HUMAN-ML COLLABORATION

LESSONS FROM PUBLIC HEALTH

AZRA ISMAIL

Assistant Professor, Biomedical Informatics,

Emory University

https://www.azraismail.me/

azra.ismail@emory.edu

CDC reorganization centers equity, data collection as priorities

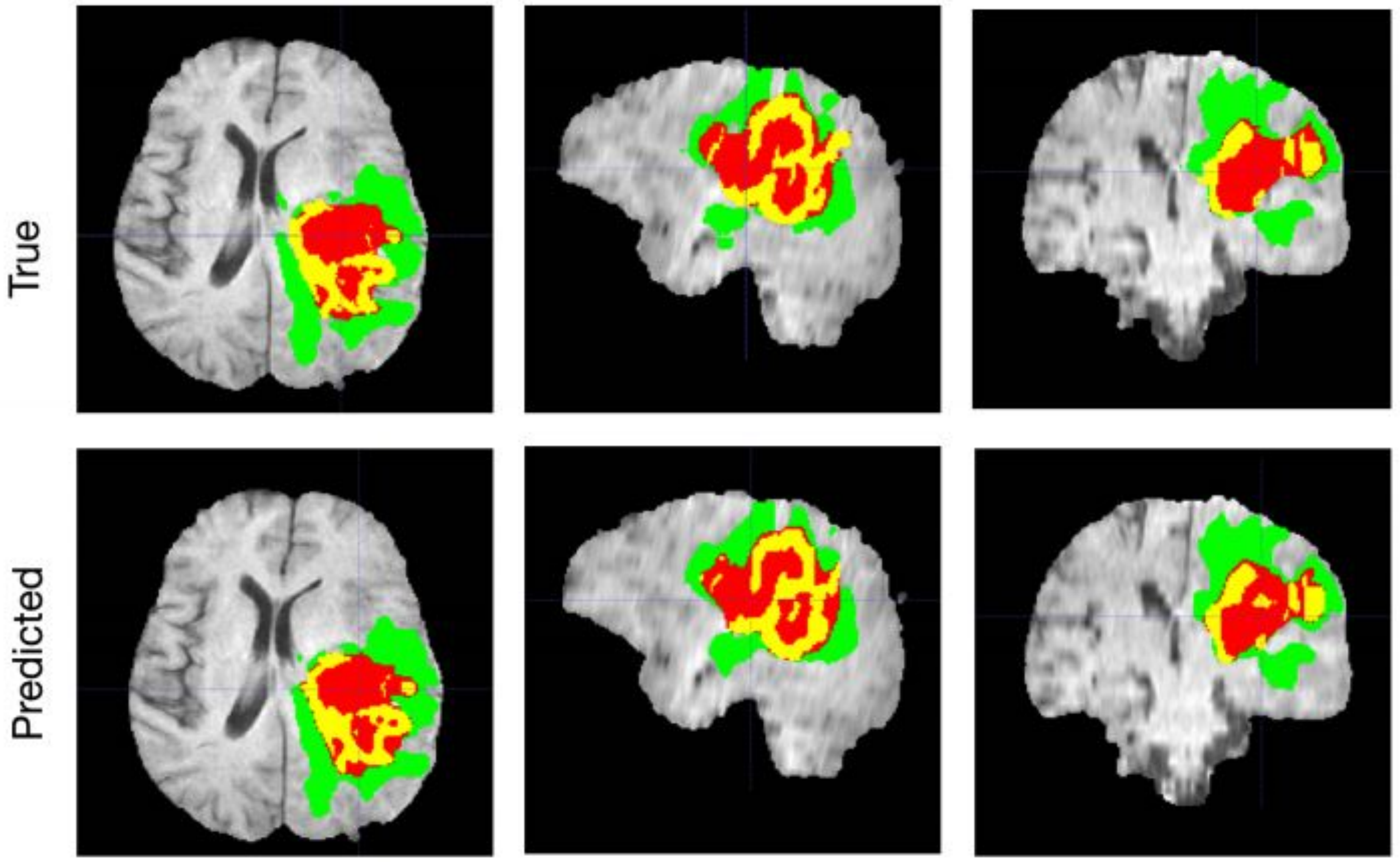
Credit: Jason Getz / Jason.Getz@ajc.com

COVID-19

By Donovan J. Thomas, The Atlanta Journal-Constitution

Updated Feb 16, 2023

Focuses on racial, economic and access disparities and inequities that affect health outcomes.




AZRA ISMAIL


AZRA ISMAIL


AZRA ISMAIL

AZRA ISMAIL

Move from humans in service of AI

→ AI in service of humans

CENTERING CARE IN DESIGN

Who needs care and why?

