AI in Global Health: The View from the Front Lines

Azra Ismail
Georgia Institute of Technology
Atlanta, Georgia, USA
azraismail@gatech.edu

Neha Kumar
Georgia Institute of Technology
Atlanta, Georgia, USA
neha.kumar@gatech.edu

ABSTRACT

There has been growing interest in the application of AI for Social Good, motivated by scarce and unequal resources globally. We focus on the case of AI in frontline health, a Social Good domain that is increasingly a topic of significant attention. We offer a thematic discourse analysis of scientific and grey literature to identify prominent applications of AI in frontline health, motivations driving this work, stakeholders involved, and levels of engagement with the local context. We then uncover design considerations for these systems, drawing from data from three years of ethnographic fieldwork with women frontline health workers and women from marginalized communities in Delhi (India). Finally, we outline an agenda for AI systems that target Social Good, drawing from literature on HCI4D, post-development critique, and transnational feminist theory. Our paper thus offers a critical and ethnographic perspective to inform the design of AI systems that target social impact.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**.

KEYWORDS

AI; Social Good; Healthcare; India; HCI4D; Qualitative

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1 INTRODUCTION

Emerging research has brought to light the problematic roles that artificial intelligence (AI) systems play in exacerbating marginalization [79, 127, 174], privacy violations [252], and the exploitation and unemployment of workers [21, 97]—even as they claim to improve human lives [222]. The various agendas of government and industry actors aspiring to leverage AI are also increasingly being subject to scrutiny [94, 252]. Amid these concerns, a cautiously optimistic parallel discourse has also surfaced around leveraging AI to address "social good" or "global development problems" [114, 160], rather than advancing capitalist goals [252]. Emerging perspectives from the Global South seek to center the majority of the world's population residing in contexts typically characterized as "low-resource", "marginalized", or "developing" [120, 223].

A key motivation driving the social good narrative in underserved contexts is the desire to address inequities, optimize existing scarce resources, and overcome workforce shortages [82]. These reflect the optimism that technology can help countries in the Global South leapfrog or accelerate the pace of development [140]. Along these lines, the fourth annual United Nations Global Summit on AI for Good in September 2020 invited an array of global stakeholders to present their visions on how AI might be channeled towards positive societal impact [40, 114]. There have also been more localized initiatives. For instance, several state and non-profit institutions in India have taken the lead in ideating possible AI futures for the country [2, 11, 17]. These efforts have also been supported by industry through research [86, 196, 197] and grant funding, such as the USD 25 million fund provided by Google.org in support of organizations using *"the power of AI to address social and environmental challenges"* [86]. Within academia, workshops at prominent AI research venues such as the International Conference on Machine Learning (ICML) and the Conference on Neural Information Processing Systems (NeurIPS) are asking how their fields might take on development and social good challenges [62, 83, 160, 235]. Global health is one among several application domains that has garnered significant interest [235].

Leading global health organizations have proposed and funded AI systems, and these efforts have been accelerated during the COVID-19 pandemic [161, 228, 230, 248]. Many of these interventions aim to improve existing frontline health infrastructures that deliver last mile healthcare, especially critical in countries of the Global South [154, 195]. However, the perspectives of the frontline health workers (FHWs) operating these health infrastructures and the marginalized communities accessing the healthcare system find rare representation in this discourse. In particular, the voices of the women who largely make up the healthcare workforce, most in lower-tier positions, and are frequently the primary care providers in the home, are glaringly missing.

In this paper, we draw attention to FHWs and their communities that are targeted by proposed AI interventions to identify more inclusive opportunities for design. We begin by presenting a thematic discourse analysis of academic and grey literature published by governments, industry, and researchers on AI for healthcare in resource-constrained contexts. We identify prominent applications of AI in frontline health, stakeholders involved, motivations driving this work, assumptions made about context, and level of engagement with local actors. We then uncover gaps in these efforts and outline opportunities for design, drawing from data collected over three years of ethnographic fieldwork with women FHWs and women from marginalized communities receiving care in Delhi,

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India. Our focus on this population is motivated by the scholarship of transnational feminist scholar, Chandra Talpade Mohanty, who posits that an *"experiential and analytic anchor in the lives of marginalized communities of women provides the most inclusive paradigm for thinking about social justice"* [165]. Our analysis highlights how the "AI for Social Good" discourse reflects structures of power that disadvantage FHWs. Acknowledging our feminist stance [23, 164], we are troubled by these power differentials and their impact on technology design. We draw from lessons learned across Human-Computer Interaction for Development (HCI4D), post-development critique, and transnational feminist theory to propose opportunities for the design of AI that targets social good outcomes, while attending to the power inequities between developers and target communities. Our paper offers a critical and ethnographic perspective from the Global South to a growing body of HCI research that is engaging with the design of AI systems, particularly research that aims to support healthcare workflows in resource-constrained settings.

2 BACKGROUND: TECHNOLOGY-MEDIATED FRONTLINE HEALTH

Since the early 2000s, information and communication technology (ICT) interventions have been designed, deployed, and studied across a range of global health domains such as maternal health [67, 134, 186], sexual health [118, 175], and tuberculosis [59]. A sizeable portion of this work has focused on *frontline health*—healthcare infrastructures that aim to provide care directly where they are most needed. Early work in this field has focused on the use of low-cost mobile phones to deliver interventions [151]. Technologies have been designed and developed to digitize data collection by FHWs [179], track their workflows and provide feedback on performance [67], enable peer-learning [246], and disseminate health information [136, 167, 193]. ICT interventions have also been developed to offer last-mile care support by FHWs such as follow-ups with patients after hospital visits [176], and antenatal care via chat [186, 187]. As the costs of accessing the internet have fallen dramatically, FHWs in many parts of the Global South have also begun to use smartphones and the internet to access digital financial services [124], chat for work and leisure [113, 125], and for accessing training materials [244]. More recently, frontline health has become a target of technology efforts during the COVID-19 pandemic [126, 138, 227]. Alongside these research contributions, critical perspectives have emerged to examine the extent to which such interventions, as they are most commonly designed, can impact the most marginalized groups [111, 134, 171]. Our paper further contributes towards an understanding of how emerging AI technologies might be designed appropriately for the FHWs and marginalized populations that they aim to serve.

Prompted by the shortage of medical personnel and equipment in many countries, there has been an increasing interest in AI-based technologies for frontline health [236]. A report by key foundations in global health—the United States Agency for International Development (USAID), Rockefeller Foundation, and Gates Foundation—outlines promising applications of AI, such as AI-based population health tools, virtual assistants for FHWs and patients, and various diagnostic tools [82]. AI systems have been developed to help with early detection and diagnosis [5, 27], drug discovery [47], and outcome prediction and prognosis evaluation [107, 226]. Within the Global South, AI has been used primarily to address tropical and infectious diseases, such as by using machine learning to forecast the spread of dengue [98] and ebola [39], and in tuberculosis screening [9, 156]. AI tools are also being developed to support maternal and child health such as for early screening of low birth-weight and preterm infants [11, 53, 198], and to identify mothers not engaging with a health program [173]. In India in particular, a report by NITI Aayog, the policy think tank of the government, identifies diagnostics, personalized treatment, and early identification of pandemics as key AI applications that can enable affordable healthcare for all [2]. Many of these efforts above rely on or target existing primary health and frontline health infrastructures. In this paper, we detail current AI efforts and identify gaps in this body of work.

The growing popularity of AI has helped attract resources to frontline health, as in other domains. However, to build sustainable and impactful solutions, an HCI perspective would argue that it is critical to attend to the context in which the technology is designed and deployed. The field of HCI has begun to explore how AI systems might be better designed to consider the needs of potential users and developers. Guidelines have been proposed for the design of AI systems that collect data from, impact, or interact with humans [15, 86, 147]. Recent research demonstrates how ethnographic and participatory design studies could inform the design of AI systems in healthcare [24, 182, 245]. For example, Yadav et al. examined the potential of chatbots for breastfeeding education by conducting a Wizard-of-Oz experiment with FHWs and breastfeeding mothers [245]. Researchers have studied how AI could support the routine, "unremarkable" work of clinicians [247], and help with collaborative decision-making among medical experts [41]. In a rare example of a study of the real-world deployment of an AI system, Beede et al. undertook an ethnographic study of a deep learning system for diabetic retinopathy in hospital settings [24]. Given limited opportunities for design iterations of AI systems post development, they argue that "formative research that provides a strong understanding of clinical users and their context is critically important to the success of such a system" [24]. We provide this formative research in the case of frontline health workflows, and contribute a critical and ethnographic perspective from the Global South to emerging HCI literature on the design of AI systems.

3 METHODS

Our research combines a thematic discourse analysis of literature on AI and global health with an ethnographic perspective based in data from fieldwork in frontline health. While the former allows us to understand *what is* with respect to developments around AI and global health, the latter lets us illuminate *what could be*. We began by constructing a corpus of scientific and grey literature to situate our analysis in the context of emergent conversations around AI and global health. We first applied thematic discourse analysis to identify common themes across AI initiatives targeting healthcare provision in resource-constrained settings [91]. We then situated our analysis in fieldwork conducted with women frontline health workers (FHWs) and women from underserved communities in Delhi (India). We paid close attention to the *articulation work*

involved in frontline health, or the labors associated with coordinating and planning work-related activities, often invisible to others [221].

