Systems in the Subcontinent: Data, Power, and the Ethics of Medical Machine Learning in India

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Abstract

The disruptive effects of the Fourth Industrial Revolution (IR4) have the capacity to rapidly alter the course of India's social and economic progress. For the healthcare sector, plagued by poor infrastructure and latency, advances in big data computing and Machine Learning (ML) can have a transformative impact. However, in a socio-political landscape marred by historic hierarchies of exclusion and disparity, the data-driven technology of ML may serve to mechanise and automate social divergence based on class, caste, sex, religion or region.

The research frames the issue of medical ML in India as one of lethal biases and data privacy. Through an analysis of the two, the ecosystem of such technology has been brought to light. As instances of bias in ML systems reveal more about social hierarchy and discrimination than they do technological prowess, the dissertation aims to evaluate the ethical dimensions of medical ML in India.

Technology is found to not only mediate the actions of individuals but also power dynamics of human and nonhuman actants within the social whole. Notwithstanding the challenges of integrating medical ML in India, the research highlights the ethics of design and the ethics of use to ameliorate the risks of machines with lethal consequences. With a focus on the Indian subaltern, the research on encoding ethics into machines reveals confrontations on agency and accountability in attempts to *materialise morality* in the critical industry of healthcare.

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Lastly, I would like to thank every individual who broke the barriers for women of colour entering academia and science. The actions of a few have paved the way for me to learn, grow, and succeed.

Contents

List of Abbreviations

AI	Artificial Intelligence
ANN	Artificial Neural Network
ANT	Actor Network Theory
BJP	Bharatiya Janata Party
CNN	Convolutional Neural Network
CTA	Constructive Technology Assessment
EMR	Electronic Medical Records
FDRTs	Facial Detection and Recognition Technologies
GDPR	General Data Protection Regulation
ICT	Information and Communications Technology
IoT	Internet of Things
IR4	Fourth Industrial Revolution
IT	Information Technology
LMICs	Low- and Middle-Income Countries
MDGs/SDGs	Millennium Development Goals/ Sustainable Development Goals
MHA	Ministry of Home Affairs
ML	Machine Learning
MMA	Ministry of Minority Affairs
MoHFW	Ministry of Health and Family Welfare
NLP	Natural Language Processing
OOPE	Out of Pocket Expenditure
PDP	Personal Data Protection
PoD/PoT	Philosophy of Data/ Philosophy of Technology
SC/ST/OBC	Scheduled Caste/ Scheduled Tribe/ Other Backward Classes
STEM	Science, Technology, Engineering, Mathematics
STS	Science and Technology Studies

1 INTRODUCTION

From the imposing northern frontiers of the Himalayas to the vast waters of the Indian Ocean, the Indian subcontinent is an expansive and heterogenous physio-geographic region in South-West Asia. Not merely a geographic area, the Indian subcontinent is one of the largest geostrategic regions in Asia and the world (Kapur, 1998). Nestled at the historic cross-roads of both land and naval trade, the subcontinent has borne witness to millennia of progress, occupation, revolution, and strife which continues to mark the histories of the countries occupying the region: India, Nepal, Bhutan, Pakistan, Bangladesh, Sri Lanka, Maldives, and other islands of the Indian Ocean (Kumar, 2004). However, in contemporary parlance, the Indian subcontinent is often indicative of the eponymous sovereign state whose history cannot be severed from those of her neighbours.

The ethnic, linguistic, social, political, and economic communities of 1.2 billion individuals (Census, 2011) have contributed to the diverse fabric of the modern Indian state. Where similarity is in shared Indian citizenship, diversity in India manifests in the geographical landscape of formidable mountains, fertile plains, marshlands, dense forests, both arid and high-altitude deserts, plateaus, extensive contiguous coastline, and numerous islands speckled across the Indian Ocean and the Arabian Sea. The provision of government services to the populace inhabiting this expansive topography was a mammoth task for the first Constituent Assembly organised to replace British colonial rule in 1947. Guided by a Preamble which accentuated the Republic of India's sovereign, socialist, secular, democratic and egalitarian values, policymakers endeavoured to serve and protect regardless of sex, caste, creed, or religion. However, 75 years after Independence, the subcontinent navigates perilous fault lines and growing divergence.

The celebrated diversity of India is marked by a hierarchy of categories not limited to income, class, caste, sex, and religion. Despite the founding beliefs of equality and justice, the Indian subaltern faces an uncertain future where structural disadvantage is generational (Asher, Novosad and Rafkin, 2018; Nakkeeran et al., 2020). Porous borders and zones of conflict have further added to the myriad of challenges (Sur, 2020; Vogt, 2018). People inhabiting the region confront a future where citizenship, identity, and rights are subject to recurrent examination (Jayal, 2019). For those living permanently in mountainous settlements in the world's highest conflict region of the Kashmir Valley, that future is decided by three nuclear-armed states of China, Pakistan, and India, leaving little to their own autonomy (Tavares, 2008). On the other hand, tribal communities of ancient forests laden with mineral wealth are under threat of expanding corporate interests, reducing them to outliers in the land historically occupied by them (see Sahoo, 2015). Thus, in a country lauded across the world for diversity, the dimensions of hierarchy are perennially re-envisioned by both state and corporate interests.

The onset of the COVID-19 pandemic, caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), has revealed the discontinuities that plagued the nation long before the disease. The global race to curb the spread of the virus, as it continues to bring the most powerful to their knees well into a second year, has refocused attention to a critical industry: healthcare. Serving as the first line of defence, healthcare systems across the globe seemed to buckle under the growing pressure of an ostensibly insurmountable pathogen (Dalglish, 2020).

Like many other Low- and Middle-Income Countries (LMICs), India attempted to stem the rising death toll, but infrastructural constraints (Singh, Ravi and Chakraborty, 2020; Sahoo et al., 2020) and poor management failed to mitigate the exploding infection rates (Kar et al., 2021). Announced with only 4 hours warning, the entirety of India was subject to the world's strictest lockdown on the 24th of March 2020 (Miglani and Anand, 2020). As cases reduced in the latter half of 2020, the country gradually reopened various sectors to restart the economy. Restrictions were almost entirely removed, public gatherings of thousands could be observed across the nation. The organisation of state and village elections were also accompanied by large assemblies of people for electoral campaigns; many of which not only disregarded social distancing and mask measures but were also viewed as a commendable feat by the incumbent Prime Minister Narendra Modi (Das and Ahmed, 2021). Hundreds of thousands gathered on the banks of the river Ganga in the small town of Haridwar for the Hindu festival of Kumbh Mela, often recognised as one of the largest public congregations (David and Roy, 2016).

Consequently, by early April 2021, infection rates saw a steep increase boosted by the emergence of new variants (Singh et al., 2021). The unprecedented rise of infections was accompanied by shortages in oxygen, beds, ventilators, vaccines, and medication while cremation and burial grounds were operating beyond capacity; funeral pyres burned from dawn to dusk till even the steel rods began melting (Pal, 2021). With long lines at even the largest hospitals in the country and a race to acquire the oxygen cylinders that hospitals could no longer provide, Indian healthcare had collapsed. However, the cracks in public health have been painfully apparent for decades.

For those living below the poverty line, in rural hamlets, or marginalised communities, Indian healthcare had failed to protect the most vulnerable (Johri et al., 2021). While the ruling Bharatiya Janata Party (BJP) prematurely celebrated the end of the virus by reporting low death and infection rates (The Quint, 2021), the situation on ground was radically different. During the first lockdown, migrant workers embarked on an arduous journey back to their villages where many died from hunger, thirst, and exhaustion (Mathur, 2020). Even in cities, for those who could not afford excessive costs of admission in private hospitals preventing death was a distant dream (Pal and Siddiqui, 2021). The situation, as chaotic as they were in cities, was worse in rural India where nearly 70 per cent of the population lives (Census, 2011). Arundathi Roy (2021) noted observed how,

> "At the top end, you might need to sell your land and home and use up every last rupee for treatment at a private hospital. Just the deposit alone, before they even agree to admit you, could set your family back a couple of generations."

Set against this amorphous socio-political landscape, the transformative impacts of the Fourth Industrial Revolution (IR4) are taking hold. Data is the new currency in a global world order increasingly designed by binary code. Improvements to storage and computing have revolutionised the future of technology in society. Wearable devices and the Internet of Things (IoT) have further allowed for data collection and categorisation in real-time with the estimated creation and consumption of 59 zettabytes of data in 2020 (International Data Corporation, 2020). Availability of stream data has buoyed the growth of Machine Learning/Artificial Intelligence (ML/AI) as it penetrates the fields of business, education, medicine, law, and order and so forth.

Healthcare, in particular, may be radically altered by efficient machines. The capacity to engage with dynamic datasets through ML/AI systems has improved the functionality of healthcare practitioners (Nambiar et al., 2013; Sakr and Elgammal, 2016). Conversely, the industry is plagued by latency, low penetration, and historical socio-political fault lines (Kasthuri, 2018). Within this novel global cyberspace of 0s and 1s, where do complex human actors with multifarious characteristics and dispositions lie? Is the Anthropocene marked by human dominance or of those *objects* made by humans? Where human actors across the globe struggle to claim agency, can claims of artificial and artefactual agency hold ground?

As the contemporary international landscape has been influenced by health crises and the big data disruption, a comprehensive scholarship focusing on marginalised communities will not only fill lacunae in research but also inform policy. Indian forays into ML/AI and healthcare mandate a critical evaluation of the associated deficiencies in two key dimensions: data collection and data security. The heterogeneity of the Indian populace may influence ML/AI robustness and generalisation if datasets do not account for ethnic and demographic variance. Concurrently, the necessary legal regimes for the protection of personal data utilised in ML/AI have been limited.

Emphasising the demographic and territorial diversity of the Indian subcontinent, the dissertation endeavours to evaluate the capacity for big data and Ml/AI to disrupt the healthcare sector. As a global leader in pharmacology and health tourism, greater critical discourse on the role of technology and innovation in Indian healthcare is necessitated. Moreover, ascertaining the potential for technology, through medical ML/AI, to influence or mediate power dynamics in a territory occupied by over a billion individuals is imperative for three reasons. Firstly, limited data collection from marginalised groups may contribute to biases in ML/AI systems which may potentially lead to fatal outcomes. Secondly, technology can longer be categorised as mere objects owing to increasing autonomy of systems. Finally, understanding agency, accountability and responsibility of medical ML/AI is necessary to monitor and regulate the deployment of such systems not only within the diverse landscape of India but also the world. Thus, the dissertation identifies the primary research question as:

To what extent can biased Machine Learning (ML) systems[1] in healthcare influence power dynamics in India? Are contemporary data security and regulatory regimes prepared for the Big Data disruption through ML?

Additionally, the research will also aim to answer sub-questions.

(i) **What are the ethical implications of introducing ML/AI algorithms into healthcare infrastructure?**

(ii) **How can accountability and responsibility of nonhuman actants be reviewed for policy making and regulation?**

The dissertation aims to evaluate the extent of the big data disruption in healthcare in two streams. Firstly, as minimal healthcare penetration and latency into marginalised communities can result in lower quality data sets over time, the bioethical concerns of deploying ML/AI systems will be addressed. Indian diversity is belied by a dark underbelly of disparity and social inequality based on class, caste, gender, and religious affiliation. Further exclusion of communities from national healthcare databases can arise through regressive laws or incomprehensive policies. With a few avenues for the poor and marginalised to access reliable healthcare, particularly in rural India, collection, and analysis of data on healthcare may be skewed in favour of the urban elite or those with greater access to medical care. As such, unaccounted medical discrepancies arising from biased datasets will contribute to biased ML/AI systems with lethal consequences.

Secondly, an evaluation of data protection measures is necessary owing to the national scope of such legislation. Moreover, data protection regimes are closely entwined with regulatory

[1] It may be noted that the dissertation will make use of the term ML/AI to cover the domain in a simplified manner.

mechanisms on ML/AI. By constructing a sociotechnical imaginary of the Indian healthcare landscape through the human and nonhuman systems, the political powershift brought about by technology can be presented. Thus, the dissertation aims to provide greater contextual and technical analysis of the ethics and efficacy of ML/AI in the Indian healthcare sector whilst focusing on the unique social fabric of the world's largest democracy.

Divided into 7 chapters, the research will provide foundational arguments and evaluation for future policy processes. The second chapter will cover existing scholarship and research on both the technical and social aspects of medical ML/AI through a comprehensive literature review. Based on available resources, the chapter will identify gaps in research and map out those areas which this dissertation can address. Additionally, owing to the nature of the dissertation, the scope and limitations of the study will be presented while noting the potential and necessity for future research on the same.

Effective methodology and theory serve to provide an epistemological and ontological skeleton through which cogent arguments can be made. As such, the second chapter will present the use of subaltern theory and epistemes from Science, Technology and Society (STS) scholarship. To simplify the use of theory in a meaningful way, key assumptions on the nature of the subaltern will be included. The toolkit of this qualitative study will incorporate document and content analysis while addressing physical and legal constraints in accessing certain documents.

The main analysis will be divided into three chapters. Chapter 3 will provide a layout of the Indian healthcare industry through a historical overview as well as the present conditions of medical care. The root of Indian indigenous medicine reveals the parallel philosophies that contributed to a rigid caste system. Under British colonial administration, the caste system was further entrenched but, at the time of independence, policymakers turned to western models of healthcare. The vision of a medical system driven by modern science and technology constructed the socio-technical imaginary which has moulded Indian national and state policies on public health. However, laws have seldom reduced rampant inequality and disparity in the country.

Destroying the hierarchies which sustained itself in the subcontinent for millennia was a priority of Indian administration. Through digital means, attempts to improve access and costs of public healthcare have turned the nation's attention to the disruptive technology of Big Data Analytics and ML/AI. Yet, with historical and contemporary socio-political fault lines, mechanisation of healthcare has also been a mechanisation of social order. Thus, the fourth chapter evaluates the challenges of data collection and the impact on ML/AI systems. Lethality of automated systems is not limited to biased diagnostic or clinical tools. As machines, deemed to be objective, mediate the actions of individuals and states alike, the chapter will also evaluate the scope of ML/AI systems as a socio-political artefact.

