INTELLIGENT BUT GENDERED

Lessons from Welfare Automation in the Global South

Shehla Rashid

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Research and writing

Shehla Rashid, Independent Policy Consultant

Editing and review

Khawla Zainab and Anuradha Ganapathy, IT for Change

Proofreading, design and layout

Intifada P. Basheer, IT for Change

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Table of Contents

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Shehla Rashid

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Abstract

This paper brings aboard examples of automation at welfare interfaces to draw certain theoretical takeaways, especially surrounding the gendered experience of digitality. Examples from various countries are discussed and three case studies from the Global South, purposively selected, are elaborated upon to illustrate specific points. It argues that while artificial intelligence (AI) holds the promise of improving human lives in its emphasis on 'augmenting' human capabilities, this does not seem to be the priority of welfare automation systems which are deployed by private entities at the behest of governments with an overt emphasis on cost saving. Automation could mean either the deployment of machine learning (ML) algorithms and/or automated decision-making (ADM), or profiling of welfare recipients based on integration of various databases. AI as an approach, today includes ML (both supervised and unsupervised), deep learning and neural networks, etc. (different from an earlier generation of rule-based AI systems). Owing to the inductive nature of reasoning in ML models, there is inductive bias both in their output as well as in the process of framing questions or 'tasks' because of 'what's possible'. Further, large and very large datasets necessitate huge computational capabilities, upskilling of personnel, cybersecurity measures, and constant upgradation of equipment. Hence, the costs of AI-based means-testing might offset much of the purported cost savings of targeted welfare delivery using AI. While digitisation can be rule-based, automated models tend to introduce arbitrariness which is the opposite of justice. Digitisation is a requirement today, but automation is a Big Data-enabled affordance, implying that algorithms need data more than welfare needs algorithms. This explains the current push for 'smart' governance across the Global South which offers huge real-life datasets and often, a regulatory vacuum. This paper highlights the risks of diversion of resources from welfare toward digitisation and automation; of private capture of public data; and of the use of public data and public infrastructure to build private capabilities without any improvement in welfare. It argues that while consent is an important issue, it is internal to the logic of datafication and is often vitiated in digital welfare initiatives.

1. Introduction

Artificial intelligence (AI) has tremendous potential to transform public service delivery, by making interfaces accessible using natural language processing (NLP), in identifying bottlenecks, and in freeing up human labour from routine tasks so that it may be deployed for empathetic problem solving. It has demonstrated clear promise in applications such as assistive care, water management by fine-tuning irrigation, and in augmenting medical diagnosis. While the priority in the first three phases of the industrial revolution (IR) has been to relieve humans of physical drudgery, the focus of the fourth industrial revolution (4IR) has been on identifying cognitive capabilities where machines can outperform humans. Algorithms are better at cognitive drudgery – repetitive application of simple criteria, recognising known patterns, etc., but humans continue to be better at creative thinking, emotional intelligence, empathy, and at recognising unknown or new patterns with very little data or training. Originality, sentience, and ingenuity are, after all, human traits. As a result, proponents of the so-called 'fifth industrial revolution' propose a harmonious application of machine intelligence in such a way as to reduce drudgery[1] and to 'augment' human cognitive capabilities, rather than seeking to replace them. Applied to welfare, this would mean that while the bulk of 'routine' applications is processed by an algorithm, human attention can be reserved for cases requiring special consideration, empathy, and creative thinking. Currently, this seems to be the strongest argument in favour of automating governance.[2] However, instances such as the 'digital only' nature of welfare automation in the UK with no recourse to appeal or human intervention belie this promise (Alston and van Veen, 2019). Also, as the example of Poland's now-scrapped automated profiling system for unemployed persons showed, clerical staff were unlikely to question profiling decisions made by the algorithm 99% of the time due to fear of reprimand, lack of time, or presumption of objectivity of the system (Misuraca and van Noordt, 2020), requiring closer scrutiny of AI's promise as a sidekick rather than as taskmaster.

Even if one were to take at face value AI's promise of reduction of drudgery, the way automation tends to be deployed at welfare interfaces does not necessarily reflect this priority. Major applications of AI for welfare tend to be centered around risk modelling and fraud detection, resulting in welfare cuts and, at times, even in phantom debts asking welfare recipients to repay "overpayments" as calculated by an algorithm with retrospective effect (Pilkington, 2019). It is not difficult to see why automation tends to prioritise austerity over the unrealised potential of AI, namely, empathetic problem solving – the companies that develop these technologies do not work for the poor, they work for government(s).[3] Technological systems incur huge costs, and public expenditure on them must be justified through cost savings in the long run. Once deployed, maintenance costs, upskilling of personnel, upgradation of equipment, cyber-security costs, etc., add up, making the goal of long-term cost savings ever more elusive. Cioffi et al., (2021) point out that the budgetary spending on the Ugandan national digital ID *Ndaga Muntu* was a little less that on welfare itself, demonstrating how digitalisation becomes an end in itself. In effect, the digital welfare state as a self-perpetuating entity becomes a mechanism for privately-owned technology companies to use public data to train and test their algorithms on, losing sight of welfare objectives or democratic imperatives. Alston (A/74/493, p. 5) notes that the digitisation of welfare systems is often accompanied by reductions in welfare budgets, exclusion of beneficiaries, strict forms of conditionality, and so on.

1 Automation, thus, tends to result in job polarisation or "hollowing out" of mid-skill jobs , see https://www.ilo.org/newyork/voices-at-work/WCMS_363034/lang--en/index.htm)

2 Earlier, minimising prejudice by 'impersonalising' decision-making was proffered as a promise. However, an increasing corpus of evidence shows that machine learning has only served to encode and automate prejudice.

3 See, for example: https://law.justia.com/cases/indiana/supreme-court/2019/19s-pl-19-0.html

AI has demonstrated promise in making healthcare more high-tech – allowing for collaboration, accelerating diagnoses, and for enhancing the experience of both doctors as well as patients. However, many aspects of digitality in the Global South have the effect of putting healthcare out of the reach of people at the margins. Healthcare automation firms insist on "experience" as the key for success of digital healthcare systems,[4] but while the digital as an enabler can enhance the experience of the digital 'haves', the digital as a conditionality can adversely affect the experience of digital 'have-nots'. Even after the Covid-induced push for digitalisation, stories of exclusion continue to pour in from the Global South. On 2 November 2022, a pregnant woman in the Indian state of Karnataka was turned away from a public hospital for not possessing a biometric identity card or a maternity card, even as she was under excruciating labour pain, resulting in her death, as well as the death of her newborns.[5] Access to healthcare should be universal, and there should be no conditionality for accessing maternal care in the first place, especially at a public health facility. For context, the capital of Karnakata is the Indian city of Bengaluru, which is an IT hub, showing how digital high-rises exist alongside underbellies of exclusion. Stories such as these abound and are indicative of social cleavages in impoverished, post-colonial contexts which are exacerbated by digital divides and exclusion.

Governments may respond to concerns of digital exclusion by retaining the analog mechanism(s) of governance processes (hybrid processes) while rolling out digital equivalents.[6] While analog equivalents of digital systems already exist, or can be implemented (see footnote 6), owing to simple and finite number of rules, the same is not true of AI systems which can classify, predict, profile, and exclude without a transparent, legible set of rules[7] (Kuziemski and Misuraca, 2020). The 'black box' nature of machine learning and deep learning systems implies that neither the public nor the designers themselves can trace back the 'rules' that were employed in arriving at a decision. These 'rules' are very often statistical 'patterns' that the system 'learns' from existing datasets and may be inferred through "post-hoc explainability" techniques, meaning that the 'method' used by the system for arriving at decisions is not legible in the ordinary sense (Ghassemi, Oakden-Rayner and Beam, 2021). This introduces arbitrariness, which is, by definition, the opposite of justice.[8] Thus, while digital systems done right can enhance transparency (APO, 2021), predictive analysis using artificial intelligence is obfuscatory, as its decisions cannot be traced back to a clear and legible application of rules (O'Neil, 2016; Dastin, 2018; Eubanks, 2018; Lecher, 2018; Niklas et al., 2018; Ghassemi et al., 2021).

2. Digitisation versus Datafication: Requirement versus Affordance

Digitisation and datafication are not the same thing. Digitisation of data and records, provision of online service delivery, digitisation of interfaces, e-governance, etc., is one thing. Predictive profiling – by training machine learning algorithms on population data to discover patterns, or by integrating various databases with welfare data to create 'risk profiles' and taking decisions based on these – is quite another (Fuentes and Venturini, 2021). Predictive profiling is a symptom of a datafied regime. Datafication is informed by the

4 See https://www.mobihealthnews.com/news/emea/roundup-philips-announces-new-chief-innovation-and-strategy-officer-robotics-improve-adult, for instance

5 See https://www.hindustantimes.com/cities/bengaluru-news/woman-newborn-twins-die-after-hospital-refuses-admission-in-karnataka-101667524802147.html

6 India's digital rollout of vaccination appointments through the 'CoWin' platform is arguably the first case of a digital-first public service delivery programme in the country. Initially - from April 2021 when the vaccination drive was inaugurated, till June 2021 - online registration was mandatory to avail of vaccination facility, leaving open the question of India's multi-layered digital divide. In June 2021, the government announced a 'walk-in' option for people aged 18-44 years, providing an analog equivalent to a digital-only public service delivery rollout.

7 The earlier generation of AI systems – rule-based AI – is different from AI in its present form which includes, predominantly, machine learning. Machine learning can be supervised or unsupervised. When supervised, the algorithm learns from training data that is labeled. Labeling may be done by a human expert, or the data may already be labeled (such as data from social media). When unsupervised, the algorithm itself classifies raw, unlabeled data into clusters, and discovers hidden patterns in it. Since both types of machine learning use real-life datasets (that is, datasets generated from human action whether in the physical or virtual world), both run the risk of encoding human biases (see Zhao et al., 2018).

