Inheriting Discrimination: Datafication Encounters of Marginalized Workers

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Informal and precarious workers are increasingly subjected to data-driven systems worldwide. While there has been increasing attention to processes of datafication in state sponsored welfare programs, not much attention has been focused on everyday encounters of the marginalized, such as at their workplace, particularly in the Global South. In this paper, we examine the everyday datafication experiences of sanitation and domestic workers, marginalized by caste, gender, and class, in India that goes beyond a welfare program setting. Contrary to the modernist narratives around data and development, we find that datafication processes invisibly inherited discriminatory properties from societal and institutional practices and further marginalized informal workers.

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1 INTRODUCTION

Datafication of the activities and behaviors of informal and precarious workers have found many uses, including to assess workplace performance [43], determine credit eligibility [79], sanction social welfare benefits [13], and in predictive policing [48]. Across the globe, the systems that act upon these data are increasingly impacting the personal and professional lives of informal and precarious workers. Informal and precarious workers often lack financial, educational, cultural, and legal capital to confront, raise concerns or provide suggestions. Though techno-optimists position these interventions as panacea for numerous social problems, a plethora of studies have critically examined the ramifications of data-driven systems on the deployed communities [90]. In particular, studies have shown that the datafication processes and the data-driven systems tend to exhibit the discriminatory norms and values of the social setting where they are deployed [33]. A large body of work in this space have focused on the forms of discrimination—such as race, gender, age, and disability—that are within the experiences of the communities in the West [14, 20, 35]. ICTD has called

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the attention of the community on issues that are plaguing the Global South, the forms of data based discrimination that are native to non-western geographies—such as religion, caste or tribe—largely remain under-studied [49].

Current literature on participatory design [57], assets-based design [91], value-sensitive design [26], decolonial design [32], data feminism [22], and design justice [17] have proposed theories, provided recommendations, and developed principles in including experiences of marginalized communities in design of data-driven systems. However, these techniques may not scale up or generalize to non-Western communities because of the differences in norms and values, high power distance, invisible and unlabeled marginalization, and literacy challenges among others [50].

Characterized by linguistic, cultural, economic, and religious diversity, India is witnessing a datafication era where behavior and perceptions of diverse populations are being digitized that extends beyond welfare programs, affecting marginalized citizens [50]. In general, the aspirational, modernistic, and progressive perceptions around technology in India have catalyzed the adoption of datafication with minimum resistance [50, 61]. However, past research has discussed that datafication of marginalized communities, in particular, require non-conventional methodologies, in order to avoid adding further layers of discrimination to the already existing social inequities [51, 72, 73]. Less attention to the methods and techniques followed in the data production stage could trigger undesired compounding effects on the systems built with the collected data [74]. While there has been increasing scholarship of datafication in welfare schemes [50] and app-based platforms [42, 66], there has been less attention on quotidian datafication situations that examine the perspectives from the standpoint of marginalized citizens in the Global South, which is what this paper focuses on. We foreground the perceptions and experiences of marginalized workers in India where they are increasingly becoming the subjects of data-driven systems[1] for workplace monitoring [3], delivering public services [2], sanctioning micro-credits [1], and more.

We examined the practices and experiences of sanitation and domestic workers, from Bangalore and Madurai, in South India, with the datafication process in three applications that impacted their everyday lives—workplace monitoring, credit-rating systems, and public welfare delivery. Sanitation and domestic workers are an economically poor and oppressed caste demographic in India, who are still devoid of their basic rights despite the various legislation that seek to protect them [70]. Though substantial in numbers[2], the experiences of these workers are largely understudied empirically [11, 23]. We share our insights from qualitative semi-structured interviews with 14 sanitation workers, 11 domestic workers, and 7 leaders from these communities. Our research and its implications are shaped by Ambedkarite perspectives on emancipation of the marginalized, and we analyze the experiences and practices of workers against the context of caste and untouchability. Our study addresses three research questions: (1) how are workers perceiving data-driven systems? (2) how does the current data infrastructure exacerbate or contribute to overcoming the existing social inequalities? (3) what are the impacts of these systems on their everyday practices? These questions provide unique lens to understand how the data-driven systems could distort existing power relations from the perspective of workers, who have been systematically sidelined in designing these systems.

Overall, we found that the existing data-driven systems largely aim to track the integrity of workers, prevent resource leakage, and increase the efficiency of monitoring/flagging functions. However, these systems invisibly inherited three properties of the institutions where they were deployed. First, the workers had to adhere to certain rigid and laborious data recording procedures in order to feed data into these systems. Such implicit and unreported practices were introduced into the designs of these systems, without considering the workers' cost of complying

[1]By data-driven systems, we refer to those deployments where the workers were decision-subjects, and the owners, makers, or other users of the systems collected digital data and used them for reporting, analyzing and informing decisions [5].

[2]It is estimated that there are at least 2 million domestic and 5 million sanitation workers in the country, but the official statistics largely remains unsettled and invalidated to date [37, 81].

to them. Second, the technologies for collecting data and tracking activities often overlooked the perspectives of workers and missed operationalizing their concerns and struggles, by only considering those variables that are easily quantifiable, standardized, and expressed mathematically. Finally, while the data-driven systems made the functions of supervisors/employers convenient and efficient, there was no transparency in the other direction, which in turn, exacerbated the existing power inequalities between workers and higher-ups. Altogether, while these data-driven interventions are branded as transformative antidotes to corruption, and *"promoted by an aspirational discourse of modernity"* [62], we empirically show that they largely tend to inherit the institutional properties and, in fact, increase the oppression along caste, gender, and income lines.