Beyond the lethality of bad data, the fundamental challenge for policymakers is to implement strong legal regimes to protect the sensitive personal data utilised in medical ML/AI systems. However, the nature of automated technology has revealed the pressing need to understand technology not merely as a means or instrument. Instead, by providing foundational arguments on the scope of agency of ML/AI, subsequent dilemmas on accountability and responsibility may be addressed. Through the ethics of design and the ethics of use, the fifth chapter will lay out the potential to materialise morality while advocating for comprehensive data protection and security regimes within the subcontinent.

As scholarship in these areas have been limited, the aim is not to sensationalise or argue against technology. Instead, through a comprehensive analysis, the research will reveal the issues of healthcare, scope for big data, lethality of biased machines and potential remedies. Therefore, such scholarship will be useful in both academic discourse and national policy making strategies for India and the world.

2 LITERATURE REVIEW

With every iteration of progress in achieving robust and replicable ML/AI software, ascertaining the nature, role and evolution of its constituent elements is imperative. Understanding the socio-political landscape in which such systems are deployed calls for an evaluation of the approaches utilised in contemporary and historical discourse. As such, this literature review endeavours to highlight the burgeoning scholarship on the building blocks and ML/AI systems alongside a critical evaluation of extant theories and approaches to disruptive technology with a focus on India. The literature review will reveal key gaps in scholarship. Firstly, the role of ML/AI as a form of technology capable of influencing power dynamics in the diverse subcontinent of India. Secondly, the critical nature of healthcare to play a socio-political role as an *objective* technology may be used as a medium to manifest the goals of a hegemony. Finally, the potential future of Indian legislation and jurisprudence on data protection and the regulation of ML/AI to mitigate threats of biased technology in the industry of healthcare.

2.1 Data: The Great Divider

The advent of data science and technological innovations capable of calculating large volumes of data and information, be it the Turing Machine or the Electronic Numerical Integrator and Calculator (ENIAC), has been central to the development of ML/AI. Automated systems are consistently subject to improvements that aid in creating more replicable and generalisable models. Yet, the field of ML/AI, as it exists today, is far from the idealised machines of science fiction. Before one attempts to present the state of knowledge on the field, a definitional overview can assist the research.

The development of robust ML/AI software is reliant primarily upon the data from which it may, like the development of human intelligence, *learn* and grow. ML/AI is understood to be a programme capable of automatically carrying out tasks and producing decisions from data without being explicitly programmed to do so (Beam and Kohane, 2018). Through algorithms designed by a programmer, the system or agent is *soft coded* to learn from experience or repetition (El Naqa and Murphy, 2015). The degree of autonomy is primarily understood by the level of human involvement in the decision-making process. While conventional ML/AI programs were restricted in their capacity to process raw and unlabelled data, Deep Learning (DL) can extract features and determine classification from mammoth datasets (Le Cunn et al., 2015). At the heart of the domain and its progress is data. In an era of increasing digital connectivity afforded by innovations like the IoT, access to data on a plethora of fields has augmented development of ML/AI programmes designed to mimic human learning and experience at a faster rate.

Innovations and improvements to software and hardware have catalysed the production, storage, and access to data (Hilbert and Lopez, 2011). The value of these units of information to domains including weapons systems (Morgan et al., 2020), policing software (Babuta, 2017; Ridgeway, 2018), cybersecurity (Oseku-Afful, 2016; Subroto and Apriyana, 2019) and healthcare (Dash et al., 2019) is unbounded. Accordingly, understanding the ontology of data is pivotal to answering the dual dilemma of *what it is* and *what it is not*. Moreover, as ontology is one of the four cornerstones of the research paradigm, alongside epistemology, methodology and methods (Scotland, 2012), setting up the philosophical foundations of research is central. Variations in the same amongst researchers may lead to differing approaches (Grix, 2004) and, consequently, diverging outcomes.

Adler (1986) and Weinberger (2011) present an ontology of data by proposing that data is a foundational element upon which information and knowledge may grow. Data can be viewed as "atomic units of information" (Ballsun-Stanton and Bunker, 2009, p.2) in the domain Philosophy of Data (PoD). In our contemporary high-technology culture, the close relations, and overlap, of the PoD with the fields of Information Science, Technology and Semiotics have been critically evaluated (Ballsun-Stanton and Bunker, 2009). However, the disposition of leading authorities themselves have resulted in divergence in definitional scholarship. Nevertheless, the central ideas and approaches of associated fields reveal the nature and role of data as it exists within a complex web of physical and metaphysical objects.

The traditional notion of data driving information which, in turn, drives knowledge has been critiqued by Illka Tuomi through the reverse-hierarchy model. Instead, they propose that "information can be created only after there is knowledge, and data emerge as a by-product of cognitive artifacts that assume the existence of socially shared practice of using these artifacts" (Tuomi 1999, p. 115). While both approaches subscribe to a set of apriori beliefs to support their ontological claims, they are similar in revealing the relational complexity of data.

Attempts to assess the nature of data from the domain of semiotics (Chartier et al., 2018), the progress of technology (Dreyfus, Dreyfus and Athanasiou, 1986) and Artificial Intelligence (Borgmann, 1984) has been noteworthy, but the metaphysical divergence has manifested the research.

To a degree, the being and nature of data, as well as associated technology, can be further understood through its history. Hong Liu (2014) addresses the transformations of data through two categories appropriately termed "revolutions". The first data revolution is captured in the scientific models, which pursued progress and accuracy in natural sciences through quantification, and the second data revolution is characterised by the advancements of larger volumes of data (Liu, 2014). The scope and utility of data have moved beyond the confines of natural sciences with applicability in a myriad of social science domains. By utilising the term *revolution*, Liu's (2014) reflections on data highlight the symbolic value associated with the evolution of data. The dynamic nature of data is captured alongside its transformative impact. Regardless of the field of inquiry, discourse on data has concentrated on utility and impact, thereby relegating the nature of data to a secondary ideal. Notwithstanding the significance of the debates and approaches to the PoD, any attempt to provide a greater, in-depth evaluation of these philosophical claims is beyond the scope of this dissertation.

In earlier iterations, observed in the first revolution, the success of statistical models in natural science was sought after by the positivists, from Auguste Comte to Carl Hempel (Hasan, 2014), who aspired to replicate these models for generalised laws on social behaviour (Turner, 2001). The second revolution too has seen scholarship like Dodig-Crnkovic (2003) advocating for a contemporary *synthesis*, like the centuries prior where natural sciences would inform the discourse on social behaviour and vice versa. Such attempts maintain that social and natural sciences are of the same epistemological disposition (Hughes and Sharrock, 1997) while asserting the objectivity of data. However, many scholars argue against notions of objectivity in the social domain. While Smith (1976) contended that claims of objectivity reduce humans to objects and restrict the scope of research, Feyerabend (1987) goes further to assert that objective truths just do not exist. Liu (2014, p. 65) appropriately highlights that, "[data] comes from the results of human's cognitive activity, which is the subjective reflection of the objective things, and is a logical language for characterizing the phenomena of things."

For data science, objectivity is deemed a fundamental characteristic. Yet, as most studies are concerned with statistical models and biases (Tempelaar, Rienties and Nguyen, 2020), reflections on the use of subjective data in technology are limited. Following the advancements of big data, the focus of studies on data objectivity is often concerning the technology (Manyika et al., 2011; Goda and Kitsuregawa, 2012; Khan et al., 2014), storage models (Wang, 2011) or domain of use (see Marin and Leder, 2013); evaluating the same within the socio-political landscape of diverse nation-states is limited. If the data does not account for variation and diversity, can its use in healthcare be fatal? Moreover, can biased technology, steeped in assumptions of objectivity, be utilised to influence power dynamics?

2.2 The Moral and Political Facets of Technology

Political outcomes and processes surrounding the design of technology is a predominant concern (Winner, 1980). Aristotle noted that humans, as social beings, are viewed to be inherently political irrespective of the governance architecture as it ranges from democratic to authoritarian. Axiomatically, the *things* produced by society are also assumed to influence the socio-political landscape of its deployment. Langdon Winner (1980) argues that these technical things, or *artefacts* of and from production, are intrinsically political. Utilising examples of town planning and infrastructure, Winner (1980) has effectively revealed the political facets of artefacts. In the instance of low hanging overpasses in Long Island, the US, African Americans who relied more extensively on buses rather than personal cars were disadvantaged by reducing their access to the beach. An inanimate physical structure is seen to manifest the racism prevalent in the US.

Bernward Jorges, in response to Winner, noted the intersection of politics and artefacts by restructuring the question as “Do Politics have artefacts?” (1999) which revealed the moral elements within the Philosophy of Technology (PoT). The moral dimension of PoT has also been assessed by Bruno Latour, Luciano Floridi and Peter-Paul Verbeek. In Latour's influential article of 1992, he urges for reflection on morality beyond humans by looking for answers within material things. In this radical approach, reality is reconstituted in a way where objects and humans interact in a network based on "scripts" which dictate their behaviour. By ascribing morality to nonhuman artefacts, Latour argues against the separation of technology as a mere means and instead urges for the technical space to be *folded* into reality. Thus, by reimagining technology as a constituent element of humanity, narrow views on technology as a means are replaced by an approach where technology is seen to mediate human action and morality. However, Latour rejects viewing objects, and indeed humans as well, as moral beings *in themselves*.

By turning to philosophy and theory to ascertain the extent of mortality and what, human or nonhuman, constitutes a moral being is an arduous task. Luciano Floridi and J.W. Sanders attempted to determine the agency of "intelligent systems" in their 2004 paper titled "On the Morality of Artificial Agents." Their abstraction of the concept of agents rejects the inclusion of free will and responsibility for moral considerations. Unlike moral patients which are acted upon by moral good and evil, moral agents have the capacity to make moral choices. Their formulation involves "interactivity (response to stimulus by change of state), autonomy (ability to change state without stimulus) and adaptability (ability to change the 'transition rules' by which state is changed)" (Floridi and Sanders, 2004, p.1)). If an agent's actions can be understood as "morally qualifiable," without what they consider an unnecessary focus on intentionality (owing to the limits on perceiving if agents possess a meaningful insight into their intentional states), insight into normative ethics and responsibility can be better perceived. Many objects within the architecture of an ML/AI system, say a microchip, cannot easily fit the parameters of agency despite having a political outcome; proving responsibility for the im/moral actions to the human programmers or developers (potentially an entire team) is insufficient. However, with an expansion of the concept of moral accountability and responsibility to include nonhuman agents can be a fruitful factor for bioethical evaluation.

In a similar vein, and more relevant to this body of research, Meredith Broussard (2018) chronicles the advent of political artefacts in the domain of technology and data science. Dominated from its origin by white, heterosexual, cis-gendered men, the development of data sciences, technology, and the general body of STEM (Science, Technology, Engineering and Mathematics) research has been a result of their choices. As such, the design and outcomes of technology are encoded in a way that, volitional or otherwise, may have harmful impacts on society. For example, the use of technology to aid departments enforcing law and order has been found to often target marginalised or minority communities. Programmers and designers have incorporated datasets into predictive technology often without reflection on questions like how, when, where and why the data was collected. A fundamental issue is the scale of these models. Cathy O'Neil (2016) demonstrates how the inclusion of petty or nuisance crimes, often committed in impoverished neighbourhoods of the US, in models meant to identify serious crimes of arson or murder will increase police efforts to these neighbourhoods. As more incidents of crime are recorded into these models, the feedback loop concentrates efforts in poor and marginalised communities without tackling the key issues effectively.

Deconstructing how power and social structures are further consolidated by technology has led to scholars identifying *postcolonial computing* as a crucial line of inquiry (Irani et al., 2020). The peregrinations of technology from transatlantic or European development centres to deindustrialised and poor economies have revealed instances of localisms and reinforcement of power hierarchies. Attempts to mitigate disparities in the migration of technology have included cultural or local generalisations which, in turn, have consequences of their own (Marsden, Maunder and Parker, 2008).

India is no stranger to the wielding of technology against insurgent groups at varying times and in different regions in the interest of national security. Amongst numerous communications and internet shut-downs across the subcontinent, the Indian-administered region of Kashmir is of particular importance as it has been subject to history's longest internet blockade (Internet Society, 2019). Lasting a staggering 213 days, the curbs on the internet and outright ban on social media platforms were found to have done little to reduce threats of misinformation or online extremism (Shah, 2020). Limitations on access to the internet above 2G, nonetheless, has been viewed as a form of collective punishment (UN, 2019). Thus, raising a critical area for reflection: can technology, or lack thereof, be utilised in a manner to subjugate a given group without explicitly achieving the primary stated goal?

As with other literature on the region of Kashmir under the Indian administration, data is often collected and analysed by independent scholars, international organisations, or news agencies; government data is severely limited and potentially riddled with biases. Without effective analyses on the role of technology, developing counter-narratives and recording the evolution of conflicts in the 21st century would be inherently myopic. In zones of conflict, the discourse has often focused on this aspect of technology. Yet, the disruptive effects of ML/AI as it seeps further into the fabric and actions of society is limited in academic and journalistic works by its very nature of being novel. Despite the embryonic stage of ML/AI development, there exists a need to uncover both the positive and negative externalities before such innovation takes hold in an unprecedented manner.

2.3 Medical Machine Learning in the Indian Subcontinent

Currently, no critical discourse has effectively drawn out the role of ML/AI in healthcare in zones of conflict thereby supplying a novel area for this research project.

When venturing into zones of conflict, research on the use of automated systems has focused on the military and the civilian implications (Sharkey, 2018; Hynek and Solovyeva, 2021; Leys, 2018). However, the inclusion of ML/AI technology into civilian infrastructure of conflict-affected areas is limited owing to, among other things, high-costs of production and low data.