3.1 Thematic Discourse Analysis

We studied the *discourse* around AI for frontline health, as expressed in scientific and grey literature published by academic, government, and industry actors. The study of discourse has its roots in Foucault's argument that discourse is how we come to shape realities, subjectivities, and power relations [84]. Discourse analysis allows us to examine how structures and processes of power and control are reproduced via discourse [91]. In this paper, we employ *thematic discourse analysis* to identify common themes across articles on AI and frontline health [91]. This method has previously been used by HCI researchers to study the representation of the "human" in research on predicting mental health status [48], intersectional identities of research participants [208], and the agency of autistic children in technology research [217].

Before we describe our discourse analysis process, we clarify what we mean by "AI". We define AI as digital artifacts that extend any of the capacities related to natural intelligence [35]. Intelligence requires the capacity to perceive contexts for action, the capacity to act, and the capacity to associate contexts to actions [35]. Using on this definition, we identified AI technologies being proposed and developed in global health (see category 1 in Table 1).

We cast a wide net to construct our corpus. We analyzed news articles, academic publications in a range of journals and conferences, and white papers by global health organizations, consulting companies, policy think tanks, and government organizations. We also included short papers published in conference workshops in our search as these are relatively more accessible to researchers from the Global South. We focused on items published between January 2010 and June 2020. We used the ACM Digital Library, Scopus, and Google Scholar for our search, using the search terms described in Table 1. This resulted in a total of 1631 document results. We did not limit results by type of document or venue, but discarded results where we could not find the document online. We did not add papers that were literature reviews to our corpus. In the case that more than one publication reported on the same AI system, we only included the most recent one. We used Google Search to supplement our data, screening results from the first five pages for each combination of search terms in Table 1. This helped us identify 63 more potentially relevant sources—white papers, web pages, and blog posts. We excluded mental health and pharmacology as part of the health domains that we considered. We then manually screened through the titles and abstracts of these 1694 sources using the following filtration criteria:

(1) The paper or article proposes or reports on the design, development, or deployment of an AI system (see category 1 in Table 1).
(2) The technology explicitly targets a resource-constrained or Global South context (see category 2 in Table 1).
(3) The technology targets a challenge in the health domain, barring interventions relating to mental health or pharmacology.

Table 1: Filtering strategy for constructing the corpus. Note that the "+" sign in category 2 indicates the AND operator.

Category	Keywords
Artificial Intelligence (1)	artificial intelligence, machine learning, chatbot, computer vision, neural network, deep learning, prediction, precision health, NLP
Global Health (2)	global health, developing countries + health, marginalized + health, low resource + health, low income + health, LMIC + health, primary health, frontline health, maternal health, newborn health
Search term	**(1) AND (2)**

Table 2: Breakdown of papers reviewed by domain.

Domain	Number of Papers
Computer Science	100
Engineering	70
Medicine	72
Public Health or Environmental Science	49
Industry, Non-profit, or Government	25
Other	31

Table 3: Breakdown of papers reviewed by type of publication venue.

Publication Venue	Number of Papers
Journal Articles	183
Conference Proceedings and Workshop Papers	121
Book Chapters	13
Science Articles and White Papers	7
Web pages and Blog posts	23
Total	347

We ended up with 383 articles and papers through the initial filtering process. We also used this list of papers generated to seed our search for similar applications by looking through papers that referenced these publications. This yielded a few more papers. We manually scanned the body of these articles and papers using the same list of questions to further filter results. Through this process, we arrived at a final list of 347 papers, articles, and web pages.

We then conducted a thematic analysis of this data following the approach outlined by Braun and Clarke: familiarizing oneself with the data, coding, generating themes, reviewing themes, defining and naming themes, and writing up results [31]. Through the initial process of familiarizing ourselves with the data, we arrived at a set of questions that we were interested in asking of the data. We started by coding the data around the following: the AI technologies are proposed, stakeholders involved, global health challenges targeted, motivations for an AI solution, level of engagement with the target context, and assumptions made about the context. For example, some codes that emerged through this process were "predicting disease spread," "automating health workflows," "obtaining data from local organizations," and "designing for resource-constrained

environments." We also recorded the following aspects of each paper: the field that it was published in, the location of the work, and venue and year of publication. Tables 2 and 3 offer a breakdown of papers in our corpus by discipline and publication venue. We then searched for and finalized a set of broad themes in the discourse such as "AI for disease surveillance and forecasting", "unsustainable intervention", and "engagement with local context". Section 4 details the themes that we generated. Section 5 offers an ethnographic perspective on these themes to highlight what is assumed or left unsaid in the discourse, drawing on data from fieldwork. We describe the analysis of this ethnographic data next.

3.2 Ethnography

The second set of data that we draw on in this paper was collected as part of a long-term ethnographic engagement in a peri-urban neighborhood in Delhi from May 2016 to August 2019. This is located in a predominantly Muslim region of South-East Delhi, with relatively poor infrastructure, and illegal settlements located beside the Yamuna river. Many residents in the area are migrants originally from the nearby states of Uttar Pradesh and Bihar.

We began our ethnographic work with the study of government and private clinics accessed by slum residents in the region. Our engagement with government clinics brought us into contact with Accredited Social Health Activists or ASHAs [158]. ASHAs are FHWs employed by the state government to deliver care at the last mile. Their everyday tasks include data collection, healthcare provision, and information dissemination, with special attention paid to maternal and child health. They receive monetary incentives for their work but are not salaried government employees; their work is considered to be voluntary. Recognizing the role of ASHAs as key intermediaries between communities and the government healthcare infrastructure, our goal through our extended engagement was to gain a situated understanding of their healthcare provision activities. We collected data over five extended visits to Delhi between 2016 and 2019, and through continued engagement with ASHAs between visits through phone calls, WhatsApp, and Facebook.

Our research has been approved by the Institutional Review Board at the Georgia Institute of Technology, along with necessary permissions from local institutions where we conducted our fieldwork. As one of the options for multi-sited ethnography recommended by Marcus [152], we followed and stayed with the movements of the ASHAs as they went about their work, immersing ourselves in their worldviews to the extent possible. Gaining privileged access to these worldviews and sensitive information around their lives involved building trust and nurturing relationships with these ASHAs over the years, in-person and remotely. ASHAs were compensated for their time and care when possible and appropriate as a token of gratitude, such as with *chai* and snacks, sweets, mobile recharge cards, and transportation costs, but their contributions to our research cannot be measured in material terms.

We conducted interviews, focus groups, and in-person participant observation with a total of 21 ASHAs, all of whom report to the same Primary Health Center (PHC) aka the dispensary. We gained access to the ASHAs through snowball sampling [96]. We conducted multiple interviews and focus groups with most ASHAs, each session lasting between 30 minutes to 3 hours. Additionally, we shadowed eight ASHAs during their lengthy house visits, observing their interactions with over 250 households. We also interviewed household members during 50 of these visits. The annual household incomes of the ASHAs as well as the families we interacted with fell into the low to low-middle income categories, defined as earning less than USD 5840 per year [131]. Two ASHAs we interacted with have completed 12th grade education, while the others have completed 10th grade. All are married women with children, and two have grandchildren. Six of the ASHAs identify as Hindus and work in predominantly Hindu neighborhoods, while the remaining identify as Muslim. Our engagement with five (Muslim) ASHAs who frequently work together has been particularly deep and steady for over three years, and they have offered us rich insight into how their aspirations, engagement with the healthcare infrastructure, and situations at home have evolved over time. All interactions and data collection were undertaken by the first author, Azra, and took place in Hindi or Urdu, then translated to English. Interview and observation data was collected in the form of field notes, audio recordings, and photographs. All data was recorded only after the consent of the participants, and was later anonymized. Participant names used in this paper are all pseudonyms. Tables 4 and 5 offers demographic information about our participants.

The qualitative data was collectively analyzed by both authors—Azra and Neha—using the inductive process outlined by Merriam [157]. We conducted several rounds of open coding, discussing the codes after each iteration. The first round of coding closely followed the text. The next round of coding was more high-level and

Table 4: Demographic information of ASHA participants

Participant	Age	Region	Participant	Age	Region
Farida	50-55	Jogabai	Aisha	50-55	Batla House
Maryam	30-35	Jogabai	Rida	35-40	Batla House
Hiba	20-25	Jogabai	Arti	55-60	Khizarabad
Hafsa	45-50	Jogabai	Karishma	25-30	Khizarabad
Khadija	25-30	Jogabai	Reshma	30-35	Khizarabad
Amna	30-35	Batla House	Susha	40-45	Khizarabad
Tasneem	25-30	Batla House	Rekha	25-30	Khizarabad
Saba	20-25	Batla House	Meena	45-50	Khizarabad
Zainab	25-30	Batla House	Afsana	35-40	Okhla Village
Bushra	25-30	Batla House	Naima	55-60	Okhla Village
Nadia	30-35	Batla House			

Table 5: Demographic information of interview participants from the community.