2 RELATED WORK: DATAFICATION AND OPPRESSION

Over the last few decades, the practices of transforming social aspects of human life into a computationally-manipulable, quantifiable form are becoming pervasive [90]. This process of transforming human life into a continual source of data, a stream of numbers [18], is known as datafication. This process of datafication is becoming increasingly accepted as the norm in wide-ranging fields (e.g., healthcare, finance, social benefits) [90], however it is a form of dominance, albeit subtle. The power structures that govern practices of datafication are inherently asymmetrical. Datafication can be extractive with lopsided gains to the creators and could push the decision-subjects to a disadvantageous position [74]. Datafication also potentially bakes in various biases that reflect which communities or social groups are over/under-represented, whose data is of high/low quality, and what societal disparities and stereotypes exist around them [10, 53].

There is growing body of evidence to suggest datafication worsens racial [20, 38, 44, 47, 76] and gender biases [12, 64, 84, 94]. Buolamwini and Gebru [14] find that widely used benchmarking datasets have intersectional accuracy disparities, that is, they perform much worse for darker-skinned females than lighter-skinned males. Recent work has also explored the other axes of discrimination such as sexual orientation [29] and disability [35]. Another emerging area of research is examining the axes of discrimination with the deployment of algorithmic systems in non-western communities (e.g., caste, religion) [48, 72].

While data has been quintessentially attached to the ideas of state led 'development', more recently, the processes and practices of datafication are penetrating the Global South through the use of digital technologies by non-state institutions and large corporations [7, 40, 55]. As these institutions acquire the tools for datafication, they also acquire the means to assess, and surveil already marginalized groups. With *"fragile democracies, flimsy economies, and impending poverty'* [54], it becomes important to examine the ways in which digital technologies are introduced, and if they perpetuate and exacerbate existing inequalities [80]. Several scholars over the last few years have studied and documented the socio-cultural and economic impacts of these technologies introduced in the Global South [8, 34, 36, 60, 85]. As Heeks and Shekhar [33] describe, part of this research focuses on the constraints of datafication (e.g., digital divide, data quality). Other researchers focus on the dis-benefits or harms realized through the process of datafication in the Global South [4, 49, 50]. However, the forms of discrimination that are native to non-western geographies and their implications on datafication have received little scholarly attention so far. Historical injustices based on caste, religion, and tribe are some prominent examples in the context of Indian subcontinent. In particular, the caste system plays a crucial role in determining social, cultural, economic and political relationships between people from these societies. Compared to the age of this centuries-long practice, the documentation of caste and its manifestations began only very recently.

For centuries, the art of history writing across India was dominated by upper-caste males. *Dalit literature*, texts written by Dalits about their own lives, emerged only recently in the 1960s [93]. Though few upper-caste history writers have written on Dalits, it is often difficult to truly understand the Dalits' struggles holistically only from their writings, as they lack the lived experiences of being a Dalit person themselves. For instance, consider MK Gandhi and BR Ambedkar, who are two prominent advocates of eliminating caste-based discrimination. While Gandhi, an upper-caste male, approaches the idea of caste from a reformative and idealistic perspective, Ambedkar, a Dalit, takes a revolutionary and pragmatic approach and argues for annihilating the very idea of caste [30, 41, 63, 69].

Several studies on caste and its implications have mostly found interest in the fields of social and political sciences, economics, and anthropology [45, 77, 88]. Recently, the interests on analyzing the impact of caste have expanded to other domains such as HCI, CSCW, and business management. For instance, Vaghela et al. [87] studied the influence of caste in the social media politics of India, and Damaraju and Makhija [19] researched the role of caste networks in CEO appointments in India. A related area of research examines how platforms enhance existing forms of organizational control in workplace contexts mediated by algorithms [6, 39, 68]. Kellogg et al. [39] review the six mechanisms through which employers exert algorithmic control to observe and shape behaviors— by restricting and recommending work opportunities, evaluating workers by recording and rating practices, and disciplining them through replacement or reward. Anjali Anwar et al. [6] studied beauty workers' experiences with on-demand home service platforms, and find that the workers experience app-based control from platforms (*e.g.,* quantity of work is surveilled) and bureaucratic control through customers, which is shaped by the caste and class dynamics. For instance, the beauty workers in their study were expected to leave their footwear outside, and sit on the floor or carry portable stools for sitting [6]. Similarly, Rosenblat and Stark [68] find that Uber drivers experience information and power asymmetries which favor the platform, for instance, by not informing drivers about a passenger's destination before accepting a trip.

However, there is a lack of academic attention at the intersection of caste and datafication. While Sambasivan et al. [72] discusses the role of caste, among other axes of discrimination in India, in developing data-driven technologies, the perspectives of the marginalized in datafication largely remain understudied. Similarly, while past works have focused on the datafication experiences of low-income health workers [89], garment, and gig workers [23, 56] in the Global South contexts, the relations between caste and labour largely remain under researched in the context of everyday practices of datafication. We address these gaps in this study where we examine the datafication experiences of sanitation and domestic workers, an informal and oppressed workforce who are increasingly becoming subjects of datafication and whose occupation, even at present, in many parts of the country, get dictated by the caste they are born into.

