combined with the ability to deploy AI/ML systems.

The most influential approaches to regulating data, data-intensive processes, and data-driven innovation have emerged from centres of political and economic power. The European Union's GDPR is generally considered to be the global standard on data regulation, and many regulatory frameworks in other parts of the world take their cue from its approach.

However, a key limitation of these approaches is that because of their specific geographical and political outlook, they are not as sensitive to the historical experiences and priorities of communities in other parts of the world. They assume democratic governance, institutional endowments and developmental attributes that are often not applicable to developing countries. Moreover, postcolonial and indigenous perspectives are lacking in regimes of data governance. As data flows and usage reinforce and accentuate geographical power imbalances, this is of deep concern to communities witnessing the extraction of their data as a means of economic accumulation and cultural production. Current policy frameworks do not respond meaningfully to these complex but pervasive dimensions of exclusion through data.

Data is sometimes seen as a neutral by-product of social relations and interactions, reflecting the world as it is. However, the way data is collected, processed and used involves decisions about what information has value, how it should be interpreted, and how meaning is ascribed to information. As (mostly private interests within) some regions dominate the accumulation, utilisation and regulation of data this can have the consequence not only of perpetuating uneven economic relations, but also uneven epistemological relations (or knowledge frameworks—ways of understanding the world). Without representative global data governance which takes these complex processes into account, the result is the domination and imposition of specific cultural norms, and the marginalisation of indigenous and other non-hegemonic values and knowledge systems. As data becomes ever more fundamental to daily life, it is important that data policy does not reproduce the epistemological aspects of colonisation, which also feed into uneven patterns of development.

Informed especially by Western cultural and legal norms, current data regulation frameworks are narrowly focused on areas where data practices impact the personal rights of property and privacy (Dencik et al., 2016). Concepts such as “data protection”, “data rights” and “data security” are central to these frameworks, and refer to the importance of peoples’ ability to own and have control over their personal data as their property.

While personal data is a category of data which does require special protections, because it can be used to identify and target individuals and violate their privacy, current approaches focus exclusively on personal data ownership rights, and ignore other important rights—such as the positive rights to data access, usability and integrity. Moreover, the focus on protecting certain categories of data as private property fails to adequately reflect or understand the nature of data as a societally-produced resource. Data is generated by and about people through our activities, and much of the economic value of data lies in its collective (or aggregate) nature—whereby those with the infrastructural and computational capabilities can identify trends and patterns in large repositories of data, and use these to develop AI and other data-driven systems.

Without such systems-level capabilities, individuals are unlikely to be able to generate value from their personal data, even when their ownership rights over that data are legally protected. Understanding data as personal property arises from a liberal tradition of individualism and privatisation, but this focus on protecting personal data ownership obscures the true nature of data as an aggregate and collectively produced resource and has the perverse effect of enabling the extreme concentration of ownership of valuable non-personal data. This is a crucial yet overlooked aspect of data protection, and theoretical and policy work is only beginning to grapple with the economic distributional outcomes of data collection and use, and how data can be understood instead as a public good or commons. An example of progress in this area is the European Union’s Data Governance Act, which will provide a legal basis for neutral and transparent data sharing and governance through special “data intermediaries”(for more on this see IT for Change, 2022).

In addition, while privacy is an important pillar of data governance, existing frameworks overlook collective aspects of privacy—such as where data from different individuals can be used to expose an identity group or community (Dencik et al., 2016). For example, recent concerns have arisen around the potential use of data from menstrual tracking apps to limit womens’ reproductive rights. This poses a risk to individuals who use menstrual tracking apps and may be targeted on the basis of their personal data, but also presents a risk to a marginalised or disadvantaged group (people who menstruate), who are collectively discriminated against, and require special data protection on the basis of their identity or categorisation.

The collection and use of data can result in myriad collective harms. Researchers have documented the processes by which AI encodes and perpetuates bias and discrimination against existing marginalised groups, and historical social injustice. The data used to develop AI, because it is derived from our social activities, reflects existing biases and inequalities. The real world impacts of AI systems depend on what data is used to develop these systems, how that data is processed, and who controls these activities. For example, a dataset containing many images of faces can be used to train a classification model to recognise faces. If, for instance, black women’s faces are underrepresented in the dataset, the model will be less effective at identifying black women’s faces compared to other faces. When a system like this is used in practice—such as in government services or policing—biases in data can affect the underrepresented group prejudicially (Buolamwini and Gebru, 2018; Noble, 2018).