Total	50 participants
Education level	Completed college: 4, Completed 12th grade: 8, Completed 10th grade: 11, Completed 8th grade: 15, Below 8th grade: 12
Age (years)	18-25: 9, 26-35: 16, 36-45: 15, 46-55: 6, 55-65: 4
Annual household income	Below INR 2 lakhs: 32, INR 2 to 3 lakhs: 18

resulted in codes such as "managing disease outbreak," "coordinating work with other ASHAs," and "providing emotional support to patients." Subsequent rounds of coding combined several codes to generate high-level codes such as "care-driven work," "lack of data transparency," and "power dynamics across stakeholders." We then analyzed these codes in relation to the themes that emerged from the thematic discourse analysis, centering the perspective of the FHWs. Our analysis highlights how the "AI for Social Good" discourse, as it operates currently, may exert power by diverting resources from other solutions, silencing local knowledges, extracting limited resources, and reinforcing structures of oppression. We offer design recommendations to address these challenges, and identify workflows that could be supported by AI interventions.

3.3 Positionality

Both Azra and Neha have experience conducting fieldwork with (predominantly) women FHWs in rural and urban India. Azra was also involved in a newborn health project with a non-profit research institute in India focused on AI for Social Good—an experience that offered invaluable insights into conversations at this intersection. Our analysis in this paper is shaped by our postcolonial feminist leanings and a growing sensitization to the marginalizations resulting from intersectional factors such as gender, religion, caste, and class that surfaced in our fieldwork. Despite our sincerest attempts to understand and portray the perspectives of women from the marginalized contexts where our research is located, we acknowledge that our lived realities are starkly different from those of our participants, and we can at best offer a partial perspective [99].

3.4 Limitations

A major constraint of our discourse analysis was that we did not include literature in languages other than English. We realize this means that our review likely excludes valuable perspectives and approaches that may have been published in other languages. We reviewed articles and other grey and non-academic literature to identify efforts that we would have missed otherwise, but emphasize nevertheless that this cannot be a complete account. Finally, though our analysis is situated in an underserved setting in India, we cannot claim to speak for all Indian settings, much less the rest of the Global South. We contend, however, that there are high-level commonalities across frontline health contexts in India, and takeaways that may be relevant far beyond the urban Delhi setting. Leveraging our ethnographic findings, however, we highlight the gaps that might arise in designing AI when sociocultural complexities are crucial to account for, and offer takeaways that might be more broadly applicable.

4 AI IN GLOBAL HEALTH

Our review of academic and grey literature on AI and global health uncovered diverse perspectives from across geographies, academic and non-academic fields, application domains, and technologies. Most applications we uncovered targeted South Asia (96), or did not target any specific region (55). This was followed by Latin America (47), Africa (46), East Asia (38), Southeast Asia (24), the Middle East (18), with several targeting multiple settings (see Table 6 for details). We also found five papers from North America and Europe that targeted "low-resource" or "developing" settings. An application was characterized as targeting one of these regions if the work was motivated by the incidence of disease or a particular workflow in that region, the dataset used was based there, or if this was the location where the system was deployed. We now present key themes that emerged from our analysis.

Table 6: Breakdown of papers by region targeted.

Region	Number of Papers
South Asia	96
Latin and Central America	47
Africa	46
Middle East	18
East Asia	38
Southeast Asia	24
North America	3
Europe	2
Not Specified	55
Other or multiple regions	31

Table 7: Breakdown of papers by application area.

Application Area	Number of Papers
Disease Surveillance and Forecasting	87
Diagnostics and Screening	161
Risk Assessment	32
Epidemiology	22
Resource Allocation	9
Behavior Prediction	4
Health Systems Measurement	3
Information Delivery	11
Data Quality Control	7
Other	11

4.1 Application Areas

Of the 347 AI applications that we reviewed, we found that a significant fraction fell into two categories: diagnosis and screening (n=161) or disease surveillance and forecasting (n=87). A complete breakdown of the kinds of AI interventions in our corpus is presented in Table 7. We note that several of them could have fallen into more than one category. For the purpose of analysis, we placed these into a single category that the authors mutually agreed was the closest fit. Below we describe the various application areas of AI that we found, the stakeholders driving them, the approaches they take, their stated motivations, and the underlying assumptions they reflect about the targeted setting.

4.1.1 Disease Surveillance and Forecasting. We found that most AI interventions in the Public Health or Environmental Science domains focused on predicting and analyzing the spread of disease over a region or population, though this was also a popular application area in Computer Science and Medicine. This involved the use

of a variety of environmental, spatial, demographic and temporal data. A recent example of the use of AI for disease forecasting is during the COVID-19 pandemic, to predict growth in positive cases and spatial spread globally [92, 161, 228, 248].

We found that environmental factors in particular, such as climate data (temperature, precipitation, humidity), vegetation, or proximity to water bodies were frequently used in the case of vector-borne diseases such as malaria [192], dengue fever [203], Zika [12], and others that were more unique to a specific region (*e.g.*, scrub typhus in Nepal [6]). This approach was also used in the case of a variety of infectious diseases, ranging from diarrhea [238] to influenza [56] to Ebola [39]. Our analysis indicated that the use of AI in such cases was primarily aimed at enabling early warning systems for policymakers to take early action. For example, one study described the motivation of the work thus:

> "Since malaria is preventable and treatable, one of the solutions towards reducing the number of deaths is by implementing an effective malaria outbreak early warning system that can forecast malaria incidence long before they occur. This way, policymakers can put mitigation measures in place." [153]

There are limitations to how far this method can impact underlying issues. For instance, one paper conducted a spatio-temporal analysis of the spread of Chagas disease in Brazil using demographic and environmental data [216]. Though it found a relationship to *"different types of deforestation identified in the municipality, as well as agglomerations of cases,"* it did not offer how they expect a policymaker to act upon this finding. Neither did the authors take a political stance on the issue. We also found environmental factors employed to forecast non-communicable diseases in two cases, both studying the impact of air pollution on health [19, 249]. In one of these, the authors themselves acknowledged the limitation of their approach:

> "We understand that the best action to improve air quality is reducing emissions, however it is not possible in a short term…they could be used to estimate hospital admissions and alert government and hospitals for possible increases of hospitalizations due to high air pollution episodes or adverse meteorological conditions." [19]

None of the other papers on disease forecasting were similarly open about limitations of their work. Another approach to disease surveillance that we found was through analysis of social media posts and online search queries (n=6), correlating posts and search terms to data on disease incidence (*e.g.*, [14, 170]). These aim to offer real-time disease monitoring and inform health promotion-based interventions on social media, though there is little evidence of their effectiveness in practice and the extent to which they can be integrated into existing surveillance systems [51, 234].

4.1.2 Diagnosis and Screening. We found diagnostic tools to be the most popular applications of AI in healthcare, particularly in Computer Science and Engineering (representing 59.41% of systems from these fields, and 46.39% overall). We encountered several terms that were used interchangeably in this area—diagnosis, screening, triage, detection, and decision support. Our analysis revealed that their usage reflected little meaningful difference with respect to system design or outcomes of the system, but were related to their intended use. *Diagnosis* (n=90) typically referred to systems that aimed to provide a result on whether someone does or does not have a certain medical condition. *Triage*, *screening*, or *detection* (n=51) were terms used to refer to systems that offer an indication of whether expert advice needs to be sought or if additional medical tests need to be conducted. *Decision support* (n=9) was used to describe systems that provided a suggestion to a medical professional or health worker on what step to take next with a patient.

We found that several AI systems were motivated by limited access to expensive equipment used in diagnosis in low-resource regions, and aimed to offer alternative methods that were low-cost and accessible (*e.g.,* [29, 95]). One AI application used a smartphone camera for skin disease analysis, stating that *"patients in remote areas, poor and developing countries can scan, analyze and make regular skin examinations in any place"* [29]. Apart from making tools themselves more accessible, AI were aimed at addressing lack of specialized medical expertise in many regions (*e.g.,* [121, 155]). One paper was particularly critical of the poor quality of healthcare stating that *"…millions of people have to put up with inaccurate medical care services due to lacking of experienced doctors, especially in the developing countries and areas"* [74]. Though this may appear dismissive of healthcare professionals, it might also reflect how patients in that region view their healthcare system. The below quote is a more representative statement of motivation:

> "Cervical cancer is the most common cause of cancer death for women in Kenya, where there is only around one pathologist for every million people. That's not nearly enough to analyze Pap smears, the routine screening tests that detect abnormal cells in the cervix, from all the women who should receive them regularly…aims to facilitate screening and catch abnormal cells before full-blown cancer develops." [240]

Many such AI systems that support with diagnosis, triage, screening, or detection were designed to automate workflows, such as the identification of head CT scan abnormalities [54]. Others were aimed at reducing the time taken by healthcare providers, such as through the use of convolutional neural networks to more quickly classify chest X-ray images to detect tuberculosis [43, 108, 142]. However, only one of these studies measured the impact on time spent by health workers [24]. It found that the AI system they designed for diabetic retinopathy screening occasionally introduced unnecessary delays for some patients, such as due to network issues or poor lighting conditions of images [24]. Some AI applications we reviewed aimed for their system to be used by a less skilled health worker to reduce the burden on more skilled professionals. For example, the following AI intervention that was built using data from mobile clinics: *"In health consultancy with caravan health sensing, doctors' task becomes the bottleneck of the whole process because of the cost and the huge workload, and we try to delegate some of them to health workers who are less skilled"* [119]. We note that this reflects the assumption that less skilled healthcare professionals have more time available.