3 METHODOLOGY

In this paper, we focus specifically on the case of sanitation and domestic workers, who predominantly belong to the oppressed castes. It is estimated that about 60% of the sanitation workers are employed in rural areas and almost everyone belong to the most discriminated sub-castes of what the Indian government classifies as 'scheduled caste' community [28]. Further, about half of sanitation workers in the country are estimated to be working in high risk conditions [37], and one worker die every five days on average [58]. Indeed, a majority of sanitation workers join the workforce as replacements to their parents who die of workplace hazards. Since most of the sanitation and domestic workers belong to 'scheduled castes' and their supervisors/employers come from castes considered hierarchically 'above' them, they are often harshly treated and face risks of losing their jobs if they raise their voices and concerns. Further, the terms of employment of domestic and most of the sanitation workers are informal, often relying on verbal consent without any formal registration, and there is also a lack of stringent laws and policies to protect them [71]. In particular, due to insufficient legislation and prevailing social norms, domestic workers are often subjected to long working hours, low pay, less rest days, and face discrimination by caste and gender [81].

Between January 2021 to June 2021, we conducted semi-structured one-to-one interviews with 14 sanitation workers, 11 domestic workers, and 7 community leaders in Bangalore and Madurai, India. Of the entire sample, all the domestic workers, 13 sanitation workers, 2 supervisors, and 3 community leaders self-identified as female. The rest self-identified as males. Participants ranged from 29 to 56 years old. Though it was challenging for us to collect data during the COVID-19 pandemic, we had an opportunity to gather insights about some of their unique experiences which they would not have encountered at usual times. Interviews lasted between 60 to 90 minutes. All the authors contributed to the construction of the research approach, interviews questions, and data analysis, and the first author moderated the interviews. The authors share diverse ethnicities and sexualities and most of them come from privileged positions of class and caste. The authors do not have Dalit lived experience but share political solidarity on emancipation of marginalized communities [78]. The first author comes from the same locality as some of the participants and knew them from childhood.

Participant demographics.
Domestic workers: Their nature of work involved cleaning, cooking or care work. This sector remains informal for several decades now, and the total number of domestic workers in the country is still unsettled and invalidated. The numbers from various sources were all from survey estimates only and ranged from 2 to 90 million, highlighting the degree of informality of the sector [67, 81]. Since the domestic workers worked independently and were dispersed across different locations in a city, they were less organized and lacked strong unions to raise their voices.
Sanitation workers: Their work primarily involved septic tank cleaning, faecal sludge handling and road sweeping. While a majority of the sanitation workers worked as contract or daily wage laborers and earn meager income, a small number of them who were permanently employed by the government had relatively better pay and benefits.
Community Leaders: Born into their community, most of the community leaders we spoke to had undergone the struggles of their marginalized community firsthand and had developed into representatives over time. Some of them educated, skilled, and organized their people for harmony, in addition to voicing out their community's demands and helping in mobilizing their people for a common cause. Most of the workers we engaged with shared that they trusted their community leaders and in many cases, the latter were the only ones who truly understood their concerns. Some of these leaders were also well connected with outsiders of their community such as supervisors at work, politicians, and bureaucrats who play crucial role in the social, political, and economic lives of the marginalized. They thus bridged distinct sets of people and hence possessed unique knowledge about the strengths and weaknesses of the complex institutional arrangements in the society, and knew the tactics and strategies required to navigate the political and social systems in place.

Participant Recruitment and Moderation. We recruited the participants through a combination of NGOs, local community members and personal contacts of the first author, using snowball sampling. All our interviews were conducted through normal audio calls. Majority of the participants owned only feature phones while a few owned smartphones. Some of the participants who possessed smartphones shared them with other members of their family. We conducted interviews in participants' local language and translated to English during transcription in order to do comparative analysis [59] across our team. The participants were informed beforehand and at the start of interviews about the nature of the study and were compensated INR 1000 (via bank transfer) for their time.

Through our initial engagement with workers who were in the personal contacts of the first author, we identified and conducted interviews with few other participants who had established trusted connections with many from our target community. While these members constituted mostly community leaders, there were also a few sanitation and domestic workers who maintained very good rapport with everyone in the community. They then introduced us to more members from the community, most of whom interacted with us without much apprehension since we were presented to them through their acquaintances. Similarly, we recruited participants through our engagements with community leaders who were associated with NGOs. Within our available recruitment resources, we ensured to recruit participants who were representative of the our target community of different age, gender, and socioeconomic status.

The community leaders in our sample have worked with the community at large and in many cases, have made efforts to represent the voices of the community in various forums when required. So, while the interviews with the workers and supervisors were centered in most cases around their individual experiences, the interviews with the community leaders were aimed at gathering collective and diverse perspectives about the workers' encounters and situations.

Analysis and Coding. During our interviews, we probed into participants' real-life encounters of data-driven systems to understand their reality, existing struggles and general perceptions about datafication. We conducted multiple rounds of thematic coding and identified key ideas from the data around datafication and marginality. In particular, our analysis focused on understanding participants' socio-cultural, economic, and political lives and their experiences around (1) workplace monitoring, (2) credit rating systems, (3) public welfare delivery, (4) data infrastructure, (5) automation, (6) transparency, and (7) role of formal and informal support systems in redressing grievances. We then consolidated our findings into three top-level categories which showed how the datafication process on marginalized communities inherit characteristics of past institutions.

