Towards Responsible Data Practices for Machine Learning in India: Health & Agriculture

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Acknowledgements

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List of Abbreviations

AGMARKNET
Agricultural Marketing Information System

AI
Artificial Intelligence

ANM
Auxiliary Nurse Midwife

APMC
Agricultural Produce Marketing Committee

ATARI
Agricultural Technology Application Research Institute

ATMA
Agricultural Technology Management Agency

AWS
Amazon Web Services

CABI
Centre for Agriculture and Bioscience International

EHR
Electronic Health Records

e-NAM
Electronic National Agriculture Market

FAIR
Findable, Accessible, Interoperable and Reusable

FATE
Fairness, Accountability, Transparency and Equity

GDPR
General Data Protection Regulation

ICAR
Indian Council of Agricultural Research

ICMR
Indian Council of Medical Research

ICTAI
International Centre for Transformational Artificial Intelligence

IDSP
Integrated Disease Surveillance Programme

IndEA
India Enterprise Architecture

ISRO
Indian Space Research Organisation

KVKs
Krishi Vigyan Kendras

KYC
Know Your Customer

MINE
Microsoft Intelligent Network for Eyecare

ML
Machine Learning

MoU
Memorandum of Understanding

NDHB
National Digital Health Blueprint

NDHM
National Digital Health Mission

NGO
Non-Governmental Organisation

NHS
National Health Stack

NITI
National Institution for Transforming India

NPD
Non-Personal Data

NSSO
National Sample Survey Office

PDP
Personal Data Protection Bill

PPP
Public-Private Partnership

SASA
State Agricultural Statistics Authorities

Executive Summary

There is ample evidence to show that data quality influences the outcomes of an AI model– 'garbage in, garbage out' is a common adage used in data science to describe this problem.

The numerous decisions that AI developers make while working with data, such as what data to collect or how much data to collect, can also impact how the AI model functions. Such decisions enter the AI lifecycle early on and can have unforeseen and adverse effects further down the line. Much of the recent critical scholarship on AI has focused on the social impacts of its deployment. Along with this, a better understanding of the data work and practices at the various stages of AI development is needed to mitigate AI harm.

This study examines the data practices entailed in building AI systems for healthcare and agriculture in India. Health and agriculture have been identified as priority sectors in India's national AI strategy and the use of AI in these sectors is likely to have population-wide impacts.

What social and ethical challenges do research and development teams face while working with data at various stages in the machine learning pipeline? How do they navigate these challenges? How can we foster more responsible data practices in India?

Analysis and findings are based on: a review of secondary literature; 25 semi-structured interviews with AI engineers and data scientists from academia and technology companies who work closely with developing AI for healthcare and agriculture in India; and an expert workshop to share and test our research findings and iterate priorities for building responsible data practices.

With this study, we seek to develop a bottom-up, and contextually situated agenda for Responsible AI in India, that starts with its core building block – data. As India embraces AI as an instrument for economic growth and social progress, it is necessary to examine the foundations and practices upon which such promises of AI are expected to materialise.

Rather than simply being 'raw' or pre-factual pieces of information that precede any analytical processing, data are always imbricated in institutional and social norm and

worldviews. In this study, we analyse 'data practices' for AI as not only a series of technical activities, but also the social and institutional practices and relationalities that frame the production and use of data.

Findings: Healthcare + Agriculture

These two chapters highlight the multiple actors, practices and relationships involved in collecting and processing data for AI-based interventions in healthcare and agriculture. Since almost all our interviewees primarily discussed the challenges faced at the data collection and annotation stages, our study focusses on these two stages.

The data ecosystem in both sectors is a messy and fragmented space, characterised by data duplication, data gaps, unreliable data, and a lack of data interoperability. Even where data are available, allied factors such as the outcome of an intervention, or the context in which it was generated, are often missing. This further reduces the usability of existing data. As a result, technology companies must collect data from scratch. To do this, they have entered partnerships with a range of on-ground stakeholders.

In the health sector, data are collected through three main pathways – by partnering with medical institutions who have digitised data; collecting data through community health workers; or crowdsourcing data through social media or other channels. However, there is little information on the nature of these agreements – what data are shared, how they are used, and whether patient consent is sought. The entry of new technology players is also creating a market for health data – hospitals and medical facilities are incentivised to seek out the most lucrative partnerships for monetising data.

The case study also highlights the 'humans behind AI' and issues around the distribution of technology gains. Developers rely on the invisible labour of frontline health workers, and the bonds of trust and solidarity they have established with the community. It is not clear how these workers benefit from these partnerships. It is also not clear how they are compensated for their data work – data collection increases the workload and forces a reorientation of established practices among already over-burdened health workers.

The involvement of multiple intermediaries and institutions – each with its own motivations, practices, and capacities – creates room for errors in data collection and recording; the process of data collection also reflects the subjectivity of these actors. The same is true

for data annotation, particularly because of the uncertainty of biomedicine and lack of available expertise. This case study also shares insights on how ethical principles such as privacy and fairness can contradict each other in practice and draws attention to the discretionary powers of developers in interpreting and applying ethical principles.

In the agriculture sector as well, technology companies must collect data from scratch. To do this, technology companies are building partnerships with relevant government agencies. Private-public partnerships in the agricultural sector are not new. However, private players have an increasing say not only in developing appropriate solutions, but also in defining or identifying the problem to be solved. Government agencies typically lack the technical expertise to be able to evaluate the fit between the stated problem and the proposed solution. As with the health sector, there is little clarity on the terms of these partnership agreements – questions such as why certain private sector actors are selected, what type of data they collect, how they will be used and shared, remain mostly unanswered.

Technology companies also rely on relationships with local extension agencies and progressive farmers. These actors bring their own subjectivity and biases to the data collection processes. It is also not clear how these local actors are recognised and compensated for their labour. The role of extension agencies is also changing – from providing information and education to farmers to becoming data enumerators for AI developers. This issue extends to crowd-sourced data as well – farmers contribute their labour and knowledge by taking photographs and sharing them with AI developers, but these image banks may then be locked behind proprietary business models. Technology companies also struggle to find skilled data annotators, and the best ones are typically contracted by better-resourced companies. Outsourcing annotation work also makes it harder for AI developers to understand the context and provenance of the data.
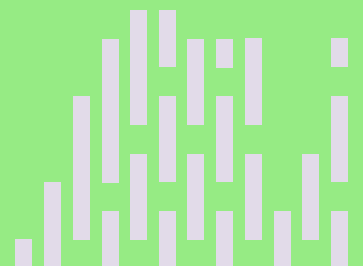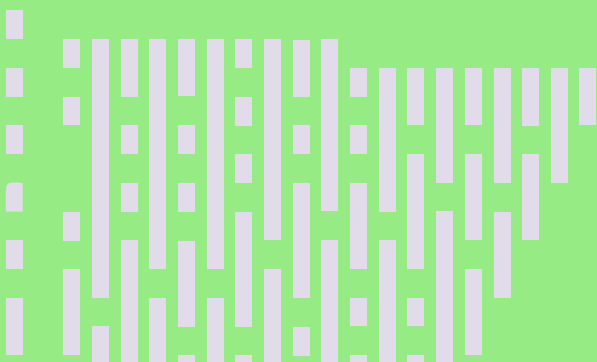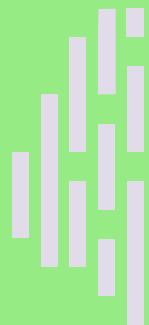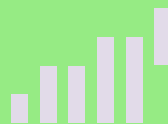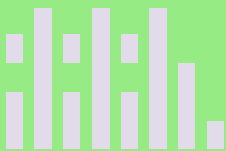
Towards Responsible AI

In this report, we identify six pathways towards building responsible data practices. These pathways also identify the priorities for building a bottom-up agenda for Responsible AI in India.

—— Question underlying assumptions about data

The creation of data is imbricated in social relationships and subjectivities. How data are collected, by whom and for what purpose is not value-free or neutral – it is embedded in social relations of power and reflective of worldviews and interests. An examination of data collection practices on the ground in the healthcare and agriculture spaces indicate the misplaced faith in the truth-telling abilities of data.

—— Practice data documentation

Documenting the decisions made at various stages of the ML cycle, such as objectives and data sources, can further the accountability of the actors involved in AI production. Data documentation practices are particularly important in India because of the inconsistencies, gaps, and errors in health and agricultural data.

—— Recognise labour and redistribute technology gains

Data collection for AI is deeply reliant on the knowledge, trust, and networks that front-line health workers, farmers, and grass-root organisations have within their communities. We need to go beyond applying principles of fairness, accountability and transparency to datasets or algorithms, and apply them instead to the social relationships that are integral to building AI.

—— Develop participatory models for data-based innovations

Since data are the product of collective intelligence and inter-connected human labour networks, we need participatory models and collective deliberation on the proper use of data. Participation must incorporate genuine knowledge sharing, transparency, and an acknowledgement of the myriad networks of labour that are required to build and maintain AI systems.

—— Institute greater transparency and accountability over data flows across public and private actors

An oversight framework is required both at the start and completion of any engagement and it should be be accessible for public scrutiny. It should include points around: why a particular tender has been released and why certain private players were selected; clear rules about what type of data can be collected, its purpose, and how it can be used; an indication of how potential risks and harm may be mitigated; and mechanisms for grievance redressal.

—— Induce broader cultural shifts by developing a data ethics curriculum and codes of professional ethics

It is incumbent upon the data science community and AI practitioners to recognise themselves as political actors and develop a critical lens to evaluate the diverse impact of their work. Such measures are not a panacea for addressing the ethical challenges and harm of AI or all ethical problems posed by AI,[1] but are a necessary part of any long-term and systemic strategy towards building responsible data practice for AI.

1.   Bowyer, K. (2001). *Ethics and computing: living responsibly in a computerized world.*

1 Introduction

a. Why this Study

Machine learning utilises vast amounts of data to detect patterns and produce probabilistic results.[2] Some of the most advanced AI models today, such as GPT-3, rely on massive amounts of input data to work well.[3] There is now ample evidence to show how data quality and quantity influence the outcomes of an AI model.[4] Unrepresentative, fragmented, or incomplete datasets can lead to biased or flawed results. For instance, within medical AI, a popularly used melanoma detecting algorithm was less accurate when detecting the condition on black and brown skin due to the unrepresentativeness of the data used to train the algorithm.[5] Similarly, Amazon's recruitment tool was found to be biased against female candidates; trained on historical hiring decisions, which favoured men over women, the tool learned to do the same.[6] A common adage in data science describes this phenomenon as 'garbage in, garbage out', where low-quality data can lead to unfair or inaccurate outcomes.