8 See https://plato.stanford.edu/entries/justice/

belief that data tells the complete truth about a person or situation or society, and that humans may be disintegrated and resurrected by collecting disparate pieces of information on them and then integrating these disparate acts of data creation by linking various databases and mining this corpus of 'Big Data' for patterns. For example, the government can collect and analyse data about college dropout rates by gender and discipline. The digital nature of such data can facilitate better analysis and visualisation. Evidence-based policymaking might analyse this data to ensure greater retention of women in certain disciplines and create pull factors. Predictive algorithms coupled with ADM, on the other hand, tend to use this data to assess suitability (creditworthiness) of women for an educational loan, and to classify them as 'bankable' or otherwise, without taking into account their circumstances. The two can have diametrically opposite effects: while the first approach aligns with policy imperatives pertaining to inclusion, the other automates stereotypes and serves to exclude and triage people at the margins. Using AI and Big Data for predictive profiling, risk modelling, and 'fraud detection' is a political choice informed by assumptions about the poor or the vulnerable, and is geared toward saving costs by narrowing down criteria of eligibility. It is not a digital inevitability, but a Big Data-enabled affordance, meaning that there can be other uses of AI geared toward inclusive development and arising out of social necessities. For example, Japan has deployed AI, robots, and smart devices for assistive care in elderly homes – a prudent choice arising out of its demographic peculiarities. Often, however, welfare systems seem to follow a top-down approach where cumbersome solutions are deployed on unwilling populations, and not for fulfilling a social need.

The push for 'smart' governance and deployment of 'intelligent' (AI-based) systems at welfare interfaces in the Global South is an unfolding phenomenon (Fuentes and Venturini, 2021). Most vision statements mention "efficiency" and "welfare fraud detection" as potential objectives (see Kirkham, 2021, for instance). Even in the European Union, Misuraca and van Noordt (2020) found that the predominant use of AI in governance is in the use of "Chatbots" or "AI providing data-based predictions, through the recognition of patterns in datasets".[9] So, unlike digitisation, which has long become integrated in everyday actions, including governance, AI use in the public sector is currently, at best, basic or experimentative (DeSouza, 2018; Fuentes and Venturini, 2021). In this context, the availability of large public datasets in the Global South, coupled with weak data protection regulation, offers a ripe scenario for private players to leverage public data without limitations. Empirical evidence shows that machines can get better at identifying patterns over time, even as the human learning curve experiences stagnation due to cognitive overload after learning a certain number of patterns (Kühl et al., 2022). However, machines need significantly larger datasets to learn with accuracy (ibid.). This means that, at present, algorithms need datasets more than data subjects need algorithms. This 'scramble for data', especially when foreign firms are involved, has been critiqued for having colonial undertones (Coleman, 2019; Couldry and Mejias, 2019). As Halevy, Norvig and Pereira (2009) wrote of Big Data-based models: "simple models and a lot of data trump more elaborate models based on less data".

The Global South offers large datasets, weak data protection regulation, very little data literacy, and privacy awareness among welfare recipients, trailing legal frameworks and, very often, fiscal obligations on governments to reduce spending under structural adjustment programmes (SAPs). This mix favours a certain kind of tech-solutionism geared toward cost-savings. Not only are the legal frameworks trailing, but also missing are the cost-benefit analyses, pilots, risk-assessment studies, etc. Fuentes and Venturini (2021) note how the adoption of AI-driven solutions for the Global South often results from a pitch made by a private party, rather than from a needs-based assessment by a public agency. Cioffi et al., (2021) describe it as the reversal of evidence-based policymaking. The framework of algorithmic colonisation is being used to

9 See report summary at https://joinup.ec.europa.eu/collection/elise-european-location-interoperability-solutions-e-government/document/report-ai-watch-artificial-intelligence-public-services-overview-use-and-impact-ai-public-services

describe both AI solutions parachuted into former colonies, as well as extractive Big Data practices (Coleman, 2019; Couldry and Mejias, 2019). Chile's controversial Sistema Alerta Niñez (children at risk system) has seen the involvement of some of the same consultants whose similar efforts in New Zealand had earlier been shot down by the Fifth National Government (Kirk, 2015; Ballantyne, 2021; Peña, 2021; Valderrama, 2021). The recycling of solutions for the Global South shows that necessity might not be the mother of invention here, but the other way round.

Digitisation has enabled useful mechanisms such as direct cash transfers which have a wide subscription base in countries such as India and Brazil, testifying to their success and utility. However, as critics of India's biometric identification system (*AADHAAR*) have pointed out, direct transfer of benefits is contingent neither upon possession and production of a biometric ID, nor upon its linkage with other governmental and financial databases (Khera, 2019c, footnote 6). As of October 2022, after several legal challenges to the mandatory nature of *AADHAAR*, the Government of India's webpage[10] on Direct Benefit Transfer (DBT) explicitly mentions that *AADHAAR* is not mandatory for DBT, illustrating the point that it is not an inevitability but an affordance. While DBT is an example of digital systems done right,[11] its *AADHAAR* linkage has been criticised as being a symptom of a datafied regime, as it can track the social and financial behaviour of beneficiaries and result in surveillance.

Having a very large training dataset necessitates significantly higher computational power, higher training costs, longer training time, etc., which means that their implementation to welfare interfaces may not result in cost-savings in the short- or possibly even medium-term; it might, in fact, take away from welfare efforts by virtue of being more expensive and resource-intensive than welfare itself. In other words, deployment of high-accuracy AI might necessitate welfare cuts. It also necessitates the 'discursive regularisation'[12] of the idea of welfare fraud and may, thus, stigmatise welfare in the process. Bender et al., (2021) have also famously pointed out the environmental impact of large language models that rely on 'too much data' and their implications for much of the Global South which is already at the receiving end of environmental injustice. Targeted delivery of welfare using algorithmic means-testing incurs high costs, including environmental, which may not be offset by cost-savings on welfare in the long run, not least because human development fosters national productivity.

3. Datafication and Gendered Experience(s) of Digitality

Datafication is the belief that every human act that creates data can be leveraged for value creation through data processing and interlinkages, even though these human actions might be discriminatory or value-laden. As pointed out earlier, a datafied regime tends to collect disparate pieces of data on humans (such as shopping habits, health statistics, search queries, data on debt repayment instalments, hiring decisions, etc.) – thus disintegrating humans – and then resurrecting them by 'mining' the large datasets thus obtained for 'patterns' which can tell the truth about humans through 'personas' or profiles. Virginia Eubanks puts it rather succinctly:

10 See https://dbtbharat.gov.in/page/frontcontentview/?id=MTc=

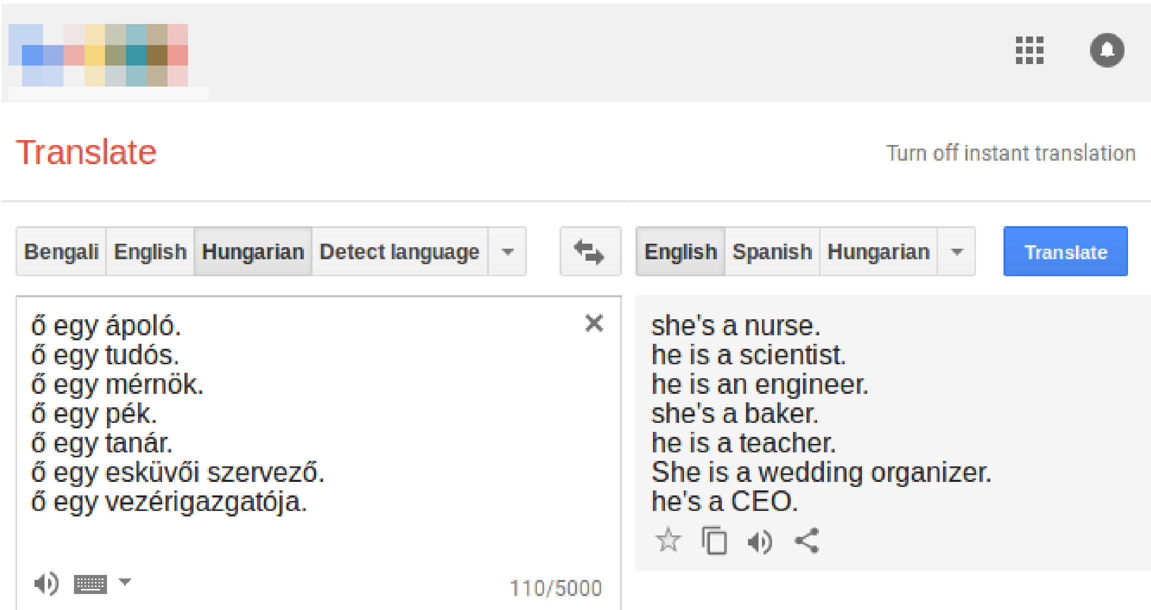
11 DBT has been criticised for facilitating centralisation of state power because the payments are perceived as being made by a central authority, even if they are made out of state- or local-level funds, but that's a separate issue.

12 Nissenbaum draws on Bryan Pfaffenberger to define 'discursive regularisation' as "the processes that establish the political aims of a technology".

Predictive models promise more effective resource allocation by mining data to infer future actions of individuals based on behavior of "similar" people in the past.[13]

Such 'inferred identities' can be devoid of context, uncritically depicting the results of discriminatory human social action as 'the truth', and worse, taking automated decisions based on it. At times, this process of resurrection might over-emphasize certain patterns[14] which get over-represented through data. In mimicking human behaviour, algorithms can end up mimicking us a 'bit too well', foreclosing alternative possibilities. A well-known case is that of a recruiting engine employed by e-retail giant Amazon, which observed hiring data to 'learn' that women were less employable in the IT industry, thereby filtering out their resumés using gender-based markers such as participation in women's clubs or enrolment in women's colleges (BBC, 2018). While this is an example of allocative harms caused by a 'skew' in real-life datasets, there are also representational harms whose effects are less immediate, more long-term and diffuse, that are much more difficult to quantify or pin-point, as their impacts are cultural.[15] Prates, Avelar and Lamb (2019) conducted an experiment where Google Translate was tasked with translating sentences from gender-neutral languages into English. They found that the translations ended up encoding androcentric assumptions about job roles (see Figure 1).

