Data in New Delhi's Predictive Policing System

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ABSTRACT

In 2015, Delhi Police announced plans for predictive policing. The Crime Mapping, Analytics and Predictive System (CMAPS) would be implemented in India's capital, for live spatial hotspot mapping of crime, criminal behavior patterns and suspect analysis. Four years later, there is little known about the effect of CMAPS due to the lack of public accountability mechanisms and large exceptions for law enforcement under India's Right to Information Act. Through an ethnographic study of Delhi Police's data collection practices, and analysing the institutional and legal reality within which CMAPS will function, this paper presents one of the first accounts of smart policing in India. Through our findings and discussion we show what kinds of biases are present within Delhi Police's data collection practices currently and how they translate and transfer into initiatives like CMAPS. We further discuss what the biases in CMAPS can teach us about future public sector deployment of socio-technical systems in India and other global South geographies. We also offer methodological considerations for studying AI deployments in non-western contexts. We conclude with a set of recommendations for civil society and social justice actors to consider when engaging with opaque systems implemented in the public sector.

CCS CONCEPTS

• **Social and professional topics** → *Governmental regulations*; *Race and ethnicity*; *Cultural characteristics*; • **Computing methodologies** → *Reasoning about belief and knowledge.*

KEYWORDS

Fairness-Aware Machine Learning, Predictive Policing, Interdisciplinary, Sociotechnical systems

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1 INTRODUCTION

As of 2019, law enforcement agencies across India are in the process of deploying machine learning systems for crime prevention, criminal tracking, and better allocation of resources. In Chennai, one of the major Indian metropolises with a population of 11 million, facial recognition systems are deployed in crowded places to identify criminals and individuals who "look suspicious" [18]. In the south Indian state of Telangana (estimated population of 40 million) smart law enforcement has come to be deployed with a view to create a "360 degree view" of citizens [28]. Elsewhere, in the north Indian state of Punjab (estimated population of 30 million), the Punjab Artificial Intelligence System received a Smart Policing Award for its use of facial recognition in crime solving [30]. The National Crime Records Bureau of India recently published a tender for the Automated Face Recognition System which would be used for "criminal identification, verification and its dissemination among various police organizations and units across the country" [16]. One of the first initiatives towards the use of machine learning (ML) in law enforcement was pioneered by the Delhi Police. For context, Delhi is a city with a population of close to 30 million people. It is the national capital, and is also anecdotally referred to as the 'rape capital' of India due to historically high records of violence against women. This is important to understand to follow the larger safety discourse in Delhi and why policing interventions of a certain kind may gain public legitimacy. In 2015, Delhi police announced the use of the Crime Mapping, Analysis and Mapping System (CMAPS), a predictive policing system [20] that would access data directly from the Dial 100 call centre to plot the geographic location of calls and calculate crime hotspots.

The limitations and dangers of predictive policing have been studied in jurisdictions like the United States and Europe. It is well understood that these systems risk over-policing vulnerable populations [15] and exacerbate problematic institutional biases [14]. The implementation and quotidian experience of these systems in the global South (or post-colonial) jurisdictions like India remain to be studied. It is particularly crucial to study such deployments in India at this juncture because of the ongoing efforts at wholesale deployment of various ML technologies in all aspects of public life in India with little to no meaningful consideration of potential harms. In this paper, we study the process by which crime hotspot mapping is currently carried out by Delhi Police, and the existing infrastructure and data on which CMAPS will be developed. We zoom in on what the "spatial distribution of crime" entails in New Delhi, and also investigate the creation, collection and classification of data. We draw on observational and unstructured interview data to answer the following questions:

(1) What kinds of biases are present in police data currently, and how do they arise?

(2) What kinds of social and political assumptions inform these practices, and how do they find their way into predictive policing systems like CMAPS?
(3) What can current data practices tell us about future tech uses within the same institutional reality?

The paper offers four substantial contributions to existing literature in the field. Firstly, this paper is the first of its kind to present a study of a predictive policing system from the Global South. Operationalising findings from previous work by Seaver [23] and Haraway [8], we analyse daily activities of human, institutional and societal actors, and situate our analysis of the system within its local context, drawing from on-the-ground observation and interviews. Second, we explore the extent and types of biases that exist within Delhi's crime hotspot mapping system. A significant component of studying predictive policing initiatives is to study the data that trains these systems [6]. However, as Suresh & Guttag [29] have argued earlier, the phrase "training data bias" in the context of machine learning applications is too broad to be useful. We use their framework to bring about a more granular understanding of how current practices within Delhi Police influence technical systems like CMAPS. In doing so, we also present new evidence which can be used to engage with similarly placed predictive policing systems in India and beyond.