The numerous decisions that AI developers make while working with data can also impact AI outcomes. In 2019, the case of machine bias illustrated by Propublica on a Northpointe's recidivism prediction tool (COMPAS) exemplified how decisions made by research teams to include proxy parameters such as 'friends arrested', 'parents separated', have an unfair impact on a person's risk score. The use of such proxies, which reflect both individual choices and a person's

A common adage in data science describes this phenomenon as 'garbage in, garbage out', where low-quality data can lead to unfair or inaccurate outcomes.

2.   Elish, M. C. & Boyd, D. (2018). Situating methods in the magic of Big Data and AI. Communication monographs, 85(1), 57-80.

3.   Wiggers, K. (2020). OpenAI's massive GPT-3 model is impressive, but size isn't everything. https://venturebeat.com/2020/06/01/ai-machine-learning-openai-gpt-3-size-isnt-everything/

4.   Barocas, S. & Selbst, A. D. (2016). Big data's disparate impact. Calif. L. Rev., 104, 671. Also see, Selbst, A. D. (2017). Disparate impact in big data policing. Ga. L. Rev., 52, 109; Flores, A. W., Bechtel, K. & Lowenkamp, C. T. (2016). False positives, false negatives, and false analyses: A rejoinder to machine bias: There's software used across the country to predict future criminals. and it's biased against blacks. Fed. Probation, 80, 38.

5.   Lashbrook, Angela. "AI-driven dermatology could leave dark-skinned patients behind." The Atlantic (2018).

6.   Dastin, J. (2018, October 10). Amazon scraps secret AI recruiting tool that showed bias against women. Reuters. https://www.reuters.com/article/us-amazon-com-jobs-automation-insight-idUSKCN1MK08G.

cultural context, contributed to the tool's disproportionate bias against black Americans over white Americans.[7] Such decisions enter the AI lifecycle early on and can have unforeseen adverse effects further down the line.

Legal scholars Lehr and Ohm say that much of the scholarship around the impacts of AI/ML tends to treat it as a 'monolith', and that there is a disproportionate focus on the AI/ML model and its outcome rather than the processes behind developing these models.[8] Sambasivan et al. similarly argue that AI researchers often focus more on building the algorithmic model, at the expense of the data work that is required to create the model.[9] They feel that attending to the practices that surround data at the various stages of AI development is essential for mitigating against AI harm.

b. The Relevance for India

Data is increasingly associated with visions of political and economic progress in India. Policy makers and leading industry voices frequently refer to India as a 'data rich country' and point to the opportunity this creates to support inclusive economic growth. Much policy attention in recent years has thus focused on mechanisms to 'unlock' or 'unleash' the value of data and promote 'data empowerment' architectures. The use of AI is central to this vision - various government ministries and industry bodies have been working to grow the AI ecosystem in India. It is therefore important to understand data work or practices that go into building AI systems – to help anticipate and address challenges even before AI models are deployed in real-world contexts.

In response to evidence about the harmful effects of AI, several countries and organisations are developing frameworks for 'Responsible AI.' In 2020, NITI Aayog published its position paper on Responsible AI that identified six guiding principles – equality, safety and responsibility, inclusivity and non-discrimination, transparency, accountability, and privacy and security.[10] These principles closely resemble other

7.   Angwin, J., Larson, J., Mattu, S. & Kirchner, L. (2016, May 23). Machine bias. ProPublica. < https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing.

8.   Lehr, D. & Ohm, P. (2017). Playing with the data: what legal scholars should learn about machine learning. UCDL Rev.51, 653

9.   Sambasivan, N., Kapania, S., Highfill, H., Akrong, D., Paritosh, P. & Aroyo, L. M. (2021, May). "Everyone wants to do the model work, not the data work": Data Cascades in High-Stakes AI. In proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (pp. 1-15).

10. NITI Aayog, November 2020. Towards Responsible AI Enforcement of Principles. https://www.niti.gov.in/niti/sites/default/files/2020-11/Towards-Responsible-AI-Enforcement-of-Principles.pdf

emerging global frameworks for Responsible AI. But, like other global frameworks, these principles are abstract and can be differently interpreted, and may not provide adequate guidance for action. Such frameworks also tend to gloss over the tensions or trade-offs entailed in the application of these principles. The meaning and prioritisation of these principles may also differ across different socio-cultural contexts; actors may also have varied capacity to implement and monitor the application of such frameworks. A survey of over 80 policy documents globally shows that while responsibility is one of the most evoked ethical principles across these documents, almost none of them define what is meant by responsibility.[11]

Through this study, we seek to develop a bottom-up, and contextually situated agenda for Responsible AI, which starts with one of AI's core building blocks. As India embraces AI as an instrument for economic growth and social progress, it is necessary to examine the foundations and practices upon which such promises of AI are expected to materialise.

c. Research Design

In this study, we examine the data practices involved in building machine learning solutions for health and agriculture in India. Health and agriculture have been identified as priority sectors in India's national AI strategy and the use of AI in these sectors is likely to have population-wide impacts.

> **What social and ethical challenges did research and development teams face while working with data at various stages in the machine learning pipeline?**
>
> **How did research and development teams navigate these challenges, and what were (if any) the established best data practices that were followed?**
>
> **How can we foster more responsible data practices in India?**

11.   Jobin, A., Ienca, M. & Vayena, E. (2019). The global landscape of AI ethics guidelines. Nature Machine Intelligence, 1(9), 389-399.

Analysis and findings are based on: a review of secondary literature; 25 semi-structured interviews with AI engineers and data scientists from academia and technology companies that work closely with developing AI for healthcare and agriculture in India; and a workshop with experts to share and test our research findings and iterate priorities for building responsible data practices.

This study primarily presents an analysis of the data collection and processing aspects in AI/ML pipelines. While data practices within AI/ML constitute a wide range of tasks (see Chapter 2), we found, through our interviews, that data collection and processing (annotation, labelling, and cleaning) activities are a major challenge for developers building AI/ML systems. These two processes present first level barriers to responsible AI development.

To address some of the challenges posed at these stages, researchers and ethicists have proposed building better data documentation practices, which document the motivation of researchers and product developers and the characteristics of data and how they were collected. This can support transparency, accountability, and ethical reflection among developer teams.[12] Much of this literature, however, originates in a select few industrialised economies. We need to contextualise conversations on data practices and ethics to reflect local moral worlds and situated practices - a one-size-fits-all approach is likely to be inadequate.

While the discourse on data ethics and ethical AI might hold certain ideas of fairness or justice in common, research indicates that the prioritisation and substance of these values might differ across communities and cultural contexts. For instance, based on a study of notions of 'fairness' in seven countries, researchers found that while children from all cultures demonstrate an aversion towards disadvantageous inequity (avoid receiving less than a peer), advantageous inequity aversion (avoid receiving more than a peer) was more prevalent in the West.[13] Data work thus does not operate in a neutral or scientific vacuum, but is shaped by broader socio-cultural beliefs and contexts.

12. Gebru, T., Morgenstern, J., Vecchione, B., Vaughan, J. W., Wallach, H., Daumé III, H. & Crawford, K. (2018). Datasheets for datasets. arXiv preprint arXiv:1803.09010. Also see, Madaio, M. A., Stark, L., Wortman Vaughan, J. & Wallach, H. (2020, April). Co-designing checklists to understand organizational challenges and opportunities around fairness in ai. In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (pp. 1-14).
13. Blake, P. R., McAuliffe, K., Corbit, J., Callaghan, T. C., Barry, O., Bowie, A. & Warneken, F. (2015). The ontogeny of fairness in seven societies. Nature, 528(7581), 258-261.

2 A Framework for Interrogating Data Practices

a. What is Data?

Studies on the origins of the concept of 'data' suggest that the usage of the term goes back to the middle of the seventeenth century, when it was first used to supplement existing terms like 'evidence' and 'fact'. Over time, data came to be understood as a 'pre-analytical' and 'pre-factual' category, different from facts, evidence, or knowledge, but fundamental to their production.[14] Data is considered raw, as something that exists 'out there', which is then processed to become facts, evidence, or knowledge. Arguments for data as a natural resource, or that see data as necessary for bringing objective evidence to policy making, often rest on these assumptions about data.

Data itself are a cultural and political artefact and production of data, therefore, is both a social and political process.

But as recent scholarship from critical data science and sociology argue, data are always manufactured. Rather than simply being 'raw' or pre-factual pieces of information that precede any analytical processing, data are always imbricated in institutional and social norms and worldviews. Moreover, data are embedded in, and generative of, relationships of power and knowledge.[15] What counts as 'data' is a product of dominant knowledge paradigms as well as the interests and beliefs driving the collection of data; and the collection, analysis and use of data enables new forms of social shaping and control.[16] Data itself are a cultural and political artefact and production of data, therefore, is both a social and political process.[17]

14.   Rosenberg, D. (2013). Data before the fact. Raw data" is an oxymoron, 15-40.
15.   Gitelman, L. (Ed.). (2013). Raw data is an oxymoron. MIT press. Also see, D'ignazio, C., & Klein, L. F. (2020). Data feminism. MIT press. Kitchin, R. (2021). Data Lives: How Data Are Made and Shape Our World. Policy Press. Iliadis, A. & Russo, F. (2016). Critical data studies: An introduction. Big Data & Society, 3(2), 2053951716674238.
16.   Ruppert, E., Isin, E. & Bigo, D. (2019). Data Politics: Worlds, Subjects, Rights. Also see, Couldry, N. & Mejias, U. (2019). The Costs of Connection: How Data Is Colonizing Human Life and Appropriating it for Capitalism. Stanford, California: Stanford University Press.
17.   Ruppert, E., Isin, E. & Bigo, D. (2017). Data politics. Big data & society, 4(2), 2053951717717749.

To illustrate, consider the example of the ImageNet - a database of 14 million annotated images, used in object recognition software research.[18] Analysing the politics inherent in classifying images, Crawford and Paglen show that the database contains several descriptors that belie the underlying social and institutional norms and relationalities that shape how we sort through pictures and the meanings we assign. For example, the image of a woman sleeping in an airplane seat, her right arm protectively curled around her pregnant stomach, has been labelled as "snob". In another example cited by the authors, a young woman lying on a beach towel has been labelled "kleptomaniac". As Crawford and Paglen note, the circuit between image, label, and referent is flexible. It can be reconstructed in any number of ways. Further, those circuits can change over time as the cultural context of an image shifts and can mean different things depending on who is looking and where they are located.[19]

Data practices, therefore, are never simply about performing operational procedures and 'cold' analysis upon data. Instead, data practices must be understood as both *constituted by* and *constitutive of* broader normative and institutional contexts and the social relationships. In this report, therefore, we analyse 'data practices' for AI as a composite of not only activities such as creating or curating datasets, but also the social and institutional practices and relationalities that frame the production and use of data.

b. Data Work in the Machine Learning Lifecycle

Machine learning can be defined as a 'set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data, or to perform other kinds of decision-making under uncertainty.'[20] The training of machine learning algorithmics occurs via the optimisation of an objective function or a particular goal.