As the *prospects* and utility of technology in domains beyond defence increases, more reflexive accounts on the limitations of the same have been released (Forge 2009; Wolpert 2020). Progress in technology and innovation, despite drawbacks, has been critical to economic and social development. The rise of big data technology has afforded the world new opportunities and improved efficiency. As data drives knowledge, the impact of big data on economies as an agent of production has also received scholarly attention (Manyika et al., 2011; Zikopoulos et al., 2012). The potential for big data in the healthcare industry has been addressed by concentrating on the computational methods (see Ngiam and Khor, 2019; Qayyum et al., 2020), healthcare management and diagnostics (see Rajkomar, Dean and Kohane, 2019) or operation-specific studies (see Zhang et al., 2017; Gilbert, Degeling and Johnson, 2017; Bates et al., 2014).

Despite substantive advantages to incorporating technology into various domains, increasing use of predictive, black-box ML/AI models has warranted critical reflection into the model architecture. Predictive models are concerned with accuracy in predictions over answering the question of why it occurs. The issue arises, as Hannah Wallach notes,

> "...when datapoints are humans, error analysis takes on a whole new level of importance because errors have real-world consequences that involve people's lives. It is not enough for a model to be 95% accurate—we need to know who is affected when there is a mistake, and in what way." (2018, p. 2)

Incorporating models driven by a goal of accuracy over interpretability into healthcare may prove more fatal than instances of bias found in facial recognition or crime identification technology. With black-box algorithms, reduced explainability may render these models' incapable of *aiding* human decision-making and instead serve to replace the human (Wallach 2018). Thus, the importance of ethical considerations in ML/AI deployment is once again made prominent. Yet, critique offering corrective measures are embroiled in altering the technical aspects of an ML/AI model rather than the systemic marginalisation and oppression which gives rise to bias in the first instance (Hoffman, 2019; Green, 2018). Notwithstanding the importance of addressing the issue of treating symptoms over the root cause, the aim of this research paper is to highlight how technology can reinforce marginalisation.

The tidal effects of big data and ML/AI in Indian healthcare have been the subject matter of several studies. Kumar, Pal, and Singh (2017) highlight the utility of certain models and challenges within the Indian healthcare architecture. However, engagement with technical discourse is limited and the challenges only receive brief recognition. As the field of ML/AI stays unregulated, particularly in India, the negative externalities of ML/AI in the context of Indian healthcare have been the subject of Parry and Aneja's (2020) report. While advocating for improved regulation and legislation, the report has ignored the technical underpinnings of

ML/AI. Without adequate critical evaluation of the potential for bias within the programme itself, legislation too may not be comprehensive in scope. An ethical gap on responsibility and accountability, necessary for both cognition of issues and legislation, is brought to prominence; a gap this paper aims to comprehend and, potentially, fill. Furthermore, effects on marginalised communities have been restricted to gender, income, and caste without a restructuring of research to incorporate conflict as a weight. Hamid Rather (2017) draws out the importance of this line of a query as the decades-long conflict has expanded marginalisation from a few groups or communities to the entirety of Kashmiri society.

The effects of conflict and violence exposure on the health of Kashmiris have been documented by de Jong et al. (2008). With widespread government and insurgent inflicted injuries and fatalities, the impact on mental health is made clear (de Jong et al., 2008). Similar studies on Kashmir are predominantly conducted by independent groups rather than governmental bodies giving rise to varying narratives and datasets. Periodic documentation to collect data and measure trends is also limited which can contribute to biases encoded into blanket ML/AI models. As such, this study endeavours to explain the lethality of biases in programmes arising from demographic variations and inequalities; an evaluation of privacy and protection concerns surrounding the data collected is subsequently necessitated.

The plethora of risks associated with weak cybersecurity and data protection cannot be understated. As ML/AI systems require large datasets for training to provide accurate decisions, ensuring the protection of data and the larger cyberspace is imperative. Legal scholarship, including Ananthpur (2011), Basu (2010), and Banoo (2020), has evaluated the propensity for draft legislation on data protection while underscoring the pitfalls of earlier laws under the Information Technology Act (2000). The particularities of data protection within the domain of medicine have been critically evaluated from the rubric of technology architecture (Aboulmehdi et al., 2010) and cyberattacks (Mrčela and Vuletić, 2018). Computational studies have assessed the necessity for frameworks that protect patient data exchange (Wadhwa et al., 2015) as well as encryption methods (Shreshta et al., 2016). Nevertheless, the necessity of ML/AI-specific legislation has thus far been viewed purely from a law-making outlook (Singh, Lohani and Poorva, 2020). The barriers to regimenting the science and innovation behind ML/AI will be a pivotal section within the research project.

Ethical considerations of technology within the medical domain necessitate consistent evaluation. It may not be limited to the technical objects but instead the larger environment within which these objects play decisive roles. One study maintains that capacity building of big data research in Low and Middle-Income Countries (LMICs) will require an understanding of the social fabric within which it is deployed (Dereli et al., 2014). An approach to the bioethics of big data in the contemporary socio-political landscape ought to consider the ontology of collective and individual history thereby avoiding any "datafying" of the human mind (Chan, 2017, p. 1). However, bioethics in the Indian subcontinent has been relegated to a secondary position. Thus, the research project can provide the socio-political foundation upon which discourse on bioethics in India can be catalysed.

In essence, the research lacunae in case-specific legislation, technical underpinnings, biases from socio-political disparities and philosophical discourse surrounding ML/AI applicability in Indian healthcare can be overcome through the dissertation.

3 THEORETICAL FRAMEWORK AND METHODOLOGY

Within the diverse social, political, linguistic, economic, and geographical landscape of the Indian subcontinent, many communities are relegated to the margins of society. While some cases of marginalisation may be attributed to recent developments, other attempts to establish social hierarchy within the general geographic area of the subcontinent can be found in political and religious texts dating back millennia. The social hierarchy thus created is a melange of indigenous and foreign influences which may still be subject to evolution or consolidation. Regardless of the static or evolving nature of the contemporary social hierarchy, any attempt to evaluate technology within this fabric necessitates an acknowledgement of potential bias which may arise from incorporating one or the other theoretical approach. As the aim of the dissertation is to highlight the effects of bias in healthcare through ML/AI, this body of research will focus on the iterations of marginalisation in India exemplified through examples on caste, class, gender, religious and regional divides. By drawing on Antonio Gramsci's work on the subaltern, the theoretical and epistemological approach of the paper will be centred on the *other*.

Rooted in the socio-political landscape of Italy, Gramsci's analysis of the subaltern, or subordinate, was structured around Marxian class-consciousness and economic relations. From the 1980s, the term became the research mainstay of scholars focusing on reconstructing historical narratives of colonial India. Like Gramsci's conceptual focus on the peasantry, Ranajit Guha (1989) placed this dialectic in the context of India. Gayatri Chakraborthy Spivak (1988) further extends this line of inquiry to cover a more intersectional post-colonial subject and their inability to *speak*. However, as Louai (2011, p. 5) argues that Gramsci's ideas "are clear enough to be given any other far-fetched interpretations," the broadening of the subaltern to include groups based on race, caste, gender and so on might prove the theory's futility.

Amongst the critiques of subaltern postcolonial theory, a few are of relevance as they present the essential caveats in utilising the theory in this research endeavour. Firstly, the broadening of the concept of subaltern can include, quite simply, anyone as the subjugated *other;* the dichotomy arising from classification, not unlike Marxian division of the proletariat and the bourgeoisie, overlooks class and social mobility (Ludden, 2001). Spivak (1988) acknowledges the fluidity in the use of the term as well as mobility between differing groups. However, the ambiguity in how the concept was employed does allow for dynamism in interpretation at the cost of juxtapositions.

Secondly, the political-economy classification used by Gramsci to divide Italian society under Mussolini is replaced by South Asian subaltern theorists with a cultural one (Ligouri, 2015). For Spivak (1988), the heterogenous identity and collective consciousness of a given socio-cultural category contrast with Gramsci's subaltern owing to the former's inability to *speak*. Yet, marginalised groups across the world are employing a variety of modes for securitising, speaking, and politically organising themselves against hegemonic power. Nevertheless, it may be noted that the perceived success of the political organisation of some groups cannot be considered universal within the group or across others. For example, a given political or cultural movement may have the ability to organise but not all individuals in the group, such as women or transgender folk, may not be afforded the same opportunities.

Finally, within the domain of International Relations, by securitising and *speaking for* the subaltern, academia and institutions are increasing instances of illocutionary disablement wherein this securitising group may not have the authority to securitise on behalf of the subaltern (Spivak, 1988). Securitisation *for* can lead to dual issues: the silenced subject is spoken for by others while also being unable to securitise for themselves (Bertrand, 2018). Spivak (1988) even acknowledges the role of the academy in silencing the subaltern but contends its necessity for long-run gains. It may then be necessary for a rephrasing as forwarded by Maggio (2007, p. 421): "can the subaltern be heard?"

Despite the criticism of Subaltern Studies, the ideas captured in the theory may be beneficial to understanding the effects of disruptive technology on a marginalised group. Applying Derridean deconstruction, the meaning of a subaltern as posited by Gramsci cannot be assumed to be set in stone. Instead, if meaning itself is seen to be fluid and dependent on the changing relations of a subject, then the idea of a *subaltern* may inform theory beyond its economic origins. While theory cannot be a panacea to the issues it describes, prescribing the palliative role of perspectives to a theory can aid in understanding an issue.

3.1 Key Assumptions

For efficiency, the theoretical framework will be built upon the following assumptions to drive the body of arguments:

(i) Definitions of the subaltern are replete with ambiguity and heterogeneity. In the landscape of the subcontinent, extant hierarchies within and between groups of peoples produce a disparate amalgam of power and knowledge systems. The goal of this research endeavour is not to define or delineate those groups which comprise the subaltern as such attempts have the potential to manufacture and reproduce new hegemonies of knowledge. Instead, perspective on Scheduled Castes (SC), Scheduled Tribes (ST), Other Backward Groups (OBC) as well as the region of the Kashmir valley within the larger context of the Indian subcontinent will be prioritised.

(ii) A framework of analysis dominated by perspective may still reinforce or reproduce inherent biases of the author and the knowledge available. Assuming the entirety of the zone of conflict to constitute the subaltern, variation within the subaltern can be mapped out by the *degree* to which technology affects subgroups. The cultural, social, and economic epistemes of the Subaltern scholars and Gramsci can be formulated. The categorisation of a subaltern whole is drawn from the sociological theories of meaning-making wherein an individual is part of a larger group or whole (Thomas, 1914).

(iii) The aim of this research is not to produce generalised laws or principles. The rubric employed attempts to illustrate the disruptive effects of ML/AI on socio-political environments divided by class, caste, gender, religious affiliation as well as regional identity; providing dynamism through ambiguity to extract negative externalities in a way it may be replicated, to different degrees, in other regions of the subcontinent or even the world. Thus, rather than asserting that technology affects marginalised groups in the same way in every zone of conflict, the goal is to arrive at a framework that can understand the effects of ML/AI on the *other*.

3.2 The Sociotechnical Imaginary and Science and Technology Studies (STS)

Evaluating the implications of science, innovation, or technology on a subject through the form of case studies on social groups is central to the heterodox of STS. However, instead of a traditional approach to case studies, different examples of marginalisation will be contrasted against instances of technology-induced disparity from around the world. By placing the subaltern and technology in the same contrapuntal framework of analysis, the research incorporates two important drivers of power dynamics. For example, on the one hand, the Kashmiri society is viewed as a subjugated *other* to the governments of both India and Pakistan while, on the other hand, data-driven innovation and technology have enforced a new form of power wielded by and subjecting a given sovereign. The disruptive effects of technology can be used by a given authority while also affecting the entirety of the Indian subcontinent, including the very institutions which control its evolving power. Notwithstanding the pluralist criticism of contrapuntal analysis wherein no voice finds prominence in a fight for attention, the 'worlding of texts,' as argued by Geeta Chowdhury (2007), can be pivotal to producing a 'non-coercive and non-dominating knowledge.'

The tacit power dynamics which permeate academic scholarship and knowledge-creation necessitates a reflection of the drawbacks in methodology as it concerns this research project. Reliance on scientific methods, quantitative studies, and data in human and society-centric research has long been criticised for assumptions of intrinsic objectivity. Preconceived notions of the objectivity of machines and technological artefacts stand as a primary element of this analysis. The theoretical framework, method, empirical tools, logical reasoning and so forth are *tools* for comprehending the depths of culture and discourse but fall short of effectively mirroring the social world in recorded knowledge (Law, 2008). Moreover, the tools themselves are shaped by ideology and cannot be separated from prejudice or social agenda (Slack, 1972).

To overcome or even attempt to subdue the subjectivity of scholarship, one can reflect on the propositions of Donna Haraway (1988): *to locate the social disposition and bias while also subjecting the same to critical reflection and deconstruction*. As such, this research project acknowledges the limitations of being an external viewer of the selected subaltern and the ideological bias which may filter into the analysis. The construction of a sociotechnical imaginary, as developed by Sheila Jasanoff and Sang-Hyun Kim (2015), will reveal how the confluence of technology and healthcare in India is in line with policy aspirations but fails to include all groups within society. Additionally, the sociotechnical imaginary how the process of incorporating modern science into Indian healthcare has not only been a result of decades of policymaking but is also likely to influence future policy prerogatives.

Owing to the competing sovereign claims over territories within India, the geographical area has a distinct strategic value and presents an inventory of space wherein the ecology of groups, organisations, and activities can be understood as relational. As a growing "theory/methodology package" (Clarke and Star, 2008, p. 117), the utilisation of epistemological and ontological assumptions of the social world concept in Science and Technology Studies (STS) has been fruitful in qualitative analysis. The feminist approaches in STS will be of particular importance as it aims to restructure discourse by moving to intersectional subjects within the social whole. Additionally, this approach attempts to reveal variation, or correlation, between the subgroups.