4.1.3 Risk Assessment and Epidemiology. We also found AI systems that aimed to stratify a population based on certain underlying

"risk" factors. Though closely related to triage systems mentioned previously that also aimed to identify patients for follow-up, *risk assessment* (n=32) systems worked on a population level rather than an individual level. Such systems focused on predicting patients at risk of a medical condition or mortality and in need of additional care, using demographic and behavioral data. The following excerpt from a paper offers an example of such a system:

> "Nowadays, developing countries face serious health issues such as Sexually Transmitted Infections, unintended pregnancies and other Reproductive Tract Infections. To tackle those health issues, customized awareness programs are necessary. To provide customized education and training to the women in developing and under developed regions, it is necessary to classify the women in those regions into different health risk segments and sub groups within the segment." [16]

A significant number of the papers that we found in this space (n=20) similarly focused on maternal, child, or sexual/reproductive health. The above paper offered an information-focused intervention, but several others focused on predicting the death of a patient, such as newborns from sepsis or asphyxia [106, 117, 144] and women during their pregnancy [169, 199]. They aimed to inform a healthcare provider to pay additional attention to patient identified to be at risk. We caution that though such systems are well-meaning, they can be problematic. We see this in the case of Plataforma Tecnológica de Intervención Social (Technological Platform for Social Intervention) set up by the Ministry of Early Childhood in the Province of Salta, Argentina [188]. A machine learning system was developed by Microsoft to help public authorities prevent school dropouts and teenage pregnancy. The governor of Salta has claimed: *"With technology, based on name, surname and address, you can predict five or six years ahead which girl, or future teenager, is 86% predestined to have a teenage pregnancy"* [188]. The reliance on demographic data in such cases means that AI could be used to police groups that are already made vulnerable, and may reflect and reinforce historical biases.

AI in *epidemiology* (n=22) offered a counterpoint to the prediction approach. Epidemiology is the study of the factors (social, demographic, environmental, and more) that impact the presence or absence of disease in a population. It is typically studied in relation to a population considered to be at risk. While the above risk assessment interventions seek to "predict,", epidemiological applications were focused on informing policy makers and healthcare authorities about appropriate actions to take. For example, the following paper was also around newborn health, but framed differently:

> "Recognizing the urgency in reducing stillbirths globally, multi-pronged strategies should be designed to promote gender equality and strengthen the reproductive and maternal health services in Africa, Eastern Mediterranean, South Eastern Asia, and other countries with disproportionately high stillbirth rates." [8]

In the above text, we see that the focus is on informing structural issues that impact reproductive and maternal health rather than offering AI as the solution. We found no applications of epidemiology in industry. However, in a similar vein, we did find applications of AI in industry for *resource allocation* (n=9). These were aimed at better directing limited resources and improving work efficiency. Macro-Eyes is a for-profit organization doing such work, and is developing a machine learning system that *"predicts vaccine utilisation at the facility, district, and regional level. The predictive supply chain for vaccines offers 96% reduction in vaccine misallocation"* [146]. The applications of AI in epidemiology and resource allocation above also align with recent suggestions to use computing to diagnose and formalize social problems [3], and the latter reflects the mechanism design approach [4].

4.1.4 Other Applications. We also found implementations of AI for information delivery, behavior prediction, verbal autopsy, health system measurement, data digitization, and data quality control (breakdown in Table 7). Information delivery (n=11), in particular, was popular in industry, typically taking the form of chatbots to provide patients and clinicians with information. Ada Health, for example, is a for-profit company that developed a multi-lingual app-based chatbot to provide information on a variety of health conditions [215]. Chatbots have also been used in counseling, such as on HIV and breastfeeding practices [245]. These aim to address "inadequate access to medical experts" [180], providing affordable and accessible means to get care and answers to common healthcare questions.

The use of AI for behavior prediction and health systems measurement (n=7) that we reviewed were tightly coupled with existing programs run by non-profits or hospitals, and the AI solutions were frequently implemented in collaboration with academics. For instance, 99DOTS is a medication adherence tool developed by Everwell Health Solutions, a non-profit organization [128]. An AI solution was implemented using historical data on adherence from their Tuberculosis program, to identify patients likely to miss medication or for whom the treatment is less successful and need additional attention from health workers [128]. Other examples include the use of AI to identify children who are likely to default on immunization visits [49], and to evaluate the effectiveness of an SMS- and IVR-based information delivery program, and potential spaces for improvement [173]. These, however, represented a small fraction of all AI applications that we reviewed (2.02%).

4.2 Localization and Deployment

We mentioned above that many papers in our corpus (n=55) were not motivated by or did not target a specific context. However, far from this work being driven by the Global North, as we might assume, these papers were largely led by researchers in the Global South, sometimes in collaboration with US or Europe-based institutions. Though these papers did not explicitly reference a specific context, the researchers' location may have impacted their choice of topic and framing of the problem (and the interest in global health). Most of these papers focused on diagnostic tools (70.9%), and may have been attempting to speak to a broader audience. All other papers we reviewed focused on a specific region, ranging in scale from a country to a specific community.

We found that data used to develop systems was rarely exclusively generated in the region targeted. Many papers were motivated by a challenge in a particular region, but used data generated elsewhere (typically open-source data from the US or Europe), particularly the case in diagnostics [90, 209]. Others obtained data from the target context through a partner, sometimes supplementing with data generated elsewhere [25, 210]. These were typically collected in hospital settings for diagnostic tools [9, 232], or with community organizations in risk assessment or behavior prediction [128, 173]. Datasets used for disease forecasting were either generated by global health organizations such as the World Health Organization (WHO) and USAID [61, 110], or were obtained from local health units (*e.g.,* Heng County's Center for Disease Control and Prevention in China [239]) alongside other openly available geospatial and meteorological data. In some cases, forecasting was based on collected samples [71, 116]. In epidemiology, data was collected through household or patient surveys [130]. We note that many of the systems we reviewed mentioned data-hungry approaches like deep learning (n=47) or big data (n=12), despite being largely motivated by resource-constrained settings. Only a few (n=4) were designed specifically for settings with data and technical infrastructure constraints (*e.g.,* [22, 129]).

Our analysis also indicated that there has been limited engagement with target users and populations. Only two studies in our corpus, both in HCI, engaged substantially with users [24, 245]. None of the papers on disease surveillance that we analyzed mentioned whether these applications had been used, reviewed, or discussed with target stakeholders. Though many diagnostic tools were developed using data obtained from a hospital, the researchers rarely engaged more deeply with the context. One tool to detect cervical cancer was exceptional in that it described plans for follow-up sustainable implementation. It noted: *"There's an ethical problem to identifying precancerous lesions if you can't do anything about them"* and therefore focused on cervical cancer screenings where *"one effective treatment for abnormal cells involves freezing them off with cryotherapy, and can be safely done at low cost by midwifes or nurses"* [240]. We note that some for-profit organizations appeared to have engaged in design or market research, and may have been incentivized to engage with stakeholders to attract and retain users. For instance, an article we reviewed on Ada Health stated that they were collaborating with Muhimbili University of Health and Allied Sciences in Tanzania and Foundation Botnar to make the tool culturally and linguistically appropriate [7, 215].

Finally, we found very few extended implementations of AI, most of which were either led by startups (*e.g.,* [54]) or large software companies (*e.g.,* [24, 109, 225]). This may be due to the additional work and financial resources required to undergo regulation, ensure high accuracy, and build robust systems. For instance, in June 2020, Qure.AI received one of the first clearances by the U.S. Food and Drug Administration (FDA) for an AI-based diagnostic tool [189]. The startup was founded in India in 2016. Another example is Facebook's use of AI to match blood donors to local hospitals and blood banks, only possible because of its existing scale [225]. Tools for diagnosis and resource management, in particular, have mostly seen uptake and received funding from venture capitalists and US-based foundations like the Gates Foundation [146, 189, 220]. However, some small-scale and short-term deployments have been undertaken by academics, in collaboration with hospitals and non-profit organizations [231].

5 AI IN FRONTLINE HEALTH

In our discourse analysis, India emerged as a country with high research and industry activity around AI and global health (n=69). This is partially due to the state's push in recent years to develop a robust digital and data ecosystem [190]. We now draw from ethnographic data on the healthcare system in an underserved region of Delhi, centering the experiences of women seeking and providing care. We uncover the gaps between the AI systems being proposed and healthcare workflows and needs as observed. We also highlight opportunities for AI-focused efforts to support existing workflows, strengthen healthcare systems, and address resource gaps.

5.1 Recognizing Where the Stakes Lie

Our discourse analysis revealed that AI developers were largely agnostic to local political and economic specificities, and how they influence the entry points for AI and sustained uptake. Below we lay out the healthcare ecology in our field site and implications for AI interventions, starting with the **political and organizational context**.