Data practices must be understood as both constituted by and constitutive of broader normative and institutional contexts and the social relationships.

18. Gershgorn, D. (n.d.). The data that transformed AI research-and possibly the world. Quartz. https://qz.com/1034972/the-data-that-changed-the-direction-of-ai-research-and-possibly-the-world/.
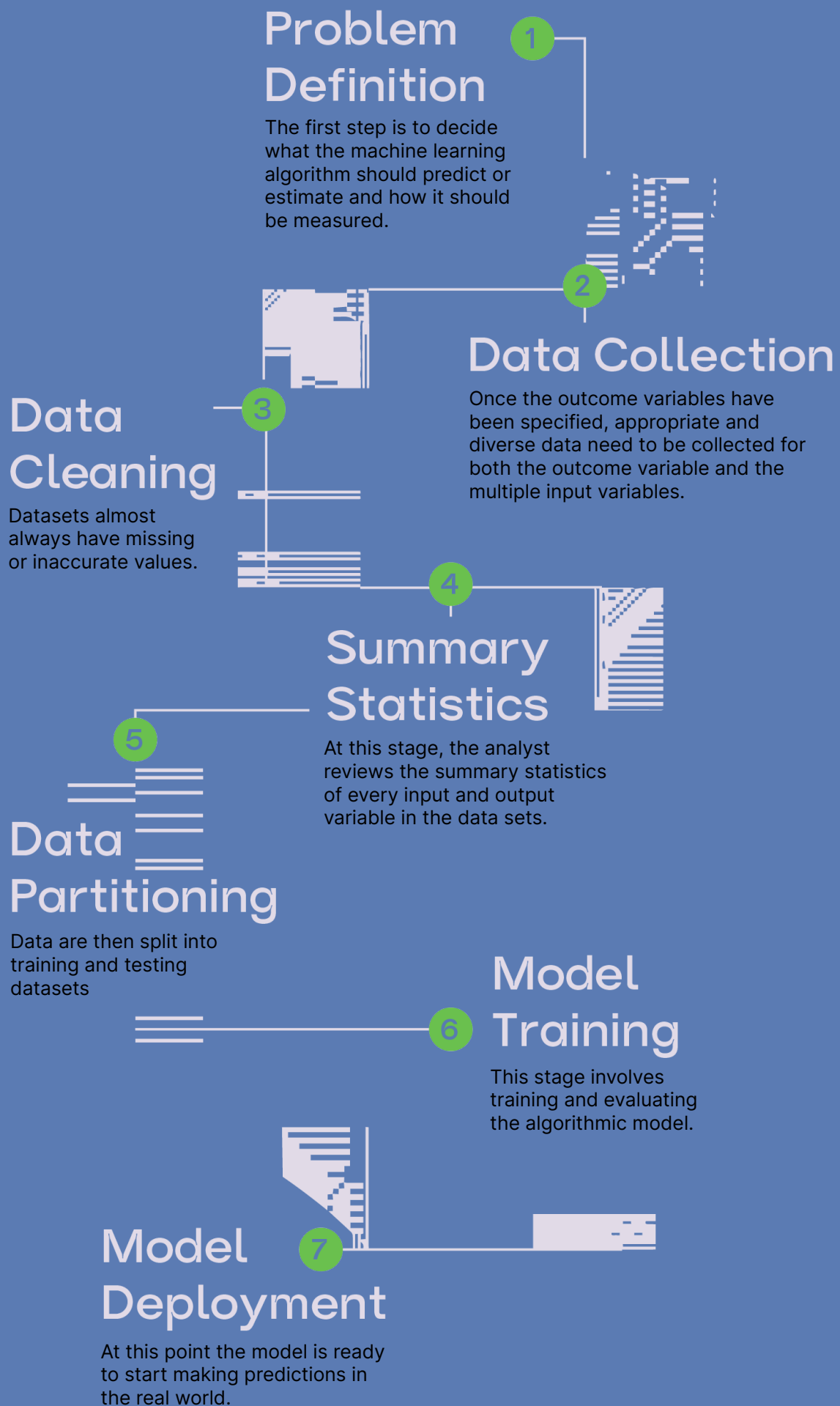
19. Crawford, K. & Paglen, T. (2019). Excavating AI: the politics of training sets for machine learning. Excavating AI (www.excavating. ai).

20. Murphy, K. (2012) Machine Learning : A Probabilistic Perspective.

The table below, adapted from Ohm and Lehr's article 'What Legal Scholars should learn about Machine Learning', lists the key steps in the machine learning lifecycle and the questions or challenges faced by analysts or developers.[21] Keeping the focus on the data work required for machine learning, we do not discuss the various sub-steps entailed in model training and deployment.

As the table illustrates, preparing data for building machine learning is far from an objective science – it requires complex and subjective decision-making by analysts or developers. These decisions are necessarily shaped by a range of normative and institutional factors. Data are thus manufactured through these decisions and the resultant practices, and these decisions and practices around data have cascading effects on the outcomes of algorithmic systems.

21. Lehr, D. & Ohm, P. (2017). Playing with the data: what legal scholars should learn about machine learning. UCDL Rev.51, 653. Also, Kiri Wagstaff. 2012. Machine learning that matters. arXiv preprint arXiv:1206.4656 (2012); Roh, Y., Heo, G. & Whang, S. E. (2019). A survey on data collection for machine learning: a big data-ai integration perspective. IEEE Transactions on Knowledge and Data Engineering; Polyzotis, N., Roy, S., Whang, S. E. & Zinkevich, M. (2018). Data lifecycle challenges in production machine learning: a survey. ACM SIGMOD Record, 47(2), 17-28.

Problem Definition

1

The first step is to decide what the machine learning algorithm should predict or estimate and how it should be measured.

2

Data Collection

Once the outcome variables have been specified, appropriate and diverse data need to be collected for both the outcome variable and the multiple input variables.

3

Data Cleaning

Datasets almost always have missing or inaccurate values.

4

Summary Statistics

At this stage, the analyst reviews the summary statistics of every input and output variable in the data sets.

5

Data Partitioning

Data are then split into training and testing datasets

6

Model Training

This stage involves training and evaluating the algorithmic model.

7

Model Deployment

At this point the model is ready to start making predictions in the real world.

1

Problem Definition

The first step is to decide what the machine learning algorithm should predict or estimate and how it should be measured. Developers and analysts must translate abstract goals into measurable outcomes.

If, for example, the abstract goal is to identify good employees, the analyst will need to first define what kind of outcome variable measures the goodness of an employee and then develop ways to measure it. This is necessarily a subjective and complex task. Data scientists may not have the institutional knowledge to choose and evaluate appropriate variables. Outcome variables may also be chosen based on convenience and resource constraints, in terms of what data are readily available or easily collectable.

2

Data Collection

Once the outcome variables have been specified, appropriate and diverse data need to be collected for both the outcome variable and the multiple input variables. This is a time-consuming step that has enormous downstream consequences. Data scientists need to make sure they have collected enough data, but there are no definitive rules about how much data are enough. Data scientists also need to ensure that the variables for which they are collecting data are a suitable measure for what they are supposed to be measuring. Is coming to working on time, for example, a suitable indicator for identifying a good employee? Data scientists are also concerned about generalisability of the algorithm across different data sets. Training data thus need to be adequately representative of the real-world context in which the algorithm will be deployed.

3

Data Cleaning

Datasets almost always have missing or inaccurate values. These errors may arise for multiple reasons – from sloppy handwriting during the manual collection of data to weak computer skills of the person digitally entering the manually collected data sets. Analysts and developers must decide whether they want to delete the fields with missing values or to impute them through a combination of automated processes and educated guesses. It is even harder to check if values are correct as analysts may not always have contextual knowledge to accurately assess the values.

4

Summary Statistics

At this stage, the analyst reviews the summary statistics of every input and output variable in the data sets. This is done to weed out outliers and reduce the noise in data. For example, studies show that data about minority groups tend to be noisier, and algorithms could generate less predictive rules for these groups.

5

Data Partitioning

Data are then split into training and testing datasets. Analysts and developers must decide how much data should be allocated for training and testing – allocating a larger proportion for training can help the algorithm learn predictive rules. However, a large training dataset does not necessarily lead to better modelling, for example, if a particular category of information, or data point, is consistently missing across the entire data set. A small testing data set may give only a weak sense of how the algorithm performs on other data sets or in the real world. The subject matter knowledge of the analysts can play a significant role in shaping this decision.

6

Model Training

This stage involves training and evaluating the algorithmic model. There is a degree of trial-and-error, as developers experiment with different sets of parameters hoping for the intended outcome.[22] It is often left to the development team to decide how much further it wants to evaluate and re-train the model, to determine when the model has reached its optimum accuracy.

7

Model Deployment

At this point the model is ready to start making predictions in the real world. These real-world interactions further influence how the model learns and operates. For example, product recommendation systems run on real-data time, requiring a continuous feed of new data into the training algorithms. Back-end infrastructure is needed to re-train and assess the algorithm. This process is time-consuming and expensive, and organisations may vary in their inclination and capacities to carry out these processes consistently.

22. Witten, I. H. & Frank, E. (2002). Data mining: practical machine learning tools and techniques with Java implementations. Acm Sigmod Record, 31(1), 76-77.; Berk, R. A. (2008). Statistical learning from a regression perspective (Vol. 14). New York: Springer.

Data Practices
in Healthcare

3 Data Practices in Healthcare

a. Overview of Current Policy Landscape

Health policy in India is increasingly focused on the digitisation of health data to support data-driven innovation in the sector. Between 2016 and 2021, the Ministry of Health and Family Welfare released several proposals and policies to fast-track the digitisation of health services, such as the Electronic Health Record (EHR) Standards for India (2016), the National Health Policy (2017) and the National Health Stack (2018). The National Health Stack will create a database of national health data, that can be accessed by various stakeholders through open APIs and standards to develop solutions for improved access, efficiency, and quality of healthcare services. As per NITI Aayog, one of the key purposes of the health stack is to "facilitate collection of comprehensive healthcare data across the country," and to generate "vast amounts of data, that will put India at the forefront of medical research in the world."[23]

In December 2020, the government also approved the Health Data Management Policy. The Policy provides guidelines for secure and consent-based data processing and lays down guidelines for the collection and sharing of all data for a wide range of actors such as healthcare professionals, pharmaceutical companies, insurance companies and research institutions.[24] In September 2021, Prime Minister Modi launched the National Digital Health Mission (NDHM) to develop integrated health infrastructure - its key pillars include a unique digital health ID, an integrated registry of patient health data and healthcare professionals, a consent manager, and a digital health analytics platform.