Research Ethics and Anonymization. At the beginning of each interview, we informed our participants the purpose of our study, the types of questions we would ask, and our affiliations. We obtained verbal consent, in participants' own language, before starting the interviews and provided them an opportunity to decline participation prior to interviews. We also informed them they had the right to terminate the interview at any point without forfeiting the incentive. We stored all interview data in a private Google Drive folder with access permissions given only to our research team. In the interview and research files, we deleted all identifying information such as names and contact details. Further, when presenting our findings, we report only pseudonyms and age ranges to protect participant privacy.

Limitations. Our study may be subject to common limitations of qualitative studies such as observer bias, participant self-censorship, and limited generalizability, considering the huge number of domestic and sanitation workers spread across different demographics. We acknowledge that some of the nitty-gritty in our participants' experiences with datafication could have been lost in translation due to the caste/class differences. Further, due to the COVID-19 pandemic, we had to avoid conducting in-person visits to the field and limit ourselves to semi-structured interviews through normal voice calls.

4 FINDINGS

The domestic and sanitation workers we engaged with were *datafied* for three major purposes—*monitoring* their workplace activities, *flagging* or identifying eligibility for microcredit, and for public welfare benefit. The technologies that were used for the above purposes were fingerprint/face-recognition based biometrics, CCTV cameras, WhatsApp, and credit risk assessment tools. We found that the design of these data-driven invisibly inherited three major discriminatory properties from past institutions: laborious and rigid data recording procedures in order to feed data into these systems, misguided mathematization, and one-sided transparency. We observed that, in most cases, workers perceived these systems as opaque, discriminatory, and rigid, and put forth nuanced arguments on the existing datafication process and suggested alternatives for burden-free deployment. Further, these systems afforded legitimacy to supervisors, exacerbating some of the already existing economic, social and cultural inequities experienced by the workers.

4.1 Laborious and Rigid Data-Recording Procedures

The data-driven systems required our subjects to adhere to specific procedures in order to feed their data and make these systems function. These procedures were often implicit, unreported, burdensome, and hard to challenge. In this section, we discuss the experiences of our participants with such procedures that were often simply demanded without considering the workers' cost of complying.

Demeaning Manual Labor. The century-long connection between caste and occupation still prevails in many parts of India [27, 86], and in particular, the intergenerational mobility in occupational attainment is still very low for lower castes [21, 46]. This is evident in the case of our participants where most of them come from lower castes and still do manual works that are looked down upon by the rest of the society. These systems, built with fingerprint-based biometric sensors, were deployed at specific locations that were often decided based on the employers' convenience and availability of limited financial resources; and stationed far away from the work location of most workers. Since only one biometric system was placed for every 3 wards in a district, most of the participants had to travel 2-3 kms daily by walk or had to spend money out of their own pocket to meet the travel expense to record data.

The monitoring systems thus added financial burden for some workers. Few workers spent as high as Rs.40 per day (which is 8% of their daily income) on travel to just mark their attendance. Further, some workers could not mobilize required funds on a daily basis, which in turn made them vulnerable to local money lenders who charged an exorbitant 10% interest rate *per day* for lending microloans of Rs.50-100 every morning. So in addition to their daily travel, food, and safety equipment expenses that the workers incurred from their own pocket for work (which they would not spend otherwise), since marking attendance added further financial pressure, few workers avoided going to work whenever they suffered from financial crunch even though they were available. While discussing alternatives to such practices, all the participants agreed on the need for decentralizing self-recording data collection process, and shared how a mobile-based attendance marking system, introduced during COVID to avoid physical contact with workers, saved both their time and money.

Other than at work, our participants experienced similar treatment in registering their information of obtaining public welfare benefits. They explained that when the administrative procedures demanded at government offices to receive benefits are unmanageable and discriminating, they prefer *not* to visit these offices at all to avoid financial burden and save time for other income yielding activities. In general, they had to procure many identity documents, proof of residence and employment and so on, and typically had to visit the offices multiple times for information recording, updation, retrieval, and deletion. Since such procedures cost them a day of pay, they often choose not to register. For instance, consider the free health insurance scheme that the government provides for poorer sections of the society. Most of our participants have not received any insurance-related benefits before nor have seen someone enjoying the benefits. Further, since the process of registering with their information would often take at least a few days, they generally become indifferent towards such schemes.

Rigid and Humiliating Recourse Process. In addition to being laborious, the implicitly demanded procedures were rigid and hard to challenge. D11 shared her experience with one such bureaucratic procedure where *only* unique phone numbers were required for enrolling in a welfare scheme for economically poor women which credited Rs. 1000 in their bank account every month. She shared that her mobile accidentally fell into a hot curry container while cooking and she did not have sufficient funds to buy a new mobile phone immediately. Also, her social situation did not allow her to use a new sim in someone else' phone. Eventually, she became ineligible for the scheme even though she had a number of other valid unique IDs such as ration card and Aadhaar.

D11, and other participants who were stuck with challenging such rigid procedures, often had to physically visit a police station or a government office for grievance redressal. In addition to such visits costing them a day/half a day of wage, they were abused, discriminated, and humiliated based on their caste, economic class, occupation, and the types of clothes they wear when they visited these offices. Since the nature of work done by our participants involves heavy cleaning in various environments, from kitchen and toilets to dirty streets and drainage pipes, their clothes would not look close to how they were when the workers started their day [15, 52]. Several participants reported that they get looked down upon and treated condescendingly by the officers due to their "dirty" dresses. C3, a community leader, in his words,

> *"The sanitation workers, if they reach out to officers to get help on their issues, will go wearing lungis and shirts. But the officers look down upon this and expect them to visit the office in "decent" dress. The officers don't understand that lungis are their typical and in most cases the only clothes they have..."*

Thus a recourse process to address problems with datafication processes, do not start and end with the device, they spill over to the physical spaces. Access to physical spaces are mediated by caste based discrimination, where policing the type of dress mediates access to these state spaces.