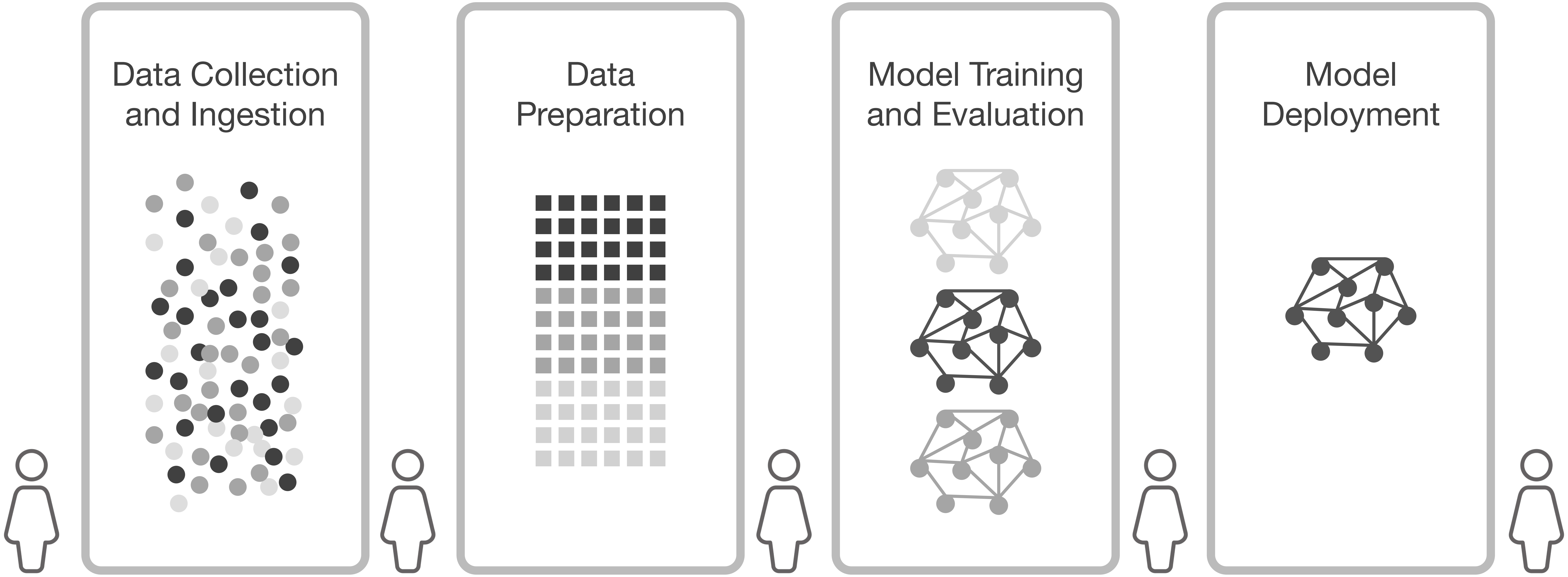
What care is needed?

How can this care be provided?

GILLIGAN. IN A DIFFERENT VOICE: PSYCHOLOGICAL THEORY AND WOMEN'S DEVELOPMENT. HARVARD UNIVERSITY PRESS, 1982.

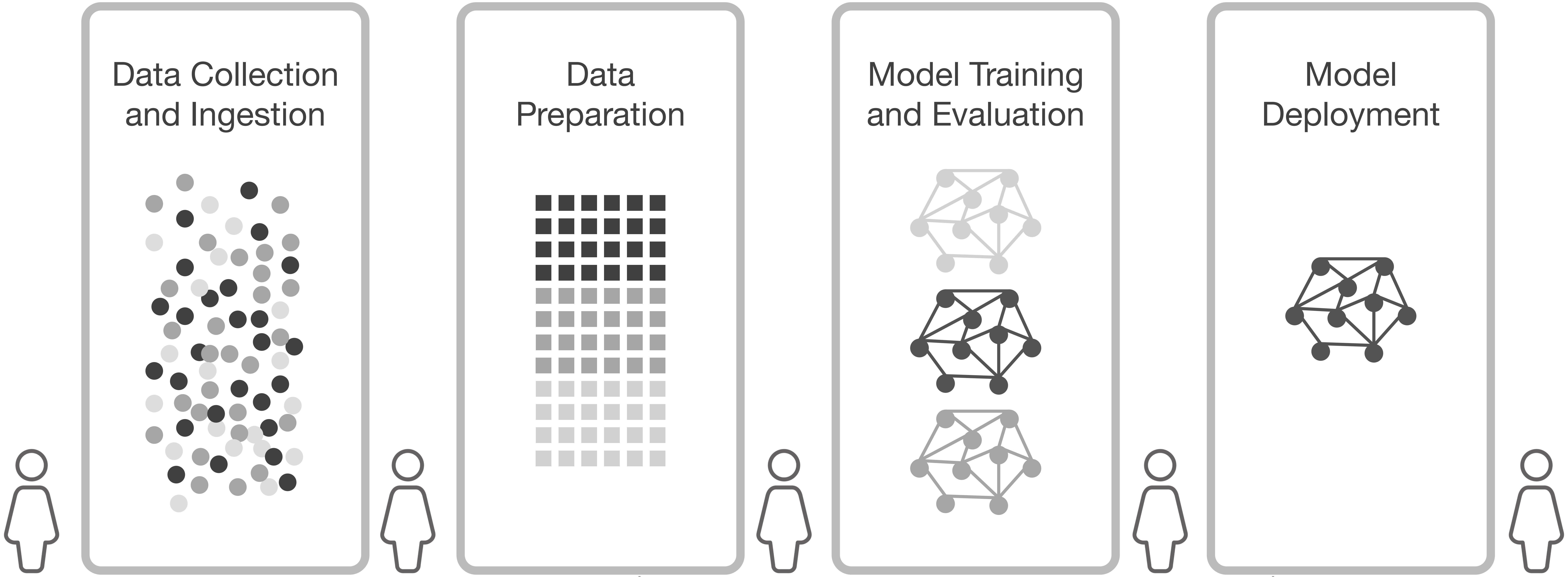
NODDINGS. CARING: A FEMININE APPROACH TO ETHICS AND MORAL EDUCATION. UNIVERSITY OF CALIFORNIA PRESS, 1984.