In 2018, NITI Aayog's white paper on India's AI Strategy (NSAI) highlighted healthcare as a key sector for AI intervention.[25] Following the NSAI, NITI Aayog has conducted a number of pilot experiments such as an anthropometry-based measure for detecting the weight of newborns (in partnership with Wadhwani AI and Piramal Swasthya) and an AI-based test for diabetic retinopathy in public health (with partners such as PGIMER, SigTuple, Forus

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23. Ibid.
24. Ibid.
25. NITI Aayog, 2018. National Strategy for Artificial Intelligence.

and EyeNuk).[26] Different state governments have also signed Memorandums of Understanding with technology companies and rolled out a number of pilots. For example, the Government of Maharashtra has signed a Memorandum of Understanding with NITI Aayog and the Wadhwani AI group to launch the International Centre for Transformational Artificial Intelligence (ICTAI) for rural healthcare. In 2019, Telangana became the first state in India to deploy Microsoft's Intelligent Network for Eyecare (MINE), an Artificial Intelligence platform for eye screening.[27]

b. Challenges in Current Data Ecosystem

The health data ecosystem in India has been widely acknowledged as a highly complex and fragmented space.[28] Three challenges stand out from the perspective of building reliable and useful AI systems – duplication and reliability, data interoperability and data gaps.

b. 1. Data Duplication and Reliability

The development of multiple health data collection initiatives over the past decade has led to an explosion of data collection systems in the public sector. This has also created conditions for data mismanagement, misreporting and overlapping databases. For instance, data on tuberculosis are collected under three government programmes - the Health Management Information Systems (HMIS), the Integrated Disease Surveillance Programme (IDSP), and the Expanded Programme on Immunization (EPI). Balsari et al., show that in a single primary health centre in one state in India,

Research shows that in a single primary health centre in one state in India, there are over 3,000 discrete fields of data captured in paper-based and electronic forms, contributing data to 70 different databases.

26. NITI Aayog. Data Management And Analysis, And Frontier Technologies. https://www.niti.gov.in/verticals/data-management-and-analysis

27. PTI. (2017, August 3). Telangana to use Microsoft cloud-based analytics for health plan. The Financial Express. https://www.financialexpress.com/india-news/telangana-to-use-microsoft-cloud-based-analytics-for-health-plan/793125/.

28. Patel V., Parikh R., Nandraj S., Balasubramaniam P., Narayan K., Paul V. K., et al. Assuring health coverage for all in India. Lancet 2015 Dec 12;386(10011):2422-2435. Also see, https://thewire.in/health/imr-mmr-data-nss-srs and https://thewire.in/health/health-data-should-leave-no-indian-behind

there are over 3,000 discrete fields of data captured in paper-based and electronic forms, contributing data to 70 different databases.[29] Similarly, it has been found that the auxiliary nurse midwives (ANMs) need to send (often overlapping) data to nearly 10 different systems and manage their data with 25+ primary registers (each about a metre long), resulting in increased administrative workload.[30] Often, ANMs first enter data in physical registers, which are then digitised by the data entry operators at the primary health centres. This step also introduces time lags in data collecting and reporting and increases the risk of data errors, particularly when the terms and fields used in the manual register differ from those in new software.

Health data collection within the private sector is often not standardised and systems for creating electronic data records are not interoperable.

Researchers have also noted the existence of a 'culture of reprimand' that affects data reporting in the public health sector. For instance, Sahay and Mukherjee note that there is an emphasis on data as a means of reporting (rather than analysis) - the function of data collection is to enable a form of control within the workplace, rather than improve the quality of care. In their research on datafication of the Indian health care system, Kelly and Noonan note how a public health official reported that health workers frequently misreported (or "beautified") the data to avoid being reprimanded.[31]

b.2. Data Siloes and Interoperability

The public health system collects a large volume of data, but there is a lack of standardisation across different data tools and processes.[32] Incongruence between data

29. Balsari, S., Fortenko, A., Blaya, J. A., Gropper, A., Jayaram, M., Matthan, R. & Khanna, T. (2018). Reimagining Health Data Exchange: An application programming interface–enabled roadmap for India. Journal of medical Internet research, 20(7), e10725.

30. Sahay, S., Nielsen, P. & Latifov, M. (2018). Grand challenges of public health: How can health information systems support facing them? Health policy and technology, 7(1), 81-87.

31. Kelly, S. & Noonan, C. (2017). The doing of datafication (and what this doing does): Practices of edification and the enactment of new forms of sociality in the Indian public health service. Journal of the Association for Information Systems, 18(12), 3.

32. Balsari, S., Fortenko, A., Blaya, J. A., Gropper, A., Jayaram, M., Matthan, R. & Khanna, T. (2018). Reimagining Health Data Exchange: An application programming interface–enabled roadmap for India. Journal of medical Internet research, 20(7), e10725.

fields in the physical registers and digital portals for the same programme have also been reported.[33] The transition from paper-based records to digital records has also been uneven.[34]

Healthcare service delivery in India occurs to a large extent through the private sector. The private sector provides about two-thirds of inpatient care and three-fourths of outpatient care treatment in India. It has been estimated that 60% of the total volume of health data is produced by non-state actors.[35] Public health databases such as that for reproductive health data do not cover data from private hospitals and treatment centres, leading to significant data gaps for a large percentage of the Indian population.

Health data collection within the private sector is often not standardised and systems for creating electronic data records are not interoperable. Reports on EHR adoption in the private sector often single out a few well-known corporate hospitals, such as Max Health, Apollo, Sankara Nethralaya and Fortis which have integrated and comprehensive ICT systems in place, including registration, billing and laboratory and clinical data. Even then, it is noted that EHR/EMR data is rarely exchanged between hospitals.[36]

b. 3. Data Gaps

Despite several on-going data collection and reporting initiatives, the health data landscape in India is characterised by multiple data gaps. For instance, as Kurien notes, the core health statistics in India are available only for a select few states. Similarly, regular, reliable numbers on Neonatal Mortality Rate, Under-5 Mortality Rate, and Life Expectancy are available only for under 20 states (not counting Telangana). Disaggregated data across caste, class, gender, or region are unavailable for most of these indicators.[37] Further, it has been found that the overall data collection volume for aggregate data (HMIS data and state-specific data) varies between 3,000 to 8,000 data elements per month. However, only 10% of these data elements are used to generate indicators, nearly 20% are

33. Khurana, N. (2021). Issue Analysis: A Use-Driven Approach to Data Governance Can Promote the Quality of Routine Health Data in India. Global Health: Science and Practice, 9(2), 238-245.
34. Kurien, O. C. (2017, January 11). Why it's a challenge to make quick sense of India's health data. The Wire. https://thewire.in/health/imr-mmr-data-nss-srs.
35. Ibid.
36. Srivastava, S. K. (2016). Adoption of electronic health records: a roadmap for India. Healthcare informatics research, 22(4), 261.
37. Ibid.

inactive (returned no values), and about 50% consistently returned blanks or zeros. Thus, data fed into the portal is significantly incomplete, with a high proportion of fields being left empty.[38]

India's Open Data programme is also marked by issues of quality, non-standardisation, and data gaps.[39] Datasets fail to meet requisite standards for AI use, due to the lack of metadata and information about methodology of data collection and outdated information.[40]

The fragmented health data ecosystem in India, as noted above, creates challenges for AI development. Unreliability makes a lot of the data produced by the system unusable for AI development. For instance, an AI engineer interviewed for this study pointed out that even if data are available, say in the form of chest x-rays for tuberculosis, or lung cancer, the absence of allied data on factors such as outcome of treatment, significantly reduces the usability of the data.[41] Another AI developer said that "data collected within organisations in India is often messy and chaotic, lacking information about the provenance of the data and semantic context (i.e., metadata about the origins and contexts in which it was collected/entered)."[42]

Data provenance is not simply about knowing the point of origin of data (where they came from), but includes the circumstances/contexts of their development. To give an example - a few years ago, ML researchers found that an AI tool used to predict probability of death (POD) for pneumonia patients pointed to a low risk for patients with asthma. The reason for this error was that the hospital from which data were collected had a process whereby it sent people who had asthma and were suspected to have pneumonia directly to the ICU (as a preventative measure, because they are at higher risk.) Because of this protocol, asthma sufferers almost never developed severe complications when they got pneumonia. This led the algorithm to wrongly predict low risk rates for asthma.[43] Thus, AI developed along similar lines, without knowledge of the contexts within which data are produced, can have severe downstream consequences - especially when used in critical areas such as health care.

38. Khurana, N. (2021). Issue Analysis: A Use-Driven Approach to Data Governance Can Promote the Quality of Routine Health Data in India. Global Health: Science and Practice, 9(2), 238-245.
39. Larquemin, A., Mukhopadhyay, J. P. & Buteau, S. (2016). Open Data and Evidence-based Socio-economic Policy Research in India: An overview. The Journal of Community Informatics, 12(2).
40. Wright, G., Abraham, S. & Shah, N. (2012). Open government data study: India. Available at SSRN 2071605.
41. Respondent Interview with Digital Futures Lab, July 2021.
42. Respondent Interview with Digital Futures Lab, July 2021.
43. Caruana, R., Lou, Y., Gehrke, J., Koch, P., Sturm, M. & Elhadad, N. (2015, August). Intelligible models for healthcare: Predicting pneumonia risk and hospital 30-day readmission. Proceedings of the 21th ACM SIGKDD international conference on knowledge discovery and data mining (pp. 1721-1730).

c. Data Practices in the AI / ML Lifecycle

c. 1. Data Collection

Because of the challenges discussed in the previous section, AI developers, be they private companies, start-ups, or researchers, typically need to collect data from scratch. Respondents reported a few different modalities or pathways for data collection. First, data are often collected through private partnerships with medical institutions, multi-specialty hospitals, clinics, private and public healthcare facilities, and diagnostic labs that are likely to have digitised data. A second pathway for data collection is entering into partnerships with state governments to induct and train community health workers and collect the necessary data from scratch. A third pathway is by crowd-sourcing data or using from existing open datasets. For instance, the National Institute of Health (NIH) in the U.S. has one of the largest datasets of chest x-rays used by researchers and developers globally.[44]

Commenting on the nature of partnerships for data-sharing for AI in this sector, one respondent, an AI scientist, noted:

> **"If an AI company today wants to enter into a data sharing agreement with a medical institution, they can simply pay for the data. Alternatively, they can enter a partnership for joint research publications, where they can access the data for free, and can also use that data later to build other solutions on top of it. A third possibility is to provide equity in your company through a revenue share mode."[45]**

In recent years, several partnerships between tech companies and private medical institutions have been announced in the public domain. For instance, Google partnered with Aravind Eye Care, Sankara Nethralaya, and Narayana Nethralaya as far back as 2013 to develop a deep algorithm to detect diabetic retinopathy and diabetic macular edema.[46] The dataset for model training was sourced from these three institutions, as well other sites in the U.S. and France.[47]

44. https://www.nih.gov/news-events/news-releases/nih-clinical-center-provides-one-largest-publicly-available-chest-x-ray-datasets-scientific-community
45. Interview, Digital Futures Lab, July 2021.
46. Sharma, S. (2017, June 12). Google is working with Aravind Eye hospital to train its AI in diabetic Retinopathy screening. FactorDaily. https://archive.factordaily.com/news/google-india-aravind-eye-hospital-ai-diabetic-retinopathy/.
47. Gulshan, V., Peng, L., Coram, M., Stumpe, M. C., Wu, D., Narayanaswamy, A. & Webster, D. R. (2016). Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. Jama, 316(22), 2402-2410.