Another concern around collective protection of data is in relation to indigenous communities who may require limitations on access to their data and knowledge systems. This is critical to guard against colonial practices of knowledge extraction which might occur in data collection and data-driven systems. However, it adds a layer of complexity to wider efforts which attempt to respond to the concentration and enclosure of data assets—through open data. Without responsible stewardship mechanisms, open data carries risks not only for personal privacy, but for the appropriation of indigenous knowledge systems. Indigenous data sovereignty has been identified as a key concern by indigenous scholars, in advancing a decolonial data policy agenda (Kukutai & Taylor, 2016).

In addition to the fact that dominant policy frameworks advance norms, perspectives and priorities from a few regions, the frameworks are also often too general to be useful for implementation by actors in diverse places. Specifically, they typically lack good testing, evaluation, verification, and validation methods and standards that gauge the real-world performance of ML models. Moreover, they have generally not been accompanied by requirements for third party auditing and other localised accountability mechanisms which help to identify biases in AI systems.

As AI increasingly underpins and shapes many aspects of our lives, various ethical standards for AI have also emerged from both industry bodies (e.g. IEEE, n.d.) and global policy forums (e.g. UNESCO, 2021), to encourage developers and decision makers to give greater consideration to the ethical impacts of AI design and deployment. While United Nations Educational, Scientific and Cultural Organization (UNESCO)'s recent recommendations go somewhat further in advancing a rights focus, many of these frameworks tend to focus on building technical solutions to technological harms, rather than interrogating the social structures and human choices that harmful technology emerges from.

AI ethics has proliferated across sectors in recent years, but it is attracting increasing criticism for its overall toothlessness, and the fact that it attempts to regulate something that profoundly affects societies, yet is not rooted in political democratic processes (for example see Munn, 2022). An emphasis on governance through ethical codes can risk sidelining democratic institutions, political engagement and important contestations over rights. Many ethical codes are adopted with limited consultation or accountability mechanisms, and can serve to buttress powerful actors against criticism around how their activities perpetuate inequality or injustice.

These forms of voluntary or private regulation fail to respond to (and in many cases obscure and even reinforce) platform economic power. Digital capitalism is characterised by the extraction of valuable data from communities, which become the de facto proprietary data assets of a small group of platform companies (Sadowski, 2020; Zuboff, 2019). This process is often called data extraction or extractivism. Data holds enormous speculative value, and can be monetised in the future in ways we might not be aware of today. This incentivises firms to accumulate as much data as possible from and about human activities. However, due to a lack of trade and competition regulation of digital corporations, and economic regulation of data flows, established firms with proprietary data streams have a virtually unchallengeable advantage in both accumulating and monetising data.

There is a large power imbalance between these actors, and the people whose data they are collecting, or who use their data products. These power imbalances shape the distribution of value, benefits and risks of data-driven innovations. The interests of powerful actors are often not aligned with the interests of affected communities.

As outlined, most current regulatory frameworks do not acknowledge how power operates and is consolidated, and how different groups can be disempowered, in data practices and systems. Most policy responses to datafication (like privacy regulation) do not adequately identify or mitigate the consolidation of power through data practices and systems, such as the extraction of valuable data from communities, or protect less powerful groups from its potential harmful outcomes. Because of a lack of regulation aimed at equitable economic outcomes, the extraction of data especially from the global South, and its accumulation in centres of wealth and power parallels historical imperialist processes of resource extraction as well as cultural production, the imposition of particular norms, meanings and values, and the othering of indigenous epistemologies.

From data protection to data justice

Beginning in 2014 a new body of research has responded to these conceptual and policy gaps, and worked to build an expansive and inclusive view of data rights, encompassing principles of social justice, equity and empowerment. This research has coalesced around the idea of data justice.

Key contributions to data justice literature include Johnson (2014), who identified power asymmetries in data governance which lead to coercive and extractive outcomes, calling for "information justice" to be achieved through open data. Dencik et al. (2016) proposed that a data justice framework is needed to broaden the conversation around datafication beyond privacy and security, and to incorporate the voices of activists and civil society. Taylor (2017) proposed a definition of data justice, as "fairness in the way people are made visible, represented and treated as a result of their production of digital data." More recently the literature has taken on an increasingly global and intercultural outlook, as scholars explore local and contextual understandings of data justice (for example, Birhane & Cummins, 2019; Kukutai et al., 2020; Sauls et al., 2022).

Data justice as a field of scholarship is quite new, and more work is needed to bridge the gap between emerging theory and research, and the ways in which data is governed in practice. Below we explain the key aspects and underpinnings of data justice, and how these may be relevant to people in government and other policymakers.