Figure 1. Andocentric translations of job roles from a gender-neutral language into English by Google Translate



Source: [Prates, Avelar and Lamb (2019)]

Similar findings have been reported in other experiments (see Zhao et al., 2018, for instance). These models might be 'intelligent' in that they mimic human social actions and structures, but this isn't necessarily desirable. Conversely, even slight deviation from mimicking human behaviour tends to be comical, absurd,[16] or dangerous,[17] a reminder that attributing 'intelligence' or emancipatory potential to machine learning is either misplaced or premature. Machine learning – whether supervised or unsupervised – broadly follows the inductive method because it is based on Big Data and past patterns. Not only does this automate inductive biases, as several commentators have pointed out, but even the range of problems that can be defined is

13 See https://www.wired.com/story/excerpt-from-automating-inequality/

14 All 'ideal types' are exaggerations at some level. The use of ideal types in sociology broadly corresponds to the use of 'personas' in user-experience modeling and marketing.

15 See https://www.youtube.com/watch?v=fMym_BKWQzk

16 See https://www.youtube.com/watch?v=eKRpiMBlu40 and https://openreview.net/pdf?id=hUzjN3Sjrc

17 See https://www.theguardian.com/technology/2017/oct/24/facebook-palestine-israel-translates-good-morning-attack-them-arrest

inductive for example, the claim that teenage pregnancy or child abuse can be predicted based on proxies for poverty. Untested, commonsensical hypotheses are framed as 'tasks' for AI, and entire systems are designed around them. Paullada et al., (2021) point out that the presumption that certain tasks are "solvable" by ML might often be "pseudoscientific", and while ML systems might learn some "shortcuts" that can be mistaken for "learning", there is a need to pay more attention to the way that questions and tasks for ML are framed. Extrapolation and prediction through inductive reasoning based on Big Data and past patterns has value in applications such as weather forecasting, but the same when applied to the human world ends up encoding human biases, automating, and potentially amplifying them.[18] These systems might be 'intelligent' insofar as they appear to (Bender et al., 2021) mimic human thinking, but they might well be gendered just as the human social world is, at times more effectively so.[19] Bender et al., (ibid.) also point out how large language models are likely to encode cis-normative language and worldviews. 'Value lock-in' is a situation where an AI system may encode current worldviews due to its data-focus and this isn't always desirable.

Studies in the Global North have documented harms of ADM in welfare and social protection schemes (O'Neil, 2016; Eubanks, 2018; Lecher, 2018) but the Global South has its own peculiarities and context.[20] For example, lopsided, often redundant and incomplete datasets might affect how poor people or persons with disabilities are accounted for. Other peculiarities include the authority structure in the household which might affect how women experience the effects of digitisation and automation. Lack of technological literacy among women is a well-known issue. While state officials who interact with the human-computer interfaces from the state's end receive training and education, no such model of training exists for welfare recipients who may often have little or no exposure to digital interfaces – this being especially true of women who may not share in the ownership and usage of digital devices in the household and whose use of communication technologies might even be stigmatised. For example, in a mother and child tracking system (MCTS) in India which promised to send SMS alerts to expectant mothers about referral, follow-ups or risk notifications, two-thirds of the women who provided a contact number at all, gave their husband's contact number (Nagarajan, Tripathy and Goel, 2016). South Asia has the widest gender digital divide in the world in terms of smartphone ownership (Gillwald, 2018). In terms of gender divide in internet access, Rwanda and Bangladesh are the worst (62%), closely followed by India (57%). These divides intersect with other inequalities and are broadly aligned with GNI per capita (ibid.), meaning that the problem is particularly acute in Global South contexts. Barring a few countries (such as Paraguay, South Africa, and Argentina), gender digital divides in the Global South are much higher than the world average (OECD, 2018).

Cioffi et al., (2021) documented cases of denial of access to healthcare to women in Uganda on account of not possessing the national digital ID *Ndaga Muntu* even if they were in labour pain, pregnant and bleeding, in need of antenatal care, in labour, and in need of surgery, etc. Uganda faces unique challenges of high maternal mortality rate (MMR) and adolescent pregnancy (ibid.) which makes the situation even more dire. About 36% of maternal deaths occurred in women below the age of 24 (loc. cit.). The situation is complicated by social and gender norms that might discourage girls and young women from seeking reproductive healthcare, especially if they have faced gendered violence (loc. cit.). Since *Ndaga Muntu* is an adult registration programme, it has been primarily targeted at registering people of voting age (ibid.). This could

18 This is not to say that errors due to inductive reasoning in forecasting weather patterns can't have consequences for the human world. In fact, the inventor of weather forecasting, British Admiral Robert Fitzroy, faced intense criticism for wrong or delayed forecasts. Fitzroy eventually killed himself in 1865 (see https://www.bbc.com/news/magazine-32483678). Simon LeVay in *When Science Goes Wrong* (2008) records another such case of weatherman Michael Fish who, a century after Fitzroy's death by suicide, earned a lifetime of notoriety for having failed to convey the prediction of Britain's 'Great Storm' of 1987. Today, however, weather forecasts are far less controversial and predictive models far more accurate, as they do not solely rely on past data and inductive reasoning, but combine inputs from satellite imagery and radar technology with modern-day supercomputing abilities.

19 See also https://www.vice.com/en/article/j5jmj8/google-artificial-intelligence-bias

20 See https://towardsdatascience.com/is-artificial-intelligence-the-frontier-solution-to-global-souths-wicked-development-challenges-4206221a3c78 for a quick overview of AI use in the global South.

mean that pregnant girls or younger women are already largely excluded from seeking access to reproductive healthcare, family planning, and exercising reproductive autonomy because of the insistence on the national ID for providing healthcare (ibid.).

Exclusion is not the only hindrance that impairs women's experience of digitality; they may be discriminated against through inclusion and subjected to unfavourable profiling. Niklas et al., (2015) note that the automation of the Polish employment assistance system relegated single mothers (besides other vulnerable categories) to "Profile III" – a kind of "junk" category indicating that they were the least employable. It is important to clarify that this exercise in profiling resembles triaging rather than affirmative action. People who were categorised adversely were less likely to have access to "active labour market programs" in violation of non-discrimination guarantees laid down in the Polish Constitution and EU law (ibid.). One of the criteria that may have led to adverse categorisation of female candidates has to do with care work or child-rearing responsibilities, since these two forms of labour are often assigned to women (loc. cit.). Once a woman was partially relieved of care responsibilities, re-categorisation was not a straightforward option. The frontline workers usually asked them to deregister and then register again (ibid.). The programme was later held unconstitutional by the Supreme Court of Poland (Supreme Court of Poland, case No. K 53/16, 6 June 2018).

While the above discussion largely pertains to women's experience of digitality, the use of algorithms in criminal justice systems might unfavourably profile men (in addition to racialised minorities) for being wanted for crimes, for being predisposed to crime, or for recidivism risk. The use of facial recognition technology (FRT) for cracking down on crime in Brazil was reported as targeting young, Black, and male individuals in most of the cases (Nunes, 2019). Within the Global South, Malaysia has deployed AI in the criminal justice system, raising similar concerns (Putera et al., 2022). The use of algorithms in the criminal justice system raises a host of issues about due process, transparency, the rule of law, the right to receive an individualised sentence, and the fairness of using gender proxies in the system.[21] Since criminal sentencing algorithms are of proprietary nature and protected as trade secrets, it is difficult to investigate the extent of bias.[22]

4. Privacy for Algorithms, Transparency for Data Subjects

A rather peculiar feature of digital welfare systems is that while people's personal data itself is not accorded due privacy – it can be extracted, stored, processed, exchanged between databases, used to train ML models, and so on – the algorithms that operate upon the data function as a black box; the profiling criteria, the weightage that is assigned to various parameters such as age, income level, health status, etc., is not disclosed; the algorithms are not open to public audit, and it is unclear as to how data is shared among databases, departments, and public and private entities. These practices of data collection and processing are often shrouded in mystery. So, while it is people who should have a right to privacy and data sovereignty, it is algorithms and data processing mechanisms and practices that are accorded secrecy. Alston (A/74/493, p. 4) notes that data-driven predictive analysis in governance systems renders citizens hyper-visible to their governments, though not the other way round, as if in a Foucauldian panopticon (ibid., footnote 5). The example of the Polish employment assistance system shows that welfare candidates were refused access to the questionnaire that formed the basis of collecting their data and of subsequently profiling

21 See https://harvardlawreview.org/2017/03/state-v-loomis/

22 This paper focuses on welfare automation, and on automation on the *pretext* of welfare, and does not engage substantively with the debate on the use of AI in the criminal justice system, which is a vast subject in its own right, given the complex and problematic histories of the criminal justice system itself.

them, even though the questionnaire was subject to disclosure under public information law (Niklas et al., 2015). The labour office employees were reported as saying that this was done in order to safeguard the profiling algorithm from manipulation by candidates, as knowledge about the profiling criteria might lead to biased answers by candidates (ibid.). This shows distrust in and suspicion of citizens, lack of good faith assumptions, and, most importantly, that certain kinds of personal data, demographic information, health status, care responsibilities (often a gender proxy), physical ability, or age might indeed result in adverse categorisation – discriminatory practices which are not permissible under the Polish constitution that provides only for discrimination that is proportionate or positive (affirmative action): whether the profiling criteria imbibed proportionality or affirmative measures was always unclear due to lack of transparency of the exercise. Another issue of transparency arose from the fact that the unemployed were not sure whether their responses to various questions were being faithfully recorded by the frontline workers in the computer system (ibid.).