Third, law enforcement's use of technology for maintaining law and order is notoriously opaque - from secretive procurement practices, to deployment that is not subject or amenable to information requests. Richardson et. al have explored the urgent need for accountability mechanisms within predictive policing systems in the United States [22]. In the context of New Delhi's predictive policing system, the first step towards accountability is peering into the functioning of the system itself. Currently, the gap between media coverage of new initiatives in re: law enforcement in India and an understanding of how, where, when and by who those systems are actually being used is huge. Our paper aims to bridge that gap. Fourth, we provide an account of observed biases within policing institutions and their transfer to technical systems that operate within these formal structures. Policing is an institution historically known for its problematic practices, reflected in its data and systems. By observing the link between historical practice and technical solutions, we avoid the "ripple effect trap" identified by Selbst et. al [25] while at the same time demonstrating the importance of analysing sociotechnical systems in the context that they are designed, developed and deployed. In the absence of accountability mechanisms and publicly available data, our research points to the value in focusing on the institutional and human aspect of machine learning in the public sector.

This paper proceeds as follows. Section 2 will provide a closer look at the current status of predictive policing in New Delhi. Section 3 describes our methodology for conducting research and field work. Section 4 provides insights from our field work and walks the reader through current data practices, Section 5 provides key points of analysis and Section 6 concludes with reflections, learnings and recommendations, and Section 7 reflects on limitations and future research.

2 CURRENT STATE OF PREDICTIVE POLICING IN NEW DELHI

It is clear through public domain reporting that CMAPS is functional, and is being used to inform resource allocation within Delhi Police [26]. Instances of predictive policing saving lives and aiding in arrests have also been reported in national news portals [19]. However, the larger societal impact of this technology, and its consequences for individuals and groups in a city of close to 30 million people, is not known at this time. CMAPS was announced in 2015 as a partnership with the Indian Space Research Organisation. Under this partnership, Delhi Police claimed it would use "space technology for effective governance" explaining that CMAPS would be capable of geographic and environment profiling of crime, would rank districts on the basis of crime reported, numbers of people affected, and produce predictive models based on these trends to assist officers to plan and deploy police forces [21]. The input data of this system is from the Dial 100 emergency call centre (the equivalent of 911 in the United States or 999 in the United Kingdom), and from First Information Report (FIR) data stored in the Crime and Criminal Tracking Network Systems (CCTNS) in New Delhi. A diagram of the data flow and relevant actors is provided below.

While CMAPS is the first attempt at automated hotspot mapping, it is predicated on previous manual hotspot mapping initiatives within Delhi Police. The first instance of crime hotspot mapping occurred in 2007 when Delhi Police mapped instances of car-jacking across the city in an effort to detect patterns and curb further instances. This effort was soon extended to four other crimes: snatching, robbery, rape and eve teasing. These would be manually entered by the Digital Mapping Division (DMD) housed within Delhi Police. According to the Standard Operating Procedure stuck on the wall of the DMD, this manual mapping would continue till such time that automatic mapping, i.e. CMAPS was set up. In our time at the Delhi Police Headquarters, we learnt that currently, both manual and automated crime mapping are being carried out simultaneously. The manually plotted maps are sent to 23 heads of police everyday, on the basis of which resources are allocated, and subordinates are briefed on the law and order status in the city. Simultaneously, the login ID and password from CMAPS is provided to all District Police Commissioners who can use them to brief their Station House Officers, who can, in turn decide on resource management, increasing patrolling/policing in 'problem' areas in their jurisdiction. The system uses background data on the geographic boundaries in Delhi, railways, metro pillars, police station jurisdictions, "problem areas" identified in historical data, etc. It is also equipped with layers that can help law enforcement analyse crimes by optimising for a variety of considerations. For instance, there are filters for crowded places like railways stations and schools, and other filters for areas historically and culturally associated with crime, such as bars. There are also filters that can point out ghettos, migrant colonies and minority settlement areas. Data practices within past mapping initiatives thus form baselines for spatial analysis of crime and for application of layers that can be used to analyse crime within CMAPS. In this paper, we study the implications of using historical data from law enforcement as ground truth for New Delhi's predictive policing system, with a focus on input data coming in from the Dial 100 helpline.

