"It cannot do all of my work": Community Health Worker Perceptions of AI-Enabled Mobile Health Applications in Rural India

Chinasa T. Okolo
Cornell University
Ithaca, New York, United States
chinasa@cs.cornell.edu

Srujana Kamath
Independent Researcher
Bangalore, India

Nicola Dell
Cornell Tech
New York, New York, United States

Aditya Vashistha
Cornell University
Ithaca, New York, United States

ABSTRACT

Recent advances in Artificial Intelligence (AI) suggest that AI applications could transform healthcare delivery in the Global South. However, as researchers and technology companies rush to develop AI applications that aid the health of marginalized communities, it is critical to consider the needs and perceptions of the community health workers (CHWs) who will have to integrate these AI applications into the essential healthcare services they provide to rural communities. We describe a qualitative study examining CHWs' perceptions of an AI application for automated disease diagnosis. Drawing on data from 21 interviews with CHWs in rural India, we characterize (1) CHWs' knowledge, perceptions, and understandings of AI; and (2) the benefits and challenges that CHWs anticipate as AI applications are integrated into their workflows, including their opinions on automation of their work, possible misdiagnosis and errors, data access and surveillance issues, security and privacy challenges, and questions concerning trust. We conclude by discussing the implications of our work for HCI and AI research in low-resource environments.

CCS CONCEPTS

• **Human-centered computing** → **Empirical studies in HCI**; • **Computing methodologies** → **Artificial intelligence**; • **Applied computing** → *Health care information systems.*

KEYWORDS

Community health worker, CHW, HCI4D, ICTD, Artificial Intelligence, AI, mHealth

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1 INTRODUCTION

Recent advances in Artificial Intelligence (AI) have led to the widespread infusion of AI technologies into digital products and services, including in critical domains such as agriculture [60], government [45], and healthcare [30, 49, 96]. Although AI could be transformational in the benefits it brings, research has shown that it can also have negative consequences. For example, studies have exposed problematic bias in facial recognition algorithms [22], commercial recidivism software [70], and racial bias being perpetuated in healthcare risk algorithms [86].

However, most of the conversations on both the positive and negative effects of AI on human societies focus on communities in the Global North (e.g., the US and Europe) that are relatively resource rich. The lack of attention on the effects and consequences of deploying AI within the world's poorest and most marginalized communities in the Global South is concerning, especially in light of growing enthusiasm and new initiatives by non-profit organizations (e.g., the Wadhwani AI Institute [7]), technology companies (e.g., Google AI India [53]), and national governments [4, 45] to use AI to solve complex societal problems in low-resource settings [8, 54]. Rushing to build and deploy AI systems, without first examining the knowledge, needs, and perceptions of the paraprofessional workers that will be expected to operate these systems within marginalized communities, risks deploying AI in ways that lead to extra work and inefficiencies, or that even harm the very communities they aim to serve [17].

In this paper, we present a qualitative study that examines the AI knowledge and perceptions of community health workers (CHWs) in rural India. CHWs are individuals, usually women, who are recruited from local communities, receive basic medical training, and then work to deliver essential healthcare services to communities in hard-to-reach areas in the Global South [1, 105]. In many rural and marginalized communities, CHWs provide a critical link between the community and the public health service [16, 107]. The importance and prevalence of CHW programs in the Global South, and in India in particular [85, 103, 113], suggests that these workers are highly likely to be the target users of many AI systems that aim to improve the health of marginalized communities via, for example, AI-assisted disease prediction and diagnosis [8, 54]. Our study is, to our knowledge, the first to examine how CHWs perceive AI.

We conducted interviews with 21 CHWs in rural India to study: **RQ1:** *What are CHWs' perceptions and understandings of AI?* and **RQ2:** *What are the benefits and challenges that CHWs anticipate as AI applications are integrated into their work?* We created an exploratory video provocation in which a CHW visits a mother and her sick child. The CHW uses a mobile AI-enabled app to scan the baby and diagnose them with pneumonia. To encourage balanced and diverse responses, we created two versions of this video provocation: a positive scenario, in which the mother embraces the use of the AI application on her child, and a negative scenario, in which the mother is suspicious and distrustful of the AI application. After viewing one of these videos, CHWs participated in a 40-minute semi-structured interview.

Our findings reveal that at the time of the study, CHWs had very low levels of AI knowledge. Nevertheless, they formed mental models of how the AI worked, often by assuming it was the same as human intelligence. CHWs were not overly concerned that their jobs would be replaced by AI, pointing out instead the potential for AI technologies to work with them as part of a team. Indeed, CHWs foresaw many benefits that AI might bring to their work, including new knowledge, community respect, and far-reaching expectations that often exceeded AI's capabilities (e.g., accurate diagnosis of all diseases).

CHWs believed that the AI app was trustworthy, often assuming that the machine's expertise outweighed their own. They also perceived that the AI app had the potential to improve the community's trust in their work. At the same time, they felt that they would be capable of determining when the AI made a mistake and take steps to correct it, usually by re-running the procedure until the AI delivered the diagnosis they believed to be correct. CHWs also saw how the data collected and stored by the AI system would be broadly useful for themselves, patients, governments, and technology companies, expressing diverse opinions about who should be granted access to this data and why. Finally, CHWs did not perceive any serious privacy or security problems associated with using an AI system to collect personal health data.

Drawing on these findings, we synthesize key takeaways for HCI and AI researchers interested in deploying AI with communities in the Global South. First, we consider what designers of AI systems need to know to maximize the chances their interventions help, rather than hurt, marginalized communities, along with what CHWs need to know to become effective AI workers. Second, we identify opportunities for future research to examine how to make AI systems explainable to novice technology users in the Global South. Finally, we discuss the challenges of developing AI systems that respect diverse communities' cultural and value differences, while ensuring safe and equitable outcomes.

2 RELATED WORK

The widespread infusion of AI into human-centered applications has led to an explosion of research at the intersection of AI and HCI. Prior research has examined the challenges in designing for human-AI interaction [131], studied the role of humans in interactive machine learning [11], and defined guidelines for effective human-AI interaction [12]. A large body of work also engages with the moral, ethical, and fairness challenges associated with the widespread use of AI technologies. A few examples include algorithmic bias [74], issues of trust in AI [133], how AI might intentionally deceive humans [28], and the benefits of planning in advance for AI's failure [9].

Another rapidly growing area of interest focuses on "explainable AI", meaning that the decisions made by AI are understandable to humans [5, 23, 71–73, 120]. Prior research has also looked at people's mental models of AI, particularly in human-AI collaboration [15, 48]. Highly relevant to our research, prior work has studied human perceptions of AI, including among data scientists [119], young children [124], and the public at large [27, 64]. For example, Kocielnik et al. studied how people's expectations regarding AI impacted their perceptions of accuracy and acceptance [65], and Jakesch et al. examined how the perception that text was written by AI affects trustworthiness [61]. Kelley et. al studied general perceptions of AI among urban residents across eight countries including Brazil, Nigeria and India, producing findings that illustrate both the positive and negative perceptions of AI's impact on society [64].

However, all of the work discussed thus far either assumes a "general" context of use (i.e., does not specify a particular context or user group) or exclusively focuses on resource-rich contexts (e.g., the US and Europe). By comparison, only a tiny number of studies have looked at the perceptions of AI in low-resource, HCI4D contexts: Medhi-Thies et al. used a Wizard-of-Oz design to explore chatbot personalities that appeal to young, urban Indians [111], Jain et al. designed a conversational agent to answer farmers' queries in rural India [60], and Thakkar et al. explored how vocational technicians perceive the possible automation of their jobs [110]. This paucity of research on AI in HCI4D is particularly concerning in light of the recent establishment of new institutes and labs, such as the Wadhwani Institute for AI [7] and Google AI Research India [53], whose explicit mission is to design and deploy AI applications within marginalized and vulnerable populations, often in high-stakes domains like healthcare [8, 54]. At the same time, academic researchers are also starting to build AI applications for use in HCI4D contexts, including chatbots [25] or informational services [19]. Our study contributes a much-needed perspective by engaging CHWs in rural India to examine their understandings and perceptions of AI and their opinions of how AI might impact their work of delivering essential health services to marginalized populations. We now discuss prior research focused specifically on the role of AI in healthcare.

2.1 AI in Healthcare

A large body of research examines the potential for AI in medicine and healthcare [30, 49, 83]. Popular domains include early detection and prediction of diseases [33, 83, 125, 128], automated diagnosis and medical image analysis [62, 95, 96, 132], personalized treatment and decision support systems [31, 104, 104, 134], and more. A cluster of projects have specifically targeted global health problems in low-resource contexts. For example, Natarajan et al. examined the diagnostic accuracy of an offline AI system for diabetic retinopathy in India [81]. Young et al. [132] and Cao et al. [26] proposed AI for tuberculosis diagnosis in South Africa and Peru, respectively.

Quinn et al. studied deep neural networks for microscopy-based diagnosis [96]. However, these studies focus on the technical challenges of developing AI systems. They do not consider the human healthcare providers who might use these systems in practice.

A narrower body of work has examined AI's impact on various healthcare professionals. A few studies suggested that doctors or other healthcare providers might someday be entirely replaced by AI [30, 91, 121]. More commonly, research has looked at how AI could complement and augment humans' capabilities [94], including AI tools for patient self-tracking [43]. Work in clinical settings analyzed the needs of medical practitioners who would use a human-AI collaborative system [24], and enabled physicians to explore AI-aided medical imaging analysis [127]. More notably, research on the impact of a deep learning algorithm for diabetic retinopathy on the workflows of nurses in Thailand exposed issues that arose when transferring AI tools from high-end research labs to low-resource clinical settings [17].

Perhaps closest to our work, a tiny number of projects have explored AI tools relevant for CHWs in low-resource contexts. A few projects created smartphone-based computer vision applications to enable CHWs to analyze rapid diagnostic tests [34, 36, 93]. For example, Park et al. [93] built and evaluated an app to let CHWs take high-quality images of malaria rapid diagnostic tests. However, these studies focused on measuring accuracy and usability of the tools, not on CHWs' perceptions of the AI that powers these systems. Finally, Yadav et al. used a Wizard-of-Oz design to look at how chatbots might be useful for answering mothers' and CHWs' questions about breastfeeding [130]. Our study contributes to this nascent literature by examining CHWs' knowledge and perceptions of AI, the benefits and challenges that they foresee in integrating AI into their work, and the resultant impact on their workflows and other stakeholders in rural healthcare. We now discuss prior work with CHWs in low-resource contexts.

2.2 Community Health Workers in HCI(4D)

The shortage of qualified medical professionals in many low-income countries has led to the establishment of community health programs that provide essential health services to hard-to-reach communities [105]. These programs depend on the work of paraprofessional CHWs, who are recruited from local communities, receive basic medical training, and then assess and refer patients based on approved health protocols [107]. For many communities in low-resource environments, CHWs provide a vital link to the broader public health infrastructure [107] and have been shown to positively impact outcomes, including reducing neonatal mortality rates [16] and positively changing behavior [69].

The HCI4D community has shown a lasting interest in CHWs and created a range of systems to motivate CHWs and improve their performance. For example, researchers have designed tools to boost engagement in community health programs [40], provide personalized visualizations for CHWs to track their performance [39, 42, 123], and engage CHWs in the design of systems to collect feedback from care recipients [79, 87, 88]. A rich body of work has also focused on tools that enable CHWs to collect data for monitoring and evaluation [50, 92], including digital tools that improve adherence to clinical protocols [41] and tracking supplies that CHWs distribute to their communities [35].

Another set of projects has worked to augment CHWs' health knowledge, including via technology-enabled collaborative learning [129] and locally relevant health-related videos [67, 78, 116, 117]. Finally, prior studies have also examined the broader socio-technical implications of deploying mobile technologies to aid CHWs' work [56], including examining the multi-stakeholder nature of community health ecosystems [87, 97], how technology deployments differ across domains and geographies [68], and how CHWs navigate the demands placed on them by society at large [57].

This body of work suggests that (1) CHWs play an essential role in the delivery of healthcare services to marginalized communities, and (2) mobile technologies play an important role in enabling, guiding, and supporting CHWs' work. Thus, as advances in AI lead researchers and technology companies (e.g., the Wadhwani AI Institute [7] and Google Research's AI lab in India [53]) to develop AI applications that target the health of marginalized communities, it is crucially important to study: **(1) What are CHWs' perceptions and understandings of AI?** and **(2) What are the benefits and challenges that CHWs anticipate as AI applications are integrated into their work?** Our study uses qualitative methods to engage with CHWs in rural India and elicit insights that answer these research questions.

3 METHODS

Our qualitative study took place from June to August 2020 in partnership with Nehru Yuva Sangthan-Tisi [101], a grassroots organization that runs multiple programs to strengthen community health systems in western Uttar Pradesh, India. As part of these programs, they frequently train and work with CHWs. To recruit participants, an organization staff member contacted CHWs, explained the purpose of our study to them, and then gave us the contact information of those who expressed an interest in participating. All of our interactions with the organization and CHWs took place remotely, primarily via telephone calls, since India was experiencing the effects of the COVID-19 pandemic.