The privacy and welfare conundrum

Welfare imperatives impart a moral veneer to extractive practices of data collection and data processing. Cioffi et al., (2021) note that the focus on privacy and data protection, though important, can posit a false dichotomy between privacy and welfare, as if privacy were the price that one pays for welfare entitlements. However, as the experience of digital ID systems shows, they have done little to enhance welfare or the experience of welfare recipients. On the contrary, the deployment of digital systems at the welfare interface has often meant the addition of “new hurdles at the finishing line” (Khera, 2019a) as the experience of various countries has shown (Gray, 2019; Youle, 2019; Cioffi et al., 2021). It is important, therefore, to avoid falling for the welfarist cloak of digital systems and question the supposed dichotomy between the right to life and the right to privacy. In fact, the Supreme Court of India in a historic judgment (Puttaswamy v. UoI, 2017), in the context of digital ID, held that the Right to Life under Article 21 of the Constitution of India includes the Right to Privacy. Finally, on the question of privacy itself, ‘consent’ seems to be offered as a kind of silver bullet. Therefore, it is important to problematise the notion of consent itself from a feminist perspective.

5. Problematising Consent in Digital Systems: Questions of Agency, Power, and Labour

The liberal critique of datafication tends to posit consent as the precondition for data extraction and processing. This sounds fair if consent is not diluted or coerced. But what are the preconditions for consent itself? Who can consent and under what conditions? A modern individual bearing the right to consent must necessarily be “free, autonomous, and rational” (Varon and Peña, 2021). When is a data subject truly ‘free’ to consent? There are two criteria for determining if a person is free:

A) When they are otherwise free, that is, not confined, and not having restricted legal rights

B) When their freedom is not contingent upon the act of consenting

The first criterion describes free citizens bearing legal rights and is true for most welfare recipients under ordinary conditions, but the second criterion describes a more substantive aspect of freedom which determines whether the capacity to consent exists in a meaningful way. For a welfare recipient, it is not enough to be ‘free’ in a literal sense alone. If withholding consent leads to denial of public services or welfare provisioning, this can severely affect the experience and meaning of freedom.

A fundamental problem with digital welfare systems is the way the notion of consent is conceived, presented, and operationalised. Welfare and/or public service provisioning is becoming increasingly conditional upon the data subject's willingness to part with their privacy, thereby vitiating the sanctity of consent and tainting it with coercion. India's *AADHAAR* biometric IDs, for example, were touted as being 'optional' for accessing public services while being *de facto* mandatory (see Johari and Jain, 2015; Divan, 2019; Drèze, 2019; Johari, 2018b; Srinivasan, 2019). While the government maintained that enrollment in the programme is voluntary, banks, welfare institutions, and other establishments insisted that citizens produce these digital IDs to access services (ibid.). Researchers have documented cases of *AADHAAR* -related deaths where otherwise eligible welfare recipients faced starvation because of exclusion on account of non-possession of *AADHAAR* or non-linkage of their *AADHAAR* numbers to their ration cards or due to failures of biometric authentication (Johari, 2017, 2018; The Wire, 2017-19). This means that (non-possession of) *AADHAAR* can literally cause exclusion to the point of starvation. In the Polish employment assistance programme, Niklas et al., (2015) note that while an unemployed individual could refuse to be profiled, they could be penalised for doing so (p. 12, 31). For refusing to consent for the first time, one could be excluded from the employment system by way of denial of the status of unemployed person for 120 days. For refusing a second time, the punishment increased to 180 days. For the third time, and for each subsequent refusal, 270 days (ibid.). This rather perverse system of getting people to consent was coercive, to say the very least. It presented a choice between profiling on the one hand, and denial of even the possibility of being considered for welfare assistance on the other. Very few candidates refused to be profiled after being confronted with the options (p. 31).

This shows that, in digital welfare systems, the logic of data processing precedes and is prioritised over the logic of welfare. So, a data subject who withholds consent (or is otherwise excluded from the system) is 'free' to starve, even if we assume that the other two conditions: autonomy and rationality of the data subject are met. In other words, the act of consenting is a function of power, and, therefore, the person who gives consent must have some power to begin with (Marling, 2017, cited in Varon and Peña, 2021). Are women (or the poor or disabled) in welfare contexts empowered enough to give or withhold consent? Are they even aware that they hold this power, or do they, on the other hand, feel obligated to consent? Does the very act of consenting to the use of their personal data disempower them by subjecting them to profiling and tracking?

While consent is an important concept and is crucial for agency and assertion of will, digital welfare systems might end up using it as a tool to legitimise practices that subject welfare recipients to exclusion and profiling. It is, therefore, internal to the logic of datafication. Even when a data subject can be said to be free, autonomous, and rational, it is pertinent to ask whether they have the capacity to fathom the possible future uses of the data, especially in the case of intelligent systems where future uses are unclear even to the designers of the system. In other words, do we even know what we are consenting to? Varon and Peña (2021) argue that this black box nature of algorithms also gives data processors enough legroom to deny full information to data subjects as to what could be the possible future uses of their data, what new data it could be used for creating, and even about the risks of the present use of the data.

The matter of consent is further complicated when the data subjects are minors (Bhardwaj, 2019). In India, several schools require children to produce a biometric ID (*AADHAAR*) to seek admission (India Spend, 2019; Roy Chowdhury, 2017a), access midday meals or other entitlements such as scholarships (Roy Chowdhury, 2017b), making it *de facto* mandatory to enrol them into the biometric ID programme. In at least one Indian state, it was reported that *AADHAAR* is mandatory for babies to get a birth certificate (Rao, 2017) implying that infants are to be enrolled almost as soon as they are born, rendering consent meaningless. Since there is no way to opt out of the system later, the issue of consent becomes especially fraught. Finally, the *AADHAAR* linkage efforts for children imposed heavy amounts of unpaid, unrewarded labour on schoolteachers who had to abandon teaching activities in order to facilitate *AADHAAR* registration for students (see Roy Chowdhury, 2017a, 2017b). Seeing as teaching at the school level is a feminised profession, this burden likely falls disproportionately upon women. Even otherwise, the issue of unpaid labour is a feminist issue. Digital systems often tend to impose extra labour on frontline workers while taking away at least some of their discretionary power, their ability to comprehend the decisions made by the system, or their power to redress grievances (Mukherjee, 2014; Niklas et al., 2021). Very often, this burden of unpaid work tends to fall upon women, as is seen in the case study of the MCTS system in India and the case of the Ugandan digital ID *Ndaga Muntu* (also discussed under the MCTS case study).

Let us now look at some of the case studies, sampled purposively, that illustrate some of the specific points made so far.

Case Study 1 – Using Public Data to Build Private Capabilities: Lessons from India's AADHAAR project

The push for digitisation of governance systems is often articulated in terms of streamlining welfare through accurate identification and targeting of recipients, an effort that immediately necessitates creation of a 'database' of welfare candidates. Such databases or 'social registries' are already in place in various countries (Guha and Viswanathan, 2021). In the absence of data regulation and purpose limitation, these databases render themselves to being used for purposes other than welfare delivery, Government of India's *AADHAAR* biometric identification system being a case in point. Even though *AADHAAR* is not a database of welfare beneficiaries, but a database of all Indian 'residents', it was initially justified in altruistic terms (welfare delivery, etc.). The *AADHAAR* ecosystem now resembles a swiss knife around which various applications have developed (Yadav, 2016; Somvanshi and Desouza, 2018; Sriram, 2019). The creation of this ecosystem is supported by the private sector in innovative collaboration patterns (Ramanathan, 2019; Sriram, 2019). The government collects and renders citizen data usable in an interoperable form (API) over which private players and/or technologists can build applications, and they can then sell the applications to either the government or to other private entities (Gandhi, 2016). Public infrastructure is leveraged to pave way for building a seamless commercial ecosystem (see Ramanathan, 2019). These collaboration patterns are in tandem with the general move toward network governance in India (Rathi and Tandon, 2019) which, though not limited to ICTs, has achieved a new summit in the digital age where the private sector seems to be leading the government, as is evident from the key role that the Indian Software Product Industry RoundTable (iSPIRT) plays in the development of public technology in India[23] (Khera, 2019a, p. 17-18). This has also triggered fears about private capture of public data (Ramanathan, 2013; HT, 2017). Even if an application simply queries the government-owned *AADHAAR* database without actually having access to the data, there isn't much stopping it from retaining the data and creating its own database of identities and associated data points, in the absence of a data protection legislation. Furthermore, the government can have access to a wide range of information about an individual's activity depending on what queries they make, or what queries are made about them because of the public-private linkages (Rajshekhar and Yadav, 2016).

23 See https://ispirt.in/who-we-are/our-game-plan/

The *AADHAAR* project has been ridden with data leaks and concerns about data security and privacy (Mohan, 2018; Somvanshi and Desouza, 2018), not least because a data protection law governing the use of citizen data is missing in India.[24] Both commercial as well as welfare payment systems are integrated with *AADHAAR*, making the world's largest biometric database a tinderbox of security vulnerabilities, with very little concern for its original constituency – the welfare beneficiaries at the bottom of the pyramid – who might often be one fraud transaction away from bankruptcy (Mukherjee, 2022). In August 2022, India's Data Protection Bill that had been pending in Parliament since 2019 was withdrawn by the government, and one of the reasons given by the Minister of State for Electronics and Technology, Rajeev Chandrasekhar, was that a complicated privacy regime would have hurt the start-up ecosystem.[25] The Minister for Communications, Electronics and Information Technology, Ashwini Vaishnaw's insightful piece on upcoming legal frameworks that will replace the now-scrapped data protection bill and the vintage telecom and IT laws signals digital economy and start-up ecosystem as priorities (Vaishnaw, 2022).