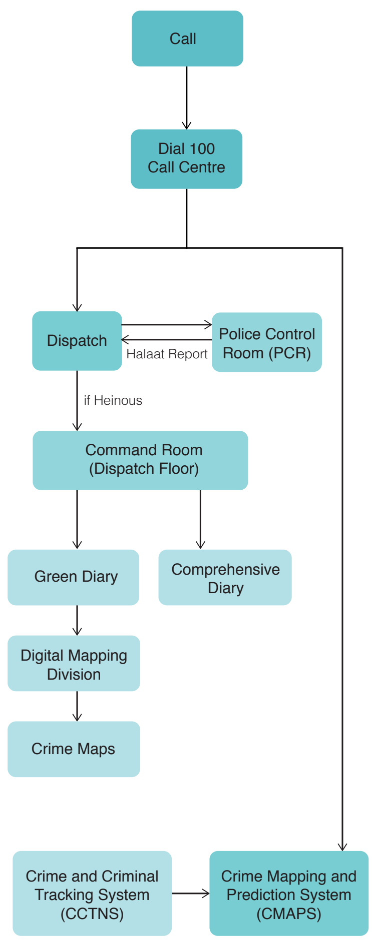

Figure 1: Diagrammatic representation of institutional actors and dataflow within CMAPS

3 METHODOLOGY

This paper reports findings from a larger ethnographic study of predictive policing in Delhi conducted over 2 years (from February 2017 to March 2019). Initially, our research questions centred around the technical systems alone and the way in which they might be aiding decision making within Delhi Police. As we spent more time at the Delhi Police Headquarters (PHQ), our concerns changed in two important ways. First, we realized that the human and institutional actors surrounding CMAPS and the processes that preceded it, substantially informed and influenced its form and use. Second, we learnt that the process of data collection and creation within the PHQ was carried out in the absence of explicitly articulated standard operating procedures and auditing mechanisms. Thus, we realized that we first needed to understand the link between individual arbitrariness and institutional standardisation in context of CMAPS. That motivated us to specifically conduct an in-situ study of the data creation processes within policing in order to understand the eventual impact of CMAPS. We collected data through marginal and participant observation with Call Takers, including those who handle emergencies, Dispatchers, Digital Mapping Division Map Plotters, and officers in the communications wing. We also conducted unstructured interviews with approximately 20 individuals to uncover the qualitative ways in which value laden decisions are taken by officers in the PHQ. Observation and interviews were conducted in parallel. The former helped us understand established processes of data collection and creation, and gave rise to specific questions which we followed up through interviews. We gained access to the PHQ as academic researchers interested in studying the technical turn to policing in India's capital. During our time there, access to documents related to mapping and predictive policing were limited due to security reasons. Access to the Call Centre and the Dispatch Command Room was considerably tougher than the DMD. We were not allowed to carry notebooks or any recording device inside the Call Centre. However, access to documents displayed publicly on the notice boards of Call Centre, and DMD was provided. To supplement the gaps in our observations and interviews and to verify some information from our interviews, we also filed two requests under India's Right to Information (RTI) Act, to illuminate the extent to which CMAPS is currently used, how the system was designed, developed and audited before deployment, how personnel operating CMAPS are trained and what the parameters of their training are, funding for CMAPS, among others. We received 13 replies to our RTI but given wide exceptions for law enforcement under the RTI Act, and a governance vacuum around the use of technology in the public sector, we were unable to furnish any information through this route. In March 2019, our access to DMD and other processes within Delhi Police were cut off due to security reasons.

4 INSIGHTS FROM THE FIELD: FROM DATA COLLECTION TO CREATION

Data practices within the Digital Mapping Division are a crucial component of CMAPS for two reasons. First, it is this data that underpins CMAPS and informs the infrastructural layers and spatial maps used for predictive policing in Delhi. Second, the way in which manual mapping is carried out is a strong indicator of the institutional practices and biases within which CMAPS will function. While the outcomes from the current system are virtually impossible to study at this point, a closer look at input data can provide important insights into the system as a whole. In this section, we provide an account of how current data practices play out in Delhi Police's hotspot mapping initiative.