ISMAIL, YADAV, GUPTA, DABAS, SINGH, KUMAR. IMAGINING CARING FUTURES FOR FRONTLINE HEALTH WORK. ACM CSCW 2022.


Data Collection and Ingestion
Data Preparation
Model Training and Evaluation
Model Deployment

INTEGRATING WITH

data flows and practices | organizational structures and goals | care workflows



RESEARCH STUDIES

STUDY 1
Data Pipelines In Machine Learning (ML)

STUDY 2
ML for Resource Allocation

STUDY 3
Chatbot Codesign in Care Work

How might we integrate AI

with care

in public health?

ABOUT

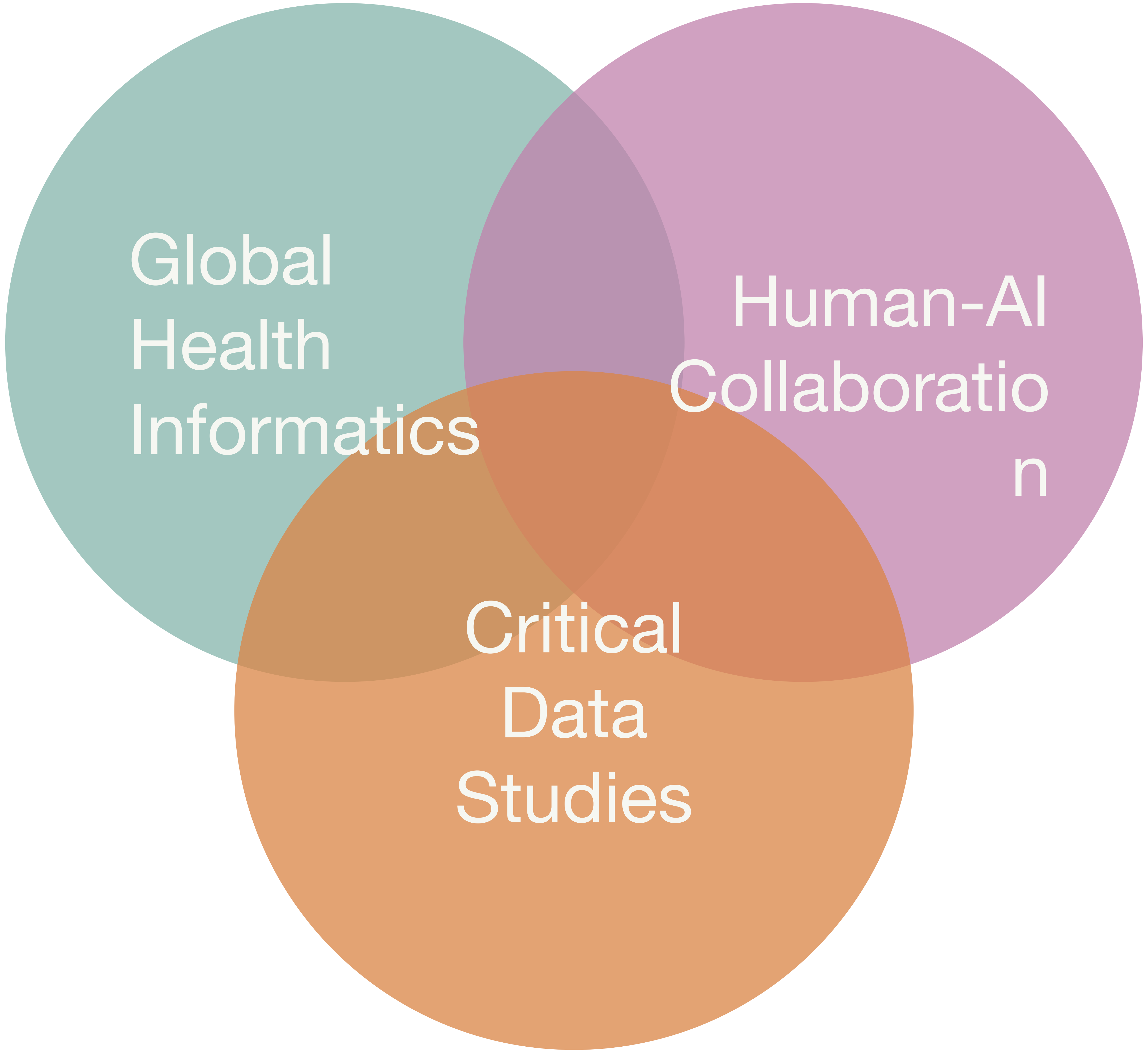
ISMAIL, KARUSALA, & KUMAR. BRIDGING DISCONNECTED KNOWLEDGES FOR COMMUNITY HEALTH. ACM CSCW 2018.