3.3 Tools and Methods

A Realist approach to the contested geographical territory of Kashmir may argue that driven by concerns national-security and self-interest, documentation on the region may be retracted, hard to access or outright unwritten into official records. Similarly, many groups inhabiting the region around the porous borders of Eastern India may also be excluded. Doubt may be cast on those accounts recorded by the inhabitants of the region while valuing official documentation at a higher level. Moreover, it is not unlikely for primary documents to be deemed factual in nature while secondary documents are viewed as mere interpretations (Scott, 1990). Such classification further empowers discourse to entrench itself in the ideological bias of a contemporary hegemony. The construction of discourse itself ought not to be mistaken with fact. Instead, it presents a "language or system of representation that has developed socially in order to make and circulate a coherent set of meanings" (Fiske, 1987, p. 14). Therefore, the argument forwarded by Weldes and Saco (1996) about the structure of meaning in use is imperative in attempts to incorporate the study of discourse. Like the social whole, the elements of discourse are relational and dependent on linguistic and non-linguistic practices.

By turning to document and content analysis, the research project will primarily focus on qualitative methods for investigation and analysis. However, owing to the hierarchy within document analysis, the research project will utilise both primary and secondary documents in tandem to strengthen a comprehensive approach to the field. Drawing evidence from a plethora of sources will increase credibility as argued by Eisener (1991, cited in Bowen, 2009).

Despite the current elementary progress of medical ML/AI, let alone its deployment in conflict-ridden societies with low access to technology, a socio-political and philosophical reflection of the confluence of technological artefacts with human subjects is necessitated. Owing to the minimal research conducted in the domain, the methodology of this project will focus on providing insights into potential futures. The utilisation document and content analysis in a comparative and investigatory framework is then a powerful tool. Primary documents, as first-hand accounts, can reveal pivotal records and data necessary to cultivate foundational arguments. However, primary data relevant to evaluation on Kashmir is limited to official government accounts. Therefore, by evaluating primary data and documents in the same framework as secondary documents, a measure of the gap between the two can assist in revealing the divergence between government and the local populace. Higher instances of such gaps are instrumental in understanding power through technological artefacts as well as social institutions.

Reports, articles, and studies conducted by individuals, universities, and national and international organisations (including but not limited to World Health Organization (WHO), the United Nations (UN), International Committee of the Red Cross (ICRC) and Human Rights Watch (HRW)) will be useful in this regard. While more neutral news agencies like Reuters will be prioritised, instances where local events are captured only by regional media will also be included. Primary data and reports on healthcare infrastructure, management, disease prevalence and so forth will be sourced from the Ministry of Health and Family Welfare (MoHFW), the Ministry of Home Affairs (MHA) and the Ministry of Minority Affairs (MMA) alongside other state departments. The access to certain data may be restricted by national security concerns, attempts to acquire the same through Right to Information (RTI) applications may not be fruitful. As such, where possible, secondary sources and non-governmental reports may assist in research.

Additionally, the use of both forms of documents originating in other states with more advanced systems (particularly the US, China, and the European Union) will be useful in understanding the trend of ML/AI growth in the subcontinent. It may be noted that there is no evidence that medical ML/AI is used in zones of conflict. The method retains its applicability as it aids in contextualising the global and regional approaches, impacts and challenges. Furthermore, in instances where primary sources and official data is limited in the subcontinent, international progress can be used as a proxy owing to the dynamism in technology. Nonetheless, the method would not forward any claims that the use of such proxies can accurately reveal and reflect the symbiosis of technology and society in states with little in common with the proxy used. For example, as the US is at the forefront of the ML/AI race where the technology is intermittently used in various domains upon its diverse population, it would be constructive to determine future implications in the subcontinent through the US paradigm. However, unlike the replicability of ML/AI systems, the manifestations of power, technology and even moral action are understood in widely diverse ways across the globe.

Moreover, ascertaining the power relations of technological progress between states may present diverging narratives and critiques. As such, the method will inform but not dictate and mirror the subcontinental experience.

Following an evaluation of ethics, technology and society, the concluding aim of the research is to better address discontinuities in data security legislation. The evaluation of morality and ethics allows for a better understanding of the responsibility and accountability of autonomous systems. Integrating such knowledge into the extant regimes on data, cybersecurity and national security will require an identification of the gaps and potential avenues for change. As an exercise in policy evaluation, the predominant source of information will be from existing law as well as draft legislation, both of which can be accessed through the Gazette of India. Additionally, judicial, and legislative proceedings in other states regarding the use of ML/AI systems or data protection and security will be pertinent for comparison. Keeping in mind how the Indian state often draws inspiration from the policy processes of the European Union, the United Kingdom, and the US, amongst others, comparative studies may reveal the future of responsibility and accountability of medical ML/AI in Indian jurisprudence.

3.4 Ontological and Epistemological Considerations

Examining the ethical and moral dilemmas of introducing automated technology requires a philosophical approach that does not explicitly delineate between human and nonhuman accountability or responsibility. As observed in the literature review, the work of Winner (1980) in assessing *things*, such as an overpass in the US, as political artefacts have revealed the influential role of inanimate objects in society. However, ethics is often viewed in humanist frameworks which divide reality into subjects and objects wherein technology may only be seen in terms of the latter. Martin Heidegger (1977) and Bruno Latour (1993) argue against a purely humanist approach to ethics and technology as it constricts subjects and objects by turning away from the larger network within which they interact. Peter-Paul Verbeek describes the issue aptly:

> "The modernist metaphysics divides reality into a realm of subjects, which form the domain of the social sciences, and a realm of objects, with which the natural sciences occupy themselves. As a result, the vast hybrid mixings of humans and nonhumans among which we live remains invisible." (2011, p. 29)

Modern ethics is occupied by two camps aligning with either the subject or object; the deontological approach focuses primarily on the subject and inward judgement while the consequentialist approach moves beyond the will to evaluate the results of multifarious actions (Verbeek, 2011). Yet, the preoccupation with "a human monopoly over agency" (Harbers, 2005, p. 259) ignores two pivotal dimensions of morality. Firstly, the agency of technology is relegated to a secondary position or not considered *in toto*. As noted in earlier sections, Latour (2002) acknowledges the imprudence of viewing humans and nonhumans alike as being moral agents *in themselves*, but as technology can have moral consequences, their role cannot be ignored.

Secondly, the role of power in a knowledge society increasingly driven by technology can be lost in focusing on one or the other end of the modernist ethics spectrum. Central to the transformations of society in the increasingly connected world of the 21st century is the reconstruction of the very nature of power (Toffler, 1990). If the sources of power are drawn from violence, wealth and knowledge, Toffler (1990) maintains that the 21st century is subject to more than cultural and technological innovation as the world is currently witness to a *powershift*; not merely a transfer of power, the current powershift has revealed how both violence and wealth are reliant on knowledge. Facts are embedded in a mesh of existing power structures leading to the creation of both a *power-history* and a *power-future* (Toffler, 1990) which give rise to what Foucault (1980) terms *power negotiations*. Thus, technology can be understood to advance novel or extant hierarchies while obfuscating its objectivity.

To overcome narrow approaches to a reality defined by both human and nonhuman actants, a bioethical analysis of ML/AI necessitates the incorporation of technology into a moral dimension occupied by humans. By *folding* the technological *actants* into the network of interactivity, one can better understand how technology *mediates* moral action (Latour, 1993; Verbeek, 2011). Verbeek's (2011) rejection of technology as moral instruments *and* as moral agents is imperative to understand the vast array of nonhuman things; moral instrumentalism is far too narrow to encapsulate the role of technology while artificial agency, as determined by Floridi and Sanders (2004), excludes many technologies which do not fit the criteria of interactivity, autonomy, and adaptability. However, ML/AI systems possess the ability to interact with the world, maintain degrees of autonomy and adapt, either through experience or by rules within their internal state. More significantly, ML/AI systems are "able to perform morally relevant actions independently of the humans who created them" (Floridi and Sanders, 2004, p.351). Thus, a post humanist approach focusing on the mediating role of technology will be employed to evaluate the bioethical concerns of medical ML/AI. Additionally, the evaluation of technology as it mediates and affects society will be conducted through Actor-Network Theory (ANT) wherein actors/actants are both human and nonhuman. The social relations which make up the network of actors will assist in revealing the dynamics not only between human and nonhuman, i.e., technological, actors but also between the institutions, individuals and technological entities which inhabit the contemporary social sphere of the subcontinent. Empirical data, where available from primary, secondary, or tertiary sources, will be useful in mapping out the relations.

The issue of black-box ML/AI systems in social systems will be analysed through the general principles of the Technology Assessment in Social Context (TASC) framework as formulated by Wendy Russell, Frank Vanclay and Heather Aslin (2010). As impact assessment of technology can often be viewed in narrow terms where the social context is an adjacent element rather than the primary focus (Vanclay, 2004; Carruthers and Vanclay, 2007), the TASC framework not only prioritises the social impact but also incorporates normative considerations. For effective bioethical evaluation of technology, particularly nascent technology such as ML/AI systems, answering the 'what ought to be' of technology in society is pertinent.

4 TOPOLOGY OF INDIAN HEALTHCARE

Providing critical medical services to over a billion individuals requires an extensive healthcare system to be within the reach of every citizen. At only 75 years, the fledgling democracy of India has been tasked with this mammoth feat. While lauded across the world for cheap pharmaceuticals and the elimination of many diseases, India still has numerous hurdles to cross including the issue of social and economic inequality. Digitising the healthcare system to deploy medical ML/AI systems requires prior information on the environment and policy setting within the nation.

The chapter aims to provide a layout of the Indian healthcare architecture while revealing the effects on disadvantaged and marginalised groups in two sections. Through a historical analysis, the close relations between healthcare and disadvantage may be brought to light. For the contemporary Indian state, the reliance on modern science and technology has been the fundamental principle guiding policy. This vision will be utilised to construct the sociotechnical imaginary of Indian healthcare in the second section to reveal the dichotomy in policy goals and ground reality. Notwithstanding the potential for technology to ameliorate healthcare-related issues, the chapter will address how groups in society are recurrently excluded from access to healthcare and medical technology. Additionally, the relations between society and technology will assist in constructing a sociotechnical imaginary of the future of ML-augmented healthcare.

4.1 History of Indian Healthcare Policy

The roots of Indian healthcare, sanitation and management can be traced to the Indus Valley Civilisation, lauded for urban town planning, and the subsequent Vedic age, originating in the fertile plains of northern India. Through religious literature contained in the Hindu scriptures known as the Vedas, forays into medicine, including surgery and herbal pharmaceuticals, was chronicled orally before text. While medical literature during the period reveals advances unlike other similar civilisations, healthcare was not the decision of mere mortals as disease and ailments were attributed to the wrath of nonhuman, divine beings (Saini, 2016). Within the texts of the *Atharvaveda* and *Charaka Samhita,* the development of Ayurvedic medicine from herbs and natural substances revealed the shift from rudimentary magico-science to a rigorous, logical, and reasoned approach to diagnostics (Mazars, 2006). However, the same corpus of knowledge used for curative, preventative and diagnostic purposes also forwarded a social hierarchy whose effects remain ingrained even in contemporary India.

The division of members of society into castes or social positions. dictating professions and status based on birth, ensured mobility would be kept to a minimum. Class stratification, empowered by royal patronage, included extreme marginalisation of the lowest castes who could not be touched by higher-ranking counterparts or even walk in their shadow. Even the spread of Buddhism, and Jainism to a degree, did not significantly improve social mobility; those who converted remained chained to casteism as ruling powers required a regimented social order which ensured their control (see Sahani, 1967). However, the extent of caste-based discrimination cannot be ascertained owing to low literacy amongst the marginalised.

Caste was further entrenched into Indian society through politicisation under British colonisation. Judicial records and legislation reveal how the British empire utilised caste to divide and stratify Indian polity. For example, courts under Warren Hastings turned to the Code of Manu, known as the *Manusmriti*, for judicial proceedings while Brahmins were empowered to participate due to their knowledge of Sanskrit (Rao, 1989). Moreover, scholars speculate that the laws from *Manusmriti*, which laid down the highest punishments for the lowest castes and vice-versa, were applied more literally than under previous rulers where it would act more as a guide (Rao, 1989; Riser-Kositsky, 2009). Ignorance and indolence permeated the policymaking of British rulers with caste not seen as separate from Hinduism and the easing of colonial governance through this established social structure (Riser-Kositsky, 2009). As India was reduced to a source of raw material through widespread deindustrialisation, divergence on class, caste, gender, and religious factors gripped the subcontinent in a manner that the policies of an indigenous government of independent India would struggle to subvert; sectors ranging from education to healthcare would soon be arenas for systemic marginalisation to manifest.

4.2 Healthcare in Independent India

Notwithstanding detractors and opposition, policymaking in a newly independent India was driven by the values of democracy, equality, justice, secularism, and socialism. For healthcare systems, the 1946 Bhore Committee Report would be a pivotal milestone in achieving primary healthcare access for all. In four volumes, the report envisioned short- and long-term plans, of 10 and 40 years respectively, for the provision of healthcare based on the level of medical capacity at the time of independence (Government of India, 1946). The second volume empowered the state and endeavoured to institute universal healthcare in an environment of international realpolitik which increasingly feared the rise of communism (Bajpai and Suraya, 2011).