4.1 Groundwork: Digital Mapping Division

In 2007, the Digital Mapping Division (DMD) set up the groundwork for a comprehensive mapping system in New Delhi. The underlying structure on which crimes are mapped and analysis is drawn was built by the DMD, which surveyed Delhi for its popular landmarks, data on metro pillars (a popular landmark of callers to Dial 100 emergency number), and updated the city's landscape given significant changes and construction. It surveyed Delhi Police Station boundaries in order to accurately set jurisdiction of crimes, a crucial process that often decides the validity of a crime report. These boundary layers were also significant as crimes were mapped according to jurisdictions, and these boundaries decided which areas see more crime than others, and consequently, which areas need more policing and resources. The process for mapping was less than consistent. In the beginning, officers in the mapping division were instructed to manually put dots indicating crime locations, on a digital map of Delhi built on ArcGIS, a popular mapping software designed by Environmental Systems Resource Institute (ESRI). This strategy did not endure the test of time for two reasons. First, the ArcGIS license expired in 2017 and its renewal has not yet been sanctioned for budgetary reasons. Second, Delhi's address database consists only of 500, 000 addresses, which is not only woefully inadequate for accurate mapping, but also riddled with errors. These addresses also did not have latitude-longitude coordinates, neither did they have social or physical information that would lend detail to the geographic structure of the city. This led to officers being instructed to plot crime locations onto relevant jurisdictional police stations. Later when this kind of mapping indicated only police stations as crime spots and made any kind of visualisation impossible, they were asked to map the locations at the nearest point of the actual location mentioned in the address (of the crime). This inconsistency in methodology, along with varying definitions of accuracy make this mapping unreliable at the very least. The DMD has been mapping data on crimes of rape, robbery, eve teasing and snatching on Delhi GIS maps, populated with all the information procured in the survey, since 2008. It is intended that CMAPS, with automated mapping will correct these inconsistencies, but having an inaccurate benchmark (or a historical dataset) against which performance will be evaluated casts doubt over CMAPS being a panacea. Another fundamental drawback of hotspot mapping in general is that because the emphasis in this mapping is on quantity alone, even grievous crimes when committed in non-selected areas tend to fall off the radar of a system like CMAPS [9].

4.2 Source of input data - Calls to 100 call centre

The Delhi Police Dial 100 call centre, situated on the third floor of the command room of Delhi Police Headquarters, has around 40 channels to which emergency calls can be routed. Each channel has its own unique number and is attended by a call taker who mentions the number in his/her introduction. The call takers enters details of crime into the "PA 100 form" that record information received through the call and categorise them into 130 pre-determined categories including one 'miscellaneous' for when it is difficult to slot the incident accurately. If there are more crimes than one, for example, snatching and murder, the call taker will only slot the crime as murder. Only the higher crime would be taken into consideration, which undermines the accuracy of this data to indicate frequency of crimes across the spectrum. The rest of the event description is put into the notes section of the form. The form captures the registered address of the caller, but that is not always the location of the crime. Call takers ask the callers to mention their addresses accurately but routinely fail because of the semi planned nature of the city. Shanty settlements, irregular colonies do not have proper addresses; most of the times callers do not know where they are calling from. Callers also mention local landmarks while informing about their location, thinking the call has landed in their local police stations. For example, in one instance, a caller stated "I am standing near the peepal tree," making it difficult for call takers to input their exact address/location. Call takers can search for the address from the 500, 000 address database but it is not usually adequate. This, combined with an incentive to conclude calls as soon as possible (given that call takers are judged on their performance based on turnaround time of calls), call takers tend to mark the location of crime as police stations instead of actual addresses, given that it's the only accurate database they have of anything related to locations in Delhi, leading to skewed results. A frequent error occurs when callers report a crime at a location different from where they are calling. Call takers resort to standardized questions about the location of the caller and do not enquire further because they are incentivized to be quick more than they are incentivized to be accurate. For example, once parents of a woman called to report the death of their daughter due to medical negligence which had occurred at a hospital in Saket. They called from their home which led to the call taker mark this as a crime at the caller's residence instead of the hospital.