ISMAIL & KUMAR. ENGAGING SOLIDARITY IN DATA COLLECTION PRACTICES FOR COMMUNITY HEALTH. ACM CSCW 2018.

ISMAIL & KUMAR. EMPOWERMENT ON THE MARGINS: THE ONLINE EXPERIENCES OF COMMUNITY HEALTH WORKERS. ACM CHI 2019.

ISMAIL & KUMAR. AI IN GLOBAL HEALTH: THE VIEW FROM THE FRONT LINES. ACM CHI 2021.

KUMAR, ISMAIL, SHERUGAR, & CHANDWANI. RESTORATION WORK: RESPONDING TO EVERYDAY CHALLENGES OF HIV OUTREACH. ACM CSCW 2019.



ETHNOGRAPHY

SURVEYS

INTERVIEWS

DESIGN PROBES

CODESIGN

PROTOTYPING

DEVELOPMENT

EVALUATION

POSITIONALITY

Study 1
—
Data Pipelines in ML

Study 2
—
ML for Resource Allocatio
n

Study 3
—
Chatbot Codesign for Care Work

ISMAIL & KUMAR. ENGAGING SOLIDARITY IN DATA COLLECTION PRACTICES FOR COMMUNITY HEALTH. ACM CSCW 2018.

THAKKAR*, ISMAIL*, HANNA, KUMAR, SAMBASIVAN, & KUMAR. WHEN IS MACHINE LEARNING DATA GOOD?: VALUING IN PUBLIC HEALTH DATAFICATION. ACM CHI 2022.

*JOINT LEAD AUTHORS

Google Research KhushiBaby Swasti THE HEALTH CATALYST armman

MOTIVATION

Human infrastructures enable collection of ML datasets

Poor quality of public health data results in poor ML outcomes

Where do gaps emerge in the data pipeline for ML in public health?

ISMAIL & KUMAR. ENGAGING SOLIDARITY IN DATA COLLECTION PRACTICES FOR COMMUNITY HEALTH. ACM CSCW 2018.

RQ1 What are interdependencies in data work across the ML pipeline?

RQ2 How is data valued at each stage in the pipeline?

RQ3 How might we address conflicts in how data is valued across various stages?

METHODS

Interviewed data workers in India, US, Singapore,

working in maternal and child care, and sexual and reproductive health in India.

Data Collectors

Navigate geographic and social boundaries

They cover challenging terrains and safety risks,

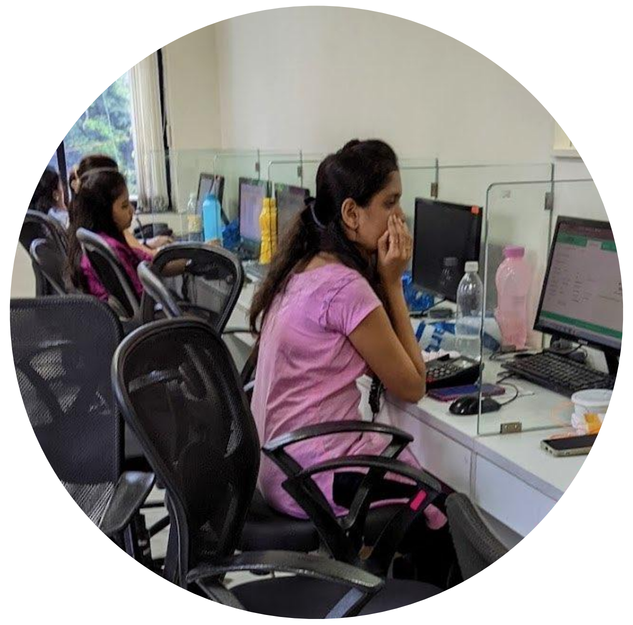
struggle with caste boundaries, and

leverage community relationships to gather sensitive data.