Procedure. Our study procedure involved two phases: **First**, participants were sent, via WhatsApp, an exploratory video provocation 30 minutes before the interview and were asked to watch it. **Second**, after they watched the video, we called them at a prearranged time and conducted a semi-structured interview over a telephone call. We discuss these phases in turn.

Video provocation: HCI4D researchers frequently use cultural probes [126], exploration artifacts [79], and technology provocations [52] to better understand the needs of underserved communities and the complexities of their everyday lives. These methods bring great value when target users lack technology know-how or when they hesitate to give truthful feedback due to demand characteristics or hegemonic power structures [38, 97, 118]. For example, Molapo et al. created a mobile phone app as an exploration artifact to get rich feedback from CHWs in Lesotho [79]. Medhi et al. used full-context videos to examine and aid non-literate people to navigate a computer application with minimal assistance [76]. Drawing on this prior research, we designed a video provocation as an exploration artifact to examine CHWs' perceptions of AI and

Figure 1: Frames from an exploratory video provocation we created that our participants watched. The video shows a CHW using a camera-enabled AI application to scan a sick baby and diagnose them with pneumonia.

the bene!ts and challenges they anticipate when integrating AI into their work"ows.

To enable CHWs to imagine themselves as users of AI technolo gies, we constructed a story in which a CHW is equipped with a smartphone-based, AI-enabled application capable of scanning patients with the phone's camera and automatically diagnosing pneumonia. Our scenario was rooted in current expertise and work- "ows of CHWs. We chose pneumonia because it is the single largest infectious cause of death in children worldwide, accounting for 15% of all deaths of children under 5 years old [89]. The prevalence and seriousness of pneumonia in the rural communities where CHWs work mean that they are familiar both with the disease itself and with the di#culties of accurate diagnosis. We chose a camera-based AI-enabled diagnostic application because several organizations have developed AI apps to enable CHWs to diagnose diseases [34, 36, 93] or take anthropometric measurements [8].

In the video provocation we created, a CHW visits a mother whose baby is sick (see Figure 1). The CHW !rst checks the baby, before using a smartphone-based AI application to diagnose the baby with pneumonia. To achieve this, the CHW scans the sick baby using the smartphone's camera and tells the mother that the AI application is checking if the baby has pneumonia. The video script mentions that the application works most of the time, but sometimes makes mistakes. After the application con!rms the pneu monia diagnosis, the CHW administers antibiotics and reassures the mother that the baby should recover in a few days.

When creating the provocation, we were concerned that depict ing the AI application in a positive light may lead to biased data, in which CHWs would simply tell us that they liked the AI application and thought it was good [38]. Thus, to encourage a more diverse set of opinions and rich discussions, we created two versions of the video provocation: a positive scenario in which the mother in the story was excited and enthusiastic about the AI application, and a negative scenario in which the mother was suspicious and distrustful of the AI application. The full script for both videos, and the exact wording di$erences between the positive and negative videos, is provided in Appendix A. We counterbalanced the two videos across participants, with eight shown the positive scenario and 13 the negative scenario. Both videos were in Hindi (still im ages, audio, and subtitles) and lasted 2.5 minutes. Participants were asked to watch the video at least once, but could re-watch it as many times as they liked.

We chose to keep our study simple with two scenarios of camera based diagnosis instead of creating more scenarios, for example, on automation, trust, or fairness. This is because CHWs were in hard to-reach communities and were already burdened with extra work of monitoring COVID cases in rural India. Thus, CHWs had limited time to participate in our study, which prevented us from holding longer workshops involving many scenarios as done by Brown et al. [21]. Our contributions could be enhanced by alternate view points, and exploring multiple scenarios via longer engagements is an area of future work.

Semi-structured interview: After CHWs watched the video provocation on their own, we conducted one-on-one semi-structured interviews via telephone. We began by reading an informed con sent script and asking for verbal consent to participate in the study. CHWs were then asked to summarize the video and their thoughts on it. If they did not provide su#cient details or had not viewed the video, we rescheduled their interview to a time convenient to them later. If they did watch the video, we then discussed the CHWs' opinions of the video provocation, before digging more deeply into their existing knowledge of AI and how this a$ects their percep tions of an AI-enabled app. Our subsequent questions sought an in-depth understanding of the CHWs' opinions on the acceptability of using an AI application to diagnose diseases, who they thought should have access to the application and/or data collected, how such an application might impact their work, and more. To ensure CHWs' responses are detailed and grounded in their experience, we carefully chose questions that focus on their responsibilities, work"ows, and interactions with other stakeholders in rural health care (e.g., patients, supervisors, government). After each interview, we revised our questions to add new probes, stopping when we reached saturation in our interview data. Our complete interview protocol is provided in Appendix B. Interviews were conducted in Hindi, lasted approximately 40 minutes, and were audio-recorded (with CHWs' consent). Participants were not monetarily compen sated at the request of our partner organization. However, they were provided with a small gift to thank them for their time.

Participants. Our CHW participants lived and worked in rural communities in Uttar Pradesh, a state that exhibits some of India's

Gender	Female: 21, Male: 0
Age (years)	Min: 29, Max: 55, Avg: 44, SD: 6.0
CHW experience (years)	Min: 1, Max: 14, Avg: 12, S.D: 4.2
Technology use	Feature phone: 4, Smartphone: 17, Computer: 0
Education level	Middle school: 4, High school: 13, Bachelor's: 2, Master's: 2
Video seen	Positive scenario: 8, Negative scenario: 13

Table 1: Demographic details of our study participants.

poorest health outcomes [2]. These CHWs (also called ASHAs in India) are female villagers who are trained to act as health educators and promoters in their communities. They have at least ten years of education and receive outcome-based remuneration. They typically perform their work by traveling door-to-door, visiting patients at their homes, and providing advice, counseling, basic medical services, and referrals to public health clinics. In addition to their normal duties, CHWs were also tasked with COVID-19 screening and reporting work, conducting periodic household surveys, and educating people in the village.

Table 1 provides participants' demographic details. All 21 participants were women—which is the norm for CHWs in India. No participants possessed or used computers. All participants owned a phone or had access to a shared phone. However, participants' levels of experience with smartphones varied widely; four did not possess a smartphone at all and instead used a feature phone. Another ten used a smartphone, but had been doing so for one year or less, while seven had used a smartphone for more than one year.

Data Collection and Analysis. Our data consisted of 17 hours of audio recordings and detailed notes collected during the interviews. Audio recordings were translated into English and transcribed. We then performed thematic analysis [20] on the transcripts and notes. We began by closely reading the transcripts and allowing codes to emerge freely from the data. Multiple passes through the data resulted in a total of 83 codes (e.g., app useful in training, data access for record keeping, privacy is expected) that we organized into a codebook. Throughout the analysis process, we held multiple discussions with all authors to discuss, iteratively refine the codes, and reconcile disagreements. Finally, we clustered related codes into eight high-level themes (e.g., AI knowledge, misdiagnosis and errors, trust and expertise). Our final codebook, themes, and the prevalence of each code is provided in Appendix C. We also tracked, but did not find any significant differences in responses between the positive and negative videos. In reporting our findings, we use pseudonyms for participants and anonymize the quotes.

Ethical Considerations. All study procedures were IRB approved. Moreover, since our research took place between June and August 2020, while the COVID-19 pandemic was impacting India, we took steps to ensure the safety of participants and researchers. For example, we conducted the interviews remotely to ensure the safety of CHWs, the rural community, and ourselves. We were also sensitive to the fact that the CHWs were still working during COVID-19, and hence, maintained flexibility in scheduling the interviews. We informed the CHWs to prioritize their patient visits and other commitments. Therefore, some interviews took multiple sessions over two to three days to finish.

Positionality. All authors are from countries in the Global South and have conducted fieldwork with underserved communities in India and other low-income regions. Three authors identify as female and one as male. Two authors have 7+ years of experience studying CHWs in South Asia and Africa. One of them has spent several years working with our partner organization and interacting with CHWs in Uttar Pradesh. We all view HCI research from a social justice-oriented design practice [44] and an emancipatory action research mindset, aiming to conduct formative research to examine the opportunities, challenges, and tensions in using AI to support CHWs in rural areas.

4 FINDINGS

Our findings show that CHWs' had very low levels of AI knowledge and ascribed far-reaching capabilities to AI. Nevertheless, they were able to critically think about how AI might impact relationships with communities they serve, its ability to provide upskilling opportunities, and how they would potentially handle AI failures or errors. In fact, many CHWs believed the AI in our video provocation already existed and asked when it would be available to them, showing that not only were the scenarios depicted in the video were feasible, but that they are open to integrating the AI app into their workflows. We begin by engaging with our first research question to understand CHWs' knowledge and perceptions of AI (Section 4.1). We then discuss the benefits (Section 4.2) and delve more deeply into the tensions and trade-offs CHWs' perceived surrounding the use of an AI app in their work, including questions of trust and expertise (Section 4.3), dealing with AI failures or errors (Section 4.4), opinions on access to the data collected (Section 4.5), and potential security and privacy implications of using AI in community health work (Section 4.6).

4.1 Understanding CHWs' Knowledge and Perceptions of AI

When asked directly at the start of the interview, *"What do you understand by artificial intelligence"*, all CHWs answered with some variation of *"I do not have any knowledge about it"* (Vanya) or *"I have not heard about this"* (Aparna). We probed further, asking participants how they thought AI worked based on what they had observed in the video provocation. We also brought up and discussed with CHWs the example of YouTube video recommendations, since most of them reported watching YouTube videos regularly. Based on this probing, four CHWs drew parallels between machine and human intelligence. For example, Maahi said, *"It works the same way as our brain. It must be the same for the machines."*

When we focused our questions more on participants' understanding of how the AI *app* in the video provocation worked, as opposed to the general concept of AI, we received an array of interesting responses. Eight participants, like Divija, were skeptical of the app and continued to express a lack of understanding:

> *"The video was saying that the condition of the child can be diagnosed with the help of an app. I don't see*

> *how it can be done using an app. It is beyond my grasp of understanding. How can the condition of the child be determined?"* (Divija)

However, nine participants quickly connected the camera-based part of the app to the idea of machine vision by describing how the app must be *"looking"* for symptoms of pneumonia:

> *"Perhaps when we connect the picture of baby in the app it detects the visuals of how the baby is breathing and decides if the breathing is normal or slow. Must be something like that I guess?"* (Anvi)

Participants also perceived that the app must be analyzing the information it collected. In many cases, participants surmised that the app must be *"counting"* or *"measuring"* signals like *"the heartbeats, breathing and chest contraction, or the crying of the baby"* (Anika). CHWs understood that, based on these measurements, the app was able to make a decision. Ten CHWs equated the process that the AI used with their own methods for diagnosis:

> *"I don't know how we can diagnose whether the child has pneumonia or not by using an app. But, we perform our diagnosis by looking at the symptoms."* (Divija)

Despite possessing generally low levels of AI knowledge, participants articulated diverse opinions and ideas for how AI might impact their work within rural communities, as discussed in the rest of this Section.

One key concern surrounding the widespread deployment of AI technologies is the extent to which AI might automate work in ways that replace human workers and make their jobs redundant [46, 75, 122]. Indeed, in the healthcare field, several prior studies have specifically suggested that AI might someday replace healthcare providers [30, 91, 121]. Thus, we were interested to understand if the CHWs in our study perceived AI as a threat to their jobs.

