



Small Data, Big Justice: The Intersection of Data Science, Social Good, and Social Services

Lauri Goldkind, Mamello Thinyane & Moon Choi

To cite this article: Lauri Goldkind, Mamello Thinyane & Moon Choi (2018) Small Data, Big Justice: The Intersection of Data Science, Social Good, and Social Services, Journal of Technology in Human Services, 36:4, 175-178, DOI: [10.1080/15228835.2018.1539369](https://doi.org/10.1080/15228835.2018.1539369)

To link to this article: <https://doi.org/10.1080/15228835.2018.1539369>



Published online: 13 Jan 2019.



Submit your article to this journal [↗](#)



Article views: 240



View Crossmark data [↗](#)



Small Data, Big Justice: The Intersection of Data Science, Social Good, and Social Services

Big Data, characterized by three features, volume, velocity, and variety (Laney, 2001), has become a buzzword and is used to predict people's behaviors and community-level trends. However, this market driven, aggregated, and dehumanized approach has also begun to penetrate social science research and practice, especially in healthcare, child welfare, and criminal justice settings. In this editorial, we aim to review the concept of Big Data from a critical viewpoint, then introduce a conceptual definition of Small Data, which we think, offers an antidote to the impersonal, machined approach of Big Data. Having defined Small Data and its relevance to social science research, practice, and education, next is established a theoretical link between Small Data and empowerment. Lastly, this editorial closes with a discussion of digital literacy as an imperative for students and professionals of human services.

The perils of big data

Big Data is a hybrid concept that accounts for both how data is created as well as how it is analyzed—the analytic techniques for making sense of the trends embedded in it (Goldkind & Wolf, 2015). Big Data, as a cultural conception, has captured the collective imagination as a solution for everything, from program development and building evidence-based practices, to enhancing policing in the form of predictive analytics and improving services in health and hospital settings (Raghupathi & Raghupathi 2014).

However, we view these applications of Big Data in the civil as well as government sectors from a critical viewpoint. First, significant reliance on such data sources could lead to challenges, in particular, a lack of representation of marginalized groups with limited digital footprints (Coulton et al, 2015). Boyd and Crawford (2012) also highlighted the cultural dimensions of Big Data, suggesting that while big data offers statistical power, it is by no means neutral; it comes encumbered with the values and choices of the individuals who program the datasets. For example, predictive analytics in the criminal justice arena, even when adjusted for factors such as race and gender, can “bake in” unfairness (Berk et al., 2017).

The significance of small data

There are a range of definitions on Small Data, which have come forward since the early 1990s, but more recently, Thinyane (2017), articulated a perspective of Small Data as a human-centric data valorization approach that incorporates the following key considerations:

1. A focus on the **individual**: where the data collected, especially within human development domains, at the individual level is analyzed and packaged to be actionable at the individual level.

2. **Heterogeneity:** A realization that Small Data is not only derived from multiple sources including crowd-sourced data, citizen generated data, and sensor data, but also that the data is inherently varied, multifaceted, and heterogeneous.
3. **Context-bound:** Data-noting that the interpretation and understanding of the data is linked to the sociocultural context from which the data is collected.
4. Data **provenance:** This is an aspect of data that allows for tracking data history and genealogy, as well as for attribution of data ownership throughout its evolution and transformation.
5. Data **utility:** Connected to the small data value should accrue toward the individuals and for their everyday well-being. Taken together, the Small Data imperatives are consistent and aligned with human services values for creating data agency and ownership.

Defining empowerment through a data lens

It is important to critically view and analyze how data is collected, who owns and can access and what purposes data is spent for. As multinational corporations (MNCs), especially information technology based MNCs, have emerged and gained more influence on society and the economy, marginalized groups and communities such as those living in poverty become even more vulnerable to “being exploited” in terms of their data (Newman, 2014). The core concepts of human-centered actionable approach and accessibility of Small Data is parallel to the human services approach. We cannot emphasize more how important it is that data should remain within the control and be accessible by those who are subjects to it. Furthermore, considering that Small Data can connect people and organizations with actionable, timely insights that are accessible, understandable, and critical for everyday tasks (Bonde, 2013), human service professionals need to work with clients to help them understand, generate, and protect data for their own needs. We believe this is an important way of “empowerment through data” in the digital age.