"They share information that they do not share with their own family,

we are their trusted friends."

— Meena, sexual health outreach worker


Data Stewards

Meet reporting requirements

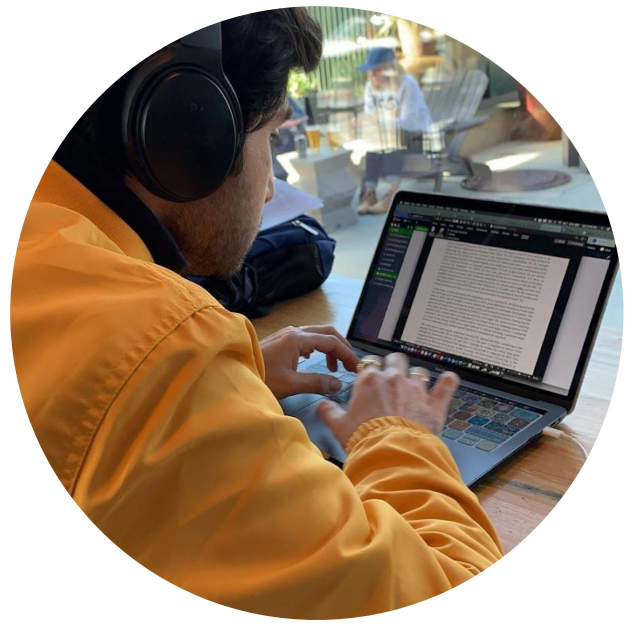
They have limited visibility into data flows,

find it burdensome to conduct data quality checks, and

lack influence and communication channels for change.

"I will check the data in my own way to see if someone has left compulsory fields empty or if they have tried to enter perfect values but all this takes time and I cannot spend all day in doing checks…"

— Soham, data entry operator



ML Developers

Make data fit for ML models

They look for standardised, feature-rich data with validated labels,

incentivized to do model development over data operations, and

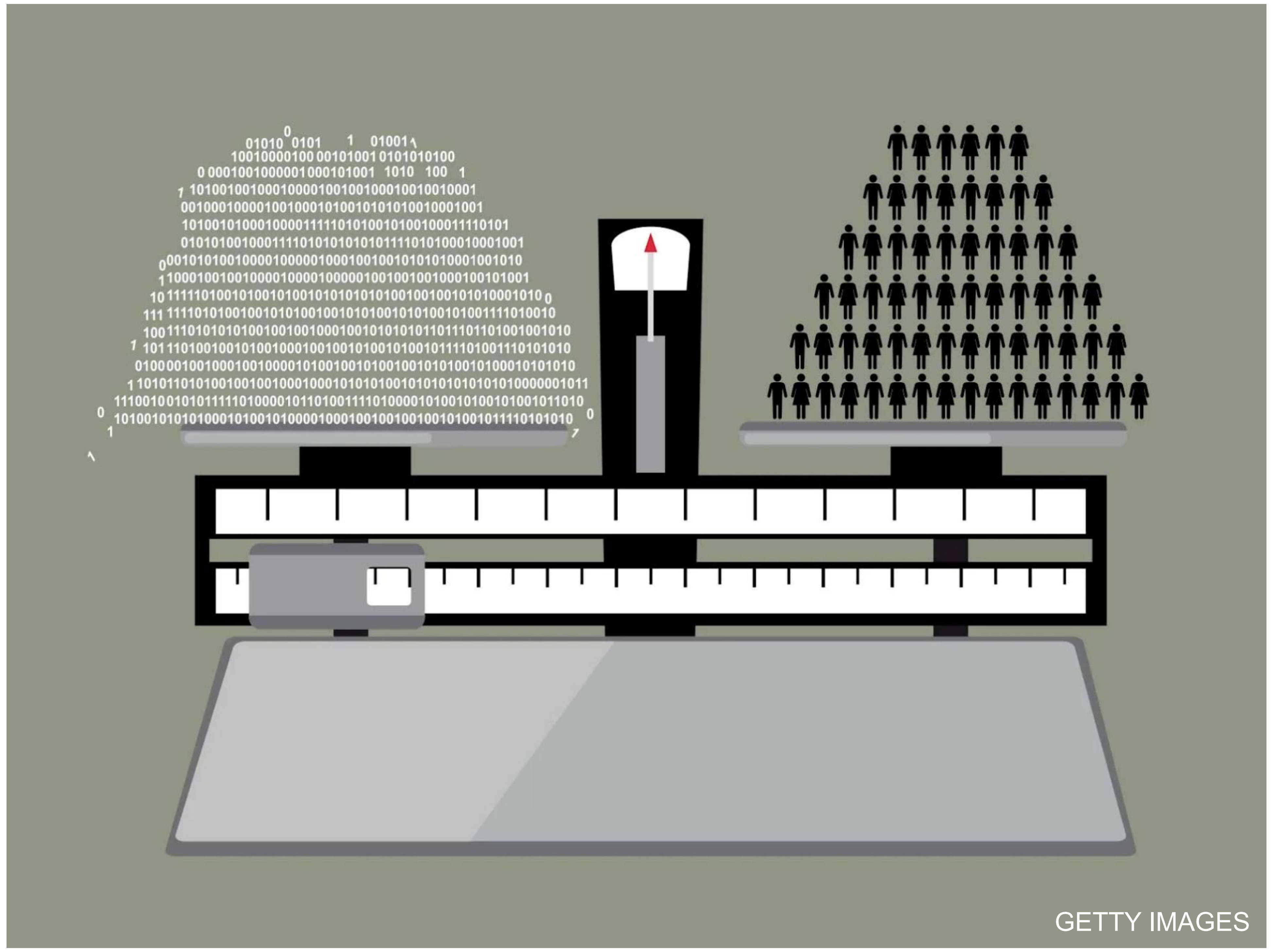
struggle to contextualize data operations and models.