The clinics and hospitals in Delhi are administered by a diverse group of institutions. At the time of writing this paper, control of *government clinics* was divided across two political parties—the Bharatiya Janata Party or BJP (which also makes up the central government and controls the Municipal Corporation of Delhi (MCD)) [200], and the Aam Aadmi Party or AAP (which makes up the state government) [237]. There are two kinds of government clinics: *dispensaries* operated by the MCD and *Mohalla (or neighborhood) Clinics* set up and operated by the state, both of which provide primary healthcare at no cost. Most *government hospitals* in the state are operated by the state, but some are under the control of the central government. The MCD is also responsible for sanitation services. Our literature review found a special focus on government actors in the case of disease forecasting and epidemiology, where it was assumed that relevant action would be taken by the municipality or healthcare authorities. In practice, who holds power to make decisions can be complicated. For example, sanitation and dispensaries in Delhi were not managed by the state government in power [93]. There has also been significant friction between the BJP and AAP around healthcare provision [93].

The government also provides frontline healthcare in underserved areas of Delhi under the National Urban Health Mission (NUHM)—an extension of the older National Rural Health Mission [158]. This program is jointly funded by the center and the state and employs women *frontline health workers* including Accredited Social Health Activists (ASHAs), Anganwadi Workers (AWWs), and Auxiliary Nurses and Midwives (ANMs) [158]. They are responsible for offering care on Reproductive-Maternal-Neonatal-Child and Adolescent Health (RMNCH+A), and Communicable and Non-Communicable Diseases. ASHAs, in particular, conduct door-to-door data collection, healthcare provision, and information dissemination [112, 158]. In rural India where healthcare may be less accessible, frontline health plays an essential role in filling gaps in coverage. Despite their key role in the healthcare system, our

literature review found only 24 systems that targeted use by health workers.

In addition to government services in Delhi that are free or heavily subsidized, there are hundreds of *private clinics and hospitals* that range in quality and cost of care. There are also health services offered by *non-profit and religious groups* located close to communities. Differences across how hospitals and clinics, or private and government services operate and are administered can have a significant impact on the uptake and use of an AI intervention. The papers we reviewed rarely considered the role of institutional differences. An exception was Chao et al.'s study that took into account the size, income, doctor degrees, number of visits, and more of government hospitals in China [50]. Only one paper considered religious groups at all, while forecasting tuberculosis incidence at a religious site in Iraq [163]. Another key stakeholder in the healthcare ecology are the local *pharmacies* or *chemist shops*. This was the first stop for many of our participants who directly purchased over-the-counter medication or supplements in lieu of visiting a doctor. None of the papers or articles we reviewed focused on the role of pharmacies, despite them being significant care providers. We also point out the presence of **competing health knowledges** in this context [111]. Alongside allopathy, or western medicine, participants also turned to religious practices and indigenous medicine with varying results [63]. The Ministry of Health in India has a dedicated effort to support AYUSH medicine (Ayurveda, Yoga and Naturopathy, Unani, Siddha and Homoeopathy)—forms of complementary and alternative medicine [63, 201]. AYUSH medicine was also available in government dispensaries and hospitals. Only two papers in our corpus relied on non-western sources of knowledge, both using traditional Chinese medicine [177, 251].

Deploying AI systems requires cognizance of the complex ecologies that involve multiple stakeholders with possibly conflicting interests. Even within a site, some stakeholders may be more open to adopting new technologies than others. For instance, the relatively new Mohalla Clinics were equipped with digital tablets to collect patient data and mobile-based diagnostic tools, unlike the older dispensaries [214]. Our prior research revealed that despite the techno-optimism of the government, doctors perceived the use of tablets for collecting patient data as a bureaucratic requirement that did not align with their workflows [111]. The multiple institutions, knowledges, and stakeholders in the healthcare ecology provide many entry points for AI interventions, but can entail conflicting goals and priorities.

5.2 Patient Choice and Agency in Care-Seeking

We next consider how patients navigate the complex healthcare ecology. We found several factors that informed care-seeking behaviors—cost, accessibility, quality of care, and recommendations of family and community members. Our participants were primarily women and our findings therefore reflect a gendered perspective.

For many residents, there were trade-offs involved between **cost, accessibility, and quality of care** when deciding where to seek care. Though free government clinics were available, they had long waiting times and were open only in the day during working hours. Taking time off from work was frequently not an option for our participants. To save time and money on travel, they visited small low-cost private clinics in their area that charged as little as INR 50 [approx. 0.67 USD] per visit. One participant who was a domestic worker explained her decision-making process:

> "I generally go to the doctor when my children fall sick. I am active all day and rarely fall sick. My kids fall sick often and if I take them to a *chhota-mota* (small-time) doctor, they charge less but the medicines are not very effective. I will end up going to the same doctor multiple times, which means more money is spent. If I go to a better doctor, like a pediatrician, then the medicines they give are very effective and I don't need to visit the doctor again. But I will have to get a number and then wait till my name is called…I can't take time off from work to take my kids to the government dispensary."—Naima, 26, resident

How the participant decided to seek care depended also on who she was caring for. She was more likely to seek care (particularly higher quality care) for her children, and appeared to be the one responsible for taking the children to a doctor. We found this trend across our participants, where women viewed themselves as the primary caregivers in the home, responsible for nutrition (cooking), hygiene (cleaning and laundry), and healthcare (hospital visits). Our discourse analysis revealed several AI efforts to make healthcare more accessible and affordable via remote consultation (*e.g.,* [7, 191, 245]). However, such programs have seen limited sustained uptake among underserved communities in the past, even when offered for free, due to lack of alignment with the local context [33, 141]. One intervention that has had a measure of success in India is Kilkari, a free IVR service that delivers maternal and child health information [45]. The content and marketing was designed over several years, informed by an understanding of family dynamics and gender roles, as well as the particular digital, health, and language literacies of women in diverse regions of India [10, 113, 133, 205]. Adoption of AI will depend on the attention paid to these aspects.

A major concern that our participants cited with government services was **long waiting times**, with *"a different line for everything—to register, see the doctor, get medicines…."* AI systems have been proposed to help reduce waiting times by automating certain workflows or supporting doctors to reduce the amount of time it takes to diagnose patients [44, 142]. However, our interviews revealed that doctors were perceived to already be *"too quick"* to assess patients. One participant stated that doctors *"just write (the prescription), and don't tell us how to use it."* This failed to meet the care needs of patients who were concerned that they were not heard properly and may have been misdiagnosed. AI tools designed for diagnosis could be used as an additional check against the doctor's recommendation to validate their response and allay patient fears, or flag a potential problem in the case of frequent differences with the AI's prediction. Consultation with AI agents could also be offered as an option for less critical ailments when doctors are unavailable, *supported by human personnel*. Our analysis of the dispensaries and Mohalla Clinics also revealed a contradiction around waiting times. Though clinics were busy at certain times of the day, wait times could be as little as five minutes at other times. AI applications can help address the challenge of **scheduling** (*e.g.,* [137, 159]), particularly in larger hospitals. Risk assessment systems could prioritize

patients at higher risk or who may have traveled from farther away, though this could increase wait times for others.

We also found that our participants frequently relied on or were influenced by the **recommendations of family and community members** on where to seek care. In particular, women could face pressure to accept the preferences of their husband or in-laws. One participant shared with us: *"Once, when my arm was broken, I was ready to get an X-ray. But since X-ray is expensive, everyone told me to go to a pehelwan (local wrestler) first, so I went. That didn't fix it so then I went to a doctor who took an X-ray and I got a plaster."* AI could support and complement hyperlocal healthcare infrastructures such as pharmacies, low-cost clinics, and indigenous knowledge sources that are the first resort for affordable care. Prior work has argued for privileging the knowledge of the doctor in AI systems because of their and their patients' lack of trust [139]. However, AI could *lend* accuracy and credibility to stakeholders who may have limited medical expertise. This might also legitimize their role in the healthcare system and check any harmful practices, expanding the reach of quality care.

Healthcare seeking was not always organic and was frequently a result of interactions initiated by FHWs, mobile clinics, or awareness camps. The hierarchical government healthcare system employed a **referral system** starting with frontline health. An individual was referred to the next tier when the care needed went beyond the expertise of the healthcare provider. This system resulted in high burdens at the top-most tier of large hospitals, where participants reported having to sometimes wait days to receive care. Our discourse analysis uncovered that diagnostic and screening tools have been proposed for use in such scenarios to make tools/expertise available at lower tiers (*e.g.,* [46, 109, 119]). However, the hold-up is not necessarily the time that referral or diagnosis takes. The systemic challenge is one of limited infrastructure (hospital beds, doctors, nurses and staff) and bureaucracy faced by lower-level staff. Without addressing these issues, a higher rate of referrals could add pressure on an already overburdened system. AI could instead play a role in resource allocation, taking a mechanism design approach [4]. Data on where patients are coming from, for which services, and with what medical conditions could be leveraged by AI researchers to propose more sustainable solutions. Accordingly, healthcare services could be offered by the government in specific regions to help reduce the overall burden.