Overall we found that, although CHWs agreed broadly that an AI app might be able to accomplish *some* of the tasks they perform, it would never completely replace them. As Diya put it, *"In my view, nobody can replace anyone."* CHWs pointed out that an AI app is incapable of spanning the breadth of activities they perform, including consultations, immunizations, and culturally-sensitive discussions on breastfeeding and family planning. Kavya told us, *"This is not possible. There are so many responsibilities on me. How can it take my place?"* Maahi elaborated:

> *"The app can tell this [pneumonia] but it can't tell the weight of the child. We check the weight. It cannot give medicine to the child. It will not take the child to the health center. Only we will do that."* (Maahi)

CHWs broadly agreed that, even if the AI app was capable of performing a wide range of functions, it would still require a human operator if deployed in the field because *"the machine can't go on its own"* (Lakshmi). As Advika put it, *"The machine can't work automatically; it can only work when we take it with us and we are there to operate it."* CHWs generally saw themselves as being the operators of the AI app (which is in line with the video they saw). When we suggested the possibility of patients downloading the app and using it on their own, eight CHWs pushed back, arguing that people in their communities would prefer to wait for a CHW rather than do things on their own:

> *"They would not even try to operate the app. They will wait for the CHW to come to their homes and let her do the testing. They will wait for us."* (Advika)

They believed that people in their communities neither possess technology skills to operate the AI app, nor medical training to interpret the results. They also felt that people placed greater trust in them, resulting from their years of hard work and community engagement. Instead of making their jobs redundant, participants saw the potential for AI apps to work *with* them as part of a team, with *"some information from the app and some information provided by the CHW"*, bringing more value to people in their community (Mishka). Indeed, as described in detail in Section 4.2, CHWs perceived many benefits that AI might bring to their work. These benefits would, in their view, only amplify CHWs' role within their communities:

> *"How will it take my place? It's a machine. I just think that when we get it, we can work more efficiently. Instead of replacing us, it will create more place in the field for us."* (Priya)

All participants were eager to learn more about how the AI app worked and receive training that would teach them how to integrate it into their daily work. They saw the app as *"being on their side"*, working with them to provide the best care to their communities:

> *"People can see that CHW and the app are both on the same side as they both just want the patients to recover. So I don't think there is any problem."* (Diya)

4.2 The Perceived Benefits of Integrating an AI Application into CHWs' work

We now discuss benefits that CHWs perceived would be afforded by an AI app like the one in the video provocation. Reflecting on how the AI app might impact their work, CHWs expressed that they thought the app would be able to replace their existing, manual processes for performing tasks, thereby saving them from needing to do that work:

> *"Like we do a manual count of breathing but it may not be accurate. But if we are using the app, it will visually show us the information and we won't need to count on our own."* (Anvi)

Many CHWs felt that having the AI app perform tasks for them would make their work much more efficient, saving both them and their patients valuable time when making decisions about if and when to seek further medical help. As Anvi said, *"The app gives us information quickly so we can take decision on diagnosis and hospitalization."* In addition, although the AI app was essentially performing the same work as CHWs already did, they felt that the technology would somehow be more accurate and precise in its measurements than them:

> *"The machine checks the temperature and confirms that it is fever. We can also check that, but we cannot tell the accurate temperature. We can touch and check if the temperature is high, but we cannot tell the exact measurement. The machine can accurately measure temperature."* (Saira)

Participants quickly identified that the improved efficiency provided by an AI app capable of accurately diagnosing diseases in the field would be especially useful in remote villages that might be located far away from hospitals or health centers. CHWs from remote villages described how they are often unable to get timely help from a doctor and that, when they call an ambulance, it may arrive too late. The app, they perceived, would be able to provide them with valuable information and recommendations for treatment that would help to mitigate this lack of resources. It would also save villagers time and money because they would not need to travel to the hospital:

> *"The patient won't have to travel to get information. We can give medicine. Patient will feel better and it will save them travelling fare and time."* (Lakshmi)

Participants also perceived that, if the AI app was capable of diagnosing pneumonia, *"then it must be able to do other things as well"* (Jia) and that *"this app will make us capable of solving all problems"* (Meera). Other conditions mentioned by various participants that the app might be able to diagnose included hunger, thirst, diarrhea, coronavirus, pregnancy problems, fever, common cold, blood pressure, cancer, and more. As Samaira said, *"If it can tell about pneumonia, it can tell about other diseases as well. This app can make our work very easy."*

Participants were also excited at the potential for an AI app to provide opportunities for learning new skills and receiving more training. Eight participants thought that the video provocation itself provided valuable knowledge to help educate the community, and that as the CHWs' knowledge increased, so did their community's knowledge:

> *"The beneficiaries [patients] will tell other people that see this, 'A CHW worker came to our house and performed tests in this manner.' So, slowly people will get to know about the app. Their knowledge will be enhanced and the word will keep traveling forward."* (Isha)

Other participants emphasized that the AI app itself could also serve as a useful training tool by reminding CHWs of techniques or symptoms to look for when working in their communities: *"It will certainly be useful. Through the use of this app we can see the visuals and get a better idea of what the baby is going through"* (Anvi).

Finally, participants also felt that the AI app would make it easy for their superiors to validate and recognize their work. Several CHWs voiced that the digital data generated and stored by the app would be useful and provide a more reliable and permanent record than their existing, paper-based registers:

> *"The information would be stored forever. You know registers can be misplaced easily. For instance, a register was sent for superior's approval, but it never returned. But with the app, if someone asks us how many people have arrived from outside the region, we can tell them by looking it up."* (Jia)

Digging into this quote, we observe that this CHW, like many others, is ascribing a number of far-reaching capabilities to the AI app: ensuring permanent and safe storage of data, the ability to replace paper-based patient registers, collecting information about topics unrelated to pneumonia diagnosis (in this case, people arriving from outside of the region, a duty taken on by CHWs during COVID-19), and easy retrieval of any collected information. **None** of these capabilities were suggested in the video provocation that participants watched. More broadly, many of these perceived benefits suggest that CHWs may possess a utopian view of AI (and perhaps technology in general) and its ability to magically solve challenging problems they face in their work. We discuss the implications of this AI utopia in Section 5.

4.3 Navigating Questions of Trust and Expertise Raised by Use of an AI App

Prior work in the field of AI has suggested that the lack of human trust in AI systems may prevent people from taking advantage of its benefits [99]. Within their respective communities, CHWs are often the primary arbiters of medical information, and maintaining trust with local residents is important to ensure that CHWs can deliver medical services without obstruction. Thus, we were interested to learn how an AI app might affect patients' trust in CHWs' work and expertise, and how CHWs and patients may navigate questions of trust in the app itself.

Our findings suggest a symbiotic relationship where CHWs' usage of the AI app may improve patient trust in both the app and the CHW themselves. Participants mentioned that patients were often reluctant to believe the diagnoses given to them by CHWs and the AI app might serve to reinforce CHWs' expertise, improve patients' understanding of the diagnosis, and cause them to *"take it more seriously"* (Samaira):

> *"They will trust us. If we show them how this machine is working, that the machine is showing that their baby is suffering from the disease, then they will start believing it [the diagnosis]."* (Samaira)

CHWs also discussed how patients' trust in the AI app would be dependent on CHWs trusting the system themselves. Isha explained how her trust in the AI app would influence a patient:

> *"Even if people do not trust the app in the beginning, if we want to make them trust the app then we would have to trust it ourselves."* (Isha)

We find that the gateway to villagers trusting the app is the CHWs' willingness to use the app in their work with the community. Across many of our interviews, there was strong consensus that if patients saw the CHW using the app, then they would come to trust it, albeit not immediately. Vanya elaborated:

> *"They [villagers] will take some time to trust the app. If I will only tell them [instead of showing the app], people will say that the app is fine. If we find a kid in any family and we did the checkup by following the app, then they will really trust the app."* (Vanya)

Beyond their role in convincing villagers to trust the AI app, 17 participants conveyed that they themselves would trust the app and believe it to be correct because, *"It is not like it won't work"* (Shreya). A few participants drew a parallel between the capability of an AI app to other machines or pieces of equipment. They often referred the AI app as a "machine." To them, this meant that the AI app would be inherently trustworthy:

> *"The app is trustworthy. This works like a screening machine. This is why apps are used by everybody. The app is a machine, hence it is trustworthy."* (Divija)

These findings are concerning, especially because the script in the video provocation clearly mentioned that the AI app sometimes makes mistakes. When we pressed further, asking CHWs whose opinion they would trust more if the AI contradicted their own diagnosis, six CHWs said they would defer to the presumed "superior" accuracy of the AI app. Despite their years of experience, these CHWs said they would trust the AI app more than themselves: *"I will trust the app more because it might happen that I have not accurately diagnosed the child and the app is more accurate."* (Diya)

On the other hand, when asked who *patients* would trust more if the AI app conflicted with the CHW's opinion, only a small number of participants felt that patients would trust the AI app more than them. Instead, 19 out of the 21 participants said that the patients would trust the CHW more than the AI app. While the patients may hold a certain degree of trust in the AI app, ultimately, the CHWs' expertise would win:

> *"The parents will always trust the CHWs. If we tell them to take the child to a doctor, they do. They would not trust an app as much as they trust us. In the past they used to ignore us, but now they understand that we are working for their good and they listen to what we say."* (Divija)

Participants' responses demonstrated that trust is not only reliant on perceived accuracy but on human interaction, something that an app cannot provide. Isha described the relationships CHWs have built up with their community and why the AI app cannot replace them:

> *"We touch the child, try everything else, and we are present there in front of the parent. They appreciate that we are explaining things to them and talking with them, so they start trusting us. Mobile phones do not get the same level of trust. Parents have a higher degree of trust on the person in front of them, no doubt. The app have an advanced technique, but still I would say that the level of trust is not as high. The arrival of this app will facilitate many things, but the trustworthiness would be a little low when compared to CHWs."* (Isha)

CHWs did perceive that a conflict or misdiagnosis by the AI app might negatively impact their hard-earned trust and lead to setbacks in their work to convince people to follow the important health-related advice they provide:

> *"Not only will they be annoyed [with a conflict], they may even stop trusting me. They'll think that I am telling different things at different times. If I tell them that there is some problem in the machine, they may be annoyed. They are village women, it takes a lot to convince them."* (Kaamini)

To avoid patient mistrust due to the potential misdiagnoses, three participants stated that they would simply not inform patients when the AI app malfunctioned or conflicted with their opinion. Kaamini explained how this would prevent patients from losing trust in her:

> *"If the machine gives problems I'll say [to the patients] that I would be back after sometime. I'll say, 'Suddenly I am feeling sick. I'll be back after some time.' I'll deal with it myself. I will not tell them."* (Kaamini)

We now further unpack CHWs' ideas for what to do should the AI app deliver an incorrect diagnosis or break down.

4.4 Unpacking CHWs' Strategies for Dealing with AI Failures or Misdiagnosis

When probed to consider how to deal with the app delivering a potential misdiagnosis, participants expressed several strategies. Many of them were familiar with the idea of getting incorrect readings from medical devices, with a few citing the fact that the thermometers they used to screen for COVID-19 sometimes malfunctioned. Should this happen with the AI app, 12 CHWs said they would simply *"check through the app twice and thrice"* (Meera). Anvi elaborated:

> *"That's why we check twice. As it's possible that the reading wasn't accurate for some reason. Maybe because the baby's photo isn't clear. Then we'll check it again."* (Anvi)

Only one participant considered that she might fail to spot the incorrect diagnosis. Instead, 15 participants felt that their existing medical knowledge and training would enable them to inherently know when the AI app was incorrect. In these cases, they would continue to re-run the test until the app's diagnosis matched what they believed to be correct:

> *"It can arrive at wrong conclusions and make mistakes. But in those times, we would have the knowledge from our experience and we will be able to tell whether the app is correct or not. If it is wrong, we will do the test again. If we want the diagnosis to be accurate in such cases, we will have to try one or two times."* (Divija)

In addition to re-running the app multiple times, two CHWs expressed that, if the app delivered an incorrect diagnosis, they would simply stop using it and proceed with their existing equipment to conduct a manual diagnosis:

> *"We will check ourselves. Like if the baby is suffering from pneumonia, heart rate would be high. The baby must be suffering from high temperature fever, diarrhea and chest contraction. If the app is not working, we will use our own knowledge."* (Samaira)

Next, we explored CHWs' willingness to *override* the app's diagnosis manually, by entering corrected data into the AI app itself. Ten CHWs were open to this idea. Maahi said that it was part of her job to ensure the correct data was entered, even if she did not know much about the technology: *"I do not know much about it, but if something goes wrong it needs to be corrected"* (Maahi). Divija implies that correcting the app would allow it to learn from its mistakes, similarly to how a human does: *"I would want to correct and educate the app"* (Divija). On the other hand, five participants said they would not feel comfortable correcting the app and/or would not want to do it. Lakshmi reasoned that inputting the data would add to her already heavy workload: *"I would choose not to write. Because it takes time. We also have to do household chores and then doing this would increase the workload."* (Lakshmi)

Beyond in-app errors and misdiagnosis, we also probed how CHWs might deal with machine or infrastructure failures more broadly. Sixteen participants were cognizant of infrastructural issues that plague mobile phone usage in their daily lives, such as slow data speeds, lack of Internet access in remote areas, not having enough mobile airtime, and running out of battery power, among others:

> *"Like sometimes the server is down. If the server is down then the app won't work. If the phone malfunctions or it gets discharged, then I would simply give the information I know."* (Advika)

Eight participants felt that their limited technology skills would hinder their ability to operate the AI app in the event of a malfunction: *"We do not even know what to do if the app stops"* (Shreya). Alternatively, three CHWs said they would seek assistance from their peers to troubleshoot the AI app. Others discussed how they would contact the app developer for technical support: *"We will contact the person who made the app and ask why it is breaking down"* (Shreya). Kaajal, who was familiar with seeking technical assistance for handling issues with her mobile phone, elaborated:

> *"If the app breaks down, like in the phone also, we have the call center's number which helps us resolve the issue. Like, the phone has airtime, but the phone is not working due to network issues. In such situations, we call them and ask for the required information. We would rectify app error in the same way, on our own by consulting someone who might solve the problem."* (Kaajal)

Regardless of whether they would be able to obtain support, 12 CHWs were confident in their ability to continue their examinations despite an app malfunction. This was expected, since participants currently perform much of their work without the assistance of a mobile phone or app. Finally, ten participants mentioned that they would forgo troubleshooting the AI app if the situation was severe, feeling that it would be safer to take the patient to the hospital:

> *"Going to the hospital is always the better option because if the child appears to be suffering, then we won't waste time in these things [fixing the app]. We will take the child to the hospital."* (Jia)

4.5 Negotiating Access to the Data Recorded by an AI App

The video that participants watched for our study depicted a CHW using a camera-enabled AI app to scan a child. We now discuss CHWs' opinions of who should have access to the potentially sensitive data recorded by the app. We use the term "data" to include photos, videos, and textual data captured and stored by the AI app.