4.2 Misguided Quantification

We observed the input variables about our participants that were fed into the monitoring and flagging systems were those that were easily quantifiable, standardized, and expressed mathematically. Since technologies for collecting data and tracking activities function by mathematizing the observed world, their application to monitoring falls in place naturally. However, data do not exist in vacuum and the contexts that produce the data were often overlooked by these systems. In this section, we discuss the concerns of our participants in their encounters with mathematized systems.

At any cost, 8 means 8! In the case of most of the sanitation workers, fingerprint- or facial-recognition-based biometric systems monitored the number of hours they spent at their workplace in order to assess their efficiency. Using the time spent by the workers as a proxy for measuring work performance was convenient for both the design of tracking systems and for the supervisors/employers, but the workers faced a number of issues in keeping up with such standards. Our participants reported that the total working hours independently do not convey the complete picture of their performance as they shared a number of other direct and indirect factors at play. In particular, the sanitation workers in our participants pool described their work routine as challenging and deleterious, and having strict 8 hours work duration is unrealistic and inhumane. S9 explained their situations as,

> *"Workers who gets into the drainage for cleaning, will definitely get breathing difficulties... asking them to work for the whole 8 hours is a crime on top of an already existing crime of making them do this job. There are so many health issues if they work for 8 hours. How can he tolerate working with human waste for 8 hours?"*

Such enforcing of stringent working conditions is characteristic of the caste system where lower castes are systematically placed in constant economic and mental distress to limit their upward mobility [70]. The digital monitoring systems perpetuate and ascribe value to this discriminatory practice, which by design could have mitigated or resisted it. Few of the domestic workers also described that they were expected to follow stringent working hours. For instance, D7 shared that, reflecting the dominant-caste mindset, her employer expects her to work for at lest one hour for the wage she receives. If she finishes her chores sooner than one hour in some days (when there were lesser or easily washable utensils), her employer provides her additional cleaning works, such as cleaning the cupboards or fans, that were not discussed while agreeing upon the terms and conditions of the employment. In sum, almost all the workers were against the introduction of any tracker that could judge their performance based only on the number of hours spent at the workplace.

Why not measure quality? Almost all participants suggested measuring their quality of work instead of the total working hours to assess their performance. They shared that qualitative metrics would reduce their work burden and at the same time meet the end goal of their employers, for instance, improving the cleanliness of the home or the city. The workers have a poor financial background and also tend to work in physically demanding jobs with limited pay. They shared if they finished their work sooner without sacrificing the quality, had the strict work duration not been there, they would have sought additional gigs for extra income.

Further, these monitoring systems added legibility to the work-duration variable, as many participants reported that employers often cared only about the working hours presence irrespective of the work quality delivered. For instance, S3 mentioned that their supervisor would shut down the biometric system and mark as absent for anyone recording their attendance from 6:31 AM, for a job duty starting at 6:30 AM. S3 also described that this hard closing time was arbitrarily decided by the supervisors, sometimes based on their personal mood, where a few allowed entries even until 10 minutes after 6:30 in some days. None of our participants' concerns were considered while fixing such thresholds: some workers had to start their day at 5:00 AM in the morning and travel 3-4 kms by local transport to reach their workplace on time, and female workers had the additional responsibility of cooking meals for the family before starting to work and taking care of children after reaching home.

Incomplete operationalization. Outside of work, our participants have encountered flagging systems whose input variables did not operationalize many factors they considered as important. A case in point was their encounters with money lending entities. Some of our participants shared that they avoid approaching money lenders to their best since the latter charge exorbitant interest rates, and instead try to approach formal financial institutions for loans. However, almost all our participants (except few community leaders) hardly earn sufficient income and meet other required criteria, such as a steady source of income and credit history, that make them eligible for availing personal loans from banks and other financial institutions. Hence, typically ten to twenty workers form a small group to avail loans from microfinance institutions at a relatively higher interest rate compared to those set by commercial banks, but at a much lesser rates than those charged by money lenders in their locality.

However, the participants shared that it is very difficult to be in the good books of these microfinance institutions because the data that is taken into account for decision-making are often distorted and lack context. Historically, the credit sector has also been persistently discriminatory against the lower castes in many parts of the country [25, 65, 75]. The participants reported that in case they default on a payment, the technology-driven credit risk assessment tools these financial institutions deploy would automatically block their credit accounts without scrutinizing the reasons behind the default and without assessing the genuineness of the borrower.

In a few instances, the heads of these community-led microfinance groups had borrowed money on behalf of the groups without the latter's knowledge and had flown away. In one instance, the group could not repay the loan and everyone got put on a denied list for future loans even though all the members were regular in their contributions to the group. In another instance, to protect themselves from falling into the clutches of money lenders who charge exorbitant interest rate, some workers repaid the loan by contributing additional money from their own pocket to continue receiving loan benefits which are offered to them at nominal interest rates. Neither the reasons for default (first case) nor their genuineness (second case) were recorded as variables for determining the credit-worthiness of these workers. In addition to missing variables, our participants believed that the digital lending systems inherited, from the pre-digital setting, the inclusion of caste or proxies of caste (such as information of geographies clustered with a particular castes) as determining variables. Their beliefs are warranted by both prior works that empirically show that caste remains important determiner of lending outcomes in India [65, 75], and by their personal experiences: several participants reported that these tools blacklisted anyone applying for a loan from the locations with high default rates, without considering other determiners.

