Digital Technologies and the Welfare System

Data Justice Lab submission

Sept. 14, 2018

Summary

This submission is a response to Part D of the Special Rapporteur's call for submissions and is concerned with uses of new technologies in the welfare system. In this submission we outline what we know about where and how algorithmic systems are being used in the welfare system at the national and local level. We also outline our concerns about the potentials for these new systems to discriminate, exacerbate inequality, infringe upon citizen and human rights and disproportionately harm poor and marginalized communities. We summarize research that is ongoing and also provide five specific recommendations.

Research: Uses of data analytics in public services in the UK

We have carried out desk research, including media reports and freedom of information requests, to map where and how data systems are being used by local authorities across the UK, and have conducted a number of interviews relating to key case studies. Whilst the implementation of algorithmic decision-making systems is in relatively nascent form, often still being piloted by local authorities, there have been some significant developments since the push to make public services 'digital by default' (Cabinet Office, 2012). However, there is no systematic review or list available of such developments. Some examples of concrete practices are provided below.

Local Government

Predictive Analytics in Child Welfare	Hackney, Newham, and Tower Hamlets are using a system provided by Xantura to create risk profiles for families
Integrated and linked datasets to detect fraud, assess risk and allocate resources	- Camden has an IBM developed residents' index that links data sources from across Camden and uses probabilistic matching techniques for identity verification and fraud detection. - Bristol's Integrated Analytical Hub integrates data sources across Bristol and is used for a Think Family Database that includes predictive analytics around children at risk of exploitation. - Manchester uses a data sharing system called iBase to collate data about individuals and their networks, primarily in relation to the Troubled Families programme - Kent has created the Kent Integrated Dataset (KID) to stitch multiple datasets together, including health data. The dataset is pseudonymised. The data is used to anticipate and respond to population needs. - Kent is in the process of contracting Optum (part of United Health) to develop what is being called the KID2. Little is known about this new system. - Newcastle provides social workers with data dashboards to identify and assess 'concern factors' - Suffolk is developing a system called Connect Measure to combine data and spot trends, specifically in relation to social care. - Gwent and Avon & Somerset Police use a system called Qlikview to measure crime, allocate resources and to predict criminality at both neighbourhood and individual level. - Durham police has trialled the Harm Assessment Risk Tool (HART), an artificial intelligence system used to evaluate the recidivism risk of offenders.
Education	- Essex is testing predictive analytics to see if it can help determine children not ready for school. Doing so involves combining multiple datasets.

Counter Fraud	- Counter fraud hubs have started across local authorities in London. The goal is to 'prevent fraud and identify losses for investigation and recovery'.

Central Government

Department for Work and Pensions	The Department is trialling the use of artificial intelligence to detect benefit fraud; using machine learning and automation to process and respond to correspondence; producing data analytics and visualizations to inform policy-making; using big data analytics to learn more about claimants and using predictive modelling to anticipate future needs and for fraud detection.
Department for Education	The Department is using predictive analytics and dashboards to assess risks and performance in relation to schools, child care and social care
Ministry of Justice	The MoJ is using predictive analytics to develop treatment targets, predict recidivism, and make decisions about preventative measures and programs.
Home Office	The Home Office is developing machine learning systems to automate information gathering, stream applications and manage border controls

Summary of Risks and Concerns

The below list of risks and concerns draws on a combination of previous studies, media reports and research interviews with civil society groups working across digital rights and poverty and equality.

Lack of transparency and public knowledge

The decision and process by which data systems are implemented in public services is not accessible to the public, and it is not clear what oversight mechanisms are in place. This is particularly pressing in decisions which produce legal effects that engage human rights. An civil society actor and expert on the Troubled Families programme noted that despite having signed a consent form about their data being shared, many families do not know fully what they have consented to and are not making informed decisions. Obscurity can pacify and disempower citizens and civil society groups from engaging with developments.

Extent of data collection and sharing

Privacy issues are a prominent concern as a 'maximisation data process' has been a trend according to civil society, and the sharing of data not just with other agencies but also private sector companies and central government. Government data enables the production of deeply intimate profiles of people, particularly their vulnerabilities. We have already seen how personal data has been used by data brokers to target and exploit people, for example by selling lists of people suffering from particular illnesses, who were victims of rape or who were prone to addiction.[1] _Data in public services includes very sensitive data, and it is often very difficult to get rid of a particular marker once you have been identified, despite changing life circumstances. This can lead to continued stigmatisation. For example, Amnesty International's[2] research on the Gang Matrix demonstrates how surveillance and secret labels can wrongly stigmatize young people throughout their interactions with government affecting their opportunities and prospects as they look for work, seek housing and go through school.

Errors and false positives

Any algorithmic system used to identify fraud will produce false negatives and false positives, meaning some people will be wrongly identified as fraudulent and the system may miss others who are in fact fraudulent. Poor data quality can lead to misidentification of people, which becomes a particular problem for those under significant stress and living in precarious situations who may have to 'disprove' they have been falsely flagged. When an algorithmic system is used to identify fraud or overpayment and primarily targets vulnerable populations there is a high likelihood that those identified will not have the time, knowledge or resources to challenge decisions made about them. This is further complicated because details about how people are identified can be 'black boxed', meaning that citizens do not have access to information about how they have been identified.