CHWs unanimously felt that they should be granted access to both the AI app itself and the data produced by the app, arguing that this access would bolster their knowledge and help them improve their work. Many participants mentioned that such access would also allow them to keep track of information about medical procedures or re-verify patient information, allowing them to provide a higher level of care: *"CHWs should have the video because if they forget something, they could watch the video again and get back the information"* (Isha). Along these lines, Kaamini was eager to improve her knowledge of pneumonia and other diseases by learning from videos like the one in our study: *"By watching the video, we saw what problems the child was suffering from. This would increase our awareness"* (Divija).

A common opinion expressed by participants was that access to the app should be restricted to those with appropriate training. Four participants felt that only CHWs, and no one else, should have access to the app because giving it to others would ruin the *"honor"* associated with being a CHW. Mishka further explained, *"If the app reaches everyone, people will think that they can solve this problem on their own"* (Mishka). As this quote implies, CHWs were critical of the villagers' ability to handle the complexity of an AI app or the information produced by it:

> *"It is better if the app is limited to CHWs. Because villagers can spread the wrong thing. We can't give them the app because they don't have any training. "* (Shreya)

Although CHWs wanted access to the AI app to be restricted from the general public, 13 were open to the idea that **patients** might be allowed to download and use the app. These participants felt that parents of sick children could also learn from having access to the app and corresponding data it produced:

> *"[By using the app,] parents can know why their child is suffering, without going anywhere. Many people feel perplexed when their child is sick. If they are unable to seek immediate medical assistance, then the app could tell them about the problem and the initial steps to cure it. Parents then can do the initial treatment at home and then take the child to a doctor for diagnosis."* (Isha)

CHWs also said that parents of children being diagnosed by the AI app had a right to view the resulting data: *"Because that video is of their child that's why they can also watch it"* (Mishka). Additionally, participants felt that parents should have access to this data to show as a healthcare record or to receive validation from a doctor in outside consultations:

> *"They should have this data so that if they take their baby to some doctor and the doctor does not understand, then they can show him this video that these are the problems with their baby."* (Kavya)

Six CHWs felt that patients do not need access to the data collected by the app. They pointed out lack of literacy skills and smartphones among people in their community as reasons to not give patients access. CHWs also felt that, beyond affirming that their child is safe and healthy, parents do not need any other data:

> *"Why would they require this? They just need information about the health of their babies whether the baby is healthy or not. They are just satisfied if baby's examination is done within the time. They just want their child to be safe and healthy, they don't need any video or report."* (Meera)

CHWs had conflicting opinions about whether the **government** should have access to data collected by the app. Some felt that, since CHWs are already required to send reports to local governments, they would have access to all data regardless: *"Of course the government must have the data. They will anyways have it, because these things always go to the government"* (Saira). However, CHWs like Shreya were wary of the government's need for access to the data due to the general lack of government's everyday involvement in CHWs' work: *"It is not necessary for the government to have the data… The government is not coming here and giving the information to our community"* (Shreya).

Other participants were more positive towards the government having access to the data. They highlighted the need for the government to be aware of what is happening and having access to data produced by the app could bolster their efforts to improve healthcare. Participants also suggested that CHWs could use this data to bargain for more resources: *"Perhaps if they know more about our work, we may get better facilities from the government"* (Shreya).

Many CHWs expressed displeasure at the government in regards to the heavy workload placed on them and the low wages they receive. They felt that they were doing a lot of "invisible" work, without any recognition from superiors and the government administrators. They were expected to not only do their work and extra duties (like COVID management in rural areas), but also to report what they accomplished, which added more burden to them. CHWs hinted at the government instituting (better) surveillance of CHW programs via the AI app and suggested that the app's data may fulfill existing bureaucratic functions which CHWs are forced to do to prove they did their work:

> *"If the government gets the video then they would also know what work we are doing and how we are doing it. Currently the government cannot effectively get a hold on what is happening in the field. They have no idea how hard CHWs work."* (Isha)

Finally, when we asked if the **tech company** that developed the AI app should have access to the data collected, participants provided interesting responses. CHWs felt the company needed to track usage and their users' experiences: *"The creators of the app should know how CHWs are using their product."* CHWs also felt that the tech company would need to provide technical support and troubleshooting help and having access to the data would make that easier:

> *"It is good if the company has this data. If you have any problem, any question, you can call them and ask them. This will make our work easier."* (Samaira)

Developers often use data collected by the app to improve their recommendation systems and prediction algorithms. A few participants were aware that the company behind the fictional AI app could potentially use the data in a similar way. Mishka provided a notable response highlighting the positive effect the data would have on the company:

> *"If they have the data then they will know whether the child has pneumonia. Only if they understand this, they will be able to improve the app. Only then will their company grow."* (Mishka)

When arguing why the company should *not* have access to the data, seven participants suggested that the company's interest is in making money from selling the app, not in the work done by CHWs, and so they do not need the data:

> *"Why would the company need this? CHWs are doing the work using the app. The company won't do any work. They just take the money and provides us the app. They don't need the data."* (Meera)

4.6 Potential Security and Privacy Implications of Using an AI App

The context of healthcare presents a potentially sensitive domain to deploy an AI app. Thus, we were interested to assess our participants' opinions on data security and privacy with regard to the AI app and the sensitive health data it would collect. Although CHWs perceived people's personal information to be sensitive, such as their phone number, residential address, and Aadhaar number (National ID number), they generally did *not* consider health information to constitute sensitive data, particularly if the data was about a baby: *"That information is only about a baby. What can people do wrong to a baby? There is nothing to worry"* (Saira). Moreover, three CHWs believed that, since the app was designed with patient care in mind, it could not cause any digital harm: *"With what I know, it will not be used in harmful manner"* (Maahi). In general, participants had faith in the app designers that they would take necessary steps to ensure that the AI app cannot be misused.

When considering their own role in collecting and storing the data, three CHWs believed that as long as they were responsible when using the device and prevented it from being stolen or lost, no harm could come to the data. Priya told us that with training, they would learn to use the app appropriately, and hence the data would be secure. Divija shared similar sentiments, and added that CHWs would never misuse health data or personal information.

Five CHWs discussed how there could be a threat to the patient's security and privacy if the data *"fell into the wrong hands."* For example, Kaajal suggested that the patient's information, for example, mobile phone number could be misused by others to make pesky calls. Similarly, Jia felt, *"If phone number falls into the wrong hands then some miscreants might cause some trouble."* Shreya shared an incident where women were harassed when their phone number became available online. She further recalled an incident of financial fraud, where someone got access to the phone number and Aadhaar number of a few CHWs, and their money got deducted from their accounts. In most of these opinions, we saw that CHWs implicitly believe that the patient's security and privacy will only be compromised if the data includes personally identifying or other official information: *"If the things like a signature and other official things are not included then I don't think there will be harm"* (Aparna). Similar to prior work in other HCI4D settings [29], we found that a lack of technology know-how resulted in the dominance of a physical threat model among CHWs. Only one CHW mentioned that sensitive information in the AI app could be hacked by another malicious app installed on the phone, subscribing to popular discourse in India about how Chinese apps can hack data from other applications. This perception is in line with the findings from Vashistha et al. who found similar beliefs among mobile money customers in rural India [115].

Another class of security and privacy issues that commonly arises in HCI4D contexts, including rural India, is that multiple individuals frequently share a single digital device [6, 100, 114]. Of the 17 participants in our study who used smartphones, 15 said that they use the device for work, and 12 told us that they shared their device with their family. However, nine participants were not concerned about their family members having access to sensitive (work) data on their devices, even though our findings suggest a number of concerning practices related to shared phone use. For example, Maahi described how, even though her husband owns his own phone, he still uses her mobile:

> *"Whenever I say that I have to take it to work, he gives it to me. When he wishes to use this phone, I leave it at home and ask him to operate it, as I would have no use for it on that particular day. I do not take it. If I need any information I come back [home] and see it."* (Maahi)

She went on to say that her husband reads her messages and informs her if any work messages arrive, a finding that implies her husband already has access to her work-related information via her device. Another six participants shared that, although their children use their mobile phones, they trust them to not access or delete important data:

> *"Children sometimes play games with the phone. But downloading something is not allowed. I say, 'don't do anything wrong with Mummy's mobile, so that she does not face trouble using mobile at work.'"* (Mishka)

By contrast, Vanya said how her children had previously accidentally deleted important health reports from her phone in the past when she let them use it, and thus felt that shared device use might cause problems. Finally, beyond sharing devices with a spouse or children, six CHWs said that they often seek help from others to operate their phone. Kaamini shares her device with her daughter-in-law, who is also a CHW. She said:

> *"We have two or three mobiles. But I can't operate them. My children run them. If there is some work or I have to send something, I ask my daughter-in-law to do it. Only she does it."* (Kaamini)

5 DISCUSSION

Over the last few decades, the HCI4D community has seen a large number of "social good" initiatives that aim to harness the potential of technologies to solve global, systemic problems. Notable examples include setting up telecenters in rural villages [18], distributing low-cost laptops in an effort to make computers available to all [13], using mobile phones to reduce poverty [32], providing free basic Internet connectivity in an effort to *"bring more people online and help improve their lives"* [55], using drones to solve problems of access to medical services [106], and using virtual reality for "impact" [3]. However, the true successes of these initiatives in achieving social good are few, fleeting, and very far between [112]. Recent advances in AI, coupled with rapid growth in the availability of smartphones and Internet access in the Global South, are driving governments [66], non-profit organizations [7], and technology companies [53] to establish new initiatives that aim to use AI to address intractable global problems. In this section we ask, *how can these AI initiatives avoid the perils and pitfalls that have caused past "technology for social good" initiatives to fail?*

In his work on amplification theory, Toyama argues that technology is only a magnifier of existing institutional forces and cannot substitute for missing human intent and capacity [112]. Sadly, the narrative that AI will lead to "*a new form of human civilization*" [82] is exactly what Toyama warns about and is in line with past initiatives that saw computers, the Internet, mobile phones, drones, or virtual reality as silver bullet solutions for complex societal problems. A future in which AI is cast as humanity's new frontier [82] risks applying AI to global problems in ways that exceed AI's capability and assume AI will be additive or transformative in and of itself, rather than simply a tool that amplifies human intent and capacity. Drawing on our findings, we now discuss (1) considerations for AI and HCI researchers interested in deploying AI in low-resource contexts, (2) the complexities of making AI explainable to novice users, and (3) the need to account for diverse values and ethics when designing AI interventions for marginalized communities.

5.1 Considerations for the Design and Deployment of AI Systems in Marginalized Communities

Our findings show that at the time of our study, CHWs had very low levels of AI knowledge. This is concerning, given that AI applications that target their work are already in active development. Indeed, early deployments of AI-enabled technologies in low-resource clinical settings have already reported failures that, at best, created additional inefficiencies in clinical workflows and, at worst, caused harm to the very communities they aimed to serve [17]. We now consider both what *designers and developers* of AI systems need to know to maximize the chances their intervention helps, rather than hurts, and what *CHWs* need to know to become effective and enabled AI workers.

What do AI designers/developers need to know to effectively create appropriate AI systems for CHWs? First and foremost, our findings suggest an urgent need for AI developers to ensure they have a *deep understanding of the context* in which they plan to deploy an AI system. While this is true of *all* HCI4D research [14, 37], AI technologies present new societal risks and complexities (e.g., inequality, fairness, accountability, transparency, unintended consequences, etc.) that must be proactively studied *before* attempting deployment.

For example, our findings suggest that AI developers would do well to *plan for failure* [10]. Potential failures that our study explored included both the possibility of the app delivering an incorrect diagnosis (i.e., misclassification) and the possibility of out-of-app failures due to infrastructural challenges (i.e., no connectivity, phone malfunction). In the face of an error, most CHWs said they would simply repeat the procedure until they achieved the desired outcome, something that they assumed they would intuitively know. However, given CHWs' low levels of AI knowledge and technology know-how, and their strong positive feelings towards the technology (discussed in Section 4.2), a more likely and concerning outcome may be that they simply do not challenge the outcome delivered by the AI system. Thus, drawing on Amershi's work [10], we argue that rather than considering the potential for system failures as an afterthought or unlikely occurrence, it is important for AI developers to systematically and proactively identify, assess, and mitigate both the failures themselves and potential harms caused by such failures in AI-based products and services, especially when those failures may be invisible to users and have serious consequences for patients.