In some other cases, some of our participants' credit history data got fabricated either without their knowledge or by exploiting their ignorance. They, however, restrained from challenging such frauds not only due to their lack of social and legal capital, but also due to the fear of abuse and humiliation by upper castes when raised their voices [9]. Since the history of loans taken and paid back are crucial inputs in determining their credit-worthiness, the participants often get rejected for successive loans for reasons other than their ability to repay. No validation of their historical data happened in our participants case. Below is one example where S1 shared how their account got blocked due to such data fabrication.

> *"We belong to the SC community. From the government they gave us interest free loans. Bank officers identify people in our community who are in need for money, and convince them to avail loans. They lure us by saying that we can get 25,000 for free if we give our card details. They use our personal details and they avail loan in our name. They give Rs 25, 000 to us and they take the rest of the money. Many times they don't repay the loan. Because of that our accounts are blocked."*

Who knows when it will detect my face? The sanitation workers reported that for a brief period of time, an AI-based face-detection system was deployed to automatically detect their faces and mark attendance. While our participants were excited in the beginning to use such a system, they soon started facing issues due to inaccurate detection. They shared that the face-detector would randomly miss faces: it detected the first face in the morning but missed the next ones, and in some cases, it did not recognize the same person whom it detected the previous day. In particular, the device could not recognize if there were any structural changes in the faces from injuries at workplace. Our participants do physically demanding jobs often without safeguards and hence are prone to injuries or accidents. However, the AI models failed to capture the workplace reality of these workers. S5 shared her struggle as:

> *"When the biometric system was introduced, out of curiosity, all the workers washed their faces, applied powder, to look good before the camera, to mark their attendance. After a few days, the curiosity faded. Some workers' faces which were swollen due to accidents or injury in the workplace were not recorded by the system. We are class D workers. We don't have much knowledge to understand the working of such machines."*

Further, both the workers and the supervisors were not familiar with these technologies so both of them were clueless about the ways to tackle this situation. The supervisors initially insisted the workers to continue using the system multiple times if it did not detect correctly. After a long struggle and multiple protests by the workers to remove such a system, the supervisors arrived at a compromise where the workers had to first use the face-detector and if it did not detect correctly, they were allowed to mark their attendance in the physical registers as how the situation was previously. However, this lead to repeated work where some workers entered their details in the registers anyway even if the system detected their face correctly, for safety. S1 described how conducting trial runs before launching any such systems could have reduced their anxiety, as their salary could be contingent on how these marking systems recorded their data. Overall, our participants had to face the effects of machine learning models that were trained on a non-representative dataset, were deployed without scrutiny, and did not adapt by learning from its behavior in production.

4.3 One-Sided Transparency

Existing monitoring systems make the workers' activities at workplace transparent. Data-driven systems aid in visibilizing specific activities of workers that the supervisors/employers want to monitor, and in turn, makes the latter's tracking function easy, efficient, scaled up, and convenient. However, our participants shared that there is no transparency and accountability in the other direction—workers often do not know how their jobs are allocated nor do they receive payslips. Further, while this one-sided notion of transparency creates a *lingua franca* among the employers of different hierarchical levels, it exacerbates the existing power inequalities between workers and higher-ups. In this section, we discuss the experiences of our participants with such data-driven systems that have this asymmetric transparency.

Extra work, no pay. Our Participants shared they find it extremely difficult to provide evidences for any extra work they are required to do outside the terms of contract. In the case of domestic workers who worked in apartment houses, there were CCTV cameras that tracked their movements in and out of the building. While their employers could challenge them for not working the stipulated number of hours or not fulfilling the expectations by monitoring them through CCTV cameras, the workers, due to their economic vulnerability, could not afford to confront any accusations made against them. They shared that they cannot challenge their employers with the hope of using the CCTV footage because they do not have the ownership of the monitoring systems and also do not have the affordance to own one. In some cases, a few employers have even threatened to file a lawsuit against confronting workers, knowing well that the workers who come from suppressed castes would most likely not have the resources to fight. Due to this inbuilt power inequalities, most technological interventions for monitoring provide visibility to only the activities of the marginalized. For instance, D4 reported that one of her employers would give her additional cleaning works in a few days in a month. But if D4 demands extra pay for the works done in addition to what was agreed for the monthly pay, her house owner would blatantly deny giving such works. D4 shared that, since they generally do not keep a track of the exact days when additional works were given nor they would not have any concrete proofs for the works done, they often give up on arguing with their employers beyond a certain point for fear of losing jobs.

On the other hand, D3 explained that while some of the employers did give more pay for the additional works, the extra earned money had still caused domestic issues. Entrenched with patriarchal norms and practices, husbands of some of the domestic workers raise doubts over the workers' characters if they bring in extra money from work. D3 explained that the extra earned money lead to a tussle with her husband since there were no proofs to show him that the extra amount had come through legitimate ways. She added that interventions that could automatically track her work and remuneration received could avoid such domestic nuisance.