"If I am trying to assess which person is at more risk, I need to know which of their health parameters in data are important to determine the risk, right? It becomes really difficult to identify the right labels without experts and sometimes even when you are able to figure out the labels, the underlying data cannot be trusted or the labels are subjective."

— Dr. Sharma, startup founder

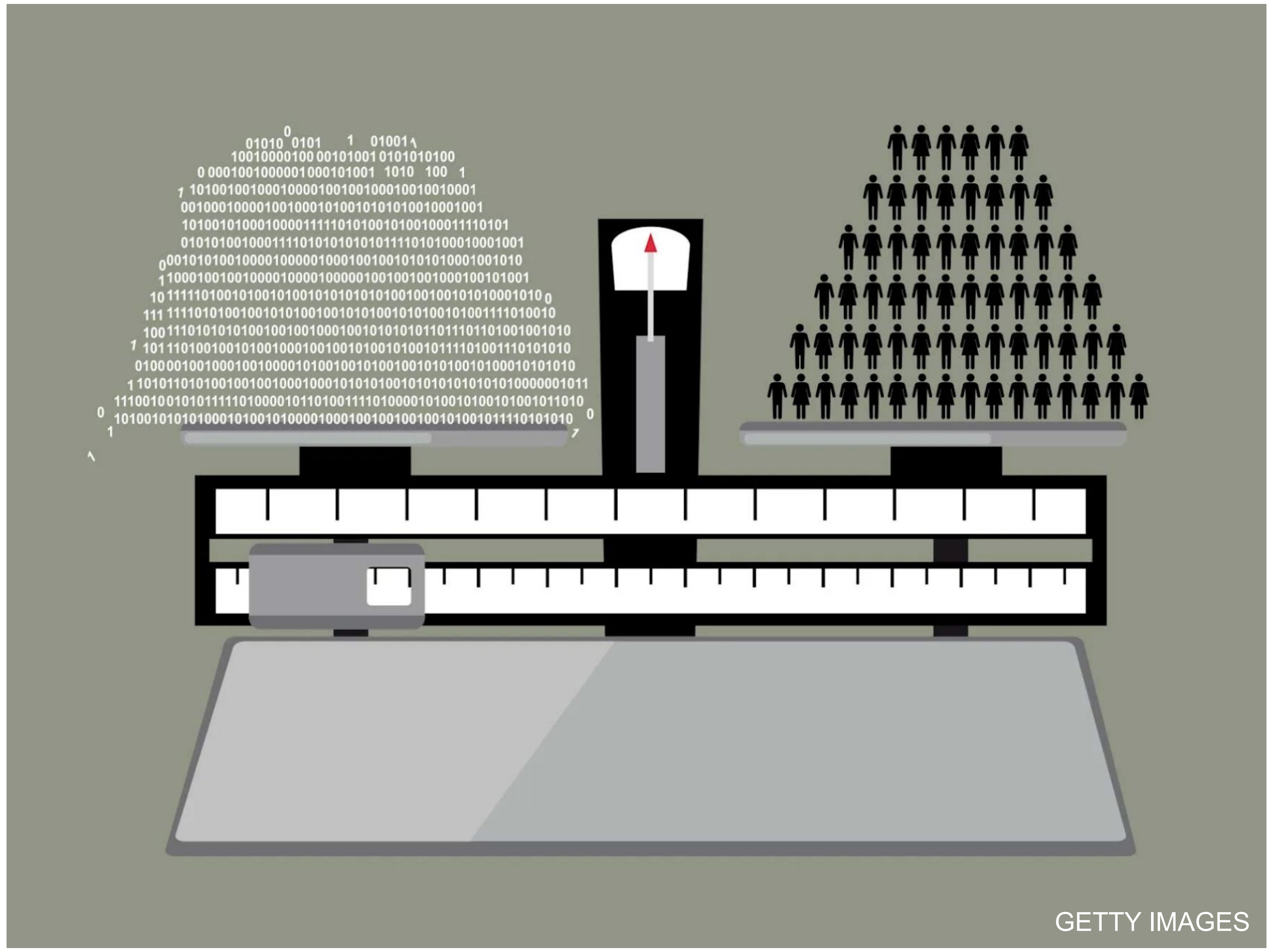
TAKEAWAYS

BUILDING TRANSPARENCY & ACCOUNTABILITY



TAKEAWAYS

BUILDING TRANSPARENCY & ACCOUNTABILITY



Organizations can create shared understanding of “good” data,

empower community voices in data flows,

incentivize data work, and

share accountability for model outcomes.

ML developers can aim to understand context of data collection to contextualise data operations.

ISMAIL*, THAKKAR*, MADHIWALLA, KUMAR.
PUBLIC HEALTH CALLS FOR/WITH AI:
AN ETHNOGRAPHIC PERSPECTIVE.
CSCW 2023.