What kind of data are collected, how are they used and shared, and what do medical partners get in exchange for sharing personal health data? Are patients aware that their data are being shared and was their consent sought?

Similarly, in 2019 Google AI conducted research to develop deep learning models for detecting clinically relevant chest radiographs. Data for this were collected from five regional centers across large hospital groups in India (Chennai, Bangalore, Bhubaneswar, Hyderabad and New Delhi).[48] Google Research worked with ARMMAN, a Mumbai-based NGO working on maternal health, to develop a churn prediction algorithm for pregnant women and mothers who are enrolled in Armman's mMitra programme. Data for this tool were collected from ARMMAN's existing data repositories. At the time of registration for the programme, demographic data such as age, education level and income group are collected. Further, during the course of the programme, every call to a woman is logged.[49] As part of a larger 'AI for Health' initiative, Microsoft in 2019, partnered with Apollo Hospitals for data pooling to develop a Cardiovascular Disease Risk Score API, which was later offered through the company's Azure platform.[50] Apollo Hospitals and Microsoft India have also been in discussions with other health systems across the world to scale up the API.[51]

While the above discussion mentions only a few examples, several such partnerships for data-sharing and AI research exist in the provision of clinical healthcare in India, even within the public sector. For instance, NITI Aayog has many partnerships with other state and private actors such as Wadhwani AI, Piramal Swasthya, IBM and Microsoft.[52]

These partnerships raise several issues. First, the nature and terms of these partnerships are not clear – what kind of data are collected, how are they used and shared, and what

48. Ibid.
49. Nishtala, S., Kamarthi, H., Thakkar, D., Narayanan, D., Grama, A., Hegde, A. & Tambe, M. (2020). Missed calls, Automated Calls and Health Support: Using AI to improve maternal health outcomes by increasing program engagement. arXiv preprint arXiv:2006.07590.
50. Mathur, N. (2019, August 1). Microsoft ties up with Apollo Hospitals to combat cardiovascular diseases. mint. Retrieved September 27, 2021, from https://www.livemint.com/companies/news/microsoft-ties-up-with-apollo-hospitals-to-combat-cardiovascular-diseases-1564646174136.html.
51. Microsoft partners with Apollo Hospitals to set up the National Clinical Coordination Committee for Combating Cardiovascular Diseases. Microsoft Stories India. (2019, August 1). Retrieved September 27, 2021, from https://news.microsoft.com/en-in/microsoft-apollo-hospitals-partnership-national-clinical-coordination-committee-combating-cardiovascular-diseases/.
52. NITI Aayog. Data Management And Analysis, And Frontier Technologies. https://www.niti.gov.in/verticals/data-management-and-analysis

do medical partners get in exchange for sharing personal health data? Second, these partnerships raise concerns around the privacy and security of patient data – are patients aware that their data are being shared and was their consent sought?

To give an example, in 2017 leaked documents regarding the partnership between NHS in the UK and Google-owned DeepMind showed that data-sharing agreements between the two gave Deep Mind access to identifiable information on 1.6 million of its patients in order to develop an app to help medical professionals identify patients at risk of acute kidney injury (AKI). After an investigation, the Information Commissioner's Office (ICO, 2017) ruled that this transfer of data and their use for testing the app breached data protection law. Patients were not aware that their data were being used.[53] Similarly, data security experts have also raised concerns about the NHS contract with iProov, whose facial verification software is used to perform automated ID checks on people signing up for the NHS app.[54]

Such issues are amplified in the Indian context due to lax data security measures and the casual way health data are often handled by many public and private medical institutions and facilities. There have been several reports of data breaches and leaks of people's private medical records, particularly during the pandemic.[55]

Third, respondents note that entry of new technology players is creating a highly competitive market for data. They said that rather than share data for public benefit, 'hospitals have started creating data moats' - 'they are beginning to realize the value of the data they are collecting and are increasingly looking for ways to monetise it." Data collected by healthcare providers, be it hospitals, diagnostic labs or clinics and dispensaries have increasingly become lucrative 'economic' objects through which value can be generated and monetised.

Role of Intermediaries

A key aspect of data partnerships is the important role played by intermediaries in enabling data collection. Intermediaries for data collection range from local NGOs to start-ups and private healthcare providers, as well as community healthcare workers.

53. Powles, J. & Hodson, H. (2017). Google DeepMind and healthcare in an age of algorithms. Health and technology, 7(4), 351-367. Also see, https://www.wired.co.uk/article/nhs-deepmind-google-data-sharing
54. Davies, R. (2021, September 24). Undisclosed private companies analysing facial data from NHS App. The Guardian. Retrieved September 27, 2021, from https://www.theguardian.com/society/2021/sep/24/undisclosed-private-companies-analysing-facial-data-from-nhs-app.
55. Kurian, Oomen C. (2021). Data, Privacy, Pandemic: India Just Had The Biggest Medical Records Breach Ever. Observer Research Foundation. https://www.orfonline.org/expert-speak/data-privacy-pandemic-india-just-had-the-biggest-medical-records-breach-ever/

Technology companies leverage the spread and reach of the on-ground partners within rural communities in India.

A respondent from a technology company which routinely collects data for direct care and health research explained:

> **"[We] begin by engaging members of the community [that have the] requisite educational qualification. Community members are trained to work as community healthcare workers [to] interface with the community and collect health data. We also have a team of health paramedics and private doctors and on ground partners (e.g., local NGOs) to develop community relationships and for entry points."**[56]

Similarly, for projects in the public health sector, ANMs and Asha-workers are typically central to data collection efforts. For instance, in 2018 Wadhwani AI recruited ASHAs and other frontline workers across 50 locations to create a data repository of images and other information for the development of an AI-enabled anthropometry tool for detecting the weight of new-born babies. These front-line health workers are being trained by Wadhwani, including periodic retraining to, 'ensure a minimal bar on data quality.[57]

There is an incongruence between data practices on the ground, and the type of policies being put forth to enable data flows and protect citizens' health data.

Data collection thus rests on leveraging existing community ties and the trust developed between local community workers and NGOs. Frontline health workers are an integral part of the AI production line, but their labour is often not recognised. Research suggests that community health workers are often over-burdened with data work, and it is not clear whether or how they are compensated for this additional work.[58]

The involvement of intermediaries in the data collection process inserts a certain degree of

56. Interview, Digital Futures Lab, July 2021
57. Wadhwani AI. (2020). From 2D videos to 3D babies: Introduction to The Anthropometry Journey. Wadhwani AI. https://www.wadhwaniai.org/2020/11/from-2d-videos-to-3d-babies/
58. Kawade, A., Gore, M., Lele, P., Chavan, U., Pinnock, H., Smith, P. & Juvekar, S. (2021). Interplaying role of healthcare activist and homemaker: a mixed-methods exploration of the workload of community health workers (Accredited Social Health Activists) in India. Human resources for health, 19(1), 1-12.

distance between actual users of data (i.e., researchers building AI models and working with data) and the site of data collection. This may result in poor understanding of the provenance of the data collected. Developers are also not aware whether consent was taken from data subjects.[59] In the case of community health workers, it has been reported that consent is often implicitly implied and not directly taken from health subjects.[60] Interviewees also questioned the validity of consent-based mechanisms since patients/data subjects are likely to share any data if they believe it will aid in treatment.[61]

Annotating medical data sets requires advanced medical knowledge. However, there is a significant shortage of qualified medical professionals in India.

c. 2. Data Processing

Once health data are collected, they need to be annotated and cleaned. According to our interviewees, three key challenges arise at this stage - the lack of expertise, the uncertainty of biomedicine which leaves data open to multiple interpretations, and the tension between various principled priorities.

Annotating medical data sets requires advanced medical knowledge. However, there is a significant shortage of qualified medical professionals in India. For instance, a 2015 report produced by the Public Health Foundation of India for the Ministry of Health and Family Welfare, found that the total skill gap is approximately 97.9% across various health workforce categories - radiography and imaging alone accounts for 88.7% of this gap.[62] It can thus be hard to find qualified medical professionals who are able to give their time. As a result, some AI companies have opted to have in-house medical teams.

Both inter- and intra-observer (IOB) bias is a well-recognised aspect of biomedicine. Research has shown that there are very low rates of agreement between radiologists on

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59. Radhakrishnan, R. (2020, June 2). Interrogating the AI hype: A situated politics of machine learning in Indian Healthcare. Economic and Political Weekly. Retrieved September 27, 2021, from https://www.epw.in/engage/article/interrogating-ai-hype-situated-politics-machine.

60. Interview, Digital Futures Lab, July 2021. Also see, Ismail, A. & Kumar, N. (2021, May). AI in Global Health: The View from the Front Lines. In Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (pp. 1-21).

61. Interview, Digital Futures Lab, July 2021

62. Akhter, S. (2019). There is a surfeit of Indian doctors globally, but we have a shortage of doctors. The Economic Times. https://health.economictimes.indiatimes.com/news/industry/there-is-a-surfeit-of-indian-doctors-globally-but-we-have-a-shortage-of-doctors-within-india-dr-sunita-maheshwari/67349998

cases, which makes it difficult to establish certainty over a diagnosis.[63] A significant amount of decision-making and diagnosis also relies on experience of past cases and the medical practitioner's knowledge. Therefore, accurate data annotation and labelling often requires opinions from multiple experts.