Informed by social justice: Data justice emerges out of and overlaps with struggles for social justice. Social justice is the commitment to building societies that are equitable, fair and capable of confronting the root causes of injustice. Social justice recognises everybody's right to have their essential material needs met, and to participate fully in social and democratic life. Data justice draws on this by centring concerns of equity, equality and inclusion in data practices and systems. While social justice struggles share many common principles, they respond to different historical injustices in different places. Similarly, data justice calls for contextualised responses to structural and historical inequality, as it manifests at the local level.

Dismantling structural and historical inequality: This acknowledges that data is created, collected and exploited in a world that is already characterised by unevenness, marginalisation and injustice. Without responsive regulation, data practices and systems will inevitably reflect, encode and perpetuate this injustice. Responsive regulation needs to be buttressed with investment in sovereign capability—to inform local regulators, and enable sovereign and local community solutions based on community data. Beyond protecting individual data rights, data justice calls on those with decision making and agenda setting power to actively identify and dismantle the root causes of injustice in and through data practices and systems.

Rooted in collective as well as individual rights: Data justice calls for the protection of individual rights to be augmented with the promotion and protection of communal rights. Data today is so closely intertwined with our social and economic organisation and outcomes, that the need to base data regulation on data rights has to be recognised as a key political imperative. Advancing data justice through an individual and collective rights-based approach must include: the right to benefit from one's data—including non-personal data that has been co-generated by a wider community; the right to avoid both individual and communal harm; the right to access and port one's data; the right to appropriate individual and collective representation in data, including to remaining invisible; and the right to participate in governing both personally and collectively-generated data, and the data systems based on it.

Democratic governance: One important way of identifying and understanding inequality and injustice is through greater participation, representation and governance, specifically of those currently most marginalised. Impacted communities should have a voice in how their data is collected and used, and the ability to participate in data-driven systems. Beyond tokenistic forms of engagement and consultation, the participation of impacted communities in data collection and use must be advanced in representative democratic institutions and political processes which ensure accountability.

Sovereign skills and infrastructure: An investment in sovereign skills and infrastructure empowers the creation of local solutions and benefits from locally generated data, and gives local regulators expert knowledge to draw upon to develop local policy solutions that meet local needs. Without a concurrent investment in sovereign capability, effective policy will be difficult to create and enforce, and there will be no competitive pressure for larger companies to meet local expectations.

Fair data sharing: Communal data rights also encompass responsible data sharing. Calls for “open data access” can sometimes risk opening up opportunities for existing commercial interests to appropriate and exploit data assets, alongside raising privacy and data sovereignty concerns. Advancing data justice calls for the establishment of robust regimes of social licence and public consent, so communities can equitably access and benefit from their data. This includes by ensuring the provision of public data infrastructure which allows people not only to port or own their personal data, but to gain access to and beneficially use public data resources.

Fair representation in data: The ways in which data is collected and used can have the effect of imposing inappropriate categories and labels onto people, or erasing distinctive identities in data’s representation of the world. Cleaning, sorting and categorising data in order to train AI/ML systems involves human choices. The humans who make these choices are influenced by their specific social and cultural contexts and worldviews. This can result in binary categorisations being imposed onto people in the treatment of their data. This can reinforce the dominance of particular groups, and erase the identities of other groups, miscategorise them, or render them less visible. Data justice calls for us to mitigate and challenge the grouping-together, erasure or omission of identity characteristics which are valued or claimed by people whose data is represented or used.

Fair distribution of ownership and value: Data is a societally-produced resource which has the ability to create enormous value, but ownership and value is concentrated amongst a few powerful firms in the data-driven economy. This is enabled by processes of data extraction, where people and communities are dispossessed of the data they produce, and do not benefit from it. The uneven distribution of the value and ownership of data follows uneven historical and geographical patterns of dispossession. Data justice calls for the economic value of data to be shared equitably across and within countries.

Conclusion

The concept of data justice has been advanced by a global community of researchers and activists as a way to challenge the broad and diverse harms that have resulted from processes of datafication. Data justice moves beyond individualised understandings of data rights as revolving around privacy, to interrogate the root causes of inequality and injustice, and how this is reproduced through data-intensive processes. This primer has described how the collection of data and its use in innovation including ML and AI systems can exacerbate existing patterns of social and economic marginalisation.

There is an urgent need for policy responses to datafication which advance data justice, by, localising and contextualising data rights and protections, and building sovereign data and infrastructure, ensuring affected communities can participate meaningfully in data governance, and guarding against the extraction and concentration of data as a resource and means of production, and ensuring equitable access to data resources and infrastructure.

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