Bias

Previous research has identified a number of ways that bias can be embedded in algorithmic systems. This can happened based on skewed datasets that include historical biases or asymmetries in data-sets (e.g. overcollection of data on certain subgroups, or exclusion of some parts of the population). Overwhelmingly, this has been linked to issues of marginalisation, poverty and inequality. Other research has highlighted the prevalence of bias in how variables are weighted in algorithms. For example, factors like employment, previous access of benefits, family history and education if highly weighted will reinforce bias.[3]

Inferential guilt: from citizens to suspects

Research has highlighted the risk of assigning inferential guilt to individuals.[4] Digitally generated suspicion compromises human rights. For example, fraud detection systems that pool and comb through all citizen data in effect are treating all citizens as potentially guilty. This can lead to a dangerous feedback loop as increased scrutiny may lead to increased enforcement. Moreover, one civil society actor noted how such an approach advances a system of risk management of personalised risk that is fundamentally at odds with the welfare state model that stems from societal risk pooling. The danger is that responsibility of attributes associated with risk becomes personalised and individualised.

Data literacy and technological dependency

Accuracy is a big problem when it comes to making use of algorithmic systems, but the accuracy rate of data systems is seldom discussed amongst practitioners using them (e.g. social workers). Research has shown that the outputs of predictive systems can influence and bias those using them even when they know that accuracy rates are an issue. The production of a risk score or a data visualization gives the impression of being scientific, objective and neutral when the system is embedded with assumptions and compromises.[5] This also raises concerns about the way in which technology may be used to pursue policy agendas whilst bypassing political deliberation about them.

Complexity and failure
Automated systems, particularly within the public sector, have been prone to fundamental flaws and failures, sometimes leading to a system collapse. In surveying reviews of failures a common refrain is that when 'modernizing' IT systems and services, failure often occurs when governments do not account for the complexity of the efforts they are undertaking. Such failures have huge costs both for the public sector as well as individuals who may suddenly stop receiving services.[6]

Public Private Partnerships
Government bodies often do not have the infrastructure and data science skills needed to make use of algorithms and artificial intelligence and this motivates them to develop public private partnerships in this area. Civil society groups highlighted how this can effectively lead to the 'outsourcing' of governance functions to technology companies. Further, technology companies are changing their strategy to be more involved in decision-making, expanding their remit of 'solutions' to include social issues and increasing private sector control over government data and services.[7] Sometimes local authorities will also seek to buy demographic data from consumer-oriented data brokers, transforming government knowledge of populations to be more marketing-driven. These trends introduce concerns with accountability, lack of transparency of how data is collected and combined, and raise questions about the extent to which profit motives come to displace public service motives.

Recommendations

Based on our research and expertise, we outline some recommendations below.

1. National and local governments should provide maps, or lists, of where and how algorithmic systems are being used and related data sharing. Publishing a list of where algorithms with significant impact are being used in central government, along with projects planned for public service algorithms, was a key recommendation of the Science and Technology Committee, but has so far been side-lined by Parliament. In addition to aiding transparency and public knowledge, local authorities should also be aware of developments, risks, benefits and challenges in relation to uses of data analytics that have happened elsewhere.

2. Proper consultations with stakeholder groups, including frontline staff, civil society groups and service-users, should be integrated into the decision-making process

surrounding any implementation of data systems for public services to allow for wider engagement, debate and intervention. Onus for engagement cannot lie solely with individual citizens.

3. Oversight and regulation pertaining to data protection, anti-discrimination and human rights needs to be transparent and properly enforced. A human rights impact assessment of any algorithmic process that involves decisions on access to or distribution of welfare should be a base-line requirement.

4. The possibility of 'opting out' needs to be prominently available and data collection and sharing practices within and beyond government should uphold a minimisation principle to protect people's privacy and avoid the risk of stigmatisation.

5. Anyone using data analytics to inform decision-making relating to welfare should be provided with data literacy training to be able to consider and reflect on issues of data quality, bias, errors and false positives.

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[1] Dixon, P. (2013) Congressional Testimony: What Information do Data Brokers Have on Consumers? World Privacy Forum, available: https://www.worldprivacyforum.org/2013/12/testimony-what-information-do-data-brokers-have-on-consumers/

[2] Amnesty International (2018) Met Police using 'racially discriminatory' Gangs Matrix database, available: https://www.amnesty.org.uk/press-releases/met-police-using-racially-discriminatory-gangs-matrix-database

[3] Gillingham, P and Graham, T (2017) Big data in social welfare: the development of a critical perspective on social work's latest electronic turn. *Australian Social Work* 70(2): 135-147. Keddell, E (2015) The ethics of predictive risk modelling in the Aotearoa/New Zealand child welfare context: Child abuse prevention or neo-liberal tool? *Critical Social Policy* 35(1): 69-88.

[4] Hu, M (2015) Big data blacklisting. *Florida Law Review*, 67: 1735-1809.

[5] Eubanks, V (2018) *Automating Inequality*. New York: Macmillan.

[6] Omar et al. (2017), Eubanks, V. (2015)

[7] Garrido, S, Allard, MC, Béland, J, Caccamo, E, Reigeluth, T, Agaisse, JP. 2018. IoT in the smart city: ethical issues and social acceptability, Montreal: CIRAIG, February, available: http://ville.montreal.qc.ca/pls/portal/docs/page/prt_vdm_fr/media/documents/ido_vi_revue_litt_final_en.pdf; Kitchin, R (2014b) *The Data Revolution*. London: Sage