Apart from challenges regarding annotation, respondents also reported tensions between mitigating bias and protecting the privacy of data subjects. Interviewees suggested that with the AI developer community, there seems to be a significant concern for privacy-related issues. For instance, one respondent reported that many product teams do not collect data on sensitive attributes, such as gender or race. The primary reason for this is to avoid legal complications; a data leak of sensitive information could lead to reputational damage for the company or organisation. To check and mitigate for bias however, they would need to collective extensive and granular data, and this could violate patient privacy; it may also place an additional stress on the privacy of marginalised social groups. Respondents also noted that the absence of legal frameworks for principles other than privacy protection leaves a large amount of discretionary power in the hands of AI developers as to how to apply other principles, such as fairness, during the design and development of AI.

d. Conclusion

This case study highlighted the multiple actors, practices and relationships entailed in collecting and processing data for AI-based healthcare solutions. Because of the problems with legacy data, technology companies must collect data from scratch. They do this by partnering with medical institutions and local civil society organisations. However, there is little information on the nature of these agreements – what data are shared, how they are used, and whether patient consent is sought are all issues that require greater public scrutiny and oversight. The entry of new technology players is also creating a market for health data – hospitals and medical facilities are incentivised to seek out the most lucrative partnerships for monetising data.
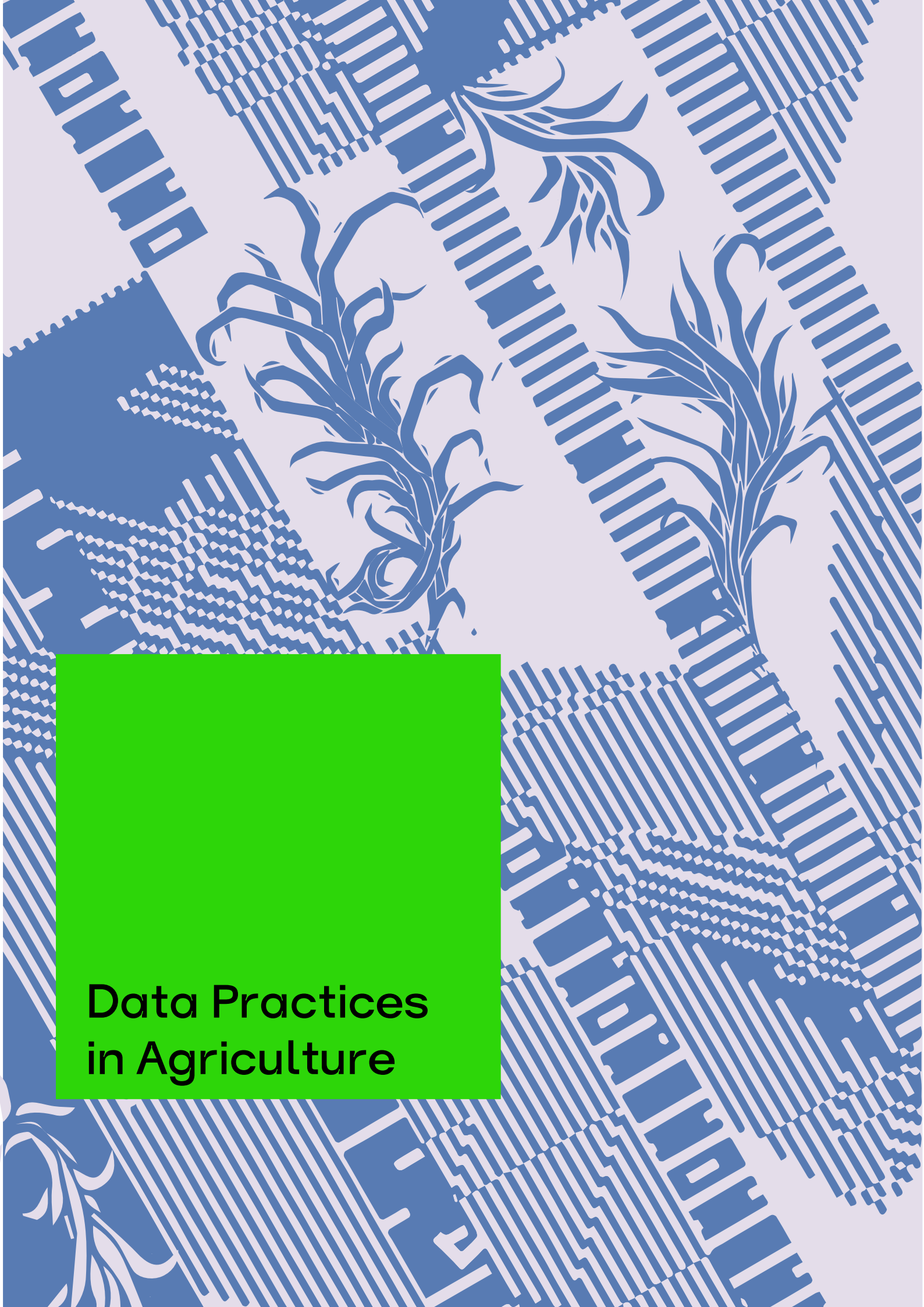
Data collection is reliant on building partnerships with local civil society organisations. These organisations have established relations of trust and solidarity within communities and thus provide a vital link between technology companies and communities. The case

63. Lee, J., Nishikawa, R. M., Reiser, I. S., Zuley, M. L. & Boone, J. M. (2017). Lack of agreement between radiologists: implications for image-based model observers. Journal of Medical Imaging, 4(2), 025502.

study also highlights the 'humans behind AI' and issues around the distribution of technology gains. Developers are reliant on the invisible labour of frontline health workers, and the bonds of trust and solidarity they have established with the community. It is not clear how these workers benefit from these partnerships. It is also not clear how they are compensated for their data work – data collection increases the workload and forces a reorientation of already established practices for already over-burdened health workers.

The involvement of multiple intermediaries and institutions – each with their own motivations, practices, and capacities – also creates room for errors in data collection and recording; the data collection processes by these actors necessarily also reflect their own subjectivities. The same is true for data annotation, particularly because of the uncertainty of biomedicine and lack of available expertise. This case study also reinforces insights on how ethical principles such as privacy and fairness can contradict each other in practice and draws attention to the discretionary powers of developers in interpreting and applying ethical principles.

Finally, this study also suggests that there is an incongruence between data practices on the ground, and the type of policies being put forth to enable data flows and protect citizens' health data. For instance, the health data management policy of the Ministry of Health and Family Welfare does not refer to the data flows that already exist through private partnerships between medical institutions and AI research companies in India.

Data Practices
in Agriculture

4 Data Practices in Agriculture

Data-driven and AI-enabled solutions are at the centre of current policy interventions to reform India's agricultural sector. Currently, 80+ government programmes seek to digitalise agricultural data and develop new data-driven insights – these include e-NAM, Soil Health Card, Meghdoot, Rythu Bandhu (Telangana), KALIA (Odisha), FarmStack (A.P.). India's National Strategy for AI identifies agriculture as a critical sector for AI intervention in India, to improve farmer productivity and make significant value contributions across the agricultural value chain. A recent consultation paper sets out the government's vision for an 'Agri-stack', which will consolidate information about farmers, their landholdings, production details and financial information, and make it available to a wide range of stakeholders to develop data-driven innovations.

a. Challenges in Current Data Ecosystem

Multiple types of actors, including central government departments, state level authorities, district level agricultural offices, and various intermediary organisations, collect agricultural data. Each actor creates datasets with distinct objectives, ideas, aspirations, intentions, and outcomes in mind. Datasets are thus the result of collective action of multiple teams of individuals with diverse skills, expertise, and resources.

a. 1. Data Quality

Public sector agencies, including central and state statistical authorities and extension agencies (like ATMA, KVKs, ATARI) collect data across agro-climatic zones. These are available on the KVK portal and can help ascertain the needs of specific agro-climatic zones. These data, however, are of poor quality. The 2014 High Power Committee, for example, highlighted how infrastructural, administrative, financial, and human resource challenges directly impacted the quality of the datasets of these agencies.[64] Discrepancies in data also arise as data are manually entered into relevant portals.

64. Report of the High Power Committee on Management of KVK, 2014, https://www.icar.org.in/content/report-high-power-committee-management-krishi-vigyan-kendra-kvk

For example, e-NAM is a pan-India electronic trading portal for agricultural commodities which creates a national market by networking Agricultural Produce Marketing Committees (APMCs). It is meant to provide access to information 24*7 on prices of commodities, allow advance registration facility (lot numbers) and viewing of bids by farmers for their produce. Mandi officials gather data at the time of quality assaying or directly from traders/commission agents, and discrepancies arise when these are entered manually into the e-NAM portal.[65]

a.2. Enumerator Bias

Data sets across various state and central ministries suffer from a lack of interoperability.

Enumerator bias is another problem. For example, the Ministry of Statistics and Programme Implementation's report of 2014 states that data related to crop area in most of the NE states, Andaman and Lakshadweep are based on conventional crop estimates based on 'personal assessment' of the patwaris.[66] The High Power Committee's report also notes that agriculture officers and university students or patwaris who are responsible for collecting data from the ground are often unaware of the parameters needed to be collected. The design and organisation of the survey questionnaires differ, based on the enumerator's knowledge of the subject matter and ground experience.[67]

a.3. Duplication and Multiple Mandates

Data collection surveys such as the Irrigation Census, Agriculture Census, and NSSO survey are the responsibility of the Central government. However, since agriculture is a state subject, the responsibility for collecting data is delegated to state and local governments. Each state follows its own standard operating procedure for training, skilling and collecting data. Central government ministries also use their own formats. As a result, data sets across various state and central ministries suffer from a lack of interoperability.

65. Interview, Digital Futures Lab, May 2021

66. National Statistical Commission, Report of the Committee on Statistics of Agriculture and Allied Sectors. https://mospi.gov.in/documents/213904/0/Report_Statisticsof+Agriculture+%26+Allied+Sectors.pdf/391e4661-dbbb-232e-4fc8-8d0c4caa5fb4?t=1599044838482.

67. Report of the High Power Committee on Management of KVK, 2014 https://www.icar.org.in/content/report-high-power-committee-management-krishi-vigyan-kendra-kvk

For example, agriculture and irrigation are two closely linked sectors, but under different ministries, which collect data in their own respective formats. The Planning Commission observed discrepancies between the two datasets and rendered them non-usable.[68]

b. Data Practices in the AI / ML Lifecycle

b.1. Data Collection

According to an interview, these partnerships are often based on what 'feels or looks right' or a personal connection, rather than a rigorous technical or social impact assessment.

The challenges discussed above, and the need for contextual and localised data across varied agro-climatic zones to build AI solutions, has led private companies to collect agricultural data from scratch. New public-private partnerships are being forged to support data collection in the agricultural sector. One of our interviewees noted that this gives these companies a large role in not just developing the solution, but in defining the problem as well. It may also mean that challenges are identified or defined in terms of the data that are most readily available. As in the health sector, there is little publicly available information or oversight of these partnerships.