Amongst 66 other subjects, public health and sanitation is a part of List II, or the State List, which delineates the domains for state supervision while the Union government in New Delhi oversees the implementation of national policies on population, family welfare, drug quality review, medical education, and programmes for the prevention of communicable diseases, amongst others (Chokshi et al., 2016). The deficiencies in public provision of healthcare would be counterbalanced by numerous private hospitals and insurance providers, albeit concentrated almost entirely in urban areas. The mix of public-private healthcare, while allowing for improved services, is yet another embodiment of the disparity between the poor and rich in modern India. With limited infrastructure and high unemployment in a country with a surging population, the future would be an uphill battle. Nevertheless, the aim was to institute a three-tiered system- primary, secondary and tertiary- for both rural and urban India managed by public bodies and funds.[2]

Following on the heels of the British 'Welfare State' model of access to healthcare, the Bhore Committee rejected the Soviet model of 'Healthcare as a Right' which Bajpai and Saraya (2011) maintain was the biggest mistake. Not only would the people play a negligible role in the healthcare process, but the model did not account for the variation in approaches to healthcare by the Indian polity. Relying on ideals of advanced sciences, the Indian government overlooked how traditional science continued to be the mainstay of healthcare for both the literate and uneducated masses as noted by Bajpai and Saraya:

> "The degeneration brought about due to particular social, economic and political conditions led the committee to virtually declare the indigenous systems of medicine as 'unscientific,' rather than propose ways and means of isolating and developing the scientific content of these systems in order that they may serve better the millions who continued to have faith in these systems." (2011, p. 225)

Public-funded medical services are seldom sufficient to meet the demands of over 1.2 billion people. Poor and/or rural households receive low-quality and unreliable care from public health

[2] see Chokshi et al. (2016) for a comprehensive overview of the Indian healthcare system.

centres (Das and Mohpal, 2016; Bannerjee and Chowdhury, 2020) leaving many to turn to costly, often debt-inducing, private hospitals and clinics. Commendable attempts to address the shortfalls in medical care include the creation of the National Rural Health Mission in 2005 and the Ayushman Bharath insurance scheme in 2018, alongside other programmes to eradicate polio, HIV (human immunodeficiency virus), and tuberculosis. Yet, the old Persian proverb of "*Hanuz Dilli Door Ast*," transliterating to "Delhi is still far away," continues to ring true. The national capital not only sits at a comfortable distance from the impoverished corners of India but also serves as a reminder that the laws passed in Delhi are far from actualised in the tiny hamlets, dense forests, and arid peninsulas in which nearly 70 per cent of the populace resides. Moreover, it is particularly within the rural backwaters of India that many find themselves gripped by age-old social stratification and regressive outlooks.

Affirmative action for Scheduled Castes (SC), Scheduled Tribes (ST) and Other Backward Classes (OBC) have had little success (Bhojani et al., 2019); policies aimed at social determinants have overlooked the underlying social processes which gave rise to the disparity (Graham 2004). Furthermore, rigid socio-economic categories are buttressed by regional and territorial variation. A study noted how poorer states in India not only utilised public health infrastructure more but also incurred higher out-of-pocket expenditure (OOPE) with OOPE accounting for 95 per cent of hospitalisation costs in India (Dash and Mohanty, 2019).

The lack of reliable healthcare is a prominent factor in the territories of India facing domestic and international conflict. For example, the state of Chhattisgarh is resource-rich, but income disparity is staggering. One third of the population belongs to indigenous tribal groups (Census, 2011) and the state has been witness to a protracted Maoist-Naxalite insurgency over the decades. Inevitably, Chhattisgarh has secured the second-highest rate of state-funded insurance in the country (IIPS, 2017). In a similar vein, the conflict-ridden Kashmir Valley has one of India's most dismal medical environments. Fuelled by insurgency, terrorism and competing claims to the region, the conflict has not only directly caused thousands of deaths, but the imposition of recurrent curfews and lockdowns has further strained access to critical medical attention. An alarming 45 per cent of the population faces mental illness (Housen et al., 2017) in a region housing only one hospital dedicated to psychological care (Amin and Khan, 2009).

In a nation renowned for pharmacology and health tourism (Chakraborty 2020), where do marginalised communities gain access to life-saving curative and preventive medicine? Is healthcare, a critical public industry, only for the elite in metropolises far away from the barbed wire-enclosed zones of conflict? Therein lies the scope for the democratising power of digital technology and innovation.

4.3 The Sociotechnical Imaginary: Modern Science and Historical Hierarchies

Through hardware and software, the world is enveloped by a digital network transferring and manipulating an ever-increasing barrage of information through packets of data. Thomas Friedman (2005) noted the *flattening* power of Globalisation 3.0 after visiting India's very own Silicon Valley: Bengaluru. At the turn of the 21st century, the world is no longer driven by states or even multinational corporations (MNCs). Individuals, particularly those from non-transatlantic backgrounds, are fuelling Globalisation 3.0 as well as the Fourth Industrial Revolution (IR4) where the most valued commodity is data. The externalities have seeped into healthcare with scholars like Mitchell and Kan (2009) supporting the replacement of the traditional model of facility and doctor-centric medicine with one buttressed by technology.

Technological advancements, such as telemedicine, have not only reduced costs but also have the potential to increase access to critical medical care in regions marked by physical limitations of infrastructural constraints and/or natural geography (Gupta et al. 2019). At an astounding 13000 feet above sea level, the Apollo Telemedicine Networking Foundation has set up the highest telemedicine network in the world in the Himalayas (ANTF, 2017). Progress in wearable devices and integrated systems through the IoT has ushered in a new era of medical care through tasks not limited to imaging, surgical procedures, patient monitoring as well as operations and management (Deloitte, 2018; Gómez-González et al., 2020; Buch, Ahmed and Maruthappu, 2018). Moreover, the data collected in real-time through IoT infrastructure has contributed to the development of ML/AI models for diagnostic, preventative and curative decision making (Mohanta, Das and Patnaik 2019).

No longer limited to the mere outsourcing of work from tech-based MNCs, Indian entities are forging a new path for the development of medical ML/AI. From diabetes diagnostics through a single check-up of the eyes or imaging for cancer and tuberculosis (Roy and Jamwal, 2018), predictive algorithms are being incorporated into India's healthcare environment. More pertinently, many companies are seeking to deploy medical ML/AI in rural India where the penetration of public-funded health infrastructure is dismal or unreliable. Advances in Natural Language Processing (NLP) have not only laid the foundation for more robust telemedicine through platforms like MedBot (Bharti et al., 2020) but have also assisted healthcare practitioners in reducing the margin of error that results from burnout and tedious data-entry (Parry and Aneja, 2020). Instances of computer-aided diagnostics, as precursors to the medical ML/AI revolution, can be traced back to 1998 where the Early Detection and Prevention System (EDPS) developed for rural use recorded a 94 per cent rate of consistency (KIMS, 2002). Respondents in the study were positive about relying on technology. Over 20 years later, the intersection of technology and Indian society has been brought closer together.

On the other hand, the disruption and eventual collapse of Indian healthcare during the subsequent waves of the COVID-19 pandemic revealed age-old fault lines which ML/AI technology can potentially ameliorate. However, as science, technology, and innovation accelerate in a socio-political environment riddled with reified social order and hegemony, how does the medical ML/AI revolution reveal a new sociotechnical imaginary for India?

For one, access to such avenues is still determined by the ownership of devices capable of carrying out digital medicine. A disparagingly small proportion of Indians own a smartphone at only 24 per cent but over 50 per cent own a non-smart mobile phone (PEW Research Centre, 2019). The same study noted how the gender gap in access to mobiles has increased by 10 points from 2013 to 2018. At the same time, India has not only recorded dismal economic growth rates but the proportion of public expenditure on healthcare is insubstantial; within this dyad, aspiring to achieve technological prominence in healthcare is myopic and obtuse. Despite the costs of cloud-computing and storage reducing alongside the increasing ease of access to basic programming, establishing ML/AI infrastructure with trained staff may not be within the financial or infrastructural scope of India (Paul et al., 2018); even non-government corporate entities may not have access to funds and data (Ajmera and Jain, 2019; Patil, 2018). The infusion of technology in healthcare may be within the vision of the Bhore Committee of advanced science informing medicine but, like the imperception of the early policymakers, may not be cognizant of rampant illiteracy and technophobia in many parts of the subcontinent.

To assume that society and technology exist independently of each other is futile. Moreover, maintaining that technology is only an extension of society without acknowledging how technology permeates and mediates the course of society would also be imprudent. Viewed within a system where society and technology are co-produced (Latour, 1990), the subcontinent's imaginary of the future of medical technology can be constructed to reveal the multifarious ways in which technology influences, and is influenced by, different social groups (Pinch and Bijker, 1992; Bijker and Law, 1992). For example, eradicating polio through extensive national vaccination programmes were accepted and denounced by various groups within the populace. In regions with weak infrastructure and medical penetration, the drive was akin to the family planning and sterilisation policies of years prior where the burden of reducing population growth invariably fell upon poor and marginalised classes not limited to income, religion, or caste (Singh, Das and Dutta, 2010; Green, 2018). Through community-based measures incorporating negotiation, communication and education, resistance declined across the board with India declaring the eradication of polio in 2014 (Solomon, 2019). Thus, the artefact of polio vaccination was received in a divergent manner determined by caste, class, religion, and region. Moreover, the vital vaccination drive and the procedures for its implementation was a result of the sociotechnical imaginary envisioned by the elite who comprised the Bhore Committee. Despite being a collectively held notion- of science and technology directing the course of Indian healthcare- the imaginary was forwarded by a dominating social group through existing power structures and institutions.

The desirable future is characterised by innovation bred through the confluence of science and technology. The sociotechnical imaginary of Indian healthcare, forged by the Union and State governments, falls under the revised definition of Sheila Jasanoff and Sang-Hyun Kim (2005, p. 4) wherein they are "collectively held, institutionally stabilized, and publicly performed visions of desirable futures, animated by shared understandings of forms of social life and social order attainable through, and supportive of, advances in science and technology." As the primary referent object in human security discourse, the individual is bound to a vision of a desirable and normative future determined by the governance architecture. For those individuals who fall into marginalised categories, (re-)imagining the vision requires adoption at large which is marked by the power of the majority. Within India's sociotechnical imaginary of healthcare, the marginalised can scarcely control outcomes in a system moulded by exclusion.

The collective future has already been subject to change by way of its evolution from the inclusion and predominance of modern science to telemedicine. The disruptive effects of IR4 have further introduced new innovations of Big Data and ML/AI. Even if one were to assume that this future will ensure access and infrastructure, a fundamental challenge may persist: biased data. The capture and categorisation of personal, private, and critical information through data is instrumental to robust ML/AI programmes. However, in a nation of various ethnic, linguistic, and social groups, data on healthcare and allied industries support the claims of many who maintain that there is no concept of *unbiased* data. Holding a mirror up to society, data capture not only key indicators and pivotal information of the participants but also reflects intrinsic biases which, consciously or otherwise, spill over into the architecture of datasets. The advances of the Big Data Revolution and ML/AI, within the sociotechnical imaginary of former and contemporary governments, may then be the largest catalyst for exclusion, marginalisation, or oppression.

5 LETHALITY OF BIAS

The changing gears of Indian governance have adhered to the vision of the Bhore Committee where modern science and technology would serve as the pillars upon which Indian healthcare would be built. Innovation was viewed as the enzyme capable of acting on the substrate of medical infrastructure to create a homogenised product of social harmony and well-being. Despite the commendable efforts to create a shared imaginary of innovation driving social change, Indian policymakers effectively ignored the penetration of social stratification whose talons clung on to every domain of social life.

As Information Communication Technology (ICT) was embraced by the growing youth populace of a newly liberalised India at the turn of the new millennium, the disruptive effects were felt by polity far from the cities that housed tech-giants and employed Indians en-masse (Kumar, 2017). From improved smartphone technology to internet-based e-commerce services, more Indians were participants in the IR4. The tidal wave of change was one envisioned by the elite, shared by the growing middle class and indifferent to the hierarchies that empowered, and indeed were empowered by, technology. When this indifference is compounded into autonomous systems capable of rapid calculation and categorisation, the scale of disruption may be unprecedented. However, as contemporary ML/AI systems in healthcare are at a nascent stage of development, the limitations and scope can be evaluated before widespread usage.

By providing critical scholarship on bias in data prior to lethal or catastrophic incidents, the cycle of law catching up to innovation may be broken. As such, the chapter seeks to extrapolate on the potential biases and lethal implications of introducing ML/AI to the Indian healthcare industry. Divided into three sections, the first will confront the notions of objectivity in technology and machines. By providing a historical account of how science and technology have been moulded by dominant groups within a global whole, the capacity for the resulting knowledge to influence technology can be better understood. The second section will reorient the challenge of bias within India. Although the development of medical ML/AI in India is limited, there remain fundamental challenges of access and disadvantage which can contribute to skewed datasets in future developments. Finally, the last section will advocate for a review of ethical considerations in medical ML/AI as necessitated by the critical natue of the healthcare industry.

5.1 The Veil of Objectivity

Relying on algorithms capable of learning from large volumes of data, ML/AI systems produce predictions based on trends identified by the system. In deep learning, multiple layers of the neural network present outcomes from the computation of nodes. The entire process, simplified from the complex technical underpinnings, is no different to the human approach to learning and identification. When either a human or a nonhuman system is made to classify objects and entities, associations stem from existing knowledge about the same.

Take for example, in the United Kingdom, the South Asian dish of Chicken Tikka Masala, a widely celebrated mainstay of British epicurean culture. However, if one were tasked with categorising various dishes found on the menus of South Asian restaurants, all would be deemed “Indian” without regard for the variation in cuisine across the multiple countries occupying the geographical space of South Asia (Buettner, 2008). Notwithstanding the dialectic which arises from embracing and rejecting the “other,” such categorisation raises imperative questions regarding assimilation and white colonial reconstruction of the history and culture of food. Not merely a matter of cultural appropriation, these examples do well to highlight how perception, learning, and knowledge may not only be deterministic tools in culture and society but assist in revealing how the mechanisation of such learning will (re)-imagine the world through the knowledge of dominant groups or datasets.

In a similar vein, the ML/AI models used for facial detection and recognition technologies (FDRTs) tasks are riddled with racial bias and dominance of knowledge. Despite accounting for 36 per cent of the world's population, South and East Asians occupy only 3 per cent of data from ImageNet, a database used for computer vision software, while 45 per cent is based on data from the US (Shankar et al., 2017). Even within the US, the nation leading research on ML/AI, FDRTs have been found to misidentify and discriminate against people of colour, particularly African Americans (Garvie, Bedoya and Frankle, 2016; Klare et al., 2015). At the heart of the issue is diversity in datasets. Moreover, low diversity in datasets is not a contemporary phenomenon, as the origins of the issue may be found in the development of photography in the 19th century which privileged and valued light-skinned faces (Lewis, 2019). Advances in digital photography, where computers could 'read' the data of photos, fuelled the stockpile of image datasets in the internet age which, in turn, proved to privilege white men while underrepresenting women and people of colour (Leslie, 2020).