*JOINT LEAD AUTHORS

Google Research

armman

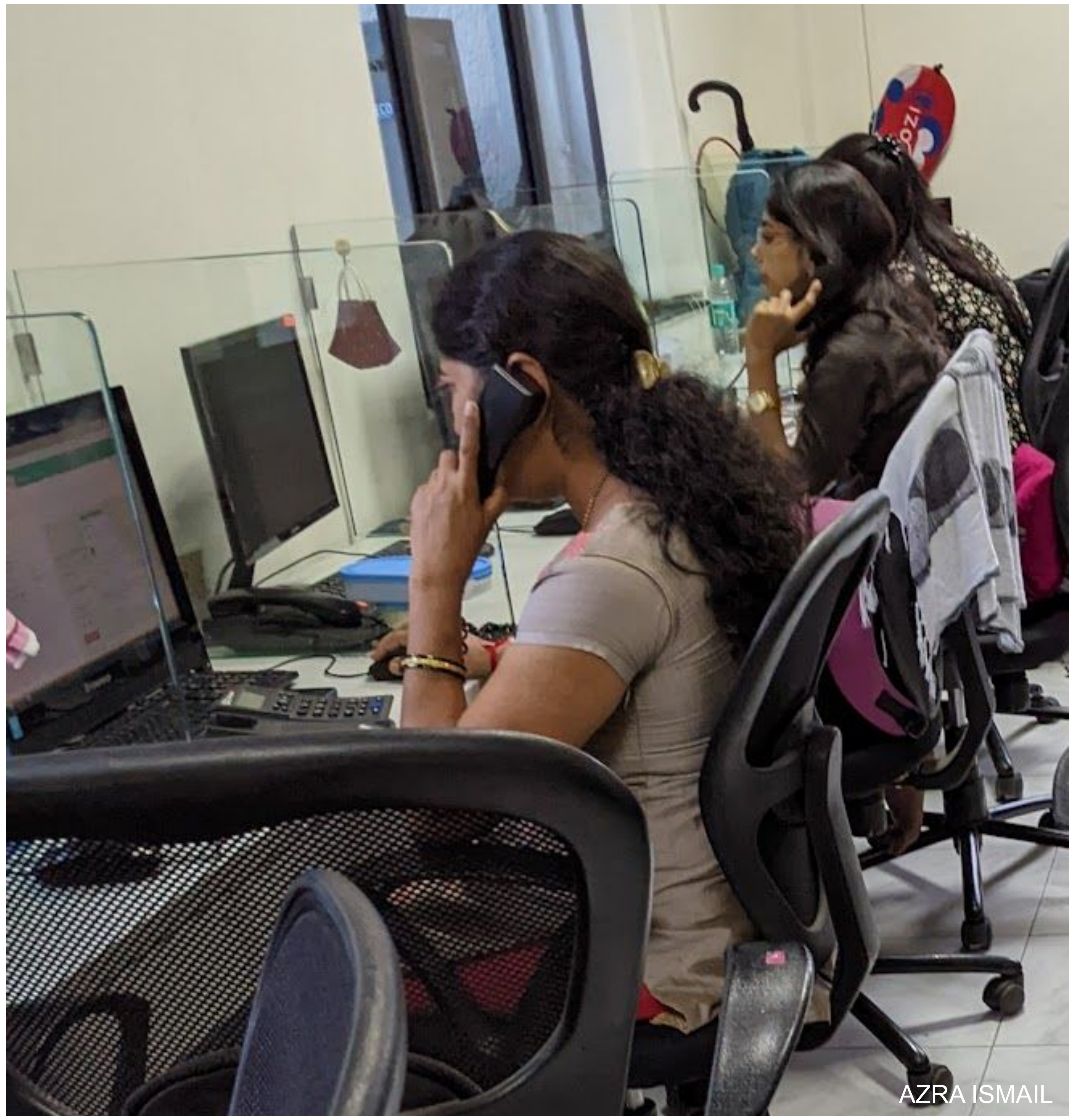
Study 1
—
Data Pipelines in ML

Study 2
—
ML for Resource Allocation

Study 3
—
Chatbot Codesign for Care Work

MOTIVATION

A mother receiving an automated voice call from mMitra