4.3 Dispatch and PCR Van

Once the form is filled with details of the crime, it is automatically sent to the dispatch section on the fourth floor of PHQ through the PA 100 software. The Dispatch floor is divided into 11 zones mirroring 11 districts of Delhi (though they have been revised to 13, the zones still remain 11). The call is transferred to its appropriate zone according to location from where it is transferred to its respective Police Control Room (PCR) van. The officer on the Dispatch console manually provides the call details to the PCR van officers over microphone. The dispatch function was planned such that as soon as the call takers close the PA 100 form, a message with all call details is sent to the handheld devices of the PCR van officers.

They would then send the investigation report (called the *halaat* report) from these handheld devices, which would also give the exact location of the scene of crime. But the plan did not work out for a variety of reasons. Dispatch and PCR personnel say that it was too much work charging the devices, and also claimed that they were not adequately trained to operate the devices. HQ officers, those in the DMD argue that carrying a handheld device would be surveillance for the PCR van officers, something that they did not want because they sometimes cut corners when it comes to actually visiting the crime locations. An investigation in HQ revealed this to be true; many PCR van officers negotiate with their Dispatch counterparts into being assigned fewer investigations during their shift. They also do not visit all the crime scenes but sometimes merely replicate the report of the investigating officer from the police station into the *halaat* report.

4.4 Heinous crimes go to green diary

Next, the dispatch officer sends a copy of four heinous crimes – rape, robbery, eve teasing and snatching – to the dispatch command room as soon as they receive them from the call centre. If the *halaat* report confirms the crime, it is entered into the 'Green Diary', a comprehensive document with verified accounts of all the calls related to four heinous crimes at the Dial 100 call centre. Understanding crime events and categorising them correctly also require certain level of interpretative understanding of categorisation rules, which are informal in the PHQ and usually taken from on-ground policing experience of the officers. For example, once a shopkeeper called to report how two men came to his shop asking for two bags of *ghee*, and when he put them on the counter, they asked for a bottle of *Chyawanprash*. As soon as he turned to get the *Chyawanprash* bottle, the men ran away with the bags of *ghee*. The call taker had categorised the crime as snatching. A debate ensued on the Dispatch floor on whether the crime was indeed snatching or if it was a case of robbery. Finally it was decided that because the two men, for all intents and purposes, snatched the ghee bags from the shopkeeper, this was snatching (The men then ran away on their bike, fulfilling more conditions of snatching). The crime was finally recorded in the Green Diary as snatching. These choices are arbitrary and based on common understandings of what every crime entails. For example, categorisation practices in HQ prescribe 'Snatching' to someone taking away another's property forcefully. But it can only be committed by one or a maximum of two people. Three people do not snatch, they rob. If a weapon is involved, it is definitely a robbery, even if committed by only one person. Crimes against women are acceptable if they happen during the day without the women being at any 'fault' at all (not wearing skimpy clothes, not inebriated, not with a 'male friend'). Officers in the DMD question women related crimes that take place at night, wondering why women are out at that time at all. One officer said, "if it is work it is okay, but most of these women are not out for work, then who is responsible for their safety?"

Official police records have always been at the mercy of police practices and whether the officers recording the crime believe an event to be criminal at all [17]. This can be extrapolated to police officers disbelieving complainants themselves. Officers in PHQ argue that most of the people who call from slums and ghettos would not do so if the calls to the number 100 were chargeable. They also believe that most of the snatching cases are inflated because of the general belief that police would not act on cases where the value of the objects snatched was low. They argue that a large majority of heinous calls for women related crimes were almost always false on the ground. "Girl will fight with her boyfriend and then to scare him would call for a case of rape. When we reach the place, she is the one apologizing, this is the reality of most of these calls," as told by multiple officers at call centre, dispatch and DMD. A status of policing in India report, released by Lokniti and Centre for Study of Developing Societies in 2018 [4], showed how the marginalised groups in India - Dalits, adivasis, Muslims and people living in slums - were the last ones to engage with the police (While the police engagement with them was disproportionately high). However, the story in the Delhi Police Call Centre is different. Here, the calls received at the emergency response number 100 are tilted towards the poorer parts of the city. The call takers confirmed that 'rich areas' called very rarely and it is the slums and resettlement colonies (for e.g. *Khichdipur* (a resettlement colony in East Delhi) that called the most. As Santana Khanikar notes [20], police is the only form of everyday governance that people of lower income colonies and slums have access to, which is why residents of these colonies share a love-hate relationship with the police. According to her, a high volume of calls might not be an indicator of high crime but a lack of access to other sections of governance for these urban poor [11]. Crime calls are thus subjectively analysed and categorised from the Call centre to the Dispatch. Most cases reach a compromise so an FIR or even an official complaint is not registered though they are recorded in the Green Diary and mapped on the hotspot map. Using calls to the emergency response number as proxy for crime is, therefore, problematic for multiple reasons [12]. First, it represents a significant measurement error as calls to an emergency number are not always indicative of actual crime, and second, it fails to engage with nuances of societal needs and access to public services and adequate governance.