Society has not existed independent of such technology. In the case of FDRTs, the evolution of photography consistently privileged the groups behind its development: white men. For the Hewlett-Packard facial recognition software which failed to recognise dark-skinned faces, reliance on optimal lighting for pale skin tones, as opposed to an equitable approach for recognition of all facial tones and features, revealed neglect and uninterest in fairness checks (Leslie, 2020). From the earliest iterations of technological progress, white men have dominated Science, Technology, Engineering and Mathematics (STEM) (Broussard, 2015).

Unsurprisingly, the ML/AI models trained for a range of tasks have been found to magnify gender and racial disparities (Kay, Matuszek and Munson, 2015). Expanding beyond the Transatlantic, even the advances of the Islamic Golden Age or the Vedic Age may be disproportionately attributed to upper class/caste men through power structures and artefacts.

Technology has been moulded by society as much as it mediates and influences society. The threat of bias reaches new levels when poor datasets are used to train models for policing, insurance, credit, and healthcare; existing systemic discrimination finds shelter in the confines of technology and automated systems donning masks of objectivity. As with other non-autonomous technological artefacts, the "othering" of communities within a populace has the potential to be reinforced through machines of the Big Data Revolution. The simple and complex mathematics used to develop and train algorithms for bias-ridden ML/AI models, the building blocks of Cathy O'Neil's (2016) aptly named "Weapons of Math Destruction," are the result of historical and contemporary social structures which favour certain forms of knowledge necessary to compound a hierarchy. Is it then inevitable for IR4 to incorporate these homogenised and hegemonic perceptions into *objective* machines?

5.2 Identifying Sources of Bias

Bias in ML/AI models can be found in every stage of both the algorithm and data life cycles. In the former, objective definition, algorithm selection, algorithm deployment, machine intelligence insights and algorithm management constitute the elements of the life cycle; correspondingly, the data life cycle comprises collection, curation, manipulation, insights, and management (Rizvi et al., 2015). The challenges associated with bias begin with the pertinent query of whether ML/AI is necessary to augment a particular task by defining the objective. Subsequently, the selection of an appropriate algorithm is dependent on what models are best suited to the defined task. Insights from the training and management will provide clarity in the successive cycles.

Of numerous ML/AI algorithms available, such as Random Forest, Gradient Boost, Logistic Regression or Decision Tree to name a few, an appropriate selection is imperative to provide a generalisable model. For example, using a Naive Bayes algorithm for an ML/AI model concerned with medical insurance might not be fruitful as the assumption of the algorithm is that factors are independent (Qiao, 2020). Assuming income and employment as separate from categories like gender, caste, race, or religion would be deleterious in India; models based on such algorithms may produce misleading outputs. Moreover, when inputs are complex and non-linear, algorithm selection may be the difference between an interpretable or a black-box ML/AI model. Within medicine and healthcare, many tasks require simple interpretation and prediction that may even be run on basic computer infrastructure. For example, relating general health indicators of diet, body mass, or lifestyle to ascertain cardiovascular or renal risks. As the variation in complexity and linearity may be charted on a spectrum (Sidney-Gibbons and Sidney-Gibbons, 2019), the potential for medical ML/AI to assist and augment the tasks of the medical practitioner is vast. Before training, model hyperparameters need to be set by the developer while accounting for the parameters set by the ML/AI model itself[3]. However, the primary focus of this research is on the role of the data cycle.

The challenges of implementing ML/AI into private or national healthcare frameworks are not limited to technical factors (Ahmad et al., 2020). Discrimination and disparity, rife in India and

[3] It may be noted that *model* and *algorithm* refer to different concepts. While the latter is concerned with pattern recognition and *learning* for best fit, models are the result after training and represent the rules, weights and parameters. For example, a model with coefficients and values results from a linear regression algorithm. See more: https://machinelearningmastery.com/difference-between-algorithm-and-model-in-machine-learning

across the industrialised world, present threat vectors which practitioners, government bodies, insurance providers and developers must acknowledge before embarking on the creation of automated systems for healthcare delivery. The process may begin at the level of healthcare data collection, curation, management, and review. For the case of India, if medical ML/AI is assumed to be a service provided by the government to mitigate the latency of extant healthcare delivery, masked biases in the contemporary medical landscape may be extrapolated alongside technical challenges. Specifically, the issues of selection, sampling, and misclassification will be evaluated alongside the pernicious challenges of feedback loops and over/underfitting.

5.3 Charting Medical Bias in India

In a territory of 1.3 billion individuals, 744 recognised tribes and 1108 caste groups spread across 28 States and 9 Union Territories with one of the world's highest linguistic diversities (Kalra and Dutt, 2020), who constitutes the core population group of medical datasets for generalisable ML/AI? Answering the dilemma requires a reflection on the contemporary state of health records in the country.

For the majority who reside in rural areas, health records are manually collected, thereby leaving digitisation a distant dream for Primary Health Centres (PHCs). Only large government hospitals like the All India Institute of Medical Sciences (AIIMS) and the Postgraduate Institute of Medical Education and Research (PGIMER) possess the infrastructure and systems for collaboration within the hospital. On the other hand, for private hospitals with the infrastructure capable of hosting large volumes of patient information, data is often restricted to the company of the first record (Srivastava, 2016); limited incentive, privacy concerns, and formatting variation act as barriers to cross-sharing of relevant data. Moreover, private hospitals may seldom contain substantive records on marginalised groups and rural poor. Thus, on a national scale, India's forays into creating Electronic Medical Records (EMRs) have been a commendable effort to reduce delays in manual documentation while improving interoperability of healthcare database management (Pai et al., 2021). Additionally, with mobile health (mHealth) platforms, digitisation of personal health data may be useful in the grand strategy of a technology-driven healthcare sector.

Yet, the fundamental issue of access and representation lingers. In India's northernmost region of the Kashmir Valley, a territory plagued by instability, hospitals are few and far between. Some reports reveal how recurrent curfews and lockdowns have further exacerbated healthcare woes as even ambulances may be stopped at checkpoints (Ganguly, 2019). During the same period of insecurity, fuelled by the abrogation of Article 370 and 35(A), which had accorded a degree of autonomy to the region, blockades on the internet and communications were found to be the longest in human history (Parvaiz, 2020). Furthermore, the region is known for half-widows (wives of those whose status of death/life cannot be ascertained (see Hamid, Jahangir and Khan, 2021)), unmarked graves (Burke, 2011), porous borders and the exodus of both Hindu and Muslim Kashmiris. Extant policies on curfews and citizenship in conjunction with poor healthcare infrastructure severely restricts the scale of digitisation of health records and real-time data.

The consequences of incorporating ML/AI models into this socio-political landscape is not only myopic but lethal. Keeping in mind the high instances of Post-Traumatic Stress Disorder (PTSD) amongst the Kashmiri populace (de Jong et al., 2008), in contrast to other states in the subcontinent, the ML/AI model trained to identify cardiovascular risk may approach them as outliers. In situations where PTSD increases their risk of ailments like coronary heart disease or thromboembolic stroke (Coughlin, 2011), a Convolutional Neural Network (CNN) trained on general aggregates without relevant labelling or regularisation functions may overfit existing data collected from digitally and economically advanced states within India that may not present a comparably high incidence of PTSD. In other words, the ML/AI model may "cheat" by memorising to provide generalisable outputs based on available data.

Similarly, low, or inaccessible healthcare infrastructure for certain population groups, particularly the Indian subaltern, initiates a biased model for diagnostics. Researchers in the US noted how the socioeconomic background of an individual was a determinant in their perception and access to diagnostics (Arpey, Gaglioti and Rosenbaum, 2017). As the predictive capacity of ML/AI is not only reliant on the data but on its outcomes as it *learns*, a diagnostic model may create two deadly situations. Firstly, low clinical data fed into a diagnostic tool may not provide sufficient information fit for the definitional threshold of the model which suggests pre-emptive testing, diagnosis, or treatment, thereby causing a delay to a more severe or critical stage (Gianfrancesco et al., 2018). The model is indifferent to the conditions which have prevented marginalised groups from accessing treatment sooner. Distance, transportation, poverty, or even violent conflict hinders an individual or a group's access to health services; issues which the developer or practitioner may consciously or unconsciously ignore.

Secondly, when ML/AI systems train on outcome data, regardless of the utility or even lethality of the predicted outcome, the behaviour is reinforced (Challen et al., 2019). For example, a prediction that terminally ill patients have a bad prognosis, or a poor future course or outcome of the disease, will suggest palliative instead of curative treatment, thus creating a pernicious feedback loop. This self-fulfilling bias has fuelled predictive policing technologies like PredPol where increased reporting of low-level crimes increases police surveillance in, often socioeconomically disadvantaged, neighbourhoods; higher crime registration resulting from increased police surveillance feeds into the ML/AI system which further increases surveillance, crime incident reports, and arrests in the area (Ensign et al., 2018; O'Neil, 2016).

The utility and associated risks of ML/AI is not limited to clinical and diagnostic tools. Biases may present themselves in pharmaceuticals, management, insurance, and epidemiology when accurate data and regularisation features are ignored. Take the latter two for example. At the forefront of the ML/AI *race,* the US is not only known for technological superiority but also deep-rooted racial discrimination and marginalisation. ML/AI systems for insurance have merely mirrored the ground reality, subsequently serving to reinforce social stratification. Numerous reports and studies have revealed how those who self-identify as African American are given lower risk scores which prevents them from accessing more suitable medical care as compared to a white person with similar sickness (Obermeyer et al., 2019). Insurance providers can use these risk scores to further entrench black Americans in a social hierarchy and create what Ruha Benjamin (2019) calls a "New Jim Code."

For India, documentation to receive healthcare not only allows for caste identification but also income. Albeit a measure to allow households from lower socio-economic backgrounds to access healthcare, algorithms may use the data to assign low-risk scores or to generate higher insurance premiums to protected classes as many Indians have turned to private medical care necessitating higher OOPE (Bhat, Holtz and Avila, 2018). However, arguing against a total exclusion of social background-based categories can lead to clinical inefficiencies where genealogy and lifestyles may be causative factors for certain conditions (McCradden et al., 2020). As medical research continues to evolve, drawing simple distinctions to avoid discrimination by coding ethics into systems would be arbitrary over time.

On the other hand, the potential for automated systems to augment epidemiology is noteworthy. As successive waves of COVID-19 infections surge across the globe, mathematical models have determined preventative measures and policy frameworks. Complex algorithms such as the Artificial Neural Network (ANN) proposed by Farooq and Bazaz (2021) for Indian epidemiological modelling of COVID-19 provide a solution for ML/AI systems that need to be updated with new datasets. Thus, the capacity for real-time forecasting is immense. However, reports reveal Indian official records of deaths are far lower than reality (Jain, 2020). As numerous bodies of potential COVID victims were strewn across the banks of one of the Ganga (Shukla and Sharma, 2021), crematoriums and graves across the country were also recording a manifold increase in funerals (Ellis-Peterson, 2021); deaths that did not make it to official records as COVID-related. While it may be argued that the low reporting was a political strategy, it ought to be noted that policies and protocols on testing, suspected deaths, and hospitalisation led to many not being counted as the fatalities from the deadly virus (see Pulla, 2020).

In the rural backwaters of India where testing is limited or inaccessible, uncertainty on the cause of death and reporting might be mushrooming into a new threat for those already affected by droughts, low employment and literacy, poor harvests, and communal spite. For many struggling below the poverty line, even cremation is debt-inducing. Even ML/AI systems trained and tested with different datasets might be inefficient if ground reporting is false. Poor management and policymaking are invariably bound to follow.

5.4 Coding Lethality into a Framework for Power

Instances of bias in ML/AI systems reveal more about social hierarchy and discrimination than they do technological prowess. Turning to future technologies as a salve for contemporary challenges, without acknowledging how the systems and structures of the past continue to hold a tight grip over society, has imbued the sociotechnical imaginary of India with new shades of the same parochial "solution." This is not to say that technology has no utility in India's diverse socio-political environment; by developing efficient algorithms, appropriate regularisation techniques, rigorous training and testing with divergent datasets, and a critical, intersectional approach to medical ML/AI systems, automated healthcare may well be the future. However, technology does not exist in a vacuum. The process of integrating medical nonhuman agents into national healthcare infrastructure is accompanied by changing power dynamics and hierarchies. For medicine, where bioethical concerns dominate discourse on morality, the introduction of automated systems raises the dilemma of what it means to be a moral agent. Furthermore, the stream of personal medical data and history, indispensable to ML/AI systems, raises concerns on data privacy and security. As such, the current state-of-the-art of ML/AI systems mandates a closer inspection of ethical and regulatory frameworks capable of informing future developments.

6 DESIGNING ETHICAL MACHINES

The journey to building a “perfect” medical machine mandates an understanding of a myriad of factors not limited to the technology itself or the social environment of its deployment. Instead, in achieving the goal of efficiency or generalisability, ML/AI is redefining the concept of perfection. Is it perfect if it produces an outcome we want? Or does it reach a stage of perfection when it is cognisant of the multifaceted social structures and hierarchies within which it operates? Is perfection based on the power of a few or of the entire democratic polity? Attempts to find a *perfect* answer require the confluence of technological capability and normative principles. Thus, in designing a capable machine, the technology requires a high standard of efficiency while accounting for the moral/ethical conundrums associated with the deployment of automated and autonomous technology.

With its roots in basic mathematics and computing, the peregrinations of technology have reached a stage of success in numerous domains. The amalgamation of healthcare, modern science, and technology has been an interaction for centuries in the making. Like the copper wires, microchips and server farms, tacit and explicit power dynamics and hierarchies have also been fundamental elements in the construction of medical ML/AI. However, as we have noted the biases that arise in, quite simply, mechanising or automating social nature and structure, it is then imperative to uncover how technological artefacts are endowed with moral and ethical dimensions that can mitigate lethal outcomes. Thus, the chapter aims to provide an avenue for designing ethics into machines while noting the role of governance systems in regulating medical ML/AI. As such, the chapter will first provide an ontological foundation on whether agency can be ascribed to nonhuman actants. By providing a dynamic approach to the human and nonhuman actors which comprise a social network, the role of technology can be understood through their mediating effects as well as causal mechanisms. While an in-depth evaluation of the ethics of machines is beyond the scope of this research, regulation of medical ML/AI will be prioritised in evaluation in two streams. Firstly, the ethics of design can reveal the process of building ethical machines from a design perspective to "materialise morality" (Verbeek, 2011, p. 90). Secondly, in exploring the ethics of use, data privacy and security measures will be highlighted. The regulation of technology is equivalent to the arduous task of regimenting science but implementing national standards for data protection will ameliorate the threats of the misuse of data by state and non-state entities. Moreover, due to the lethality of bias noted in the previous chapter, the diversity and power structures within India necessitate an evaluation of the consequences of contemporary legal regimes and draft legislations as they present the challenges to ML/AI adoption and regulation. Additionally, the protection of personal medical data within the wider environment of cybersecurity will be highlighted. Thus, both fronts of ethical design and national regulation will be comprehensively evaluated.