Our findings also suggest that it is crucial for organizations that plan to deploy AI systems to carefully consider and *plan for sustainability, maintenance, and repair* of these systems. As with any new technology, deployments "in the wild" will require constant technical support and maintenance [109]. We frequently heard from CHWs that they would want to be able to call the company for assistance. Without such scaffolding, any AI intervention is bound to fail. While the need to plan for maintenance and repair is true of all technology deployments, especially in HCI4D [51, 59], the complexity of troubleshooting and maintaining complex AI software may require continued involvement of highly-skilled AI designers and developers. It is unlikely that local repair ecosystems, such as those that have emerged for mobile phone repair [58, 59], will possess the tools or capabilities to appropriately troubleshoot complex AI systems.

Developers of AI systems will also need to *pay close attention to the impact on CHWs' work.* CHWs are already burdened by heavy workloads and the introduction of new AI tools will inevitably increase this workload (even if the ultimate goal is to decrease it [17]). Our findings show that deploying AI systems within CHWs' workflows will likely result in additional work that is both visible (e.g., actually using the AI app) and invisible (e.g., explaining and justifying use of the AI app and its decisions/consequences to their communities). In addition, this work will be unevenly distributed across CHWs, with older, less tech-savvy CHWs likely spending more time doing invisible work as they struggle to operate the AI app. AI developers need to account for this additional work and extra burdens shouldered by CHWs when weighing the benefits and harms of AI systems, and offer continued training and support. Building on this, we now discuss what CHWs might need to know to operate AI systems effectively.

What do CHWs need to know to be effective AI workers? HCI4D researchers have long acknowledged the vital role played by training and support programs in the success of technology interventions [14, 37]. Most commonly, these training programs focus on *how to use* the new technology. Indeed, prior work deploying computer-vision-assisted applications with CHWs focused heavily on teaching users to interact with the app, buttons to press, etc. [36, 93].

Although it will undoubtedly be necessary to train CHWs on how to use any new AI intervention, our findings point to a deeper set of issues that must be addressed before CHWs are able to safely and effectively use AI in their work. One concern raised by our findings is that many CHWs may possess a utopian view of AI [102], perceiving it to be infallible and ascribing to it more capabilities than it possesses. At the same time, we heard how CHWs may trust the AI's expertise more than their own, and how they thought the AI app was intrinsically safe simply because it was designed to help patients. These utopian views could have far-reaching consequences if, for example, CHWs act on incorrect predictions instead of challenging them.

These insights suggest that, in addition to training programs on how to use AI systems, there is an urgent need to teach CHWs—who will be users of AI interventions—to think critically about AI systems, develop a balanced view of their strengths and weaknesses, and instill an awareness of the risks and potential for errors. It will also be important to set appropriate expectations about what the AI is (and is not) capable of. Moreover, since AI developers will undoubtedly be expecting CHWs to collect data that is fed back into their AI training algorithms, CHWs will need to understand the properties of the underlying AI systems sufficiently to ensure that their use does not lead to biased data collection and outcomes. This will require work to make the AI explainable to novice technology users, as we now discuss.

5.2 Making AI explainable to novice users

Although the video we showed to CHWs did not explain *how* the AI app arrived at a decision, our findings suggest that CHWs nevertheless formed (often incorrect) mental models about how the AI app worked (e.g., by drawing parallels between the machine's intelligence and human intelligence). This is in line with psychology research, which suggests that in the absence of a clear explanation, people will create their own hypothesis for how something works and act according to this hypothesis [90]. For CHWs, developing and operating on incorrect mental models of how an AI system works under the hood could have serious implications that lead to unintended consequences. Thus, before deploying AI systems with CHWs, it is critical that AI designers make the AI explainable and its decisions interpretable.

A rich body of research that focuses on explainable AI has examined ways to make AI more transparent [5, 23, 120] and designed tools and frameworks to provide explanations for the decisions and actions taken by AI [71]. However, *all* prior work on explainable AI has focused on users that live in relatively resource-rich settings (e.g., the US and Europe) and that arguably have substantially more experience with digital technologies overall, and AI systems in particular, than novice technology users in the Global South. Most CHWs in our study did not use computers, had been using a (shared) smartphone for at most one year, and had almost no AI knowledge. Our study therefore raises the question: *How do we make AI explainable to novice technology users in the Global South?*

Answering this question will require the establishment of a new sub-area of explainable AI research that specifically explores how to explain AI to people with low levels of formal education, literacy, and technology know-how. Future research in this area will need to engage with a host of technical, social, and cultural questions, including: What accuracy indicators (e.g., confidence score) might work for these communities and how should these indicators be presented to novice users? How do we explain to users where the data is coming from (e.g., gender, age group, geography) and the role it plays in the AI system? How do we make transparent the features used by the AI to make decisions? How do we incorporate human explanations [77] in a way that are accessible to low-income, low-literate, novice users? The AI and HCI communities need to deeply engage with these questions using human-centered design methods (e.g., Wizard of Oz experiments, design probes, participatory design) and work with diverse communities in the Global South in ways that facilitate *safe* exploration and experimentation with explainable AI strategies *before* attempting to deploy AI within these communities, especially in precarious HCI4D settings where AI could do more harm than good.

5.3 Accounting for Diverse Values and Ethics in AI

Finally, our findings raise a number of concerning ethical questions and challenges. For example, CHWs described how they would hide an incorrect diagnosis from patients so that it would not harm their reputation or the community's trust in them. Others said they would not override mistakes made by the AI system. Still others described how they share sensitive patient data with family members who use their device.

Navigating such issues is not straightforward. Who should decide the correct course of action? Research in the West has engaged deeply with the ethical, legal, and policy implications of deploying AI in human societies [63, 80], including the potential for harmful unintended consequences [98]. However, these conversations have largely excluded the Global South. Meanwhile many low- and middle-income countries, including India, do not have laws that safeguard users from risks emanating from AI. And in healthcare, there are currently no regulatory requirements for AI systems to be evaluated through observational clinical studies, nor is it a common practice [108]. Instead, the success of AI systems is measured through accuracy, rather than on its ability to improve care. With the push to use AI to address societal problems in low-resource settings, including in healthcare, there is an urgent need to create regulatory frameworks and policies that ensure AI developers and users adhere to standards for safe and privacy-preserving AI.

At the same time, research suggests that human values are inevitably embedded in the design of technologies [47]. This leads to important questions, such as whose values should AI systems prioritize when they are designed to address complex issues of social justice and equity? How do we ensure that sociocultural biases and inequities are not replicated in AI systems? How do we ensure that people whose lives will be impacted by AI have a say in its development?

Answering these questions is, again, not straightforward. Our findings suggest that the values of AI developers, users (CHWs), and communities (patients) may at times be contradictory. For example, many CHWs were willing to share their patients' private health data with a wide array of stakeholders (including their family members), and did not perceive risks with this behavior. By contrast, Western privacy laws and norms mandate the requirement to protect the privacy of people's personal health data. More broadly, research has clearly documented large variations in how different cultures approach the topic of privacy [84, 114]. How should AI developers reconcile such value differences? Should they, via the design of the AI system, impose Western values of privacy onto these CHWs who think differently about data confidentiality? Or, should CHWs be "educated" about the privacy risks, which may intrinsically imply that Western notions of privacy matter more than their own. Alternatively, how do we create AI systems that respect diverse communities' cultural and value differences, while ensuring safe and equitable outcomes? It is essential that the HCI and AI research communities grapple with these issues now, before AI systems are deployed in ways that might harm the very communities they aim to serve.

6 CONCLUSION

This paper described an exploratory qualitative study that examined CHWs' perceptions and knowledge of AI applications, along with the benefits and challenges they foresee as AI applications are integrated into the essential healthcare services they provide to rural communities in India. We uncovered key tensions surrounding CHWs' perceptions of automation of their work, negotiating trust in the AI and themselves, navigating possible misdiagnosis and errors, opinions of data access and surveillance, and security and privacy challenges. We concluded by discussing (1) considerations for AI and HCI researchers interested in deploying AI systems in low-resource contexts, (2) the complexities of making AI systems explainable to novice users, and (3) the need to account for diverse values and ethics within the design of AI interventions for marginalized communities. The prevalence of CHW programs around the world suggests some of our findings may be relevant beyond rural India. However, future research is required to explore the extent to which our findings may generalize.

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REFERENCES

[1] 2020. About Accredited Social Health Activist (ASHA) : National Health Mission. https://nhm.gov.in/index1.php?lang=1&level=1&sublinkid=150&lid=226
[2] 2020. India States Briefs – Uttar Pradesh. https://www.worldbank.org/en/country/india/brief/india-states-briefs-uttar-pradesh
[3] 2020. VR for Impact. https://vrforimpact.com
[4] NITI Aayog. 2018. National strategy for artificial intelligence. *Paper. June* (2018).
[5] Ashraf Abdul, Jo Vermeulen, Danding Wang, Brian Y. Lim, and Mohan Kankanhalli. 2018. Trends and Trajectories for Explainable, Accountable and Intelligible Systems: An HCI Research Agenda. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (Montreal QC, Canada) *(CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–18. https://doi.org/10.1145/3173574.3174156
[6] Syed Ishtiaque Ahmed, Md Romael Haque, Jay Chen, and Nicola Dell. 2017. Digital privacy challenges with shared mobile phone use in bangladesh. *Proceedings of the ACM on Human-Computer Interaction* 1, CSCW (2017), 1–20.
[7] Wadhwani AI. 2020. Retrieved September 8, 2020 from https://www.wadhwaniai.org/
[8] Wadhwani AI. 2020. AI-POWERED ANTHROPOMETRY. Retrieved September 8, 2020 from https://www.wadhwaniai.org/work/maternal-newborn-child-health/
[9] Saleema Amershi. 2020. Toward Responsible AI by Planning to Fail. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. 3607–3607.
[10] Saleema Amershi. 2020. Toward Responsible AI by Planning to Fail. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (KDD '20)*. Association for Computing Machinery, New York, NY, USA, 3607. https://doi.org/10.1145/3394486.3409557
[11] Saleema Amershi, Maya Cakmak, William Bradley Knox, and Todd Kulesza. 2014. Power to the people: The role of humans in interactive machine learning. *Ai Magazine* 35, 4 (2014), 105–120.
[12] Saleema Amershi, Dan Weld, Mihaela Vorvoreanu, Adam Fourney, Besmira Nushi, Penny Collisson, Jina Suh, Shamsi Iqbal, Paul N Bennett, Kori Inkpen, et al. 2019. Guidelines for human-AI interaction. In *Proceedings of the 2019 CHI conference on Human Factors in Computing Systems*. 1–13.

[13] Morgan G Ames. 2019. *The charisma machine: The life, death, and legacy of One Laptop per Child.* MIT.

[14] Yaw Anokwa, Thomas N Smyth, Divya Ramachandran, Jahanzeb Sherwani, Yael Schwartzman, Rowena Luk, Melissa Ho, Neema Moraveji, and Brian DeRenzi. 2009. Stories from the field: Reflections on HCI4D experiences. *Information Technologies & International Development* 5, 4 (2009), pp–101.

[15] Gagan Bansal, Besmira Nushi, Ece Kamar, Walter S Lasecki, Daniel S Weld, and Eric Horvitz. 2019. Beyond accuracy: The role of mental models in human-AI team performance. In *Proceedings of the AAAI Conference on Human Computation and Crowdsourcing*, Vol. 7. 2–11.

[16] Abdullah H Baqui, Shams El-Arifeen, Gary L Darmstadt, Saifuddin Ahmed, Emma K Williams, Habibur R Seraji, Ishtiaq Mannan, Syed M Rahman, Rasheduzzaman Shah, Samir K Saha, et al. 2008. Effect of community-based newborn-care intervention package implemented through two service-delivery strategies in Sylhet district, Bangladesh: a cluster-randomised controlled trial. *The lancet* 371, 9628 (2008), 1936–1944.

[17] Emma Beede, Elizabeth Baylor, Fred Hersch, Anna Iurchenko, Lauren Wilcox, Paisan Ruamviboonsuk, and Laura M Vardoulakis. 2020. A Human-Centered Evaluation of a Deep Learning System Deployed in Clinics for the Detection of Diabetic Retinopathy. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–12.

[18] Michael L Best and Rajendra Kumar. 2008. Sustainability failures of rural telecenters: Challenges from the sustainable access in rural india (sari) project. (2008).

[19] Pranav Bhagat, Sachin Kumar Prajapati, and Aaditeshwar Seth. 2020. Initial Lessons from Building an IVR-based Automated Question-Answering System. In *Proceedings of the 2020 International Conference on Information and Communication Technologies and Development*. 1–5.

[20] Virginia Braun and Victoria Clarke. 2006. Using thematic analysis in psychology. *Qualitative research in psychology* 3, 2 (2006), 77–101.