Similarly, the sanitation workers sometime sought the help of their supervisors for urgent financial needs. As is typical of the lenders our participants could approach, these supervisors charged exorbitant interest rates. In such cases, since the workers had both financial and workplace obligation, the supervisors summoned the workers for urgent and unnoticed tasks without pay. In one instance, when a minister's visit was scheduled to a supervisor's area, the latter urgently demanded extra work from the workers to whom he had lent money. Some of our participants worked under this supervisor and had also borrowed money from him for managing their daily finances. However, our participants reported that these additional works they had to do always escaped the record books and was never used to measure their performance. In addition, if some of the workers showed any resistance or hesitation in doing such unrecorded work, the supervisors mistreat them and threaten to enter incorrect data about their attendance or other metrics used to evaluate their performance.

Transparent to work, opaque to care. Data-driven interventions that monitored workers threw light only on the performance of the workers, but not the overall functioning of the organisation. Participants reported how the present data-driven monitoring tools are simplifying the monitoring function of the supervisors while adding undue burden on the workers who have to adhere to burdensome rules and procedures. For instance, several of our participants explained that they have been asked to share pictures of every completed task, which they find it very difficult to comply on the daily basis as the tasks per day keep increasing over time. They reported that while the resources on monitoring are getting scaled up, the resources required for complying to the required tasks remain mostly constant. They explained both the advantages and disadvantages in using photos as evidence in monitoring work efficiency. They shared that these photos are helping in building trust with the supervisor, but at the same time the quality of work remains the same before and after this intervention. In the words of C1,

> *"Supervisors expect all the workers to have a phone. Supervisors call me on that number to check whether I am there in the field. We are also marking attendance over the phone. They ask us to send the pictures of completed tasks...... But they have stopped recruiting workers since 2013. Even next month around 15 workers will retire. So few of us are performing all the work. This won't be captured by these photos."*

Worker's performance data was in most cases used as a proxy to evaluate the efficiency of the schemes that fund these interventions. We observed that the design of the data-driven intervention was such that it visibilised the performance of the workers in quantitative terms, but did not pay much attention towards the struggles faced by the workers nor the inefficiencies of the people who are at the top of the hierarchy. Further, such selective transparency measures which did not guarantee any accountability to the workers, ignored the nitty gritties of the particular job or the health conditions of the workers who were hired for the job. For instance, several of our participants reported that the supervisor arbitrarily fix a threshold on the number of houses they want to them clean per day. In the words of S2,

> *"In a day they ask us to clean at least 100 houses. But it is possible for us to clean around 70 houses or in few cases less than that. Few houses will be on the ground floor and few houses will be on the third floor. Time taken to climb these 3 floor homes are not taken into consideration."*

In another instance where CCTV footage was used for monitoring, a sanitation worker was brutally thrashed and blamed for theft based on CCTV footage which lacked any context. Here, the monitoring technology itself was not biased in terms of detecting suspicious activity, but it helped the people in power to portray their claims as those with strong tech-supported evidence. There was no recourse made available to the worker as the burden of proof against the complaint often lies with the poor. The worker, after a series of investigations conducted by police officers, killed himself due to humiliation and fear of threats to kill his family if he did not accept the charges pressed against him. C1, a community leader described this situation as,

> *"Since this worker came to work on a holiday and his image was recorded on the CCTV camera which was positioned outside the house of an officer who lost their jewels, police suspected the sanitation worker to be the Thief. They didn't ask him. For the past one week they took him to jail, beat him very badly and sent him*

> *back home. They were doing this for 4-5 days. On Friday they beat him very badly. They said, "if you don't bring back the money we will kill you and your entire family." They also beat his son who is 15-16 years old"*

Further, one of the participants reported that since the police officer in-charge for this crime belonged to the caste of a high-ranked politician in the state, no action would be taken against him. He shared, *"There is a very big caste nexus. Sometimes, no, most of the times, officers of the same caste join together and then they delay our demands as we belong to a oppressed-caste. They don't want us to rise up."*

5 DISCUSSION

We find that the datafication of quotidian situations our participants encounter operate in highly unequal conditions. These datafication processes are refracted through lack of access to supporting infrastructure, intentional opacity, and automating oppressive institutional norms.

5.1 Lack of infrastructure amplifies inequalities

The idea that capable mobile devices are ubiquitous has driven many an AI imagination today. Indeed, those who are privileged carry multiple devices with them, have the capacity to pay for data, and live in the shadows of mobile towers at all times to assume ubiquity. The same cannot be said of marginalized communities, and thus substantial harms will be introduced if decisions about introducing technological systems assume existence of infrastructure. The sanitation and domestic workers largely come from communities marginalized by caste and class, typically have poor financial background, and lack access to basic infrastructure. For example, most of them could not afford common household appliances and had to manage between work and time-consuming day-to-day domestic tasks.

In this situation, their already existing problems get amplified if they had to shell out additional resources to fulfill the requirements of monitoring/flagging systems [24]. For instance, even if a biometric device works accurately, if a workers were to spend time and money to authenticate themselves, it poses an undue and unjustified burden. We discussed in our findings that current technologies for monitoring/flagging introduce such undue burdens that compromise their meager incomes, leisure or other basic freedoms that are already compromised. The harms get compounded when the technologies are not supported by infrastructure required for burden free deployment.

Many technology-driven systems that flag applicants for eligibility of public welfare schemes require them to own resources such as a unique phone number, thereby, limiting the eligibility to those who could afford such resources. Such requirements aid the flagging systems efficiently map beneficiaries to benefits but do not ask whether users have access to reliable technologies in fulfilling the requirements. We discussed the case of a domestic worker who lost a public welfare benefit for economically poor women since she accidentally lost her mobile phone during the time of application and did not have money to buy a new one. There is no easy path to leap-frogging to a promised land of datafication, without addressing the infrastructural challenges of access.