The rationale for linking welfare provisioning to a biometric database is usually justified by the government on the pretext of leakages in welfare. It is argued that direct cash transfers, for example, minimise the possibility of benefits ending up in the wrong hands (see Khera, 2019a). While it is true that direct cash transfers can eliminate quantity fraud and leakages, it is pertinent to ask whether a biometric ID is indispensable for such an effort. One of the most bitter critics of the *AADHAAR* project, Dr. Reetika Khera, concedes that digitisation has in fact "contributed to better implementation" of certain social welfare programmes (see, Khera, 2019c, footnote 6), but that digitisation is possible without *AADHAAR* and is not synonymous with a biometric ID system. Khera (2019a, p. 22, footnote 1) notes that "portability and interoperability of cash transfers only require access to a modern banking system". Not only is *AADHAAR* not necessary for transferring direct benefits to the poor, it has, in many cases, increased the transaction costs for the poor (Johari and Jain, 2015; Sriram, 2019). Pregnant women are denied maternal care on account of not possessing an *AADHAAR*, or for errors on their *AADHAAR* card (which are routine), or for having married into a different state, in which case they are asked to produce the husband's *AADHAAR* card – all this despite there being little to **no evidence of identity fraud or leakages in accessing maternity benefits** (Yadav and Rao, 2017; Khera, 2019b).

The question, then, arises as to what the real intent of the project is. The *AADHAAR* project presupposes functional and digital literacy, high speed internet, seamless connectivity, and electricity – factors which make its implementation in rural areas, low-income areas, and at welfare interfaces ridden with challenges. However, it works rather perfectly as a backbone for the commercial payments ecosystem. Ramanathan (2016; 2019) and Sriram (2019) argue that this is a case of using public data, public infrastructure, and public finances for the cause of building a commercial ecosystem. This should inform skepticism about claims of future technologies that are justified in altruistic terms. Welfare automation in the Global South, for instance, is justified in terms of welfare streamlining, better targeting of beneficiaries, cutting out fraud, etc. However, as discussed earlier, algorithms need data more than welfare needs algorithms. This is because AI/ML exhibit very strong network effects – while models trained on thousands of instances might not be very accurate, those trained on millions of data points tend to be very 'accurate'[26] (Halevy, Norvig and Pereira, 2009). Hence, there are, at least, two clear attendant harms that could arise from welfare automation:

24 The *AADHAAR* project itself was created without the existence of a corresponding legislation or 'Act' – often a peculiar feature of digital systems.

25 See https://www.moneycontrol.com/news/business/complicated-data-protection-bill-would-have-hurt-startups-rajeev-chandrasekhar-8947571.html

26 The use of the term 'accurate' is qualified because, as discussed earlier, this isn't always desirable.

A) Possible diversion of resources from welfare efforts toward digitalisation

B) Possible capture of public data by private entities, or worse, by rogue actors

Cioffi et al., (2021) found that the total budget for the Ugandan Ministry of Gender, Labour and Social Development (MGLSD) for the past 10 years – 770.1 Billion UGX – was a little more than the spending on the national ID project – 745 Billion UGX – over the same period. This excludes grants such as the World Bank's 10 million USD to the NIRA (National Identification and Registration Authority) through the Uganda Reproductive, Maternal and Child Health Services Improvement Project (ibid.). Grants routed through welfare departments might end up being used for the digital identity system, as digitisation is made to sound synonymous with welfare upgradation. Since initiatives for women's welfare, maternal care, elderly care, etc., make the state look benevolent, and impart a moral veneer to extractive data practices, these might be a perfect vehicle for pushing the digital ID. This could also mean that funds that are meant for, or acquired in the name of, women's welfare or elderly care might be at a greater risk of being re-routed for digitalisation. Thus, gender gets interwoven into the digital welfare state's narrative. Women's welfare can become a pretext for pushing digitalisation, often at the cost of women's actual welfare.

Case Study 2 – Poverty Profiling and Sexist Algorithms: The Case of a Teenage Pregnancy 'Prediction' Model in LatAm

The Governor of Salta, a northwestern province in Argentina, kicked up a storm on 10 April 2018, when in the midst of a debate on decriminalisation of abortion, he announced the plan to pilot an artificial intelligence program developed by Microsoft that can "predict which girls will be teenage mothers in the future, or will become pregnant, and based on that apply public policies to prevent it" (Sternik, 2018, translated using Google Translate). It is no surprise that the algorithm ended up profiling teenage girls from vulnerable sections of the society, based on lazy, prejudiced indicators such as neighbourhood, ethnicity, access to hot water, country of origin, disability, educational status of the head of the family, etc., instead of more meaningful indicators such as contraception methods or access to sex education (ibid.). However, the bigger question is whether such a system was needed at all, and whether Big Tech companies should have stronger ethics reviews in place to avoid association with questionable efforts like these. One of the most burdensome impacts of ill-informed AI programmes that ignore millennia of debates on gender issues is the additional labour that they inflict upon rights advocates who now need to piece apart the childish aspects of such efforts, reinventing the wheel on gender rights, when it is technologists who ought to have done their due diligence and done the hard work of educating themselves on such issues before rushing to touch sensitive aspects of social life. This is, of course, next only to the disastrous impacts of such AI on vulnerable people and on welfare efforts – stigma, exclusion, and digression from what could have been real efforts at change. Instead of aligning itself with and augmenting time-tested, existing approaches, the tech industry's obsessive need to position its solutionism as 'out-of-the-box' can in fact put it out of touch with reality at times.

When the system was being built, Argentina was in the middle of a debate on reproductive rights, and this AI seems to have been a classic case of techno-solutionism which can presumably 'fix' teenage pregnancy before it happens by predicting whom it will happen to! What are the problems with this approach?

1. The algorithm profiles teenage 'girls' for potential pregnancy, as if girls conceive without the involvement of a male partner. It does not make any attempt, say, to profile the men/boys who bear the other half of the responsibility for the pregnancy. As such, Peña and Varon (2021) warn that this system comes dangerously close to furthering the logic of victim blaming. Teenage pregnancy can often result from sexual assault, and 'prediction' of such pregnancies should, therefore, be logically contingent upon predicting who is likely to commit assault. Naturally, this is missing from the worldview of the AI solutionists.

2. Such an approach deflects from efforts that are actually needed to prevent teenage pregnancy, such as sex education, access to contraception, and prevention of child sexual assault. However, the conservative stance is usually against sex education and access to contraception, etc. (see Vallejos, 2018 for example). The conservative stance is also often hyperfocussed on the female body and doesn't differentiate between sex and assault. It is no surprise, then, that this effort was found to be aligned with anti-abortion movements (Sternik, 2018; Peña and Varon, 2021) given its focus on targeting girls, avoiding affirmative efforts, and avoiding difficult conversations. Peña and Varon (2021) write: "The idea that algorithms can predict teenage pregnancy before it happens was the perfect excuse for anti-women and anti-sexual and reproductive rights activists to declare safe abortion laws as unnecessary".

3. The Laboratory of Applied Artificial Intelligence (LIAA) of the University of Buenos Aires (UBA) analysed the methodology of the program and concluded (LIAA, n.d.; Sternik, 2018) that the data on which the algorithm was trained was the same data on which it was tested.[27] This could explain Microsoft's claim that the AI had an accuracy of 90% (Microsoft, 2018).

4. The data used for building this AI is unreliable, sensitive, confidential, and based on biased indicators that run the risk of profiling vulnerable sections of society (LIAA, n.d.). This is known as 'poverty profiling', a term used by Virginia Eubanks to describe oversampling of the poor.

5. The Governor of Salta who announced the project, Juan Manuel Urtubey, is a conservative politician. In his words, "With technology you can predict five or six years before, with name, surname and address, which is the girl, future teenager, who is 86 percent predestined to have a teenage pregnancy." (Sternik, 2018 cited in Peña and Varon, 2021). It doesn't take an AI expert or sociologist to explain or understand the trauma and stigma involved in being marked out as a risk for possible teenage pregnancy and as a case for 'intervention' and the impact that that could have on a girl's social life.

6. On a purely technical level, what the system did was survey girls from "vulnerable sectors of society" (Microsoft, 2018, translated using Google Translate) about whether they had had a teenage pregnancy and then, based on their answers and social indicators, draw patterns to profile other girls bearing the same social indicators for teenage pregnancy. The LIAA pointed out that this is a flawed approach at a methodological level because it relies on a subject's willingness to report a teenage pregnancy, which is a sensitive topic and is unlikely to be honestly reported (LIAA, n.d.). It warrants mention that, at the time of the events, Argentina hadn't yet legalised abortion which was

27 Machine learning algorithms are 'trained' on a dataset which is called 'training data' which must be different from the 'test data' – a previously unseen dataset that can confirm whether the model works or not.

> available to women only in extreme cases (Watson, 2020, cited in Peña and Varon, 2021). Argentina's strong Catholic Church and its allied sections vehemently oppose abortion and it is only in 2020 that a progressive abortion law was passed (Watson, 2020). It is safe to assume that the subjects did not accurately report present or past pregnancies and that there was a significant error rate in the training data.

This is a classic case of a tone-deaf system that should not exist in the first place, and it points to a need for greater scrutiny of the very process of framing questions or 'tasks'. The presumption that pregnancy can be predicted by correlating proxy variables for poverty is an example of pseudoscientific definition of an AI task highlighted by Paullada et al. (2021).

Despite criticism, not only did the system continue to be used, but it was also implemented by governments across South America such as Colombia and Brazil (Peña and Varon, 2021).