[21] Anna Brown, Alexandra Chouldechova, Emily Putnam-Hornstein, Andrew Tobin, and Rhema Vaithianathan. 2019. Toward Algorithmic Accountability in Public Services: A Qualitative Study of Affected Community Perspectives on Algorithmic Decision-making in Child Welfare Services. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3290605.3300271

[22] Joy Buolamwini and Timnit Gebru. 2018. Gender shades: Intersectional accuracy disparities in commercial gender classification. In *Conference on fairness, accountability and transparency*. 77–91.

[23] Margaret Burnett. 2020. Explaining AI: Fairly? Well?. In *Proceedings of the 25th International Conference on Intelligent User Interfaces* (Cagliari, Italy) *(IUI '20)*. Association for Computing Machinery, New York, NY, USA, 1–2. https://doi.org/10.1145/3377325.3380623

[24] Carrie J. Cai, Samantha Winter, David Steiner, Lauren Wilcox, and Michael Terry. 2019. "Hello AI": Uncovering the Onboarding Needs of Medical Practitioners for Human-AI Collaborative Decision-Making. *Proc. ACM Hum.-Comput. Interact.* 3, CSCW, Article 104 (Nov. 2019), 24 pages. https://doi.org/10.1145/3359206

[25] Vikram Kamath Cannanure, Timothy X Brown, and Amy Ogan. 2020. DIA: A Human AI Hybrid Conversational Assistant for Developing Contexts. In *Proceedings of the 2020 International Conference on Information and Communication Technologies and Development* (Guayaquil, Ecuador) *(ICTD 2020)*. Association for Computing Machinery, New York, NY, USA, Article 24, 5 pages. https://doi.org/10.1145/3392561.3397577

[26] Y. Cao, C. Liu, B. Liu, M. J. Brunette, N. Zhang, T. Sun, P. Zhang, J. Peinado, E. S. Garavito, L. L. Garcia, and W. H. Curioso. 2016. Improving Tuberculosis Diagnostics Using Deep Learning and Mobile Health Technologies among Resource-Poor and Marginalized Communities. In *2016 IEEE First International Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE)*. 274–281.

[27] Stephen Cave, Kate Coughlan, and Kanta Dihal. 2019. "Scary Robots": Examining Public Responses to AI. In *Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society* (Honolulu, HI, USA) *(AIES '19)*. Association for Computing Machinery, New York, NY, USA, 331–337. https://doi.org/10.1145/3306618.3314232

[28] Tathagata Chakraborti and Subbarao Kambhampati. 2019. (When) can AI bots lie?. In *Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society*. 53–59.

[29] Jay Chen, Michael Paik, and Kelly McCabe. 2014. Exploring internet security perceptions and practices in urban ghana. In *Proceedings of the Tenth USENIX Conference on Usable Privacy and Security (SOUPS '14)*. USENIX Association, USA, 129–142.

[30] Liang-Kung Chen. 2018. Artificial intelligence in medicine and healthcare.

[31] Ivan Contreras and Josep Vehi. 2018. Artificial intelligence for diabetes management and decision support: literature review. *Journal of medical Internet research* 20, 5 (2018), e10775.

[32] Sara Corbett. 2008. Can the Cellphone Help End Global Poverty? *The New York Times* (April 2008). https://www.nytimes.com/2008/04/13/magazine/13anthropology-t.html

[33] Darcy A. Davis, Nitesh V. Chawla, Nicholas Blumm, Nicholas Christakis, and Albert-László Barabasi. 2008. Predicting Individual Disease Risk Based on Medical History. In *Proceedings of the 17th ACM Conference on Information and Knowledge Management* (Napa Valley, California, USA) *(CIKM '08)*. Association for Computing Machinery, New York, NY, USA, 769–778. https://doi.org/10.1145/1458082.1458185

[34] Nicola Dell and Gaetano Borriello. 2013. Mobile tools for point-of-care diagnostics in the developing world. In *Proceedings of the 3rd ACM Symposium on Computing for Development*. 1–10.

[35] Nicola Dell, Jessica Crawford, Nathan Breit, Timóteo Chaluco, Aida Coelho, Joseph McCord, and Gaetano Borriello. 2013. Integrating ODK Scan into the Community Health Worker Supply Chain in Mozambique. In *Proceedings of the Sixth International Conference on Information and Communication Technologies and Development: Full Papers - Volume 1* (Cape Town, South Africa) *(ICTD '13)*. Association for Computing Machinery, New York, NY, USA, 228–237. https://doi.org/10.1145/2516604.2516611

[36] Nicola Dell, Ian Francis, Haynes Sheppard, Raiva Simbi, and Gaetano Borriello. 2014. Field evaluation of a camera-based mobile health system in low-resource settings. In *Proceedings of the 16th international conference on Human-computer interaction with mobile devices & services*. 33–42.

[37] Nicola Dell and Neha Kumar. 2016. The ins and outs of HCI for development. In *Proceedings of the 2016 CHI conference on human factors in computing systems*. 2220–2232.

[38] Nicola Dell, Vidya Vaidyanathan, Indrani Medhi, Edward Cutrell, and William Thies. 2012. "Yours is Better!": Participant Response Bias in HCI. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Austin, Texas, USA) *(CHI '12)*. Association for Computing Machinery, New York, NY, USA, 1321–1330. https://doi.org/10.1145/2207676.2208589

[39] Brian DeRenzi, Nicola Dell, Jeremy Wacksman, Scott Lee, and Neal Lesh. 2017. Supporting community health workers in India through voice-and web-based feedback. In *Proceedings of the 2017 CHI conference on human factors in computing systems*. 2770–2781.

[40] Brian DeRenzi, Leah Findlater, Jonathan Payne, Benjamin Birnbaum, Joachim Mangilima, Tapan Parikh, Gaetano Borriello, and Neal Lesh. 2012. Improving community health worker performance through automated SMS. In *Proceedings of the Fifth International Conference on Information and Communication Technologies and Development*. 25–34.

[41] Brian DeRenzi, Neal Lesh, Tapan Parikh, Clayton Sims, Werner Maokla, Mwajuma Chemba, Yuna Hamisi, David S hellenberg, Marc Mitchell, and Gaetano Borriello. 2008. E-IMCI: Improving pediatric health care in low-income countries. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 753–762.

[42] Brian DeRenzi, Jeremy Wacksman, Nicola Dell, Scott Lee, Neal Lesh, Gaetano Borriello, and Andrew Ellner. 2016. Closing the feedback Loop: A 12-month evaluation of ASTA, a self-tracking application for ASHAs. In *Proceedings of the Eighth International Conference on Information and Communication Technologies and Development*. 1–10.

[43] Xianghua Ding, Yanqi Jiang, Xiankang Qin, Yunan Chen, Wenqiang Zhang, and Lizhe Qi. 2019. Reading Face, Reading Health: Exploring Face Reading Technologies for Everyday Health. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3290605.3300435

[44] Lynn Dombrowski, Ellie Harmon, and Sarah Fox. 2016. Social Justice-Oriented Interaction Design: Outlining Key Design Strategies and Commitments. In *Proceedings of the 2016 ACM Conference on Designing Interactive Systems (DIS '16)*. Association for Computing Machinery, New York, NY, USA, 656–671. https://doi.org/10.1145/2901790.2901861

[45] Artificial Intelligence Task Force. 2018. Artificial Intelligence Task Force, constituted by Ministry of Commerce and Industry. *Government of the Republic of India, available online at www.aitf.org.in* (2018).

[46] Martin Ford. 2015. *Rise of the Robots: Technology and the Threat of a Jobless Future.* Basic Books.

[47] Batya Friedman and Peter H Kahn Jr. 2003. Human values, ethics, and design. *The human-computer interaction handbook* (2003), 1177–1201.

[48] Katy Ilonka Gero, Zahra Ashktorab, Casey Dugan, Qian Pan, James Johnson, Werner Geyer, Maria Ruiz, Sarah Miller, David R. Millen, Murray Campbell, Sadhana Kumaravel, and Wei Zhang. 2020. Mental Models of AI Agents in a Cooperative Game Setting. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3313831.3376316

[49] Abid Haleem, Mohd Javaid, and Ibrahim Haleem Khan. 2019. Current status and applications of Artificial Intelligence (AI) in medical field: An overview. *Current Medicine Research and Practice* 9, 6 (2019), 231 – 237. https://doi.org/10.1016/j.cmrp.2019.11.005

[50] Carl Hartung, Adam Lerer, Yaw Anokwa, Clint Tseng, Waylon Brunette, and Gaetano Borriello. 2010. Open Data Kit: Tools to Build Information Services for Developing Regions. In *Proceedings of the 4th ACM/IEEE International Conference on Information and Communication Technologies and Development* (London, United Kingdom) *(ICTD '10)*. Association for Computing Machinery, New York, NY, USA, Article 18, 12 pages. https://doi.org/10.1145/2369220.2369236

[51] Lara Houston, Steven J Jackson, Daniela K Rosner, Syed Ishtiaque Ahmed, Meg Young, and Laewoo Kang. 2016. Values in repair. In *Proceedings of the 2016 CHI conference on human factors in computing systems*. 1403–1414.

[52] Hilary Hutchinson, Wendy Mackay, Bo Westerlund, Benjamin B. Bederson, Allison Druin, Catherine Plaisant, Michel Beaudouin-Lafon, Stéphane Conversy, Helen Evans, Heiko Hansen, Nicolas Roussel, and Björn Eiderbäck. 2003. Technology probes: inspiring design for and with families. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '03)*. Association for Computing Machinery, New York, NY, USA, 17–24. https://doi.org/10.1145/642611.642616

[53] Google Research India. 2020. Retrieved September 8, 2020 from https://research.google/locations/india/

[54] Google Research India. 2020. Applying AI to Big Problems. Retrieved September 8, 2020 from https://india.googleblog.com/2020/02/applying-ai-to-big-problemssix-research.html?m=1

[55] Internet.org. 2020. Free Basics from Facebook. Retrieved September 8, 2020 from https://info.internet.org/en/story/free-basics-from-internet-org/

[56] Azra Ismail, Naveena Karusala, and Neha Kumar. 2018. Bridging Disconnected Knowledges for Community Health. *Proceedings of the ACM on Human-Computer Interaction* 2, CSCW (2018), 1–27.

[57] Azra Ismail and Neha Kumar. 2018. Engaging solidarity in data collection practices for community health. *Proceedings of the ACM on Human-Computer Interaction* 2, CSCW (2018), 1–24.

[58] Steven J Jackson, Syed Ishtiaque Ahmed, and Md Rashidujjaman Rifat. 2014. Learning, innovation, and sustainability among mobile phone repairers in Dhaka, Bangladesh. In *Proceedings of the 2014 conference on Designing interactive systems*. 905–914.

[59] Steven J Jackson, Alex Pompe, and Gabriel Krieshok. 2012. Repair worlds: maintenance, repair, and ICT for development in rural Namibia. In *Proceedings of the ACM 2012 conference on Computer Supported Cooperative Work*. 107–116.

[60] Mohit Jain, Pratyush Kumar, Ishita Bhansali, Q. Vera Liao, Khai Truong, and Shwetak Patel. 2018. FarmChat: A Conversational Agent to Answer Farmer Queries. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 4 (Dec. 2018), 170:1–170:22. https://doi.org/10.1145/3287048

[61] Maurice Jakesch, Megan French, Xiao Ma, Jeffrey T Hancock, and Mor Naaman. 2019. AI-mediated communication: How the perception that profile text was written by AI affects trustworthiness. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–13.

[62] Huanhuan Ji, Zhenbing Liu, Wei Qi Yan, and Reinhard Klette. 2019. Early Diagnosis of Alzheimer's Disease Using Deep Learning. In *Proceedings of the 2nd International Conference on Control and Computer Vision* (Jeju, Republic of Korea) *(ICCCV 2019)*. Association for Computing Machinery, New York, NY, USA, 87–91. https://doi.org/10.1145/3341016.3341024

[63] Anna Jobin, Marcello Ienca, and Effy Vayena. 2019. The global landscape of AI ethics guidelines. *Nature Machine Intelligence* 1, 9 (2019), 389–399.

[64] Patrick Gage Kelley, Yongwei Yang, Courtney Heldreth, Christopher Moessner, Aaron Sedley, Andreas Kramm, David Newman, and Allison Woodruff. 2019. " Happy and Assured that life will be easy 10years from now.": Perceptions of Artificial Intelligence in 8 Countries. *arXiv preprint arXiv:2001.00081* (2019).

[65] Rafal Kocielnik, Saleema Amershi, and Paul N Bennett. 2019. Will you accept an imperfect AI? exploring designs for adjusting end-user expectations of AI systems. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–14.

[66] Mamidala Jagadesh Kumar. 2019. National Centre on Artificial Intelligence: India on the Move.

[67] Neha Kumar and Richard J Anderson. 2015. Mobile phones for maternal health in rural India. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. 427–436.

[68] Neha Kumar, Waylon Brunette, Nicola Dell, Trevor Perrier, Beth Kolko, Gaetano Borriello, and Richard Anderson. 2015. Understanding sociotechnical implications of mobile health deployments in India, Kenya, and Zimbabwe. *Information Technologies & International Development* 11, 4 (2015), pp–17.