6.1 Machines in the 21st Century: Artefacts, Agency, and Accountability

The erudition of the Enlightenment afforded knowledge systems for the techno-scientific progress of humanity. At the heart of the corpus of philosophy during this intellectual turn was human-centric ethics. Not merely a matter of moral good or bad, "...but the individual person, taken as the fountainhead of moral decisions and practices, now holds the central place in ethical reflection" (Verbeek, 2011, p. 21). Despite the roots of our contemporary technology-driven culture in the Enlightenment, scientific developments have revealed the multifaceted ways in which society is mediated and actively altered through technological artefacts.

Objects, as viewed by Langon Winner (1980), have a distinctly political nature owing to their purposes and consequences expanding beyond the limits of their immediate use. Beyond intentional consequences, technology has a distinctly mediating role in society. From speedbumps regulating drivers' actions (Latour, 1999) to obstetric ultrasounds influencing parental decisions regarding an unborn foetus (Verbeek, 2011), technology is seen to mediate individuals and groups in society. With the capacity to influence and mediate human moral decisions, technological artefacts mandate a new position in ethical evaluation. However, not only does humanist ethics disregard the hybridity of contemporary society through a sharp distinction between subjects and objects, i.e., humans and their technological artefacts, but also ignores the moral agency of technology (see Verbeek, 2005; 2006).

Instead, through a postphenomenological approach, the role of technology is not limited to the polar extremes of technological determinism, where the development of technology determines the future of society, or social constructivism, where society chooses the next line of progress (Feenberg, 2017). Viewed in a continuum, postphenomenology attempts to incorporate the mediating role of technology (Ihde, 1995) while situating the subjectivity of human perception within the objective world (Verbeek, 2005). For healthcare, technology can be seen to mediate perceptions and praxis. Diagnoses not only alter the perception of a patient but also influence their choices and decisions because of the mediating role of the diagnostic test or machinery. However, as technology in healthcare is bound by critical ethical considerations, does morality work only through humans? Or, are technological artefacts, with their ability to mediate human practice, the responsible moral entities?

The moral scope of a subject can be determined through multifarious approaches. While Latour (1992) ascribes morality to both human and nonhuman actants through their relations, Floridi and Sanders (2004) follow an abstraction of *agenthood* based on interactivity, autonomy, and adaptability. On the other hand, Verbeek (2011) attempts to characterise a moral agent based on intentionality and the freedom to actualise those intentions. However, intentions and freedoms are not only dependent on the actions and decisions of both human and nonhuman actors but are actively co-shaped (Verbeek, 2011). In medical ML/AI, systems may have a degree of intentionality and freedom. In deep learning, where layers of the neural network are designed on the nodes and synapses of the human brain, the system can intentionally determine outputs and freedom to follow a certain avenue to realise the same. However, there is only a degree of autonomy in intentions and freedom as human actors formulate and design the algorithms upon which decisions are made. Furthermore, by relying on medical science, data, and technology, human agents formulate the moral dimension of healthcare. Thus, revealing how technological systems, like humans, are not moral agents in themselves (Latour, 1993; Verbeek, 2011) but coproduce their moral perspectives and decisions within a wider network of nonhuman actors as well as normative values.

Within this ontology of a human-technology nexus, morality- as a prerequisite to accountability, responsibility, and regulation- may be ascertained through a critical framework. Although an in-depth evaluation of morality and ethics of nonhuman entities may be beyond the scope of this paper, the philosophical discourse is necessary to reformulate contemporary approaches to moral agency. Moreover, by placing nonhuman and human actants within the same framework, the network of relations can be used to extrapolate power relations between groups.

6.2 The Changing Nature of Power

As noted in Chapter 3, society and technology are co-produced. However, diverse groups access, perceive, and participate in a network in multifaceted ways; technology within this network has an intimate relation to power. Although Foucault does not engage with technology in his philosophy, power is viewed as a mode of structuring society. Verbeek contrasts and relates the role of power in Heidegger's approach, where there is an ordering and man is subject to technology (Dreyfus, 1996), against Foucault's:

> "But rather than monolithically analysing power as a particular volition or metaphysical relation to reality, as in the Heideggerian perspective, Foucault investigates how structures of power are at work in concrete practices, objects, and ideas. Human existence does not take place in a vacuum but in a world made of ideas, artifacts, institutions, organisations that all have impacts on human subjectivity. Vocabularies and scientific theories help to shape how we think, our material environment organises our actions, and social institutions like schools, hospitals, armies, and prisons give shape to how we live our lives and deal with illness, criminality, and madness." (2011, p.8)

Within this ontological realm, the digital world has a defining role. Through the IoT infrastructure, data on a range of domains is being accrued and logged in real-time. ML/AI systems in healthcare are reliant on real-time data streams for efficiency (Ed-daoudy and Maalmi, 2019). However, as governments employ devices to log data on the populace, concerns over freedoms and rights to privacy may arise (Bernal, 2016). Not limited to the collection of online data activity, cameras are increasingly being incorporated by both democratic and authoritarian governments, from the United Kingdom (Ashby, 2017), the US (Lyon, 2014), Canada (Saunders, 2020) and China (Liang et al., 2018), to screen and monitor individuals in society. Notwithstanding the potential benefits of incorporating mass surveillance as an instrument to actualise security objectives (Farrington et al., 2007), these strategies are akin to the construction of a national, or even international, Panopticon capable of regulating behaviour (Stoycheff et al., 2019). Whether a CCTV (Closed Circuit Television) camera or IoT devices, technology in the digital age is increasingly mediating behaviour and moral decisions. Yet, mass surveillance has been found to mislabel and misclassify individuals, not unlike the ML/AI systems identified in the previous chapter owing to skewed data sets (Leslie, 2020; Garvie, 2019). Nevertheless, the use of video surveillance has been found to influence behaviour (Fox, 2016). Thus, as proposed by Foucault, society is witnessing power through the technological artefact of surveillance machinery and the policy structures implementing the same.

Power here is not merely a form of subjugation. Instead, it works to structure, organise, and potentially even improve society (Foucault, 1980). Moreover, power is not dependent on a group or an individual but can be found in ideas, thoughts, principles, and values which shape contemporary and future society, culture, and discourse. Viewed in this lens, the contemporary transformations in society are not only witnessing a change towards a data and knowledge-driven global economy but also in the very nature of power (Toffler, 1990). While Foucault's power episteme provides a nuanced approach, it may be argued that the centrality of sovereign power continues to hold strong. Ideas and institutions are further brought into the realm of justifiable policy through a democracy. As such, the deployment of medical ML/AI is supported by notions on machine objectivity (see Dalston and Galison, 1990) as well as government policy to modernise and systematise healthcare in a diverse landscape. Power then stems not from the barrel of a gun but the reliance on machines and visions of scientific objectivity. However, even when power arises from knowledge and ideas, the manifestation of power in contemporary society can be found to exclude rather than include groups, as Foucault (1980) argues.

6.3 Data, Power, and the New Panopticon

With data at the heart of contemporary progress, the overarching knowledge which drives innovation is both infinite and acts as a multiplier for wealth and coercion (Toffler, 1990). Innovative economies around the world are jumping the gun to invest, develop and sustain data-driven technologies. However, knowledge and technology can also be wielded to regulate or dictate social order and structure. In China's social credit system, personal data and informatics are used to create a score or rating of individuals that determine their future financial and social outcomes. Presented as a method to develop trust and integrity within the Chinese polity (Zhang, 2020), the system integrates machinery across domains ranging from commerce to law and order, to digitise data and provide citizens with a social grade (Wong and Dobson, 2019). While states like the US employ Fair Isaac Corporation (FICO) ratings for credit risk analyses, China's model goes a step further to integrate all aspects of social life. Of concern to democratic ideals and individual liberty are the punishments, in the form of point reductions, meted out to those who exercise any form of government criticism (Kostka, 2019). The resultant mass surveillance Panopticon acts as a comprehensive technological artefact for regulating and mediating behaviour.

For India, fears of implementing a similar social credit system may be brushed off with a strong belief in democracy. Additionally, an independent judiciary may provide oversight by preventing the implementation of policies that go against the democratic values of the constitution. However, the status of India as the world's largest democracy is coming under the scanner. With rising instances of communalism, sporadic violence during elections, and discriminatory policies amongst others, India was deemed to be "Partly Free" in 2020 (Freedom House, 2020). Another report noted that India was a "Flawed Democracy" as it dropped from the 27th position to 53rd in a global analysis of democracies (EIU, 2021). Furthermore, increasing curbs on internet freedom, communication blockades, online harassment through 'trolling,' and removal of content has resulted in a dismal score of 51 out of 100 with internet freedom declining for a third year in a row (Freedom House, 2020). As journalists, activists, opposition leaders and Election Commission officials alike are found victims of potential state-sponsored spyware (Kumar, 2021), the triumphs of a digital India are overcast with questionable practices. Despite a robust multi-party democracy, albeit with rampant corruption, India's democratic fabric is tearing at the seams. Within this environment, to what extent will technology assist in economic and social progress?

The real-time collection and storage of sensitive personal health data are pivotal to ML/AI systems' efficiency in diagnostic and clinical decisions (Hassan, 2020). More pertinently, for a global economy threatened by emergent and re-emergent viruses including SARS-COV-2, Nipah or Yellow Fever (Arunkumar, 2018; Friedrich, 2018), continuous and reliable data streams are fundamental to epidemic modelling (Einstein, 2018). States across the globe were quick to implement data-collection technology and ML/AI systems as a public health measure during the COVID-19 pandemic (Ting et al., 2020; McCall, 2020). Although a crucial element in modern epidemiology, data collection and tracking technology has not been favourably received by many across the world (Birnbaum and Spolar, 2020; Lehmann, 2020).

For India, the launch of the Arogya Setu mobile application was expected to improve data collection on potential infections and assist in reporting with both Bluetooth and Global Position System (GPS) capabilities. Not only did the app reach millions of downloads within weeks (Verma, 2020), but the source code was also made open source for cybersecurity reviews on GitHub (Patra, 2020). Although a step in the right direction, numerous concerns have been raised over the nature of the app and the security measures. Firstly, the use of geolocation through GPS tracking has been deemed unnecessary (see Human Rights Watch, 2020). Keeping in mind users' location could be tracked and triangulated, many may be vulnerable to external hacks or potential use by the government without adequate consent to comprehensive conditions on data-sharing (Sharma, 2020).

Secondly, the open-source code was found to contrast with the app itself (Venkatanarayan, 2020). Additionally, the Copyright Act of 1957 allows for reverse-engineering of lawfully acquired programmes to understand the fundamentals (see Section 52 clauses (ab) and (ac) of the Copyright Act, 1957), but the terms of the app prevent users from the same (see Clause 3).

Finally, protocols for the erasure of data would effectively end after 6 months (unless the pandemic continued) while the data on the app itself had no end date (Sharma 2020). Effectively, the safeguards would expire and leave users vulnerable. Moreover, no information was released by the government regarding the data collected following the end of the pandemic. Through broad terminology of "such other necessary and relevant persons" in Clause 2 (a) of the terms of service, the app allows for the sharing of data with anyone within the government; one where 43 per cent of the Lower House of parliament have registered cases for serious criminal violence and even terror (Press Trust of India, 2019).

Unsurprisingly, an index by the Massachusetts Institute of Technology rated the app only 2 out of 5 total points as data collected was not minimised, i.e., limited to only the essential requirements, and transparency in software and policies was low (MIT Technology Review 2020). As chapter 5 noted the instances of bias in medical ML/AI from disproportionate or misleading datasets, without adequate legal measures, any personal medical data collected for these ML/AI systems can be left vulnerable. Moreover, uncertainty over data protection may prove to be a barrier in the construction of appropriate epidemiology models or diagnostic tools. Even the fundamental challenge of access and digitisation is yet to be solved.

The sociotechnical imaginary constructed for India revealed a deep reliance on modern science, empirical knowledge, and Information Technology (IT). Although there is no evidence to suggest that the Indian government has used medical ML/AI systems for nefarious purposes, an environment of low data security and vulnerability can mediate the polity's behaviour during catastrophic events like pandemics. Through automated agents veiled in objectivity, technology can be made an instrument of political power and domination. However, can technology capable of mediating and altering societal dynamics be made ethical? If data is indeed the backbone of a digital global economy, are necessary policies on data privacy and security satisfactory in upholding ethical and moral principles?

6.4 Encoding Ethics into Machines and Law

Envisioning a future catalysed by data and ML/AI systems may not necessarily involve the degeneration of society caused by the erosion of freedoms and rights to privacy and security. Across the globe, states are incorporating measures to improve robustness, reduce error, and mitigate lethal threats. By ascribing moral agency to technological objects, a comprehensive approach to ethics in society can be brought to the fore. Notwithstanding the debates on the ML/AI intelligence and sentience (Hildt, 2019), an abstraction of agency is essential to expanding on ethics. As such, potential remedies to the design of ethical ML/AI systems can be understood in two avenues: ethics of design and ethics of use. While the latter can hold governments, legal institutions, and policy frameworks to account for lethal consequences, the former aims to mitigate odious outcomes by programming ethical behaviour.