Case Study 3 – The MCTS Programme in India: Decontextualising Maternal Care

The Mother and Child Tracking System (MCTS)[28] in India was launched with the aim of reducing maternal mortality rates (MMR) and improving antenatal care and childcare, providing immunization services, and encouraging institutional deliveries, especially in high-risk cases (Gera et al., 2015). Traditionally, in India, the frontline healthcare worker who monitors pregnancies, high-risk cases, and child immunization is known as the ANM (Auxiliary Nurse Midwife) and she is typically responsible for 1,000 households catering to a population of roughly 5,000 (Mukherjee, 2014). Earlier, the ANM would collect data locally and consult with the doctors at the local health centre to act upon high-risk cases, ensuring follow-up and routine examinations (ibid.). The new MCTS system centralises this process, necessitating the additional work of collecting granular data, which needs to be uploaded to a centralised computer system, as opposed to the earlier system where the ANMs would report only aggregate numbers to the higher levels (ibid.). A 2014 field-level study of the implementation of MCTS (ibid.) showed that the system created increased data entry workload for ANMs (p. 133). ANMs were found to line up at cyber cafes after work hours to update the entries. Some outsourced the data entry work to cyber cafes on their own expenses, while some took help from family members such as children (ibid.). The issue of overburdened ANMs has been documented in several field studies (Gera et al., 2015; Nagarajan et al., 2016). An overwhelming majority of the ANMs are female.[29]

Pressure is put by the Centre on the states and by the states on the officials to complete system generated enrollment 'targets' based on population metrics (Mukherjee, 2014, p. 133). These officials in turn put pressure on lower levels to achieve targets, the ANM being at the bottom of the pyramid and, as such, at the receiving end of a disproportionate performance burden. The ANMs faced salary cuts for registration below 70% and no incentives for registration above 90% (ibid.). There exists an elaborate system of punishment for ANMs including public shaming, explanation letters, and "negative performance remarks recorded in service books which are the basis for annual confidential appraisals and other benefits". (ibid.). The top health official in the state receives an SMS every morning with the performance indicators (registration percentage) and comparison with other states, putting a kind of peer pressure on them to incentivise higher registrations (ibid.). This system is clearly automated. How does the Centre know the number of pregnant people and

28 See https://apps.gov.in/apps/government/mother-and-child-tracking-system-mcts

29 Later on, the ANMs were renamed MPHW (multi-purpose health workers) and were classified into MPHW (male) and MPHW (female), once men started taking up ANM work.

ideal percentage of registrations? This number is a system-generated statistical average based on population metrics and the registration percentage is calculated based on this statistic (ibid.). The other automated component of the system is the system of SMS alerts to the ANM about high-risk cases and to the expectant mother in case she needs referral or a follow-up (ibid.). However, this system does not work perfectly (ibid.). A 2016 study found that only 80% of expectant mothers provided a mobile number, two-thirds of which were operated by their husbands (Nagarajan et al., 2016, cited in Tandon, 2019). Of the remaining one-third who provided their own numbers, a mere 22% received an SMS from MCTS out of which only one-third could actually understand its content (ibid.). The system was often very slow and malfunctioned due to lack of electricity, poor internet connectivity, slow server speed, or other contingent factors (Mukherjee, 2014; Gera et al., 2015; Nagarajan et al., 2016).

Aside from technical issues, ANMs reported de-contextualisation of their work with the focus shifted solely to registration numbers, outputs and targets (Mukherjee, 2014). While the original target of this name-based tracking system was individualisation rather than a focus on MMR aggregates, the focus is now once again on numbers and performance aggregates (ibid.). As opposed to the earlier system where focus would be on discussing high-risk cases, now it's just about numbers. Mukherjee (ibid.) contends that the very genesis of the program was rooted in data-obsession, without a theory of how data focus would strengthen healthcare (p. 134). System designers had an IT focus, not a public health focus, so they did not understand the nitty-gritties of maternal care or of child healthcare (ibid.). The system, Mukherjee writes, was "very resource intensive involving large scale computerization, servers, mobile phones and training efforts in the use of the software", (ibid.) with little to no focus on understanding the contextual setting.

Quoting directly from Mukherjee (2014):

> the needs and constraints of the field nurse were practically ignored. The information which she already had in her registers, was transformed into digital form using a complex and expensive paraphernalia, sent up to the national level, and finally returned to the nurse - but most often too late for her to take any action based on that. (p. 134)
>
> This data focus comes to a large extent at the cost of care, as she feels now they are no longer being able to find local solutions to risk cases, as they are more dependent on the MCTS to provide them with blueprints for action. (p. 135).

Mukherjee (2014) concludes that the system has not empowered healthcare workers with better information which could be used to provide better care, but has, on the contrary, disempowered them by taking away their agency to act upon the data, imposing massive amounts of unpaid labour upon them along with salary cuts and out-of-pocket costs, public shaming, reprimand, etc. – at the cost of actual healthcare. Using a framework for analysing 'empowerment', Mukherjee argues that the MCTS system has resulted in disempowering the healthcare workers by taking away their control of the data and the autonomy to act upon it (ibid.).

Tandon (2019) reports that the cumbersome process of data collection has been redressed in part through the introduction of 'tablets' which are provided to the ANMs and which can be used to record data at the source. While this has reduced the duplication of effort in data collection and recording (first manual and then digital data entry), ANMs continue to perceive data collection as "an additional burden rather than reducing or streamlining workload" (ibid.). The MCTS program is an example of system design conceived without the involvement of stakeholders and whose implementation is imposed upon them rather than taking a collaborative approach and treating them as partners. A similar experience is reported by frontline healthcare workers in Uganda who point out that the digital ID, *Ndaga Muntu,* acts more as a requirement than an enabler. Cioffi et al., (2021, p. 17) note that while local healthcare workers are supposed to collect national ID numbers of new mothers (as a pre-requisite for treating them), the same workers find themselves unable to help these new mothers acquire birth certificates for the newborns because of the complications and confused mandate of NIRA (National Identification and Registration Authority) regarding birth registrations (ibid.). As a result, the healthcare workers also face backlash within their own communities, prompting the healthcare staff to enforce their own local policy change of not requiring the national ID in order to avoid further confrontation with their communities (ibid.). Healthcare workers reported (ibid.) how the ID numbers are recorded in a notebook which is physically stored in a room forever. This, in simple words, means that while the digital ID adds nothing to the existing healthcare system, it only serves to exclude.

9. Conclusions

In light of the discussions above, it is clear that welfare and democratic imperatives need to be foregrounded while automating welfare interfaces. Deployment of technological solutions should come from a bottom-up assessment of needs and demographic peculiarities, rather than from applications recycled from dissimilar contexts. It is also important that applications be piloted, evaluated, and then implemented, so as to avoid large-scale inconvenience, tweaking, and rollbacks. In India, there is a pronounced tendency to launch "national-level" digital initiatives without piloting these. The back-and-forth tweaking and the endless adjudication it causes is likely to distract from welfare itself. There is a need to assess how far the costs of means-testing using Big data are likely to offset the intended cost-saving of targeted welfare delivery. Automated means-testing using AI and Big data incurs costs (including costs of personnel upskilling, equipment procurement and upgradation, cyber security, social impact assessment, environmental costs, etc.) which should be evaluated against the costs of universalising welfare. The government of India has, for example, universalised access to free of cost foodgrains for the poor from 1 January 2023. In general, healthcare and education should be unconditional and universally affordable. There should be no conditionality on accessing reproductive and maternal healthcare. Austerity measures in basic human development sectors are unlikely to pay off – even if the 'offset' is in favour of means-testing – as human development is an investment into national productivity. Use of AI, IoT and robotics in assistive healthcare can improve the quality of life for patients but questions of access need to be addressed through strong democratic institutions and processes. Automation should serve to improve the quality of life, and not as conditionality to triage those at the margins.

Arguments in favour of an 'augmentation' role for AI are powerful, but evidence shows that defying the algorithm (not least because of its overstated capabilities) might not be a straightforward matter. Skepticism about AI's role can be informed by theoretical analyses, from greater transparency about its error rates, its inductive nature, and from questions about the validity of its 'tasks.' In the absence of this skepticism, AI can skew human decision-making capabilities or affirm confirmation biases. Justice is the opposite of arbitrariness, and the black box nature of algorithms introduces significant arbitrariness in public functions. These issues become extremely crucial, since AI is being increasingly used in criminal justice systems, including in the Global South. The argument of 'augmenting' human capabilities and reduction of drudgery is also belied by the amounts of unpaid labour that digital transformation tends to impose on frontline staff, often women. Also, ML models often stand on the shoulders of human annotators, training datasets for algorithms, often contracted through platforms (Paullada et al., 2021) creating a new data science precariat the subjective value of whose labour is often unacknowledged, let alone understood or accounted for.

Decontextualisation of work and imposition of drudgery was observed in the MCTS case study, and it is often a feature of datafication. AI should not try to fix what is not broken. In order to achieve its ‘augmentation’ role, the very process of framing questions ought to be consultative, foregrounding human welfare, social impact and environmental concerns, not the needs of the algorithm (namely, unbridled, unrestricted access to data). A key feature of digital systems is that they develop in a regulatory vacuum, operating literally beyond the law. This is often used to push measures that should not have seen the light of the day due to their substantive effects on rights. Once these systems are fully developed, with all their technological paraphernalia, institutions, personnel, and mechanisms, they become locked-in, rendering legal challenges or recall impossible. In this way, they subvert democratic process and set bad precedents for governance. Governments must, therefore, address the regulatory vacuum surrounding AI use and establish guidelines for responsible and ethical AI, in light of concerns raised by scholars and activists.

Reproductive health has often been a site of experimentation for technologisation (including practices amounting to 'medicalisation of birth'),[30] digitisation and, increasingly, automation. Some of these can end up doing substantive harm to women and pregnant people, as the protagonists of tech-solutionism may often be people for whom reproduction is a black box. Tech-solutionism can also deflect from affirmative efforts that must be guaranteed, such as unconditional access to maternal healthcare, access to reproductive choice, access to contraception, sex education, etc. It is, therefore, important to tread very carefully, consult stakeholders, subject the hypotheses to testing and validation before framing them as tasks, and pilot solutions while following principles of informed consent to prevent harms. Corporations should have strong ethics reviews in place to evaluate what values and discourses they enable, and to anticipate harms. Greater diversity in policymaking, in AI and data science, and in public discourse might mitigate these harms to some extent.

30 See https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8079552/ for feminist critiques of reproductive technologies.