For example, in June 2021, the Ministry of Agriculture and Farmers Welfare signed an MoU with AgriBazaar, a digital marketplace for agricultural commodities. Under this agreement, the Ministry and AgriBazaar are working together to create an open-source digital platform to provide end-to-end services to farmers. Under the MoU, the Ministry will share available test datasets to kickstart the initiative. AgriBazaar has three main responsibilities - compiling farmers data from specific schemes, cleaning and verifying data to support the Agristack and collecting remote sensing data to cover the gaps in the datasets of land cover, soil degradation and crop identification, among others. The MoU explicitly states that each party shall bear its own costs and expenses, and the Ministry will not make any financial payment for the work undertaken under the MoU.[69] The MoU

68. Ministries of Water Resources Minor Irrigation Division, Report of the Working Group on Minor Irrigation for formulation of the tenth plan (2002-2007) proposals, Available at: https://niti.gov.in/planningcommission.gov.in/docs/aboutus/committee/wrkgrp/wrkg_minor.pdf, p. 87.

69. AgriBazaar. 2021. Memorandum of Understanding. https://agricoop.nic.in/sites/default/files/MOU%20AGRIBAZAAR.pdf

does not however make any provisions for how AgriBazaar may use or share the data, nor why AgriBazaar was chosen as a partner for the initiative. According to an interview, these partnerships are often based on what 'feels or looks right' or a personal connection, rather than a rigorous technical or social impact assessment. In the absence of any direct financial compensation, it is assumed that building this platform is attractive to AgriBazaar because of the data it can access to develop its own market offerings. There is also no information as to how or why AgriBazaar was chosen as a partner for this initiative.

Role of Intermediaries

Private players must forge relationships with local actors and intermediaries to collect data. This is primarily through two channels: existing extension agency pipelines and through 'progressive farmers'[70] or 'farmer friends'.[71]

Agricultural Technology Management Agency (ATMA), Agricultural Technology Application Research Institute (ATARI) and Krishi Vigyan Kendras (KVKs)[72] are the main extension agencies in India. Traditionally, these were used as primary routes to spread education, research, training and technology in agriculture among farmers. However, now the agencies' mandate also includes capturing accurate and reliable datasets, leveraging existing relationships with farmers, local NGOs and self-help groups.[73] The interactions at ground level between private players and the extension agencies are continuous. If during post-model-training the trainer thinks that the data are biased or more data are needed to make the model fairer, extension agencies are again relied upon to collect more data.

Progressive farmers and farmer friends (hereinafter referred to as 'mediators') serve as mediators between the extension system and the farmers at the village level. However, recent research suggests that these mediators tend to be from the dominant caste and gender and are often not well integrated into the social networks of the village. This can contribute to biases and misrepresentation in problem definition and data collection processes. Similar challenges can be seen along the axis of gender. For example, an

70. Progressive farmers include different farmer organisations or associations, whether registered or not. They exist in different regions and serve as important sources of information to farmers.
71. Farmer Friends are nodal persons in the village (can be head of the panchayat or any other person of influence), and point of contact for the KVKs, ATMAs and other extension agencies.
72. KVKs are set up by the State Agricultural Universities, ICAR and Agriculture Research Institutes of the State governments to organise training, demonstrations, and on-the-farm practices on various aspects of modern technology for farming.
73. Interview, Digital Futures Lab, May 2021

interviewee said that in order to provide helpful farm advisories, there needs to be sufficient data regarding the preferred crop choices of the village members. However, the progressive farmer may neglect the needs of certain social groups, such as women.

"Men would like to grow maize as it gives good market returns, but women do not select maize because the shelling process is arduous. There are differences in preference of crop/variety between gender and because the data are collected by male farmers it is often unrepresentative," said the interviewee.[74]

A respondent from the Extension Systems Management Division at ICAR Hyderabad similarly stated:

> **"In case of male enumerators during surveys, they might overlook the constraints a woman faces (like lack of time, domestic and farm responsibilities, inability to leave the children, distant travelling issues due to lack of vehicle ownership and lack of awareness). Also, in cases where female enumerators conduct surveys, the male member of the household usually respond to the questions for the female members ignoring the gender peculiarities."[75]**

Increasingly, both government extension agencies and private players are turning to digital modes, specifically social media tools, and apps to collect data and provide advisories. For example, one of our respondents, a start-up, asks farmers to upload images of plants on WhatsApp. Farmers upload photographs of infected parts of plants to gain knowledge about pest management and best agricultural practices to remedy the disease. In the process, the images are added to the growing knowledge database of pictures owned by the start-up, over which it has a proprietary interest.[76] Similarly, government extension agencies have started using WhatsApp or Facebook group features to collect images and textual data related to farmers' challenges. For instance, District Agricultural Officers are administrators of WhatsApp groups and encourage farmers to post pictures of infected parts of plants, livestock, or soil to seek diagnostic services.

74. Interview, Digital Futures Lab, July 2021.
75. Interview, Digital Futures Lab, July 2021.
76. Interview, Digital Futures Lab, May 2021.

This provides a quicker and cheaper way to collect data, bypassing the need for building local relationships. However limited education, lack of access to quality digital devices, irregular power supply, digital literacy and constrained bandwidth create inequities between farmers. Not all farmers have access to smartphones with high pixel cameras. Most agencies' product development teams use WhatsApp, but this is not the most widely used platform among the Indian population.[77] According to Nithya et al., datasets aggregated through internet connections will permanently exclude a significant population, primarily women, rural communities, and other marginalised sections, due to access constraints.[78]

Data privacy is a concern across all these pathways for data collection. Even where consent is taken from farmers, the consent forms do not include information about the possible negative effects that may arise from the use of AI and most farmers are not aware that their data would be sold to third parties. For example, civil society member organisations in India have expressed concern about Microsoft accessing the data of millions of farmers without their consent through an MoU recently signed between Microsoft and the Ministry of Agriculture.[79]

b.2. Data Processing

A common challenge at the data annotation stage is the limited skill expertise available in India. The data preparation stage entails context-specific knowledge which few experts possess. For example, one needs entomologists who know various pests and associated diseases across agro-climatic zones to annotate pest data. Annotation of pests starts by looking at corresponding diagrams of pests in a book, but this can be challenging as diagrams are often different from how the images are captured in a field. At this stage, entomologists must rely on their subject matter knowledge, as they have to calibrate and understand how pests behave in different contexts or conditions.

77.   Basuroy, T. (2022). Share of rural and urban active users of WhatsApp in India 2017-2018. Statista. https://www.statista.com/statistics/962626/india-active-whatsapp-users-share-in-rural-and-urban-areas/

78.   Sambasivan, N., Arnesen, E., Hutchinson, B., Doshi, T. & Prabhakaran, V. (2021, March). Re-imagining algorithmic fairness in India and beyond. In Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency (pp. 315-328).

79.   Divij Joshi & Anouk Ruhaak (Aug 2020), The Wire, Available at: https://thewire.in/tech/india-non-personal-data-regulation-amazon-facebook.

Further, most of the pests' images are taken by farmers, and are often of poor quality. Entomologists lack experience of working with mobile phone images, making it harder for them to annotate the data.[80] One of our respondents noted that providing quality training and skilling to experts is crucial in the agriculture sector. However, finding zone-specific experts who understand the complexities of crop disease in each zone is a "luxury," often only available to players with substantial financial resources.

Private players have an increasing say in not only developing appropriate solutions, but also defining or identifying the problem to be solved.

We interviewed an organisation involved in pest detection, that is creating a tiered system of experts for data annotation to compensate for the lack of trained entomologists in the country. In this tiered system, entomologists train and supervise a data annotation team to annotate the rest of the images. However, outsourcing annotation could mean that the people doing data annotation might have no control over the collection process or might not understand the context of the data.

To address the need for context-level information, particularly crop health, CABI is developing a knowledge bank on types of crops, diseases and the corresponding 'Plant Doctors' who possess knowledge and skill to diagnose the said crop. CABI's 'Plantwise' project helps farmers diagnose crop health issues by setting up plant clinics in rural areas in India. Data on crop health, pests and other plant diseases are collected at different plant clinics. Plant Doctors usually collect data in a paper format, which are then scanned into the Plantwise Knowledge Bank using a structured form. The paper-based methods are laborious, but the Project is also experimenting with digital methods by providing plant doctors with tablets pre-loaded with a Factsheet app containing all the content from the Knowledge Bank and a data collection app. CABI has trained 3500 extension workers as Plant Doctors and aids in running 1500 plant clinics regularly.

80. Dalmia, A., White, J., Chaurasia, A., Agarwal, V., Jain, R., Vora, D. & Panicker, R. (2020, August). Pest Management In Cotton Farms: An AI-System Case Study from the Global South. In Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (pp. 3119-3127).

c. Conclusion

As in the health sector, agricultural data is messy – multiple actors, with varying methods, motivations and capacities are engaged in the collection of data. Because of the problems with legacy data, private technology companies are entering into agreements with state governments and agricultural ministries to collect data. Private-public partnerships in the agricultural sector are not new. However, private players have an increasing say in not only developing appropriate solutions, but also defining or identifying the problem to be solved. Government agencies typically lack the technical expertise to be able to evaluate the fit between the stated problem and the proposed solution. Like in the health sector, there is little clarity on the terms of these partnership agreements – questions such as why certain private sector actors are selected, what type of data they collect, how they will be used and shared, remain mostly unanswered.

Technology companies also rely on relationships with local extension agencies and progressive farmers. These actors bring their own subjectivity and biases to the data collection processes – for example, progressive farmers are typically male and may not represent the priorities of women farmers. It is also not clear how these local actors are recognised and compensated for their labour. The role of extension agencies is also changing – from providing information and education to farmers to becoming data enumerators for AI developers. This issue extends to crowd-sourced data as well – farmers contribute their labour and knowledge by taking pictures and sharing them with AI developers, but these image banks may then be locked behind proprietary business models.

Because of the digital divide, data collection through digital means such as social media can end up excluding a significant population, primarily women and other marginalised groups. Technology companies also struggle to find skilled data annotators, and the best ones are typically contracted by better-resourced companies. Outsourcing annotation work also makes it harder for AI developers to understand the context and provenance of the data. This study thus reinforces, as Evelyn Ruppert et al., put so well, "data does not happen through unstructured social practices but through structured fields where varied agents generate forms of expertise, methods, practices, interpretations that collectively constitute power and knowledge."[81]

81.   Ruppert, E., Isin, E., & Bigo, D. (2017). Data politics. Big data & society, 4(2), 2053951717717749.

5 Towards Responsible Data Practices

Both the health and agriculture sectors in India are witnessing a rapid push towards digitisation and centralisation of data repositories and the development of AI solutions. But these efforts are compromised by a range of foundational issues such as data gaps, unreliability of datasets, a lack of interoperability, and a shortage of expertise for data annotation. With an increasing policy focus on enabling data flows across stakeholders, we also need to take a step back and consider how to handle data responsibly and who should be responsible.