4.5 Recording Green Diary

If a call regarding a heinous crime comes late at night when investigations might be slow (delaying the *halaat* report), they are entered in the Green Diary draft with a 'pending' status. The status is updated only if the *halaat* report is received before the Diary is to be sent for mapping, i.e. by 6 AM. However, if the report does not come, these calls are mapped without being corroborated by haalat reports. Spurious calls in such a manner can light up an area as criminal in mapping even though the underlying data could be completely false. Which in turn means that we do not know if these crime calls were indeed what they claimed. Though Green Diary is slated to be a verified document of all calls, there were some discrepancies in certain calls and in their *halaat* reports. We observed many cases where a crime was recorded as "no matter of snatching" – police speak for 'it was a bogus call' – in the *halaat* report, but was present in the Green Diary. Slippages between the officer managing the consoles where heinous crime details are received from dispatch, and the one who prepares the Green Diary ensure that sometimes calls that were found untrue upon investigation were also recorded as true calls.

5 ANALYSIS

One of the arguments in favor of deploying predictive policing systems is that it leverages technology to free public institutions from human prejudice [24]. Our research has shown that this is likely an untrue claim. Manual hotspot mapping will feed foundational aspects of CMAPS, and this data is the product of a series of subjective decisions, skewed reporting, and uneven policing practices. Here, we will discuss some of the common threads we identified through our research. Our findings emerge from the data practices from the DMD, given that data from the DMD feeds in foundational aspects of CMAPS, and that data practices within the Division reflect an institutional culture that will be embedded within CMAPS, the above process has significant implications for CMAPS, and any other predictive policing initiatives that may be introduced by Delhi Police in the future. Our key takeaways from this study are as follows:

5.1 Bias in three parts

While it is well understood that training data bias is a challenge in any machine learning system [1], this study helped us delineate the types and origins of biases that exist within Delhi Police's system for predictive policing, using the framework proposed by Suresh and Guttag [29]:

5.1.1 ***Historical bias.*** . While gathering information is an age old practice within policing, from compiling "badmash registers" in colonial India to maintaining a list of criminals by birth to keep track of criminal tribes [27], the act of gathering information has always been a selective one; with greater surveillance often befalling axes of disadvantage, i.e. caste, gender, class, and religious minority. It is not simply a case of more crime occurring in poorer parts of Delhi, or in places where minorities and migrants live - an additional layer of complication is introduced when a human is tasked with choosing which area or under which crime a certain call should be filed. A general apathy towards individuals living in slums, and more forgiving outlooks with respect to individuals living in posh parts of Delhi was apparent from conversations across the Call Centre. This, combined with the fact that policing as an institution has a controversial record around discrimination, brutality, and illegal practices with vulnerable individuals [11] means that historical bias is not only embedded, but actively formalised and introduced into data.

5.1.2 ***Representation bias.*** . Given that input data for CMAPS consists of calls to the Dial 100 call centre and a national database used to track crime and criminals, there is a significant underrepresentation of individuals from privileged socio-economic backgrounds, and also of upscale areas in the data. This is because the sampling methods, i.e. calls to an emergency helpline or existing records in a criminal database (not conviction database) lend themselves more readily to some areas of the city and sections of society. The DMD receives around 20000 calls a day, and in the course of our research some employees said that people from posh areas "hardly called", and that an overwhelming majority of these calls were from slums. This means that the probability of crime will be marked higher in hotspot areas where quantity of engagement is higher, leading to a vicious circle of heightened scrutiny for the most marginalised, eventually leading to more arrests and reports coming out of these areas.