5.3 Invisible Workflows in Frontline Health

We now take a closer look at frontline health workflows. An important connect to the government healthcare system for many underserved communities was the ASHA assigned to their area. The vignette below provides a window into the work of an ASHA, and is based on participant observation with ASHA Hiba during a measles outbreak. Using this vignette, we detail the workflows of ASHAs to identify considerations for the design of AI interventions.

> *After seeing her daughter off to school and her husband to work, ASHA Hiba settled down to breastfeed her six-month-old daughter. Suddenly her phone beeped with a WhatsApp message. On the group chat with other ASHAs and ANMs affiliated with the local Primary Health Center (PHC), the supervising Medical Officer had messaged:* "All ASHAs, please report to dispensary for emergency meeting." *Convincing her mother-in-law to take care of the baby, Hiba rushed to the PHC where she learned that two ASHAs in nearby areas had found cases of measles. All the ASHAs were instructed to go to each of the 400-or-so households in their areas, find and report cases of measles, and provide treatment to stem a wider outbreak.*
>
> *In the following week, rain or shine, Hiba visited as many homes as she could to conduct a survey of measles symptoms. She was sometimes accompanied by another ASHA for safety and solidarity. She focused mostly on jhuggi-jhopadis (slum dwellings) where vaccination rates were low. These visits were on top of her routine data collection and care provision duties, but were not financially compensated. There were also several instances where she had to revisit households where no one was at home, either because the family was out at work or had traveled to their native village. During house visits, Hiba advised households:* "Measles is spread in this area. Get your child immunized, you can get it done at the PHC. I can show you the way if you don't know." *In one Bengali-speaking migrant community, Hiba struggled to communicate. She relied on the Hindi-speaking members to mediate,* "What are they saying? Tell your neighbor that measles is spreading."
>
> *In one of her visits, Hiba found three children with the measles rash and immediately notified the PHC on a call. An ANM gave her instructions for dispensing treatment. A WHO representative also joined her during the visits to confirm that they had measles. After the visits, he asked,* "Why have the children not been vaccinated?" *Hiba explained,* "I have been trying to get slum residents to come to immunization drives. But they have many reasons, they have work and have no one to take care if the child falls sick. They also travel to their native village and bring these diseases…The ANM needs to come here but is unwilling. And immunization drives happen only once a month." *The WHO representative sympathized and promised,* "I will tell the ANM to visit. There should be two extra drives per month because of the high risk here."
> *Once he left, Hiba expressed her doubts saying,* "We will see if that happens."

5.3.1 Helping with Quick Response and Filling the Cracks. ASHAs were expected to adapt to and address local needs that were unmet by the healthcare infrastructure (*e.g.,* motivating a community to install a toilet or a water filter which should have been set up by the government). As a nationwide network, they were also called on to help with health-related emergency response, such as in the case of the COVID-19 pandemic [28] or measles outbreaks.

Disease forecasting has been proposed for such situations by predicting outbreaks and informing preventative action by government authorities [66, 98]. However, we need to consider what precautionary measures are targeted by such an AI system. The appropriate recommendation in response to a predicted measles

outbreak would entail vaccinating children in that region [89]. As the above example illustrates, this is *already* a key priority for ASHAs and PHCs.n The challenge then is not that PHCs are unable to predict measles outbreaks, but that residents are unable or unwilling to attend immunization drives. Our discourse analysis also revealed that AI developers assumed that government authorities would take action, but in practice, public workers such as ASHAs are the ones ultimately responsible for implementing interventions. Based on power dynamics we observed in our fieldwork, mundane and labor-intensive tasks were delegated to those with least institutional power even when other stakeholders (*e.g.,* doctors, ANMs, etc.) are involved, which ends up being the ASHAs.

AI could be used to support existing workflows at the ASHA level. For instance, AI could bring attention to places where immunization coverage is low. The companies, Macro-Eyes and Logistimo, have been using AI in supply chain management for immunization to address vaccine shortages [143, 146]. A similar approach could be applied to workflows, to identify the places where more human resources are needed. AI could also help support ASHAs in their work of identifying children likely to default from immunization programs [49]. In the vignette, we see Hiba focusing on communities that had not achieved full immunization coverage because she was aware that these were the areas at greater risk. Our interviews with her revealed that she mostly relied on her memory and operated in an ad hoc manner, and this process could be supported to be more directed and less burdensome.

5.3.2 Work Planning. Our interviews and observations revealed that work planning for ASHAs was supported by the PHC only to a limited extent. ASHAs received high-level instructions from the PHC and they were supervised, as in the case of the measles outbreak. Their work was otherwise expected to be driven by the incentive-based payment structure that paid based on the completion of tasks. Beyond being driven by the payment structure, ASHAs gave additional time and attention to marginalized populations, even if these were smaller groups that were more challenging to work with. For instance, they spent more time in migrant communities, trying to communicate and build relationships despite language and sociocultural barriers. They had hour-long counseling visits with women who faced physical and emotional abuse. Such labor was not recognized nor compensated. There was significant effort that went into completing a single incentivized task in high-risk populations, and some kinds of work were not paid at all.

AI-based risk assessment tools have been proposed to direct healthcare providers to households "at risk" (*e.g.,* [184]). Certainly, there were some cases where ASHAs were accused by residents of not visiting frequently, where such a system could help build accountability. Our interviews with women in one slum community revealed that they had last seen ASHAs three months back for polio drops, because the region was hard to reach. However, the underlying issue is of misaligned incentives. In our focus group discussions, we learned of rampant forging of data used to determine work done and salary earned by some ASHAs. This was unfair to ASHAs who made less incentives because supervision was conducted in areas where ASHAs made less money and were assumed to be doing less work. AI systems that force certain workflows could end up pushing ASHAs to find workarounds and may further impact the quality of work. One opportunity for AI is to bring attention to the misaligned incentives, by predicting the amount of time it would take for an ASHA to achieve a specific outcome in an at-risk household. Such a tool could offer more realistic work schedules, and be used to advocate for better incentives.

Finally, we highlight that much of the ASHAs' time was spent on mundane and redundant work, such as data collection. ASHAs were also the medium for reaching the beneficiaries of many government schemes, though they received nominal (if any) compensation for carrying them out. AI could be used to automate such tasks. One way to do this is through automated IVR calls that can be used by residents to determine which incentives they are eligible for, where the monetary compensation may serve sufficient motivation to use the system. This would leave the ASHA with more time for care-driven tasks. Another approach to take is to treat the ASHAs' time on specific tasks as a finite resource, and take a resource allocation approach to distribute that resource where most needed.

5.3.3 Addressing Sociocultural Dimensions of Health. A critical part of an ASHA's work was being attentive to the nuances of behavior and what is left unsaid, piecing together information across sources—other community and family members, other ASHAs, doctors, and ANMs at PHCs. This was particularly relevant in the case of taboo topics such as women's sexual and reproductive health. Over time, they gained an understanding of health behaviors and family dynamics in different households. For instance, in the measles outbreak example, Hiba immediately identified members who spoke Hindi and recruited them to help. ASHAs also relied on their personal experiences in their work. As a breastfeeding mother who had to coordinate household responsibilities with her mother-in-law, living in a Muslim household, Hiba could relate to the experiences of the women in her area. AI systems could be developed to capture such sociocultural dimensions of care, making this data available to others in the public health system. One way to do this could be to use AI to compile community profiles from household surveys. The approach followed in epidemiology that we found in our discourse analysis, could be leveraged here to identify the underlying (social and environmental) issues that are impacting the health of communities. Such a system could hold healthcare authorities accountable for addressing these issues. If the profiles are verified by ASHAs, it would also legitimize their knowledge.

We also found that ASHAs are frequently consulted on medical symptoms in the household. They could not prescribe formally, but had access to common over-the-counter medication from the dispensary. For cases that they are unable to diagnose or that require further tests, ASHAs refer the client to the local PHC. Diagnostic and decision support tools have been proposed for use by ASHAs to support consultation. Our literature review revealed that a majority of these tools have been developed for screening a specific medical condition. It is critical that we ask where these systems would fit into the varied workflows of ASHAs, and what existing workflow they aim to replace. ASHA Afsana pointed out: *"What is the point of collecting data on the phone if the government will still ask for paper documents? They ask for paper-based proof for everything."* This also applies to diagnostic tools. If the tool just refers to a doctor, or if it is not approved by the government, it increases the burden on the ASHA and community members. The incentives for using the AI

system would also need to be carefully defined. Though it would be unethical to demand more work for little to no pay, it would also be unethical to incentivize ASHAs for doing work that does not benefit the communities they serve. This could distort their priorities and existing workflows.