5.2 Intentional opacity

Globally, there is now a recognition that AI-based interventions could lead to harm in socially-sensitive applications and this has led to a wealth of work on identifying and mitigating them [53]. Current efforts are centered on algorithms themselves with a wealth of work seeking to make them fair, accurate, transparent, explainable and imbibe other desirable properties [92]. However, in our context, it is not clear how these systems were trained nor what data were fed into the system. For instance, biometric systems based on facial recognition to record attendance sometimes do not adequately capture the workplace reality faced by the workers. The devices could not recognize the same worker if there were any structural changes in the faces from injuries at workplace. Our findings also showed how the workers' data may got fabricated in the datafication process by humans vested with the responsibility of managing or recording the data. Further, there were no accountability mechanisms to supervise if higher-ups fudge the data. For instance, there were cases of fake loans taken in the name of some of our participants who subsequently got their credit accounts blocked due to default. These observations echo how opacity is intentionally designed by the powerful [48] and underscores that the data collected for monitoring or flagging should account for such localized practices.

The design of data pipelines, and the methods and techniques that go into the process play a key role in determining the performance, fairness, and robustness of the machine learning systems [31, 53, 74]. The data infrastructure around existing monitoring and flagging systems can propel their fully automated versions in the future, and make predictions about workers' future behaviour and activities [23]. Our findings showed that several factors that the workers consider as relevant were not considered in evaluating workers' performance, and determining welfare or credit eligibility. For instance, our participants suggested the need for accounting variables that better capture the qualitative characteristics of their work, instead of rigid metrics such as total work hours. Similarly, in the context of credit-scoring, some of our participants had to contribute additional money to cover for the one who ran away with all their borrowed money. However, such extenuating circumstances are not accounted for in the decision-making. Overall, despite their financial and social situations, most of their concerns, struggles, and efforts they put in to comply with the technologies, are often not operationalized in the decision-making process. This, in turn, could create distorted datasets with several important missing information about workers' activity and behaviour, and raises fairness and ethical concerns.

5.3 Automating Oppressive Institutional Norms

Our findings show that the data-driven interventions for monitoring and flagging do not work in isolation and understanding their impact on the decision subjects requires us to situate them in the *institutional* context. Institutions are formal and informal rules of the game that govern societies [82]. Formal rules specify permissible and impermissible actions and are enforced through constitution, laws, and contracts. Informal rules are cultural, implicit and have a powerful impact on human behaviour even if they are not formally enforced. Ultimately, rules seek to shape human behaviour by constraining certain actions and by enabling others. The data-driven monitoring/flagging systems we studied enforce rules around work, credit eligibility, or public service delivery, and thus primarily serve an institutional purpose of domination of putting people in place. In fact, these applications will lose their purpose if we do not consider greater efficiency in rule enforcement. Consequently, our participants indicate that these technologies, though being portrayed as a symbol of modernity and transformation, largely inherit the characteristics of institutions where they are deployed.

Our findings show that the most of these current technologies mechanically enforce impractical rules for tracking without considering the needs and concerns of the workers. For instance, we discussed how our participants were forced to adhere to strict working hours irrespective of the job nature and their health conditions. Punctuality and long working hours are culturally perceived as strong indicators of good performance in India [83] and this perception gets infused into the design of sociotechnical systems, such as biometrics, for monitoring. Hence, it is important to account the impact of cultural logics and carefully design the interface between technological measurements and institutional decisions. We suggest the designers to think of this interface as the place where power, caste, and gender inequalities manifest, and design ways of empowering marginalized communities technically and socially in this space.

Participants also talked extensively about wage theft, being forced to perform extra contractual work and other abuses that those in positions of power inflicted on them and discussed the need to curtail such abuses. In talking about the conditions of their work, many mentioned that they do not have basic protective equipment such as shoes or gloves as a result of which they suffer from illnesses frequently, but nonetheless were forced to share pictures of completed work as proofs. Even before the data-driven era, our participants discussed that many supervisors and employers, at their own discretion, arbitrarily fixed workers' in-time, out-time, and work duration, and barred entry to workers based on caste and gender differences. The datafication of these functions offered legitimacy to those in authority and offered them a space to perpetuate entrenched social discriminatory practices. It further constrains the freedoms of the marginalized while letting the powerful go unchecked. The same mechanism that is used to monitor worker attendance can easily be used to monitor whether the supervisors, employers, or the state had provided basic protective equipment. It is not the capacity of technology that limits such uses but the power of powerful people over designers of the data-driven systems [16, 22].

Moreover, the data-driven systems we studied did not offer much opportunities for its decision subjects to rise their concerns when they felt agitated about certain features of the system. In some cases, the workers exercised their imagination to ask for technical solutions that would curtail arbitrary exercise of power by their superiors. For example, they asked for automated direct deposits of wage payments into their bank accounts to mitigate wage theft. However, in most cases, the community lacked the knowledge about the working of these technical systems, making it difficult for them to provide any concrete suggestion on remodeling the systems to suit their specific needs or mitigating the harms that the systems imposed on them. Hence, before the introduction of any datafication system, it is important to establish a community driven legal support system which could come up with an open and agreed upon minimum standards and guidelines. People in the top of the hierarchy must abide by those guidelines while introducing any datafication system on the marginalised communities. Further, such standards could enforce that the rights and safeguards that should be guaranteed to the marginalized in a digitized era.

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