[69] Vishwajeet Kumar, Saroj Mohanty, Aarti Kumar, Rajendra P Misra, Mathuram Santosham, Shally Awasthi, Abdullah H Baqui, Pramod Singh, Vivek Singh, Ramesh C Ahuja, et al. 2008. Effect of community-based behaviour change management on neonatal mortality in Shivgarh, Uttar Pradesh, India: a cluster-randomised controlled trial. *The Lancet* 372, 9644 (2008), 1151–1162.

[70] Jeff Larson, Surya Mattu, Lauren Kirchner, and Julia Angwin. 2016. How we analyzed the COMPAS recidivism algorithm. *ProPublica (5 2016)* 9, 1 (2016).

[71] Q. Vera Liao, Daniel Gruen, and Sarah Miller. 2020. Questioning the AI: Informing Design Practices for Explainable AI User Experiences. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–15. https://doi.org/10.1145/3313831.3376590

[72] Joseph Lindley, Haider Ali Akmal, Franziska Pilling, and Paul Coulton. 2020. Researching AI Legibility through Design. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3313831.3376792

[73] Duri Long and Brian Magerko. 2020. What is AI Literacy? Competencies and Design Considerations. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–16.

[74] Frank Marcinkowski, Kimon Kieslich, Christopher Starke, and Marco Lünich. 2020. Implications of AI (un-) fairness in higher education admissions: the effects of perceived AI (un-) fairness on exit, voice and organizational reputation. In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*. 122–130.

[75] Paul K McClure. 2018. "You're fired," says the robot: The rise of automation in the workplace, technophobes, and fears of unemployment. *Social Science Computer Review* 36, 2 (2018), 139–156.

[76] Indrani Medhi and Kentaro Toyama. 2007. Full-context videos for first-time, non-literate PC users. In *2007 International Conference on Information and Communication Technologies and Development*. 1–9. https://doi.org/10.1109/ICTD.2007.4937400

[77] Tim Miller. 2019. Explanation in artificial intelligence: Insights from the social sciences. *Artificial Intelligence* 267 (Feb. 2019), 1–38. https://doi.org/10.1016/j.artint.2018.07.007

[78] Maletsabisa Molapo, Melissa Densmore, and Brian DeRenzi. 2017. Video consumption patterns for first time smartphone users: Community health workers in Lesotho. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*. 6159–6170.

[79] Maletsabisa Molapo, Melissa Densmore, and Limpho Morie. 2016. Designing with community health workers: enabling productive participation through exploration. In *Proceedings of the First African Conference on Human Computer Interaction*. 58–68.

[80] Michael Muller and Q. Vera Liao. 2017. Exploring AI Ethics and Values through Participatory Design Fictions. *Human Computer Interaction Consortium* (2017).

[81] Sundaram Natarajan, Astha Jain, Radhika Krishnan, Ashwini Rogye, and Sobha Sivaprasad. 2019. Diagnostic Accuracy of Community-Based Diabetic Retinopathy Screening With an Offline Artificial Intelligence System on a Smartphone. *JAMA Ophthalmology* 137, 10 (10 2019), 1182–1188. https://doi.org/10.1001/jamaophthalmol.2019.2923 arXiv:https://jamanetwork.com/journals/jamaophthalmology/articlepdf/2747315/jamaophthalmolo

[82] United Nations. 2019. Towards an Ethics of Artificial Intelligence. https://www.un.org/en/chronicle/article/towards-ethics-artificial-intelligence Publisher: United Nations.

[83] Kee Yuan Ngiam and Wei Khor. 2019. Big data and machine learning algorithms for health-care delivery. *The Lancet Oncology* 20, 5 (2019), e262–e273.

[84] Helen Nissenbaum. 2009. *Privacy in context: Technology, policy, and the integrity of social life.* Stanford University Press.

[85] Adeline Nyamathi, Alecia Y. Hanson, Benissa E. Salem, Sanjeev Sinha, Kalyan K. Ganguly, Barbara Leake, Kartik Yadav, and Mary Marfisee. 2012. Impact of a Rural Village Women (Asha) Intervention on Adherence to Antiretroviral Therapy in Southern India. *Nursing research* 61, 5 (2012), 353–362. https://doi.org/10.1097/NNR.0b013e31825fe3ef

[86] Ziad Obermeyer and Sendhil Mullainathan. 2019. Dissecting racial bias in an algorithm that guides health decisions for 70 million people. In *Proceedings of the Conference on Fairness, Accountability, and Transparency*. 89–89.

[87] Fabian Okeke, Lucas Nene, Anne Muthee, Stephen Odindo, Dianna Kane, Isaac Holeman, and Nicola Dell. 2019. Opportunities and challenges in connecting care recipients to the community health feedback loop. In *Proceedings of the Tenth International Conference on Information and Communication Technologies and Development*. 1–11.

[88] Fabian Okeke, Beatrice Wasunna, Mercy Amulele, Isaac Holeman, and Nicola Dell. 2019. Including the Voice of Care Recipients in Community Health Feedback Loops in Rural Kenya. *Proceedings of the ACM on Human-Computer Interaction* 3, CSCW (2019), 1–20.

[89] World Health Organization. 2019. Pneumonia: Key Facts. Retrieved September 8, 2020 from https://www.who.int/news-room/fact-sheets/detail/pneumonia

[90] Martin T Orne. 1962. On the social psychology of the psychological experiment: With particular reference to demand characteristics and their implications. *American psychologist* 17, 11 (1962), 776.

[91] Caroline O'Neill. 2017. Is AI a threat or benefit to health workers?

[92] Joyojeet Pal, Anjuli Dasika, Ahmad Hasan, Jackie Wolf, Nick Reid, Vaishnav Kameswaran, Purva Yardi, Allyson Mackay, Abram Wagner, Bhramar Mukherjee, et al. 2017. Changing data practices for community health workers: Introducing digital data collection in West Bengal, India. In *Proceedings of the Ninth International Conference on Information and Communication Technologies and Development*. 1–12.

[93] Chunjong Park, Alex Mariakakis, Jane Yang, Diego Lassala, Yasamba Djiguiba, Youssouf Keita, Hawa Diarra, Beatrice Wasunna, Fatou Fall, Marème Soda Gaye, et al. 2020. Supporting Smartphone-Based Image Capture of Rapid Diagnostic Tests in Low-Resource Settings. In *Proceedings of the 2020 International Conference on Information and Communication Technologies and Development*. 1–11.

[94] Sun Young Park, Pei-Yi Kuo, Andrea Barbarin, Elizabeth Kaziunas, Astrid Chow, Karandeep Singh, Lauren Wilcox, and Walter S. Lasecki. 2019. Identifying Challenges and Opportunities in Human-AI Collaboration in Healthcare. In *Conference Companion Publication of the 2019 on Computer Supported Cooperative Work and Social Computing* (Austin, TX, USA) *(CSCW '19)*. Association for Computing Machinery, New York, NY, USA, 506–510. https://doi.org/10.1145/3311957.3359433

[95] Giorgio Quer, Evan D Muse, Nima Nikzad, Eric J Topol, and Steven R Steinhubl. 2017. Augmenting diagnostic vision with AI. *The Lancet* 390, 10091 (2017), 221.

[96] John A Quinn, Rose Nakasi, Pius KB Mugagga, Patrick Byanyima, William Lubega, and Alfred Andama. 2016. Deep convolutional neural networks for microscopy-based point of care diagnostics. In *Machine Learning for Healthcare Conference*. 271–281.

[97] Divya Ramachandran, John Canny, Prabhu Dutta Das, and Edward Cutrell. 2010. Mobile-izing health workers in rural India. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 1889–1898.

[98] Ludovic Righetti, Raj Madhavan, and Raja Chatila. 2019. Unintended Consequences of Biased Robotic and Artificial Intelligence Systems [Ethical, Legal, and Societal Issues]. *IEEE Robotics & Automation Magazine* 26, 3 (2019), 11–13.

[99] Francesca Rossi. 2018. Building trust in artificial intelligence. *Journal of international affairs* 72, 1 (2018), 127–134.

[100] Nithya Sambasivan, Garen Checkley, Amna Batool, Nova Ahmed, David Nemer, Laura Sanely Gaytán-Lugo, Tara Matthews, Sunny Consolvo, and Elizabeth Churchill. 2018. " Privacy is not for me, it's for those rich women": Performative Privacy Practices on Mobile Phones by Women in South Asia. In *Fourteenth Symposium on Usable Privacy and Security ({SOUPS} 2018)*. 127–142.

[101] Nehru Yuva Sangthan-Tisi. 2020. Retrieved September 8, 2020 from https://www.nystindia.org/

[102] Edward Santow. 2020. Emerging from AI utopia.

[103] Lipekho Saprii, Esther Richards, Puni Kokho, and Sally Theobald. 2015. Community health workers in rural India: analysing the opportunities and challenges Accredited Social Health Activists (ASHAs) face in realising their multiple roles. *Human Resources for Health* 13, 1 (Dec. 2015), 95. https://doi.org/10.1186/s12960-015-0094-3

[104] Mike Schaekermann, Graeme Beaton, Elaheh Sanoubari, Andrew Lim, Kate Larson, and Edith Law. 2020. Ambiguity-Aware AI Assistants for Medical Data Analysis. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3313831.3376506

[105] Helen Schneider, Dickson Okello, and Uta Lehmann. 2016. The global pendulum swing towards community health workers in low-and middle-income countries: a scoping review of trends, geographical distribution and programmatic orientations, 2005 to 2014. *Human resources for health* 14, 1 (2016), 65.

[106] Judy Scott and Carlton Scott. 2017. Drone delivery models for healthcare. In *Proceedings of the 50th Hawaii international conference on system sciences*.

[107] Kerry Scott, SW Beckham, Margaret Gross, George Pariyo, Krishna D Rao, Giorgio Cometto, and Henry B Perry. 2018. What do we know about community-based health worker programs? A systematic review of existing reviews on community health workers. *Human resources for health* 16, 1 (2018), 39.

[108] Nigam H Shah, Arnold Milstein, and Steven C Bagley. 2019. Making machine learning models clinically useful. *Jama* 322, 14 (2019), 1351–1352.

[109] Nick Taylor, Keith Cheverst, Peter Wright, and Patrick Olivier. 2013. Leaving the wild: lessons from community technology handovers. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '13)*. Association for Computing Machinery, New York, NY, USA, 1549–1558. https://doi.org/10.1145/2470654.2466206

[110] Divy Thakkar, Neha Kumar, and Nithya Sambasivan. 2020. Towards an AI-Powered Future that Works for Vocational Workers. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–13.

[111] Indrani Medhi Thies, Nandita Menon, Sneha Magapu, Manisha Subramony, and Jacki O'Neill. 2017. How do you want your chatbot? An exploratory Wizard-of-Oz study with young, urban Indians. In *IFIP Conference on Human-Computer Interaction*. Springer, 441–459.

[112] Kentaro Toyama. 2015. *Geek heresy: Rescuing social change from the cult of technology*. PublicAffairs.

[113] Khandekar V. 2014. Strengthening Primary Health Care Through Asha Workers: A Novel Approach in India. *Primary Health Care: Open Access* 04 (01 2014). https://doi.org/10.4172/2167-1079.1000149

[114] Aditya Vashistha, Richard Anderson, and Shrirang Mare. 2018. Examining Security and Privacy Research in Developing Regions. In *Proceedings of the 1st ACM SIGCAS Conference on Computing and Sustainable Societies (COMPASS '18)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3209811.3209818

[115] Aditya Vashistha, Richard Anderson, and Shrirang Mare. 2019. Examining the use and non-use of mobile payment systems for merchant payments in India. In *Proceedings of the 2nd ACM SIGCAS Conference on Computing and Sustainable Societies (COMPASS '19)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3314344.3332499

[116] Aditya Vashistha, Neha Kumar, Anil Mishra, and Richard Anderson. 2016. Mobile video dissemination for community health. In *Proceedings of the Eighth International Conference on Information and Communication Technologies and Development*. 1–11.

[117] Aditya Vashistha, Neha Kumar, Anil Mishra, and Richard Anderson. 2017. Examining localization approaches for community health. In *Proceedings of the 2017 Conference on Designing Interactive Systems*. 357–368.

[118] Aditya Vashistha, Fabian Okeke, Richard Anderson, and Nicola Dell. 2018. 'You Can Always Do Better!": The Impact of Social Proof on Participant Response Bias. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3173574.3174126

[119] Dakuo Wang, Justin D Weisz, Michael Muller, Parikshit Ram, Werner Geyer, Casey Dugan, Yla Tausczik, Horst Samulowitz, and Alexander Gray. 2019. Human-AI Collaboration in Data Science: Exploring Data Scientists' Perceptions of Automated AI. *Proceedings of the ACM on Human-Computer Interaction* 3, CSCW (2019), 1–24.