References

Alston, P. (2017). The Populist Challenge to Human Rights. *Journal of Human Rights Practice*. Vol. 9, No. 1, pp. 1–15. https://doi.org/10.1093/jhuman/hux007

Alston, P. (2020). *What the "digital welfare state" really means for human rights.* Open Global Rights. https://www.openglobalrights.org/digital-welfare-state-and-what-it-means-for-human-rights/

Alson, P., & van Veen, C. (2019, June 27). *How Britain's welfare state has been taken over by shadowy tech consultants*. The Guardian.

APO. (2021, February). *Digitalization of public service delivery in Asia*. Asian Productivity Organization.

A/HRC/41/39/ADD.1. (2019, April 23). *Report of the Special Rapporteur on extreme poverty and human rights on his visit to the United Kingdom of Great Britain and Northern Ireland presented to the forty-first session of the UN Human Rights Council*. United Nations. https://documents-dds-ny.un.org/doc/UNDOC/GEN/G19/112/13/PDF/G1911213.pdf?OpenElement

A/74/493. (2019, October 11). *Report of the Special Rapporteur on extreme poverty and human rights presented to the seventy-fourth session of the UN General Assembly*. United Nations. https://documents-dds-ny.un.org/doc/UNDOC/GEN/N19/312/13/PDF/N1931213.pdf?OpenElement

Ballantyne, N. (2021). *"Not on My Watch!" - A Case Study in the Datafication of Child Welfare in Aotearoa New Zealand*. Ph.D. Thesis. DOI: 10.13140/RG.2.2.36088.98563

BBC. (2018, October 10). *Amazon scrapped 'sexist AI' tool.* BBC. https://www.bbc.com/news/technology-45809919

Bender, Emily M., Gebru, T., McMillan-Major, A., & Shmargaret, S. (2021). On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?. In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, pp. 610-623. https://dl.acm.org/doi/pdf/10.1145/3442188.3445922

Berryhill, J., Heang, K., Clogher, R., & McBride, K. (2019). Hello, World: Artificial intelligence and its use in the public sector. *OECD Working Papers on Public Governance*, No. 36, OECD Publishing, Paris, https://doi.org/10.1787/726fd39d-en

Bhardwaj, K. (2019). The Relevance of Children's Consent under a Mandatory Aadhaar Regime in (ed.) Khera, R. *Dissent on Aadhaar: Big Data Meets Big Brother,* pp. 166-172. Orient BlackSwan.

Chari, M., Yadav, A., & Chowdhury, M. (2017, March 5). *Not just mid-day meals: Aadhaar made mandatory for 11 more schemes, violating Supreme Court ruling.* Scroll.in. https://scroll.in/article/830946/not-just-mid-day-meals-aadhaar-made-mandatory-for-11-more-schemes-violating-supreme-court-ruling

Chased Away and Left to Die: How a National Security Approach to Uganda's National Digital ID Has Led to Wholesale Exclusion of Women and Older Persons. Center for Human Rights and Global Justice, Initiative for Social and Economic Rights, & Unwanted Witness. Available at https://chrgj.org/wp-content/uploads/2021/07/CHRGJ-Report-Chased-Away-and-Left-to-Die.pdf

Coleman, D. (2019). Digital colonialism: The 21st century scramble for Africa through the extraction and control of user data and the limitations of data protection laws. *Michigan Journal of Race and Law*, Vol. 24, No. 2, pp. 417-439. https://repository.law.umich.edu/mjrl/vol24/iss2/6

Couldry, N., & Mejias, U. A. (2019). Data colonialism: Rethinking big data's relation to the contemporary subject. *Television and New Media*, Vol. 20, No. 4, pp. 336-349. https://doi.org/10.1177/1527476418796632

Dastin, J. (2018, October 11). *Amazon scraps secret AI recruiting tool that showed bias against women.* Reuters. https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-tool-%20that-showed-bias-against-women-idUSKCN1MK08G

Divan, S. (2019). Aadhaar's Biometric Tsunami: Will it sweep away Privacy, drown Civil Liberties? in (ed.) Khera, R. *Dissent on Aadhaar: Big Data Meets Big Brother,* pp. 124-136. Orient BlackSwan.

Drèze, J. (2019). A Unique Identity Dilemma in (ed.) Khera, R. *Dissent on Aadhaar: Big Data Meets Big Brother,* pp. 59-71. Orient BlackSwan.

Eubanks, V. (2018). *Automating Inequality: how high-tech tools profile, police, and punish the poor*. New York: St. Martin's Press.

Fuentes, P., & Venturini, J. (2021). *Decisiones automatizadas en la función pública en América Latina.* Derechos Digitales América Latina. https://www.derechosdigitales.org/wp-content/uploads/CPC_informeComparado.pdf

Gandhi, R. (2016, March 30). *India Stack - How the Government is disrupting itself.* The Economic Times. https://economictimes.indiatimes.com/small-biz/security-tech/technology/india-stack-how-the-government-is-disrupting-itself/articleshow/51612453.cms?from=mdr

Gebru, T. (2019). *Race and Gender*. https://arxiv.org/pdf/1908.06165.pdf

Gera, R., Muthusamy, N., Bahulekar, A., Sharma, A., Singh, P., Sekhar, A., & Singh, V. (2015). An in-depth assessment of India's Mother and Child Tracking System (MCTS) in Rajasthan and Uttar Pradesh. *BMC health services research*, 15(315). https://doi.org/10.1186/s12913-015-0920-2

Ghassemi, M., Oakden-Rayner, L., & Beam, A. (2021). The false hope of current approaches to explainable artificial intelligence in health care. *The Lancet Digital Health*, Vol. 3, No. 11, pp. 745-750. https://doi.org/10.1016/S2589-7500(21)00208-9.

Gillwald, A. (2018, November 2). *Understanding the gender gap in the Global South*. World Economic Forum. https://www.weforum.org/agenda/2018/11/understanding-the-gender-gap-in-the-global-south/

Guha, D., & Viswanathan, A. (2021). *Social welfare delivery in the digital age.* The Times of India. https://timesofindia.indiatimes.com/blogs/developing-contemporary-india/social-welfare-delivery-in-the-digital-age/

Gupta, S. (2015). *Perils of the Paperwork: The Impact of Information and Application Assistance on Welfare Program Take-Up in India*. J-PAL. https://www.povertyactionlab.org/sites/default/files/research-paper/Perils-of-the-Paperwork_Gupta_Jobmarketpaper_November2017.pdf

Gray, J. (2019, February 11). *Amber Rudd Admits Universal Credit Increased Foodbank Use.* Huffington Post. https://www.huffingtonpost.co.uk/entry/amber-rudd-universal-credit foodbanks_uk_5c6193e1e4b0f9e1b1801925?utm_hp_ref=uk-homepage

Halevy, A., Norvig, P., & Pereira, F. (2009). The unreasonable effectiveness of data. *IEEE Intelligent Systems*, 24 (2009), pp. 8-12. https://storage.googleapis.com/pub-tools-public-publication-data/pdf/35179.pdf

Hare, A. (2020). *Overcoming under-subscription of welfare programs: Digital solutions to low take-up*. J-PAL. https://www.povertyactionlab.org/blog/11-24-20/overcoming-under-subscription-welfare-programs-digital-solutions-low-take

HT. (2017). *Aadhaar debate: Privacy remains central challenge*. Hindustan Times. https://www.hindustantimes.com/india-news/aadhaar-debate-privacy-remains-central-challenge/story-9jDKnnKbVpxcc5OyhzWZYK.html

India Spend. (2019, December 10). *Because of Aadhaar, over one million children in India were denied admission to schools*. Scroll.in. https://scroll.in/article/946285/because-of-aadhaar-over-one-million-children-in-india-were-denied-admission-to-schools

Khera, R. (2019a). Introduction in (ed.) Khera, R. *Dissent on Aadhaar: Big Data Meets Big Brother,* pp. 1-24. Orient BlackSwan.

Khera, R. (2019b, December 7). *How Aadhaar is making it harder for Indian women to access their maternity benefits.* Scroll.in. https://scroll.in/pulse/945587/how-aadhaar-is-making-it-harder-for-indian-women-to-access-their-maternity-benefits

Khera, R. (2019c) Aadhaar and Privacy in (ed.) Khera, R. *Dissent on Aadhaar: Big Data Meets Big Brother,* pp. 72-85. Orient BlackSwan.

Kirk, S. (2015, July 30). *Children 'not lab-rats' - Anne Tolley intervenes in child abuse experiment.* Stuff. https://www.stuff.co.nz/national/health/70647353/children-not-lab-rats---anne-tolley-intervenes-in-child-abuse-experiment

Kirkham, R. (2021, January 19). *7 ways AI could restore trust in public services.* World Economic Forum. https://www.weforum.org/agenda/2021/01/ai-trust-public-services/

Kühl, N., Goutier, M., Baier, L., Wolff, C., & Martin, D. (2022). *Human vs. supervised machine learning: Who learns patterns faster?* Cognitive Systems Research. Pre-print: https://arxiv.org/pdf/2012.03661.pdf

Kuziemski, M., & Gianluca, M. (2020). AI governance in the public sector: Three tales from the frontiers of automated decision-making in democratic settings. *Telecommunications Policy*, Vol. 44, No. 6. DOI: https://doi.org/10.1016/j.telpol.2020.101976

Lecher, C. (2018, March 21). *What Happens When An Algorithm Cuts Your Health Care.* The Verge. https://www.theverge.com/2018/3/21/17144260/healthcare-medicaid-algorithm-arkansas-cerebral-palsy

LIAA. (n.d.). *Sobre la predicción automática de embarazos adolescentes*. LIAA. https://liaa.dc.uba.ar/es/sobre-la-prediccion-automatica-de-embarazos-adolescentes/

Marling, B. (2017). *Harvey Weinstein and the Economics of Consent.* The Atlantic.