5.3.4 The Burden of Data Collection. For AI to make predictions or recommendations, large amounts of timely and structured data is needed. Frontline health workers such as ASHAs then constitute one of the few feasible existing (human or technical) infrastructures that is equipped to collect and send timely and detailed health, demographic, or other data. In India, ASHAs are already engaged in extensive data collection, mostly to report the coverage of health services. The amount of time spent collecting data was a significant point of tension and led ASHA Amna to say: *"This is what we do, this is our work. To do fieldwork and conduct surveys... The other actors at the dispensary (ANMs and data entry personnel) just sit and make money from our hard work."*

In the vignette shared, we also see that consent did not feature in data collection or care provision which raises data privacy and ownership concerns. ASHAs collect a lot of highly sensitive data on women's bodies and family demographics. During our fieldwork, we encountered several women who used contraceptives without their husband's knowledge and their use was recorded by ASHAs. Data-driven systems may put such women at risk if privacy is compromised. Data is likely to be collected on the ASHA's phones/tablets and then likely transmitted elsewhere. During our fieldwork, we found that ASHAs retained access to data by copying it over to a personal notebook to help with future data collection, but were not expected do so by the PHC. The communities did not have ownership over the data, though in same cases they refused to give their data. Data collected was submitted to the PHC on a monthly basis and there was little transparency in data flows as reflected in the question ASHA Meena posed to us at the end of an interview, *"Where does the data go?"*

5.3.5 Supporting Each Other and Advocating for System Reform. In the absence of support from the PHC, ASHAs leaned on each other to fill gaps in their knowledge, offer emotional support, and help plan and improve workflows. These peer relationships and informational needs could be further supported. For instance, chatbots could be used for information delivery, and such systems have been designed and developed in recent years [180, 245]. AI could also help match ASHAs who face similar challenges in their work or serve populations with similar demographic characteristics. AI systems could also help deliver personalized health information based on the learning needs of each ASHA [243], helping them continually update their knowledge base.

Finally, we consider it our ethical responsibility to point out the ongoing exploitation of ASHAs. Beyond work, ASHAs frequently gathered in each others' homes to socialize and discuss their wages and working conditions. There was widespread discontent among the ASHAs and a sense that they *"have no value."* Many of our participants were part of Delhi's ASHA Worker Union, and kept track of strikes and protests by ASHAs in other parts of Delhi and other states, which motivated them to also engage in activism [57, 212]. There was a desire to be recognized fairly for their labor. During our focus groups, several ASHAs expressed interest in tools that track their work, in order to make their labor more visible and identify ASHAs entering fraudulent data. Though such tools may leave ASHAs vulnerable to surveillance, it also indicates an opportunity to generate *counter-data* that questions dominant narratives, as proposed by feminist data scientists [70, 224].

5.4 Data from/about the Underserved

We must consider the implications of collecting data in politicized contexts. The region where we conducted fieldwork (Jamia) has a Muslim-majority population and most residents are migrant workers from neighboring states. Jamia has been the center of protests in India against the Citizenship Amendment Act (CAA) and the National Register of Citizens (NRC) in December 2019 [60, 149]. The protests were motivated by the fear that these policies would strip many of citizenship status on the basis of religion, and disproportionately impact lower socioeconomic groups who may not have documents required to demonstrate citizenship [149]. As India moves towards programs such as the National Health Stack, which aims for a *"nationally shared digital infrastructure usable by both Centre and State across public and private sectors"* [1, 148], we urgently need to consider the risk of policing and privacy violations. During our fieldwork, we learned that ASHAs have already been recruited by the government to motivate residents to get an Aadhaar number (India's national identification system) and provide this number to be able to receive social welfare benefits. Aadhaar is also planned to be integrated with the National Health Stack [1]. This places ASHAs in a difficult position, where their in-group status is used to obtain data wanted by the government. Aadhaar has already had several data leaks [172, 242], and research has uncovered the exclusions and system breakdowns that tying Aadhaar to other government welfare programs has caused [52, 115, 211]. Our fieldwork uncovered that such privacy concerns lead to ASHAs being occasionally questioned by residents who refused to provide data. As many countries move towards *"digital governance,"* we need to ask which political structures the systems we develop are working for, with, or against.

6 TARGETING SOCIAL GOOD WITH AI

Our analysis uncovered how current AI efforts tend to focus on isolated problems such as diagnosis or disease forecasting, rarely considering the broader context of implementation or engaging with communities being designed for. We showed how the "AI for Social Good" discourse reveals opportunities for futures with resource-intensive AI solutions such as disease forecasting and diagnosis, even as they target resource-limited settings. At the same time, attention/resources are diverted from alternative AI and non-AI futures that might better support workers and strengthen frontline health ecosystems overall. Current discourse also reflects who has power to shape AI-driven futures, with the targeted communities having little voice. Given the growing attention to problems of social and global relevance among AI proponents, we outline steps to check and recuperate the "AI for Social Good" discourse. We lay out considerations for the design of AI systems that target social good, drawing on literature in HCI4D and ICTD, post-development discourse, and transnational feminist theory.

6.1 Learning from the Past

Research and practice in the fields of HCI4D and ICTD have successfully brought together a wealth of interdisciplinary perspectives to engage at length with the challenges surfaced by the integration of different computing technologies, in widely disparate contexts [37, 64, 171, 218]. We contend that there are relevant lessons to be learned from prior interventions, both failures and successes, even if that technology has thus far rarely included AI.

6.1.1 Foregrounding User Agency. In the push for more data, the role of the humans and the work they do are routinely marginalized, even as they provide critical linkages to make the data/AI infrastructures work. HCI and related disciplines have invested consistently in making work visible. This body of work is wide-ranging, from Suchman's [221] and Gray and Suri's investigation of invisible work [97] to Sambasivan and Smyth's description of the "human infrastructure of ICTD" [207]. Though not integrated into the digital economy quite yet, there are similar risks to extracting (invisible) labor from the FHWs who are already overburdened on account of responsibilities touching diverse, overlapping aspects of their lives [113]. Our analysis detailed the limited compensation they receive for their ever-growing list of responsibilities. Even as FHWs are viewed as actors and changemakers across their communities [42, 112], they are vulnerable to being taken advantage of for the data collection and scale that AI systems target. We recommend that AI systems be designed to foreground user agency—by not forcing workflows and allowing users the autonomy to decide whether to use the suggestions made by an AI system. Care work has also remained consistently undervalued, additionally marginalizing FHWs' invisible labor [97, 112], even when they are frequently expected to provide the services that generally lie within the purview of trained (and far better paid) doctors. AI systems may reinforce gendered and racialized notions of devalued work [21]. A key reflex we must cultivate is to always ask *whose* social good we are attempting, and *who* (not *what*) we are centering.

If AI systems are not designed to foreground agency, researchers and practitioners may find that targeted "users" do not use these systems at all [72], use them in unexpected ways [20, 194], or work around the systems altogether [213]. Our fieldwork in Delhi clearly conveyed that FHWs were not passive actors and frequently organized to advocate for improved working conditions. ICTD research has long documented interpretative flexibility in technology adoption [37, 132, 213], giving us sufficient evidence that "use" must not be taken for granted. These are not merely "unintended consequences" but consequences that we must by now be in a position to *anticipate* [183].

6.1.2 Questioning the Unit of Scale. A key argument that has frequently been made in favor of deploying ICTs is that they are relatively easy to scale. In practice, however, most technology interventions in the field of ICTD have struggled to achieve scale. As a participant in Dell and Kumar's review of HCI4D scholarship noted, *"The problem is that showing development outcomes in any of these spaces is extraordinarily difficult. We don't try to show outcomes, we try to show outputs. Just demonstrate some development output, such as making a system work better. Outcomes are the holy grail of evaluations in any of these spaces. It happens once in a while..."* [64]. Toyama has argued that this limited demonstration of development outcomes in the field is because technology can only play the role of amplifying existing institutional forces, not substitute for missing institutional capacity or human intent [229]. Alongside this critique, a number of works have emerged on the *human infrastructure* supporting technological systems [75, 76, 185, 207]. For AI systems to be successful in supporting frontline health, we must foreground its human infrastructure, and FHWs are a significant fraction of it. Currently, there is a misalignment of incentives between what the government intends to scale and what FHWs are most concerned about. While FHWs care for more dignity and recognition of their work, as well as fairer salaries and working conditions, the government is focused on improving health outcomes at minimal cost. AI could be used to scale government intent to supervise workers or enforce certain workflows, but could also target automating mundane workflows for FHWs and maximizing their (fixed) work time on care-based tasks.

The notion of scale holds an additional complication in the case of AI systems. With data-hungry AI algorithms, as we found in our literature review, data collection must happen at scale to make AI work [123]. Such data to present date are scarce in the Global South [105]. In the case of interventions such as disease forecasting, the data also needs to be generated in real time. Data sharing is one way to manage data needs, but appropriate data protection policies for such efforts are still in progress. Further, AI developed using data from one demographic or location may not be straightforward to apply at another location when an intervention is scaled [102, 233]. Finally, scholars question whether large-scale AI systems should be built at all, if the target outcome is indeed social good [181].

6.2 Targeting Sustainable Good

We next situate ourselves in critical understandings of development, to consider the Social Good that AI interventions are attempting to achieve. The post-development discourse has argued for an abandonment of the Western growth-centered ideal [77, 202] and questioned impulses of wanting to "help" countries in the Global South [77]. It argues that development—a goal set by the Global North for all nations—has pushed communities to abandon historically sustainable modes of living [202], and that we need to instead take a pluralistic worldview [65, 78]. We discuss this discourse in relation to AI efforts for social good below.