[120] Danding Wang, Qian Yang, Ashraf Abdul, and Brian Y. Lim. 2019. Designing Theory-Driven User-Centric Explainable AI. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–15. https://doi.org/10.1145/3290605.3300831

[121] Apichai Wattanapisit, Chin Hai Teo, Sanhapan Wattanapisit, Emylia Teoh, Wing Jun Woo, and Chirk Jenn Ng. 2020. Can mobile health apps replace GPs? A scoping review of comparisons between mobile apps and GP tasks. *BMC medical informatics and decision making* 20, 1 (2020), 5.

[122] Darrell M West. 2018. *The future of work: Robots, AI, and automation*. Brookings Institution Press.

[123] Caroline Whidden, Kassoum Kayentao, Jenny X Liu, Scott Lee, Youssouf Keita, Djoumé Diakité, Alexander Keita, Samba Diarra, Jacqueline Edwards, Amanda Yembrick, et al. 2018. Improving Community Health Worker performance by using a personalised feedback dashboard for supervision: a randomised controlled trial. *Journal of global health* 8, 2 (2018).

[124] Randi Williams, Hae Won Park, and Cynthia Breazeal. 2019. A is for artificial intelligence: the impact of artificial intelligence activities on young children's perceptions of robots. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–11.

[125] Ching-seh Mike Wu, Mustafa Badshah, and Vishwa Bhagwat. 2019. Heart Disease Prediction Using Data Mining Techniques. In *Proceedings of the 2019 2nd International Conference on Data Science and Information Technology* (Seoul, Republic of Korea) *(DSIT 2019)*. Association for Computing Machinery, New York, NY, USA, 7–11. https://doi.org/10.1145/3352411.3352413

[126] Susan Wyche. 2019. Using Cultural Probes In New Contexts: Exploring the Benefits of Probes in HCI4D/ICTD. In *Conference Companion Publication of the 2019 on Computer Supported Cooperative Work and Social Computing (CSCW '19)*. Association for Computing Machinery, New York, NY, USA, 423–427. https://doi.org/10.1145/3311957.3359454

[127] Yao Xie, Melody Chen, David Kao, Ge Gao, and Xiang'Anthony' Chen. 2020. CheXplain: Enabling Physicians to Explore and Understand Data-Driven, AI-Enabled Medical Imaging Analysis. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–13.

[128] Haoyi Xiong, Jinghe Zhang, Yu Huang, Kevin Leach, and Laura E. Barnes. 2017. Daehr: A Discriminant Analysis Framework for Electronic Health Record Data and an Application to Early Detection of Mental Health Disorders. *ACM Trans. Intell. Syst. Technol.* 8, 3, Article 47 (Feb. 2017), 21 pages. https://doi.org/10.1145/3007195

[129] Deepika Yadav, Anushka Bhandari, and Pushpendra Singh. 2019. LEAP: Scaffolding Collaborative Learning of Community Health Workers in India. *Proceedings of the ACM on Human-Computer Interaction* 3, CSCW (2019), 1–27.

[130] Deepika Yadav, Prerna Malik, Kirti Dabas, and Pushpendra Singh. 2019. Feedpal: Understanding opportunities for chatbots in breastfeeding education of women in india. *Proceedings of the ACM on Human-Computer Interaction* 3, CSCW (2019), 1–30.

[131] Qian Yang, Aaron Steinfeld, Carolyn Rosé, and John Zimmerman. 2020. Re-Examining Whether, Why, and How Human-AI Interaction Is Uniquely Difficult to Design. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3313831.3376301

[132] Cheryl Young, Stephen Barker, Rodney Ehrlich, Barry Kistnasamy, and Annalee Yassi. 2020. Computer-aided detection for tuberculosis and silicosis in chest radiographs of gold miners of South Africa. *The International Journal of Tuberculosis and Lung Disease* 24, 4 (2020), 444–451.

[133] Yunfeng Zhang, Q. Vera Liao, and Rachel K. E. Bellamy. 2020. Effect of Confidence and Explanation on Accuracy and Trust Calibration in AI-Assisted Decision Making. In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency* (Barcelona, Spain) *(FAT* '20)*. Association for Computing Machinery, New York, NY, USA, 295–305. https://doi.org/10.1145/3351095.3372852

[134] Nengjun Zhu, Jian Cao, Kunwei Shen, Xiaosong Chen, and Siji Zhu. 2020. A Decision Support System with Intelligent Recommendation for Multi-Disciplinary Medical Treatment. *ACM Trans. Multimedia Comput. Commun. Appl.* 16, 1s, Article 33 (March 2020), 23 pages. https://doi.org/10.1145/3352573

A SCRIPT FOR VIDEOS SHOWN TO CHWS

	Positive Scenario	Negative Scenar
Scene 1	*[CHW comes in.]* **Mother:** Greetings. My baby has had a fever and has been coughing for the past day. I do	
Scene 2	**CHW:** Greetings. Don't worry. Let me check the baby's vitals. *[CHW checks baby temperature, weighs baby, and checks lungs.]* **CHW:** Sister, You're right, the baby does have a fever. I suspect there is some fluid in the l **Mother:** What are you saying? I am very worried!	
Scene 3	*[CHW brings out her phone to show the app.]* **CHW:** Sister, Don't be scared, I have an AI app that can help me diagnose pneumonia! *[Mother looks on with curiosity.]*	
Scene 4	*[CHW scans baby with phone.]* **CHW:** Now, the AI app is going to scan the baby with artificial intelligence or AI, a new t they are exhibiting signs of chest indrawing.	
Scene 5	*[Mother is intrigued that an AI app can do all of these things.]* **Mother:** Wow! AI is very advanced technology, it's almost like magic, I'm glad you have this, it would've taken me hours to get to a clinic to see a doctor. **CHW:** Sister, this AI app has been tested and shown to be highly effective in tracking pneumonia. It works most of the time and shows few errors.	*[Mother is skeptica* **Mother:** I don't b you what is wrong doctors do? **CHW:** Sister, Thi effective in trackin few errors.
Scene 6	*[CHW finishes testing and shows the mother the results.]* **CHW:** Look at the AI results! Your baby breathing rate is 65bpm, which is very high. The The AI indicates that your baby has pneumonia.	
Scene 7	*[CHW now pivots back to take care of the baby.]* **Mother:** Will my baby be alright? **CHW:** I have some antibiotics that should help your child. Don't worry, the baby will be fine in a few days. **Mother:** I trust this AI app. Now I don't need to see the doctor!	*[CHW now pivots* **Mother:** Will my **CHW:** I have sor worry, the baby w **Mother:** I don't t the doctor can che
Scene 8	*[Closing scene. CHW is now leaving and mother is satisfied that her baby will be alright.]* **CHW:** Okay sister, I will go now. You take care of the baby. **Mother:** Thank you so much for your help, I am more positive that my baby will recover.	*[Closing scene. CH* *that her baby won* **CHW:** Okay siste **Mother:** Thank y clinic to get the do pneumonia.

Table 2: Script for video shown to participants. Wording differences between the positive and negative scenarios are shown in blue. Note that the script is shown here in English for publication, but the video viewed by participants was in Hindi.

B INTERVIEW PROTOCOL

- **Reactions to the video**
  - How did you find this video?
  - Could you explain briefly your thoughts on the app mentioned in the video?
- **Understanding of AI**
  - What do you understand by "artificial intelligence" that was mentioned in the video?
- **Application functionality**
  - Could you also tell us your understanding of how the AI app works, based on what you saw in the video?
    * How does this AI app decide whether the child has pneumonia or not?
    * How do you think the AI app arrived at this decision?

- Do you think the AI can give incorrect diagnosis?
- What would you do in the event that the app gives incorrect diagnosis?
- Do you think that people would trust you or the AI app more?
  - Why do you think so?
- How do you think this AI app could help your work as an CHW?
- How do you think this AI app could harm your work as an CHW?
- Could this AI app replace how you diagnose pneumonia?

- **Trust**
  - Do you think that the AI can be trusted to give the correct diagnosis?
    - Why do you think so?
  - Who do you think should have access to the photos and videos captured by the AI app?
    - CHW (you); the Patient; Technology Companies; State Government
    - Why do you think so?
  - Would you want to use this app on children in your family?
  - How do you think people around you would react to such an app?
    - Extremely positive; Somewhat positive; Neutral; Somewhat negative; Extremely negative
    - Why do you think so?
  - Could data captured by this AI app be misused by others?
- **Mobile phone usage and sharing**
  - Do you own a mobile phone?
  - Do you carry your mobile device to work?
    - How frequently?
    - For what purposes do you use it?
    - Does the mobile phone help you in your work?
  - *[in the event that it is a shared device]* Has this sharing of the device affected your work in the past?
    - Can you recall an example?
- **Explainability**
  - Would you be willing to learn how AI works in this app?
  - Would you want its functionality to be explained in detail?
- **Human-in-the-loop and learning**
  - Do you think CHWs should participate in a process to enter data and be able to overwrite conclusions that the app may have?
    - Why do you think so?
  - Would you want to input any data into the app?
  - Do you think this AI app could help train you in your work?
    - Why do you think so?
- **Application/device breakdown**
  - In the event that the app (or your mobile device) stops working, what would you do?
- **Wrap-up**
  - What other concerns, fears, or comments do you have about this AI app?
- **Demographics**
  - How long have you been working as an CHW?
  - How long have you been using a smartphone?
  - How long have you been using computers (desktop/laptop)?
  - What is your gender?
  - What is your age?
  - What is your current location?
  - What is the highest level of schooling you have completed?

C CODEBOOK AND THEMES FROM QUALITATIVE ANALYSIS

Theme / Code	Count	**Theme** / Code	Count
AI Knowledge and Perceptions	**177**	**Perceived Uses and Benefits**	**377**
CHW mentions AI matches human intelligence	8	App is able to recognize symptoms	35
CHW has no knowledge of AI	15	App is useful beyond diagnosing pneumonia	26
CHW has a low level of AI knowledge	5	CHW is more efficient due to app	51
CHW mentions machine using vision like humans	13	App is useful as a prescriptive tool	21
CHW equates AI to a blackbox	39	Usefulness in low-resource or remote areas	9
App has same expertise as CHW	11	Data can be of beneficial use	47
Participants have no idea about the app functionality	25	App has limited scope beyond diagnosing pneumonia	9
CHW has confusion about using app	9	App is useful in training CHWs	52
Human-AI participation	13	CHWs learned from the video probe	13
CHW work is irreplaceable	12	App improves communication regarding diagnosis	15
CHW is less secure in job due to automation	5	App provides an information reference for CHWs	58
CHW is more secure in job due to automation	22	Interest in learning more about app or AI	41
Misdiagnosis and Errors	**277**	**Trust and Expertise**	**279**
CHW will deceive patients from app failures	5	App is better than traditional diagnosis methods	6
CHW won't enter data into app	3	App leads to improved diagnosis or treatment	53
App can give incorrect diagnosis	10	CHW demonstrates knowledge of pneumonia diagnosis	23
CHW wants the capability to manually enter data into app	31	CHW has higher expertise than the app	14
App fails due to telecommunications infrastructure	16	CHW assumes people will like app	13
App has the potential to misdiagnose or malfunction	56	CHW-Villager conflict	4
CHW will overwrite correct app conclusions	12	Techno-utopia	12
CHW has faith in capability to handle conflicting diagnosis	15	CHW trusts app	34
CHW lacks faith in capability to handle conflicting diagnosis	6	CHW using app improves patient trust of app	12
CHW has no concerns about the app starting conflict	9	Lack of patient trust	8
CHW will double-check and verify results	30	Trusting app more than CHW	6
CHW has expectation of high accuracy	19	Trusting CHW and the app equally	3
CHW will consult doctor or medical equipment to solve app issues	65	Trusting CHW more than app	30
CHW is unsure about app capability to provide an accurate diagnosis	6	Using app improves patient trust in CHW	8
CHW has prior experience with technology in patient care	31	Trust in app will take time to build up	12
App / Data Access	**207**	CHW is willing to use app on children	20
Patients should have access to use app on their own	20	CHW is working in best interest of patient	21
CHW should have access to app data	37	**Security and Privacy**	**109**
Tech company should not have access to app data	10	Believes data can be misused	10
Everyone should have access to app data	5	Lack of belief that data will be misused	27
Access to data should be given for app improvement/upgrade	7	CHW shares mobile device	24
Access to data should be given for record keeping	13	CHW has no problems with sharing mobile devices	2
Access to data should be given for trust building	6	CHW has problems with sharing mobile devices	9
Access to data should be given for validation	11	CHW uses mobile phone for patient communication	10
Government should have access to app data	29	CHW expects privacy in AI app	17
Government should not have access to app data	6	CHW has no expectation of privacy in AI app	10
Parents should have access to app data	34		
Parents should not have access to app data	4		
Tech company should have access to app data	25		

Table 3: The codebook that resulted from our qualitative analysis, showing six themes (bold), codes, and total count for each theme/code.