Attempts to "materialise morality" (Verbeek, 2011, p. 90) necessitates, in the first instance, an approach that looks beyond reducing risk while noting the agentic capacity of technology to influence moral decisions. In healthcare, these decisions are not limited to patients as they commit to morally charged actions. Nor is it only the choices of medical practitioners utilising ML/AI systems for diagnostics or clinical purposes. Instead, for the ethics in design, programmers and engineers are tasked with evaluating the outcomes of their systems as well as incorporating desirable forms of mediation, thereby highlighting the importance of morality within functionality (Verbeek, 2011). Within Latour's social network of human and nonhuman actants, Hans Achterhuis (1995) advocated for moralising the material environment alongside the human actant. However, predicting how technologies will mediate and influence society, as well as distinct groups within society, is not as simple as building predictive systems in the first instance (Verbeek, 2011).

Owing to this complexity, designers can turn to their imagination or constructive tools to inform their assessment decisions (Friedman and Hendry, 2019; Coeckelbergh, 2006). Despite instances of entities anticipating the outcomes of their artefacts, accurate forecasting through vision is not sufficient. Instead, designers can turn to methodologies like Constructive Technology Assessment (CTA) wherein stakeholders are involved at every stage of the design process (Rip et al., 1995; Schot and Rip, 1997; Konrad, Rip and Greiving, 2017). Moreover, CTA attempts to overcome reliance on *endogenous futures* of emerging technologies (Rip and te Kulva, 2008). However, CTA may not be sufficient in Indian medical ML/AI systems for two key reasons. Firstly, the predominant focus on human actors and design ignores the agentic capacity of technology as well as the "use context" (Verbeek 2011, p. 103). Secondly, while involving stakeholders will improve perspectives and contingencies, the diversity of India's subaltern may not be accounted for within these stages of assessment. Not limited to the impoverished, communities may be actively excluded within national evaluation strategies. Nevertheless, methodologies like CTA or scenario-based design can be fruitful when implemented dynamically and comprehensively.

When evaluated through a legal purview, issues of non-robust and lethal medical ML/AI systems may hold designers, programmers, entire teams, or even corporate entities responsible. Fundamentally, contemporary ML/AI technology is a human output. Although this approach may support a humanist code of ethics, the infancy in ML/AI reveals the limited agency of the technological artefact. Moreover, mediating effects are the result of human design, imagination, and programming (see Verbeek, 2011). Depending on national or international standards for consumer protection and commercial law, the companies releasing medical ML/AI systems can be held to account. As moral consequences enter the realm of legal regimes, there is a turn to the ethics of use.

Confronted with issues of explainability, copyright claims and legal decision making, the ethics of design ought to also consider broader challenges facing data security and privacy. At a regional level, the European Union's General Data Protection Regulation (GDPR) has embarked on addressing the "right to explainability" (Goodman and Flaxman, 2017). Notwithstanding ongoing debate on explainability (see Wachter, Mittelstadt and Floridi, 2017), the revised GDPR accounts for the right to information on automated systems as well as a right to not be subjected to those decisions (see Art. 13-15 and Art 22). Moreover, GDPR has been a landmark legal regime for ensuring data privacy and security across Europe. Despite only hosting 6 of the top 100 AI start-ups in the world (CBInsights, 2021), the EU approach to adaptable regulation is aeons ahead of the US, which is considered the global vanguard of ML/AI development and research. Limited to only state-level laws and few principles for a federal framework (see Draft Memo OMB 2019 and Exec. Order No. 13,859), the US approach to ML/AI regulation is yet to match measures taken by the EU. However, strong regulations are necessary to counter more authoritarian approaches taken by China, particularly as the state aims to incorporate those standards into the Belt and Road Initiative (Broadbent and Arrieta-Kenna, 2021).

India is not far behind the heavyweights of ML/AI development and research. At 6th position in the Global Vibrancy Ranking, India is notable for hiring, skill penetration, and diversity in the workforce (AI Index Annual Report, 2020). With the launch of the National Strategy for Artificial Intelligence by the National Institution for Transforming India (NITI Ayog) in 2018, considerable policy processes are being established to confront ethics, bias, and inclusivity. However, the fundamental challenge of data privacy and security is yet to be comprehensively addressed in the form of established legal regimes.

Keeping in mind the recognition of the right to privacy as afforded by Art. 21 as well as Part IV of the Constitution, relating to the Directive Principles of State Policy (DPSP) in the service of public good, the approach to jurisprudence on data privacy and citizen-state relationship is entrenched in the foremost document of the Indian. However, extant legal regimes are found to be wanting. Defined explicitly as "sensitive personal data or information," personal data is protected to a limited degree by Section 43 of the Information Technology (IT) Act of 2000. Rules 3-5 expand on the definition, lawful purposes, limitations, and consent amongst others. Although a comprehensive attempt at the time, the disruption caused by burgeoning data flows and technology architecture necessitates a broader scope of duties and limitations. More explicitly, the definition of personal data, limitations on government exploitation, data localisation, overriding powers of contractual obligations, rights to be forgotten and privacy, and enforcement mechanisms ought to receive greater attention.

Through the Justice Shrikrishna Committee on Data Privacy and Security, certain recommendations and approaches to data security and privacy in India were noted. Notwithstanding an urgent need to redefine the relationship between the data principal, to whom the data belongs, and the data fiduciaries within India, the committee also advocated for a certain degree of dynamism in the obligations and limitations on the government owing to "interests of the state." Moreover, this line of reason follows with the judgement of the Supreme Court in Union of India v. Puttaswamy wherein the court upheld the right to privacy under Articles 14, 19 and 21 of the Indian Constitution (see Justice K. S. Puttaswamy (Retd.) and Anr. vs Union of India and Ors 2017). As the state would be allowed to curtail their obligations on data privacy owing to national security concerns, personal data can effectively be processed by state agencies without consequence. Lacunae in state surveillance policies further threaten the rights and freedoms of citizens' data (Arun, 2018).

The proposals of the committee have been the foundation of the Personal Data Protection (PDP) Bill of 2019 which, at the time of writing, has been tabled in parliament. Additionally, the Ministry of Health and Family Welfare (MoHFW) proposed the creation of a National Digital Health Ecosystem for healthcare interoperability. By 2020, the MoHFW forwarded the Health Data Management Policy for personal healthcare data protection. However, without an overarching national data privacy and security law, the policies of agencies will be in a legal vacuum. Moreover, the policy of the MoHFW as separate from the PDP Bill may create friction between the two (Kittane et al., 2021).

Despite the advances in medical ML/AI systems as noted in the previous chapter, the PDP Bill may be an inadequate framework to support the data flows and infrastructure of an automated healthcare industry. Under the proposed framework, consent to data processing is limited to what the data principal might “reasonably expect” (Sec. 5(b), PDP Bill 2019). Furthermore, divided into three tiers of personal, sensitive, and critical, data may be increasingly localised in line with the tier. As Big Data Analytics and ML/AI systems rely on evolving data streams, the cross-processing of data across domains is customary practice (Burman, 2020). When a data principal consents to the processing of data by a given data fiduciary, unless exempt or explicitly defined, the data is expected to remain with the latter; depending on the tier, the data is localised to Indian servers. However, for ML/AI systems, data is not only collated from numerous domains (Joshi et al., 2012) but also through proxy models (Coleman et al., 2020). If the data collected is localised to only Indian servers, cloud-computing is severely restricted as servers are based in numerous jurisdictions (see Irion, 2017).

Notwithstanding general data privacy concerns, extant cybersecurity measures in India may not be satisfactory. Despite achieving 10th place in the Global Cybersecurity Index created by the International Telecommunications Unions (2020), a specialised agency of the UN, rising cyberattacks (Nanda, 2021) and suspected state surveillance (Biswas, 2020) present a different cyber environment for data flows in India. Thus, the utility of ML/AI models in Indian healthcare may hit a dead-end.

6.5 An Ethical Future?

The propensity for ML/AI systems to revolutionise Indian healthcare requires an evaluation of the ethical concerns of technology. As ML/AI systems, intentionally or otherwise, can mediate society and power structures, the role of technology as a moral agent allows for evaluation to incorporate the mediating actions. However, the infancy of ML/AI systems and a reliance on humanist ethics highlights a reorientation of current approaches to ethics in technology and society.

Not unlike a growing child, unknowing of moral and ethical principles of their social environment, machines too may be incorporated with normative values. The ethics of design has revealed the role played by programmers, engineers, and corporate entities in ensuring ethical ML/AI systems are deployed in critical industries like healthcare. Further, the ethics of use shows how governments may be tasked with ensuring data privacy and security for the protection and freedom of individuals utilising automated technology.

While India has been successful in establishing itself as a nascent power in the global ML/AI race, parallel protection of data used in ML/AI systems is inadequate. Moreover, as the driving force of the digital economy of the 21st century, data can be wielded to influence society either through states or technological mediation. The consequent power structures may be indifferent to those within India who have little to no access to IT infrastructure. Without legal protections on data privacy and sufficient national cybersecurity regimes, not only is the Indian subaltern vulnerable to threats but the entire subcontinent may be left indefensible against non-state or foreign influence. Nevertheless, laws may still be enacted to protect sensitive data as India further transitions into a data-powered and digitally secure economy. Foundational arguments on bioethics and technology, as provided above, can reveal the contemporary setting and the potential ramifications. The infancy of ML/AI development necessitates such approaches to cover any gaps in legal frameworks prior to deployment.

7 CONCLUSION

In a world fraught with high instances of malnutrition, poor sanitation, ailments and communicable disease, healthcare warrants a position of prominence in policymaking and academia alike. This critical industry was imperative to achieving three of the eight Millennium Development Goals (MDGs) as envisioned by the UN. Notwithstanding considerable progress in reducing infant and maternal mortality, it was only Goal 6, reversing the spread of HIV/AIDS, tuberculosis, and malaria, which was actualised (UN, 2004). The subsequent introduction of the Sustainable Development Goals (SDGs) to replace the MDGs noted health as only one amongst seventeen listed goals. However, through a comprehensive strategy of nine targets and four phases of implementation, the SDGs presented a plan for equitable healthcare and justice without an overbearing focus on only the world's poorest countries (Buse and Hawkes, 2015).

Prior to the adoption of the SDGs in 2015, the 1995 UN Human Development Report, advocating for a radical approach to security, highlighted health as a primary objective. The securitisation of healthcare witnessed a shift of the domain beyond the confines of traditional, realist approaches to one centred on human security wherein individuals, rather than states, act as the primary referent object in security discourse. However, across the world, individuals find themselves facing uncertain futures with limited capacity to mitigate the dyad of 'freedom from want' and 'freedom from fear.'

Paradoxically, however, by replacing the security focus on states with individuals, the former retains dominance due to international realpolitik's existing architecture. States are, by default, the providers of essential services that allow individuals to actualise their goals and live securely (Jayadeva, 2020). Even through democratic models of governance, states like India continue to face an overwhelming challenge.

The potential for technology to aid and support states across the globe in achieving healthcare goals is immense. Yet, to build assistive and non-lethal machines, states may need to confront the socio-political landscape upon which they fabricate a sociotechnical imaginary of healthcare moulded by technology and science. For India, the challenge lies in the expansive diversity that characterises the modern state. The contemporary hierarchy continues to marginalise individuals and communities based on sex, gender, caste, class, or their region of origin not only through social practices but also through their access to the critical industry of healthcare. When limited by physical, social and income access to healthcare, the potential for a digital India is restricted. Moreover, the datasets which are collected may not be adequate for diagnostic, clinical or epidemiological ML/AI models. Thus, the sociotechnical imaginary meant for a cohesive and progressive Indian healthcare system effectively excludes many. The reliance on objective technology without regard for the powershift caused by the big data disruption can serve to further exclude rather than include all individuals within the Indian polity.

As the research has revealed the powershift and shortfalls in a digital Indian healthcare system, the paper can conclude that the deployment of medical ML/AI can influence power dynamics. Not only for those with access to digital tools for the new era of healthcare technology, but the use of ML/AI systems can mediate policy decisions based on assumptions of objectivity. Moreover, the research has found the potential for power hierarchies to manifest through access to sensitive medical information in a country with low standards of data privacy and security.

Notwithstanding the challenges that confront Indian healthcare, when adequate measures are incorporated, technology may serve to improve society. The bioethical dilemma that arises ought to incorporate dimensions of agency, accountability, and responsibility to materialise morality (Verbeek, 2011). Through the ethics of design, normative principles can be built into machines while the ethics of use can regulate how medical ML/AI systems mitigate instances of bias. Moreover, the research has revealed that Indian legal frameworks for data privacy and security necessitate an urgent restructuring to ensure all individuals are protected. The issue of medical ML/AI in India is one of lethal biases and data privacy. Through an analysis of the two, the ecosystem of such technology has been brought to light.

As noted above, even with a human security approach, individuals may turn to state governance architecture to access and utilise life-saving medical technology. The successive waves of the COVID-19 pandemic have brought the shortcomings of Indian healthcare systems and policies to protect the vulnerable to light. On the other hand, the availability of technology and an extensive digital ecosystem can ameliorate the challenges posed by multifarious medical threat vectors. Although the regulation of technology could be translated into a regimenting of science itself, comprehensive policy and ethical technology design can ensure technological achievements while incorporating measures to ensure health security.

Even as the second wave of the pandemic essentially collapsed the Indian healthcare system, the progress of the nation cannot be undone by a few challenges. As Indians turned to the assistance of their fellow citizens through social media at the worst turn of the pandemic (Dodd, 2021), the resilience of the polity is made obvious. However, not all can turn to digital avenues. As an essential public service, no one ought to turn to social media for urgent medical care and attention. The rising death toll should be a reminder to Indian policymakers for the arduous journey ahead in securing the infrastructure and tools for a cohesive, interoperable, and accommodating public health system. With ambiguous legal frameworks, advances in digital health may not be a success soon. Nevertheless, research and scholarship in this avenue can assist in catalysing progress in technology and, more pertinently, social welfare. Still in an embryonic stage, the transformative power of ML/AI systems can be felt in households, hospitals, and battlefields. As a utopian concept finds itself at the centre of a new era of data and information, its future will certainly be an extraordinary odyssey to observe.

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