6.2.1 Moving Towards a Pluralist Worldview. In recent years, technology utopianism among those pushing for AI solutions has been severely rebuked [58]. Recent discourses have asked how AI could instead be transformative and be put to work for social justice [122, 162]. We caution that these may reflect unwarranted optimism regarding what is possible with AI, when even well-meaning efforts to include marginalized populations in data efforts have been used to enable violence against these very groups [79, 103]. AI that is aimed at subverting power structures may end up directing resources and attention away from local efforts and more effective non-AI solutions such as policy and activism.

A post-development standpoint asks how communities might be driving decisions on whether and how they might like to use AI. Assuming that researchers are deeply invested in a certain context, we favor a modest approach to aligning with this perspective—to

work closely with communities *over time* and have an open dialogue. Participatory Action Research (PAR) offers one such research approach [80, 101]. PAR is a form of research that necessitates taking action to address a problem while also generating knowledge by learning from the action [80, 101]. It involves crafting research questions in collaboration with the community partner, implementation and evaluation of an intervention, and writing up results with the partners [101]. Such an approach is reflected in many successful ICTD interventions (*e.g.,* Open Data Kit [34, 100], Medic Mobile [241], Digital Green [88], Gram Vaani [166], CGNet Swara [150], 99DOTS [59]) that have entailed years of investment of human, technical, and financial resources, relationship-building with local champions and partners, training and bi-directional knowledge-sharing, and perseverance on the part of those driving these initiatives. Many of them go beyond open-sourcing their technologies, by sharing knowledge with local groups wishing to adapt the system for their context. Some of these organizations have also increasingly been using their positions of power to advocate on behalf of the populations that they are building for, such as frontline health workers [104], farmers [87], and rural populations [104].

A shorter-term alternative is to develop strong partnerships with community organizations and allow them an active hand in guiding design, and offer technical support beyond initial implementation. The research collaboration between Google, the Indian Institute of Technology Madras (a premier research institute in India) and ARMMAN (a non-profit), is an example of an initiative that relies on the experience, knowledge, and networks of the community partner [173]. Fostering such partnerships is undoubtedly a time-consuming endeavor. We caution here that it matters *who* the partners are. In the case of Delhi's healthcare infrastructure, for example, the government overlooked the knowledge and perspectives that FHWs had to offer. AI initiatives that solely rely on the knowledge and position of the government without engaging with FHWs and communities may reinforce the existing power differential.

6.2.2 Developing Sustainable Interventions. A community-centered approach is one step towards developing sustainable interventions, there is a need to also examine sustainability from a resource perspective. Researchers have highlighted the environmental impact of data/AI systems [32, 58, 145]. Our discourse analysis revealed that many AI initiatives in global health relied on large datasets or resource-intensive algorithms like deep learning, particularly in the case of disease forecasting and diagnosis. Though a few systems were designed specifically for settings with data and technical infrastructure constraints (*e.g.,* [22, 116, 129]), they were few and far between.

We emphasize that a key step with any AI intervention should be to consider less resource-intensive alternatives, including *non-technical* solutions. If AI is still the approach taken, we recommend the following steps to check extraction of resources: streamline and leverage existing data flows rather than introducing new ones, build systems that require less data (*e.g.,* by using transfer learning [68]), be directed about collecting data when required (*i.e.* avoid collecting unnecessary data), compute less on the devices of the underserved, and build for lean computation and power consumption (*e.g.,* by eschewing deep learning [18, 219]). ICTD research has recommended similar steps for practical reasons when working with sparse or poor network and computing infrastructures, but a consequence of this approach has been less use of resources overall. We advocate this as a conscious strategy to take in the Global South *and* North, even as infrastructures improve and technology becomes pervasive.

6.3 Fostering Solidarity Across Borders

Given the global scope of the challenges targeted by AI for Social Good, we consider how one might undertake translation work across geographies, technologies, and disciplines. We offer *feminist solidarity* as a lens that could enable translation work [135]. Feminist solidarity is centered on the notion that diverse individuals and communities can find a base to work together based on *shared struggles* [165]. Even as we focus on commonalities, we pay attention to differences across contexts as feminist scholars recommend [165, 250]. We consider these differences and spaces for solidarity below.

6.3.1 Engaging with Diverse Disciplines. Engagement with interdisciplinarity begins with developing an understanding and appreciation for what other fields have to offer [168]. Feminist scholars, Parvin and Pollock, illustrate the disciplinary gap eloquently when they describe the dismissal of their ethical concerns by technologist colleagues as "unintended consequences" [183]. The prevailing view in the field of AI is one of positivism—the objectivist philosophy that only knowledge gained using the scientific method through unbiased observations is accurate and true. Like the natural sciences, positivist research seeks to explain and predict. This approach is eminently appropriate for questions such as *"how well can we predict the severity of diabetic retinopathy with retinal images?"* However, it does not allow for space to engage with broader questions like *"why are patients unable to access diabetic retinopathy screening in the first place?"* The former reflects *realism*, an ontological position that one reality exists and can be studied and understood as the "truth." Questions like the latter can reveal diverse perspectives depending on whose view is elicited and what methods are employed. This can make realists deeply uncomfortable because it reflects *relativism*, the ontological position that reality exists in the mind and each individual creates their own version of the truth. Engaging with other disciplines involves reckoning with the source of this discomfort, and choosing to listen and engage meaningfully and not only performatively when ontological and epistemological differences arise [38, 168].

The positivist view pervasively impacts how we think about computing's role in social change—as understanding and measuring social problems, helping define them, bringing attention to them, and clarifying the limits of an intervention [3]. We found these reflected across the AI systems we reviewed—to measure and bring attention to social dimensions of health in epidemiology, to measure and define disease spread, to define and then predict a specific medical condition in diagnostics, and identify and target resource deficits. Our ethnographic analysis offered a broader perspective, and revealed where such approaches may fall short. Other disciplines can similarly inform design at various points—by augmenting our understanding of what problems to focus on and where, how to approach these problems, which actors to target and what workflows, and what Good to work towards. Finally, we

emphasize that researchers from diverse backgrounds must come together to demonstrate solidarity with one another, such as in their shared interest in and commitment to a context or Social Good domain. The disciplinary differences then serve to strengthen the work and its capacity for achieving social impact.

6.3.2 Translating Across Contexts. In our analysis, we identified opportunities for AI, situated within a specific context. As researchers develop AI systems for diverse settings, we recommend a focus on common struggles to enable translation across geographies. In healthcare, for instance, this could mean that an AI system developed to address or support the struggles of frontline health workers in Delhi overburdened by mundane work, could be translated to other places where workers are facing similar challenges. Similarly, across geographies, we may find women to be overburdened by care work, and marginalized communities to find it harder to access affordable care.

Such a focus can also enable bi-directional learning across the Global North and South, as exemplified in our prior work [135]. For instance, Global South researchers can learn from critical scholarship on AI in the Global North, a site that produces *global* power structures. Scholars have uncovered algorithmic bias against women and transgender people [55, 127], people of color [26, 36, 174], and the poor and working class [79]. These concerns also largely apply to countries in the Global South, alongside other intersections with caste/tribe, language, or religion, as well as a history of coloniality. In healthcare for instance, we found that AI interventions mostly leverage existing datasets, which prior work has pointed out tends to be skewed towards men, higher castes and classes, dominant languages, and urban regions [13, 123, 206]. This can divert attention and resources from regions that are already disadvantaged, further widening the gap in healthcare access. Conversely, emerging efforts in the Global North to use technology to target social justice can learn from work in the Global South [69, 73, 85]. The COVID-19 pandemic has further highlighted health and other inequities that exist *within* the Global North [30], and the global nature of these challenges. We outlined several spaces for such engagement above, such as learning from past critiques and failures of technology for development [178, 202, 204] as well as successful technological efforts, the history and evolution of the development discourse [77, 202], and a transnational feminist approach [81, 165]. Finally, across the Global North and South, we urge AI researchers to ask themselves how they might find solidarity with the communities they target—what draws them to the underserved contexts where they work and the struggles therein?

7 CONCLUSION

As our society increasingly powers towards AI-integrated futures, there is an urgent need to examine these futures more deeply. AI for Social Good initiatives promise futures where AI is put to work to achieve "social good" outcomes. The Social Good label, however, can provide cover against charges that AI systems elsewhere have faced around enabling surveillance, automation, and marginalization. We studied the unfolding focus areas of AI in frontline health, an active application area for AI enthusiasts. We weighed this analysis against our ethnographic research conducted in an underserved frontline health setting in India, highlighting the gaps between proposed AI systems and the lived realities of the frontline health workers and underserved communities targeted by such systems. We also identified opportunities for AI to offer value in these contexts. Our paper thus offered a critical and ethnographic perspective to discourse on AI and Social Good, centering perspectives from the Global South to propose an agenda for the design of AI that targets social good outcomes. We contribute to a growing body of HCI research that is engaging with the design of AI systems, and particularly inform research that aims to support healthcare workflows in resource-constrained contexts.

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