The term responsibility is typically defined as accountability and liability, i.e., to hold someone accountable for their actions. However, this definition of responsibility as accountability is often unable to account for the distribution of agency in complex socio-technical systems such as AI, creating thereby responsibility gaps.[82] For instance, in cases of medical misdiagnosis and harm caused by AI-based diagnostic support systems, it is almost impossible to attribute it to just one individual or even a chain of individuals.

Responsibility can also be defined in terms of 'answerability' or a response.[83] This understanding of responsibility privileges the experience of those who have been impacted by actions or systems. In other words, rather than only focus on assigning accountability to a particular 'bad actor', something that is particularly difficult in complex socio-technical systems, this second meaning of responsibility points towards the need to develop anticipatory and systemic strategies to protect people from harm. Such an idea of responsibility is also closely connected to an 'ethic of care' - which actively foregrounds the needs of the other.[84] This is the normative framing of responsibility that guides our thinking on the priorities and pathways to build more responsible data practices in India.

82. Matthias, A. (2004). The responsibility gap: Ascribing responsibility for the actions of learning automata. Ethics and information technology, 6(3), 175-183.
83. Raffoul, F. (2010). The origins of responsibility. Indiana University Press.
84. Digital Futures Lab. Locating responsibility in Socio-Technical Systems (forthcoming)

1

Question underlying assumptions about data

Within the current policy emphasis on data-driven policy and solutions, there is an underlying assumption regarding the power and integrity of data - that data in and of itself can stand for truth and showcase 'reality'. However, as this study shows, the creation of data is imbricated in social relationships and subjectivities - how data are collected, by whom and for what purpose is not value-free or neutral – it is embedded in social relations of power and reflective of worldviews and interests. For example, progressive farmers collecting agricultural data tend not to interview women farmers, and the data they share is therefore not representative of the broader community. Thus, responsible data practices require, first and foremost, an understanding of the social creation of data and its resultant limitations as a single point of truth. An examination of data collection practices on the ground in the healthcare and agriculture sectors indicate the misplaced faith in the truth-telling abilities of data.

2

Practice data documentation

Documenting the decisions made at various stages of the ML cycle can further the accountability of the various actors involved in the production of AI. For example, at the problem documentation stage, the data documented may include the motivations and objectives driving the building of a particular solution, the key stakeholders consulted, and an assessment of potential risk and harm based on available evidence. Similarly, at the data collection stage, teams should document how data are collected and by whom, the reasons for choosing data sources, and any identified data gaps or challenges. At the data annotation stage, the profile, training, and responsibilities of the annotator could be documented, along with whether the annotation has been checked and verified by external experts.[85] Data documentation can help

85.   Gebru et al., (2018), Data Sheets for Data Sets

identify gaps and biases, establish transparency, provide space for ethical reflection by developers, as well as develop institutional memory on best practices within organisations.

Data documentation practices are particularly important in India because of the inconsistencies, gaps, and errors in health and agriculture data. Data documentation can also help support the certification of AI products.

A certification mechanism could be given to specific AI products based on the quality of their datasets, like the AGMARK, which is a certificate of quality assurance given to India's agricultural products. Some governments have started mandating such documentation practices. For example, Canada requires technology companies to document the source and type (structured or unstructured, inference or derived) of data used for a particular AI/ML solution.

Data documentation is not merely for AI designers or data scientists. Decision-makers across government, industry, and civil society need to understand that simply opening up data and enabling their flow is not enough. Data once collected will not immediately become usable. Without proper data documentation which outlines their provenance, and methodology of collection, much of open data can constitute what has been termed zombie data, i.e., data that float without any purpose, aim or even usability.[86]

3

Recognise labour and redistribute technology gains

As the two case studies have shown, data collection for AI is deeply reliant on the knowledge, trust and networks that front-line health workers, farmers, and grass-root organisations have within their communities. Without these social relationships, it would be near impossible for developer teams to access the data they need. The centrality

86. Gurin, J. (2014). Open Governments, Open Data. The SAIS Review of International Affairs, 34(1), 71-82.

of these actors to AI production pipelines is seldom recognised - their labour is rendered invisible in dominant accounts of 'high-tech' innovation. Building a bottom-up agenda for responsible AI must centre the experiences and priorities of these front-line workers – how their agency, work practices, workload, and relationships within the community are recast because of their participation in AI production chains. Health workers and farmers contribute their knowledge and labour for free – such as when farmers upload and share pictures of pests – but the value that is created from this is locked behind proprietary systems for the benefit of technology companies.

Responsible data practices thus also entail finding mechanisms to meaningfully redistribute technology gains and elevate the status of community-based actors who are essential, but often rendered invisible, in accounts of AI and its production. It is also important to recognise that often, the knowledge of community health workers or farmers upon which these AI solutions are built, is questioned as being unobjective or unscientific, and that should therefore be replaced or upgraded by data-driven innovation.

Understanding the relationships and institutional contexts that feed into the data assemblage, requires going beyond applying ethical principles to datasets or merely to data practices by developers/designers of technology alone. This is particularly true of the Indian context, where data practices for AI do not begin at the level of consolidated/curated datasets but at the level of villages, farms, nursing homes, homes, clinics, and hospitals - that are vital sites for AI production. Thus, there is a need to go beyond applying principles of fairness, accountability and transparency to datasets or algorithms, and apply them to the social relationships that are integral to building AI.
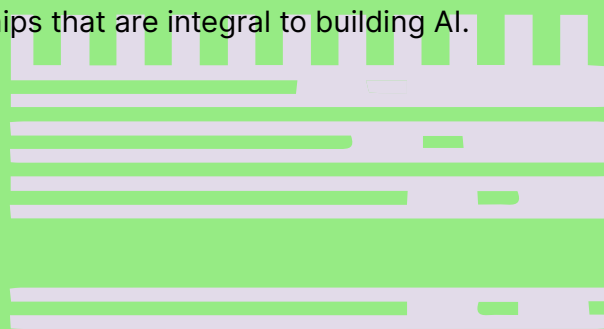
4

Develop participatory models for data-based innovations

As data is increasingly viewed as a lucrative economic object, decisions regarding what data to collect and how they should be used and shared are increasingly made by private actors with little public deliberation. For instance, as noted in Chapter 3, technology companies collect data from private clinics, hospitals, and dispensaries, but patients are unaware of how their data are shared and monetised. Recognising that data are the product of collective intelligence and interconnected human labour networks calls for participatory models and collective deliberation on the proper use of data.

In recent years, there have been experiments with the notion of building community-based data trusts that allow communities of individuals to establish collective agency over the information as an alternative to individualistic legal frameworks of personal data protection laws. However, studies on building such community-based data governance have highlighted the need to involve multiple stakeholders, including civil society organisations, to enable data flows and empower the data subjects to make informed decisions about their data - particularly in the context of India, where data relationships are often marked by unequal relations of power and autonomy.[87] Focus group discussions conducted by the Open Data Institute and RSA (Royal Society for the Encouragement of Arts, Manufactures and Commerce), show that public deliberations on processes of data collection, sharing and use can yield useful insights about the values and rules that need to govern data practices.[88]

But participation is itself a broad term and can take on many meanings. Within the AI development context, participatory methods have been used under a wide array of frameworks

87. Aditi Ramesh (October, 2020), Data Economy Lab, Available at https://thedataeconomylab.com/2020/10/29/community-data-governance-and-its-application-for-migrant-communities-in-urban-india/
88. Samson, R., Gibbon, K. & Scott, A. (2019). About data about us.

- from participation as work (user clicks that produce data for AI and captcha being key examples) to participation as consultancy (involves episodic, short-term projects with diverse stakeholders) to participation as justice (involves designing long-term collaborations with tightly coupled relationships and more frequent communication). For participatory frameworks to deliver on the promise of equity and justice, participation must not be used merely as an 'ethical scaffolding' for otherwise extractive processes and must incorporate genuine knowledge-sharing, transparency, and an acknowledgement of the myriad networks of labour that are required to build and maintain AI systems.[89]

5

Institute transparency over data flows across public and private actors

There is little publicly available information about the new public-partnerships that are being forged to develop AI systems. Concepts such as fairness, transparency, and accountability, that are typically applied to AI systems, need to be extended to these partnerships as well. Private players are not only developing solutions to problems identified by relevant government agencies, but taking the lead in defining or conceptualising the problem, creating and curating data, and proving technical know-how and skilling training.

As private technology companies begin to perform public functions, greater public oversight is needed. An oversight framework should include points around why a particular tender has been released and why certain private players were selected; clear rules about what type of data can be collected, their purpose, and how they can be used; an indication of how potential risks and harm may be mitigated; and mechanisms for grievance redressal. Such audits should be required both at the start and completion of any

89. Ibid.

engagement and be accessible for public scrutiny. As various government agencies enter PPPs, procurement guidelines also need to be developed and updated, and must include a social impact assessment which should consider all stages of the AI lifecycle, from development to deployment. New institutional bodies, such as the Ethics and Oversight Body proposed by NITI Aayog, need to be developed to support continuous oversight – this will require developing new technical skills within government and engaging more actively with a diverse range of external stakeholders.

Current thinking on data protection in India is primarily predicated on notice and consent frameworks. It is also believed that data, once anonymised, can be utilised for various ends, which are determined by state-led bodies or private actors. The category of non-personal data and the proposed transmutation of personal data into non-personal data through processes of de-identification is a case in point. While debates about the ownership of data or property rights over data are far from resolved, within the current models of data collection via partnerships, a few stakeholders exercise de-facto property rights over data by their ability to control its flow, monetise or otherwise utilise it for private gain.

6

Induce broader cultural shifts through data ethics curricula, professional ethics, and critical perspectives in data science

While legal mandates for data protection are necessary steps to ensure privacy and protection of data rights, responsibility in data practices should entail a much broader set of actions and actors. As one of our interviewee noted, it is incumbent upon the data science community and AI practitioners to recognise themselves as political actors and develop a critical lens to evaluate the diverse impact of their work. Developer teams have substantial discretionary power over whether to adopt fairness and other values in developing their models. Introducing critical data studies and ethics into engineering curricula, building interdisciplinary teams to

design and develop AI, and developing codes of professional ethics and organisational structures that support their realisation, are essential. Of course, such measures are not a panacea for addressing the ethical challenges and harm of AI, or all ethical problems posed by AI,[90] but they are a necessary part of any long-term and systemic strategy towards building responsible data practice for AI.

90. Bowyer, K. (2001). Ethics and computing: living responsibly in a computerized world.

Digital Futures Lab is an interdisciplinary research collective that interrogates the complex interaction between technology and society in the global south. Through evidence-based research, systematic foresight, and public engagement, we seek to realize pathways to equitable, safe and just digital futures.

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