Human services professionals charged with the protection of human rights should have an intimate knowledge of the emergent field of Human Data Interaction (HDI). The founders of HDI urge the discipline to take responsibility for demanding transparency and ethics as the future becomes increasingly more data saturated and data dependent. Mortier and colleagues (2014) articulate three core principles: legibility, agency, and negotiability; all of which would serve to further an empowerment agenda and help individuals and communities understand and control their own data outputs and make better choices about their data.

Legibility is a key principle of HDI and is concerned with ensuring the comprehensibility of data and the associated algorithms, so that the individuals are aware of their data and the implications of its use. Agency focuses on the individual’s freedom and capacity to opt in or opt out willingly, and to exercise discretion over access to their data. Lastly, negotiability, is concerned with the how sociocultural relationships around data and data processing change over time. Negotiability recognizes that individuals and societies norms about data, the data’s legal and regulatory frameworks are not fixed and will likely change based on cultural norms and values as well as changes that evolve over time (Mortier et al., 2014). Legibility, agency, and negotiability are all eminently consistent with empowerment in the social work tradition. Where empowerment is defined broadly speaking as increasing the freedom of choice for the poor and

underrepresented and their ability to use actions to shape their own lives (Alsop & Heinsohn, 2005).


Encouraging digital and data literacy in human services practitioners

One solution to this fraught relationship with increasingly pivotal quantitative constructs is to encourage digital and data literacy for human services practitioners. Encouraging the inclusion of such content is consistent with the Human Rights Framework calling for the protection of dignity, transparency, accountability, and non-discrimination. These literacies encompass data provenance and data ownership issues as well as data ethics and empowerment matters. As a massive amount of personal data are collected, analyzed and traded, we introduce the topic of HDI to engage users with their data.


The core values and practices of Small Data, data justice and data literacy needs to be integrated in human services professional development, social work education and practice, and all of our allied professions. Our community-based organizations and human service providers in daily contact with vulnerable and underrepresented groups, can broker the engagement and participation of these marginalized individuals within the datasphere and can serve as protectors against informational exploitation and data discrimination.

References

- Alsop, R., & Heinsohn, N. (2005). Measuring empowerment in practice: structuring analysis and framing indicators, policy research working paper (World Bank).
- Berk, R., Heidari, H., Jabbari, S., Kearns, M., & Roth, A. (2017). Fairness in Criminal Justice Risk Assessments: The State of the Art, *1050*, 28.
- Bonde, A. (2013). Defining Small Data. Retrieved February 24, 2017, from <https://smalldatagroup.com/2013/10/18/defining-small-data/>
- Boyd, D., & Crawford, K. (2012). Critical questions for big data: Provocations for a cultural, technological and scholarly phenomenon. *Information, Communication & Society*, *15*(5), 662–679.
- Coulton, C. J., Goerge, R., Putnam-Hornstein, E., & de Haan, B. (2015). *Harnessing big data for social good: A grand challenge for social work* (No. 11). Working Paper.
- Goldkind, L., & Wolf, L. (2015). A digital environment approach: Four technologies that will disrupt social work practice. *Social Work*, *60*(1), 85–87.
- Laney, D. (2001). 3D data management: Controlling data volume, velocity and variety. *Meta Group Research Note*, *6*, 70.
- Mortier, R., Haddadi, H., Henderson, T., McAuley, D., & Crowcroft, J. (2014). Human-data interaction: the human face of the data-driven society. *arXiv preprint arXiv:1412.6159*. Retrieved from https://scholar.google.com/scholar?cluster=12432613886490259925&hl=en&as_sdt=0,33
- Newman, N. (2014). How big data enables economic harm to consumers, especially to low-income and other vulnerable sectors of the population. *Journal of Internet Law*, *18*(6), 11–23.
- Raghupathi, W., & Raghupathi, V. (2014). Big data analytics in healthcare: promise and potential. *Health Inf Sci Syst*, *2*(1), 3.
- Thinyane, M. (2017). Investigating an Architectural Framework for Small Data Platforms, *17th European Conference on Digital Government - Data for Societal Challenges (ECDG 2017)*, Lisbon - Portugal.


Lauri Goldkind
 Fordham University, New York, New York
 goldkind@fordham.edu  <http://orcid.org/0000-0002-0967-3960>

Mamello Thinyane

 <http://orcid.org/0000-0001-5900-0601>

*United Nations University Institute on Computing and Society,
Macau, Macao, China*

Moon Choi

 <http://orcid.org/0000-0001-8002-0113>

Korea Advanced Institute of Science and Technology (KAIST), Daejeon, Korea