Martinho-Truswell, E. (2018, January) *How AI Could Help the Public Sector*. HBR. https://hbr.org/2018/01/how-ai-could-help-the-public-sector

McCully, J. (2020). *Explainer: What is the "Digital Welfare State"?* Digital Freedom Fund. https://digitalfreedomfund.org/explainer-what-is-the-digital-welfare-state/

Microsoft. (2018, April 2). *The use of Artificial Intelligence advances in Argentina with experiences in the public, private and NGO sectors.* News Center Microsoft Latin America. Web archive available at http://web.archive.org/web/20220120021530/https://news.microsoft.com/es-xl/avanza-el-uso-de-la-inteligencia-artificial-en-la-argentina-con-experiencias-en-el-sector-publico-privado-y-ongs/

Misuraca, G., & van Noordt, C. (2020). *AI Watch Artificial Intelligence in public services: Overview of the use and impact of AI in public services in the EU.* European Commission. EUR 30255 EN, Publications Office of the European Union, Luxembourg, 2020, ISBN 978-92-76-19540-5, doi:10.2760/039619, JRC120399.

FinTech Futures. (2018, March 26). *What is the India Stack and why is it no longer the dream it used to be?* Fintech Futures. https://www.fintechfutures.com/2018/03/what-is-the-india-stack-and-why-is-it-no-longer-the-dream-it-used-to-be/

Mukherjee, A. (2022, June 24). *Aadhaar: What's putting world's largest biometric ID system at risk?* Mint. https://www.livemint.com/opinion/online-views/aadhaar-what-s-putting-world-s-largest-biometric-id-system-at-risk-11656054154911.html

Mukherjee, A. (2014). Who's data is this anyway? Understanding relationship between power, empowerment and technology: Case from Mother and Child Tracking System (MCTS) in India in *Proceedings of the 9th Health Informatics in Africa Conference HELINA'14,* pp. 130-135.

Nagarajan, P., Tripathy, J., & Goel, S. (2016). Is mother and child tracking system (MCTS) on the right track? An experience from a northern state of India. *Indian Journal of Public Health*, Vol. 60, No. 1, pp. 34-39. https://www.ijph.in/article.asp?issn=0019-557X;year=2016;volume=60;issue=1;spage=34;epage=39;aulast=Nagarajan

Niklas, J., Sztandar-Sztanderska, K., & Szymielewicz, K. (2015). *Profiling The Unemployed In Poland: Social And Political Implications Of Algorithmic Decision Making.* Panoptykon Foundation.

Nikore, M., & Uppadhayay, I. (2021, August 22). *India's gendered digital divide: How the absence of digital access is leaving women behind.* Observer Research Foundation. https://www.orfonline.org/expert-speak/indias-gendered-digital-divide/

Nunes, P. (2019). *Levantamento revela que 90,5% dos presos por monitoramento facial no brasil são negros.* The Intercept, Brasil. https://theintercept.com/2019/11/21/presos-monitoramento-facial-brasil-negros/

OECD. (2018). *Bridging the Digital Gender Divide: Include, Upskill, Innovate*. OECD. https://www.oecd.org/digital/bridging-the-digital-gender-divide.pdf

O'Neil, C. (2016). *Weapons of Math Destruction*: *How Big Data Increases Inequality and Threatens Democracy*. New York: Crown.

Paullada, A., Inioluwa, D., Raji, E., Denton, E., & Hanna, A. (2021). Data and its (dis)contents: A survey of dataset development and use in machine learning research. *Patterns*, Vol. 2, No. 11. https://doi.org/10.1016/j.patter.2021.100336.

Peña, P. (2021). *Shielding Neoliberalism: "Social Acceptability" to Avoid Social Accountability of A.I.* Notmy.ai. https://notmy.ai/news/case-study-a-childhood-alert-system-sistema-alerta-ninez-san-chile/

Peña, P., & Varon, J. (2021). *Teenager pregnancy addressed through data colonialism in a system patriarchal by design.* Notmy.ai. https://notmy.ai/news/case-study-plataforma-tecnologica-de-intervencion-social-argentina-and-brazil/

Pilkington, Ed (2019, October 14). *Digital dystopia: how algorithms punish the poor.* Automating Poverty Series, The Guardian. https://www.theguardian.com/technology/2019/oct/14/automating-poverty-algorithms-punish-poor

Prates, M., Avelar, P., & Lamb, L. (2019). *Assessing Gender Bias in Machine Translation - A Case Study with Google Translate.* https://arxiv.org/pdf/1809.02208.pdf

Putera, Nurus., Saripan, H., Bajury, M., & Ya'cob, S. (2022). Artificial Intelligence-Powered Criminal Sentencing in Malaysia: A conflict with the rule of law. *Environment-Behaviour Proceedings* Vol. 7, no. SI7 (2022), pp. 441-448.

Rajshekhar, M., & Yadav, A. (2016). *How the government gains when private companies use Aadhaar.* Scroll.in. https://scroll.in/article/805467/how-the-government-gains-when-private-companies-use-aadhaar

Ramanathan, U. (2013, April). *Aadhaar: Private ownership of UID data- Part I.* Money Life. https://www.moneylife.in/article/aadhaar-private-ownership-of-uid-data-part-i/32430.html

Ramanathan, U. (2016, March 16). *The future is here: A private company claims it can use Aadhaar to profile people.* Scroll.in. https://scroll.in/article/805201/the-future-is-here-a-private-company-claims-to-have-access-to-your-aadhaar-data

Ramanathan, U. (2019). Aadhaar - from Welfare to Profit in (ed.) Khera, R. *Dissent on Aadhaar: Big Data Meets Big Brother,* pp. 173-186. Orient BlackSwan.

Rao, M. (2017, May 1). *Haryana is making babies enrol in Aadhaar before it will issue them birth certificates.* Scroll.in. https://scroll.in/pulse/835970/babies-in-haryana-are-being-enrolled-in-aadhaar-before-they-are-issued-birth-certificates

Rathi, A., & Tandon, A. (2019, February 12). Data Infrastructures and Inequities: Why Does Reproductive Health Surveillance in India Need Our Urgent Attention? *Economic & Political Weekly*, Vol. 54, No. 6. https://www.epw.in/engage/article/data-infrastructures-inequities-why-does-reproductive-health-surveillance-india-need-urgent-attention

Roy Chowdhury, S. (2017a, April 16). *By making Aadhaar mandatory, Delhi's government schools are shutting their doors to migrant children.* Scroll.in. https://scroll.in/article/834418/by-making-aadhaar-mandatory-delhis-government-schools-are-shutting-their-doors-to-migrant-children

Roy Chowdhury, S. (2017b, April 23). *All we've done for two years is help students with Aadhaar, say Delhi* *government teachers.* Scroll.in. https://scroll.in/article/834318/all-weve-done-for-two-years-is-help-students-with-aadhaar-say-delhi-government-teachers

Somvanshi, K., & and Desouza, K. (2018, August 23). *India's data dilemma: How to protect all of it.* Brookings.edu. https://www.brookings.edu/blog/techtank/2018/08/23/indias-data-dilemma-how-to-protect-all-of-it/

Srinivasan, P. (2019). Aadhaar - Constitutionally Challenged in (ed.) Khera, R. *Dissent on Aadhaar: Big Data Meets Big Brother,* pp. 137-148. Orient BlackSwan.

Sriram, M. S. (2019). Public Investments and Private Profits in (ed.) Khera, R. *Dissent on Aadhaar: Big Data Meets Big Brother,* pp. 187-202. Orient BlackSwan.

Sternik, I. (2018, April 21). *La inteligencia que no piensa*. Página 12. https://www.pagina12.com.ar/109080-la-inteligencia-que-no-piensa

Tandon, A. (2019). *Big Data and Reproductive Health in India: A Case Study of the Mother and Child Tracking System.* The Centre for Internet and Society, India.

The Wire. (2017-19). *Archive of starvation deaths related to Aadhaar*. https://thewire.in/tag/jharkhand-starvation-death

UN. (2021). *The Sustainable Development Goals Report 2021.* United Nations. https://unstats.un.org/sdgs/report/2021/The-Sustainable-Development-Goals-Report-2021.pdf

Vaishnaw, A. (2022, August 7). *What the new data law must focus on.* Hindustan Times. https://www.hindustantimes.com/opinion/what-the-new-data-law-must-focus-on-101659885959523.html

Valderrama, M. (2021). *Sistema Alerta Niñez: e a previsão de risco de violação de direitos da Infância.* Derechos Digitales América Latina. https://www.derechosdigitales.org/wp-content/uploads/01_Informe-Chile-PT_180222_compressed.pdf

Vallejos, S. (2018, August 25). *El imperio oscurantista.* Página 12. https://www.pagina12.com.ar/131541-el-imperio-oscurantista

Varon, J., & Peña, P. (2021). Artificial intelligence and consent: a feminist anti-colonial critique. *Internet Policy Review*. Vol. 10, No. 4. DOI: 10.14763/2021.4.1602.

Watson, K. (2020, December 30). *Argentina abortion: Senate approves legalisation in historic decision*. BBC. https://www.bbc.com/news/world-latin-america-55475036

Yadav, A. (2016, December 20). *Despite the comparisons, India's Aadhaar project is nothing like America's Social Security Number.* Scroll.in. https://scroll.in/article/823570/despite-the-comparisons-indias-aadhaar-project-is-nothing-like-americas-social-security-number

Yadav, A., & Rao, M. (2017, March 8). *The government wants pregnant women to enroll in Aadhaar to get their social scheme benefits.* Scroll.in. https://scroll.in/pulse/831175/the-government-wants-pregnant-women-to-enroll-in-aadhaar-to-get-their-social-scheme-benefits

Youle, E. (2019, February 12). *'Digital Exclusion': 470,000 Need Help To Apply For Online-Only Universal*

Credit. Huffington Post. https://www.huffingtonpost.co.uk/entry/universal-credit-online-only-help-apply_uk_5c617f69e4b0eec79b262a34

Zhao, J., Wang, T., Yatskar, M., Ordonez, V., & Kai-Wei, C. (2018). Gender bias in coreference resolution: evaluation and debiasing methods. *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, Vol. 2, pp. 15-20, Association for Computational Linguistics (2018) Short Papers https://www.aclweb.org/anthology/N18-2003