5.1.3 ***Measurement bias.*** . Occurs in DMD and CMAPS for a few reasons. Given that the spatial distribution of Delhi is less accurate among temporary settlements, and there is greater nuance in data arising from privileged neighbourhoods in Delhi, the clusters of information tend to be less quantitatively overwhelming, thus attracting less future scrutiny. This bias arises not just because of systemic blind spots, but also because of vulnerable individual's inability to engage with the system as well as others. For example, we learnt from a call taker that some people do not know their addresses even if they have been living at that place all their lives and an overwhelming majority of such people have always been women. She said women mostly stay inside the house and are not very aware of their surroundings or the exact address (name of mohalla/colony) of their location. In most cases they wouldn't even know the nearest police station by which the call taker could identify the caller's address. In such cases the call takers have no choice but to ask callers to call again once they know their address. They encourage them to ask a passerby to tell them about the landmarks of their location, a thana, police chowki or another famous place to get their address.

5.2 Disparate impact, or indirect discrimination

Disparate impact refers to a situation where a prima facie neutral policy has a disproportionate and disadvantageous impact on a protected class [1]. Findings from our research indicate that data collection and creation within Delhi Police has a disproportionate impact on historically marginalised and vulnerable groups, which we can logically extend to decision making that is informed by such data [22]. Crimes are more likely to be recorded when they come from organised colonies, with specific details and granular information relating to actual addresses, whereas crimes from shanty settlements are plotted at the same spot due to lack of accurate information, leading to an imbalance in what is classified as a "hotspot" of crime. There is also widespread selective enforcement and individual officer discretion that works against the interests of these communities. This is turn leads to over-policing areas inhabited by individuals from vulnerable groups, and also creates a cycle of confirmation bias within an institution that is already embedded with societal, cultural, gender and caste biases [11]. Article 15 of the Indian Constitution prohibits discrimination on the grounds of race, religion, caste, sex, and place of origin. While the status of disparate impact under Article 15 has been the subject of some legal debate [2], the Delhi High Court in 2018 recognised indirect discrimination [10], a.k.a disparate impact, as one that qualifies as discrimination under the Indian Constitution. Reiterating the rationale underlying Article 15, the Court stated that it existed because women and other vulnerable groups, "have been subjected to historic discrimination that makes a classification which disproportionately affects them as a class constitutionally untenable." Given our findings in this paper, thus, current data practices within the Delhi Police can attract Article 15 of the Indian Constitution.

5.3 Direct discrimination

The design of 'layers' in CMAPS software can be used to filter immigrant colonies and minority settlement areas, extending from the belief that crime rises due to the de facto existence of these areas, and the people who live in them. The observable variable that is used at the time of analysis and filtering is not merely a proxy for a protected attribute, it is the protected attribute itself, under Article 15(1) of the Indian Constitution. It is also reasonable to state that the use of such infrastructure can attract Article 14 of the Indian Constitution, which contemplates the fundamental right to equality and equal protection of laws. According to the Supreme Court of India, "equality" must necessarily be substantive, i.e. must consider whether a provision or executive act "contributes to the subordination of a disadvantaged group of individuals." [5] The use of opaque technical systems like CMAPS currently afford a veneer of objectivity and shield against scrutiny in the process, but a challenge to this usage is both possible and crucial.

5.4 Hard coding arbitrariness

Arbitrariness is a fundamental aspect of police recording crime because it comes down to how a specific officer on the scene of crime (or the officer noting the details of the call) interprets a particular crime event. These interpretations have no standardised format or prescribed form, and are subsequently encoded as categories in the PA100 form from where they make their way to the Green Diary, Manual Maps and CMAPS. Categorisation plays a major part in how data is readied for use by an algorithm, as Gillespie states, it is a "powerful semantic and political intervention" which once instituted is treated with reverence by algorithms, and the criteria used to define these categories is reified by algorithms [7]. As discussed above, categorisation of calls is arbitrary and depends on the call taker's interpretation of the calls and the dispatch officer's takeaway from the *halaat* report. More often than not, this arbitrariness works against marginalised groups, and in turn, embeds and formalises this tendency into technology. The PA 100 form (where calls are categorised) also represents the years of social understanding of crime of its designers who have used Criminal Procedure Code, Indian Penal Code and Punjab Police Rules Rules 1956 to create 130 categories in the form. Standardised forms reflect institutional notions of crime - some scholars [13] believe these forms are the very essence of a bureaucratic institutions, and that investment in such forms has been a cultural historical project to exclude residual categories. For example, genders are expressed as male/female in most government standardised forms leaving no choice for people who do not conform to both. A pre-defined form with 130 categories (the miscellaneous category is present but is not used often) limits the ability of call takers to record nuances of each call, and in the process forces categorisation into socially accepted norms that are inadequate at best. For example, one of the call takers described how crimes where the woman was beaten by the husband/in-laws was neatly categorised as 'domestic violence' but off late there have been many calls where the husband was beaten by the wife and her parents which were categorised as 'quarrel' (which one of the call takers pondered, was "happening too often now a days").

5.5 Opacity as a feature, not a bug

Opacity obscures accountability within algorithmic systems, and has a similar effect on the institutional reality within which such systems function. Through our field work and research, we found that opacity is intentionally constructed around CMAPS, both as a technical system and an institution. It is kept out of reach of the Right to Information Act to the best of our understanding and experience - which is most likely by invoking broad exceptions for security and strategic information of the State and law enforcement purposes. This extends to accessing CMAPS during field work as well. While the conceptualisation of CMAPS was celebrated in the media and publicly discussed, there is little room to uncover what it truly is. To peer into the inner working on CMAPS, thus, large scale institutional reform is as important building transparent and accountable systems in isolation.

6 CONCLUSION AND RECOMMENDATIONS

Through this research, we have sought to understand the ways in which institutional approaches to data and policing practices affect hotspot policing systems like CMAPS. By walking the reader through processes that precede and underpin CMAPS, we have demonstrated that bias within Delhi Policing is textured, unstructured and pervasive. Discriminatory and arbitrary practices mirror problematic social norms and run through the system, from institutional legacy to individual officers' subjectivity. There is little if any logical separation between bias within the technical system (CMAPS) and bias within the institution (Delhi Police). Our field work revealed that institutional bias predicates and cements bias within the technical system and thus cannot be meaningfully separated in our analysis. Our recommendations stem from this finding. Our research builds on existing work [3, 24] that focuses on ex-ante assessment of predictive policing systems like CMAPS. Here we stress the importance of focussing these assessments on institutional formalities and standard operating procedures prior to analysing the sociotechnical system itself. We propose that any predictive policing system must be studied through the lens of institutional culture and limitations within which it will function, and then through the lens of outcomes and harm for two reasons. First, harm is not always tangible, making it particularly important to address representational harms at the stage of design and development [15]. Second, transparency and accountability mechanisms are not always possible. Studying the institution ensures that even opaque systems employed by the institution are critiqued and held to a basic standard of due process. We believe this approach represents a logical progression: first study the cause and then analyse symptoms. Based on this overarching recommendation we propose renewed efforts into holding consequential systems in the public sector to account by focussing on four aspects surrounding these systems:

(1) Research into the public sector institution within which the system will function should emphasize standard operating procedures, bright lines for discretionary action, reporting formats and grievance redressal.
(2) Procurement processes for predictive policing systems should be made transparent, and should indicate the specifications required from the system, standards to which systems must adhere, and also include auditing and accountability mechanisms at the time of contracting and deploying systems.
(3) Engagement with predictive policing systems must include a critical analysis of governance limitations and reforms at a purely institutional and bureaucratic level, to understand the practices that will percolate to these systems and the dangers associated with such percolation, and finally
(4) Ex post mechanisms for fixing, appealing and correcting errors should be developed in parallel. These do not have to be limited to the technical system's audit alone - it must instead focus on what underlying accountability and redressal mechanisms exist and can be adopted to technical systems that function within the same reality.

This provides a framework for law enforcement authorities to think through the efficacy of predictive policing systems and aids civil society and activists in assessing the impact of systems in the absence of concrete evidence of outcomes. While bias in policing systems is crucial to understand at a granular level, we do not believe appropriate solutions lie in finding perfectly un-biased systems. They lie, instead, in ensuring that the surrounding mechanisms to a sociotechnical system lend themselves to checks and balances, adapting to social contexts within which they function, and to scrutiny, transparency and accountability.

7 LIMITATIONS AND FUTURE RESEARCH

This ethnographic study and subsequent analysis are based on our observation and interviews within limited divisions at Delhi Police Headquarters collected over a span of two years. Our analysis is meant to be a first step towards evidence building on the use of machine learning in policing in non-western contexts, with substantive and methodological contributions that can be used at the time of engaging with similarly placed predictive policing systems. Future areas of research would include testing our findings of bias on actual use cases within CMAPS, studying the procurement processes between policing institutions and vendors, and analysis of ongoing auditing and performance evaluation of these systems.

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