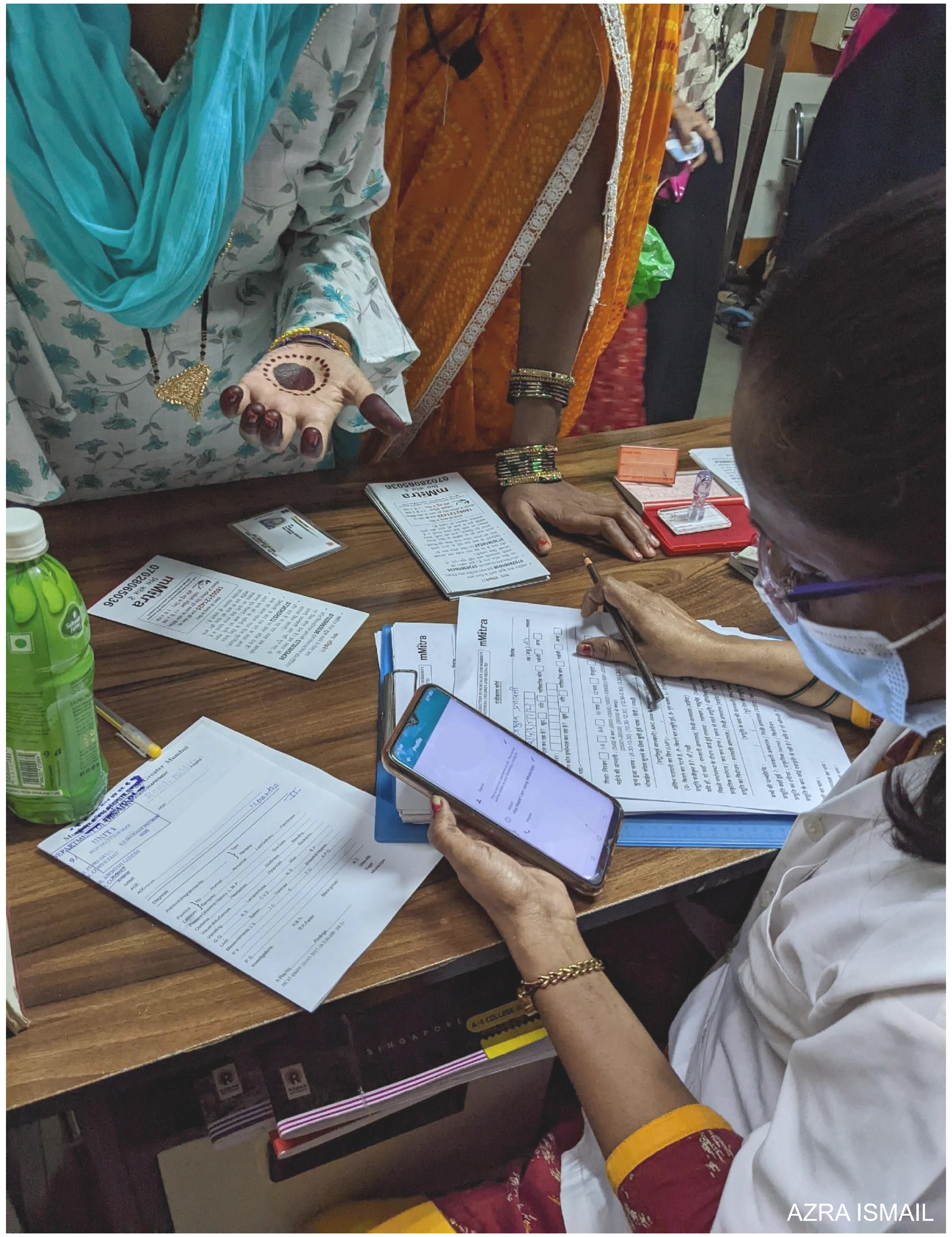
Call Center Executives (CCEs) providing personalised support on call

Low listenership in mMitra

AI used to predict women likely to drop out

Why, where, and how was AI integrated into the program?

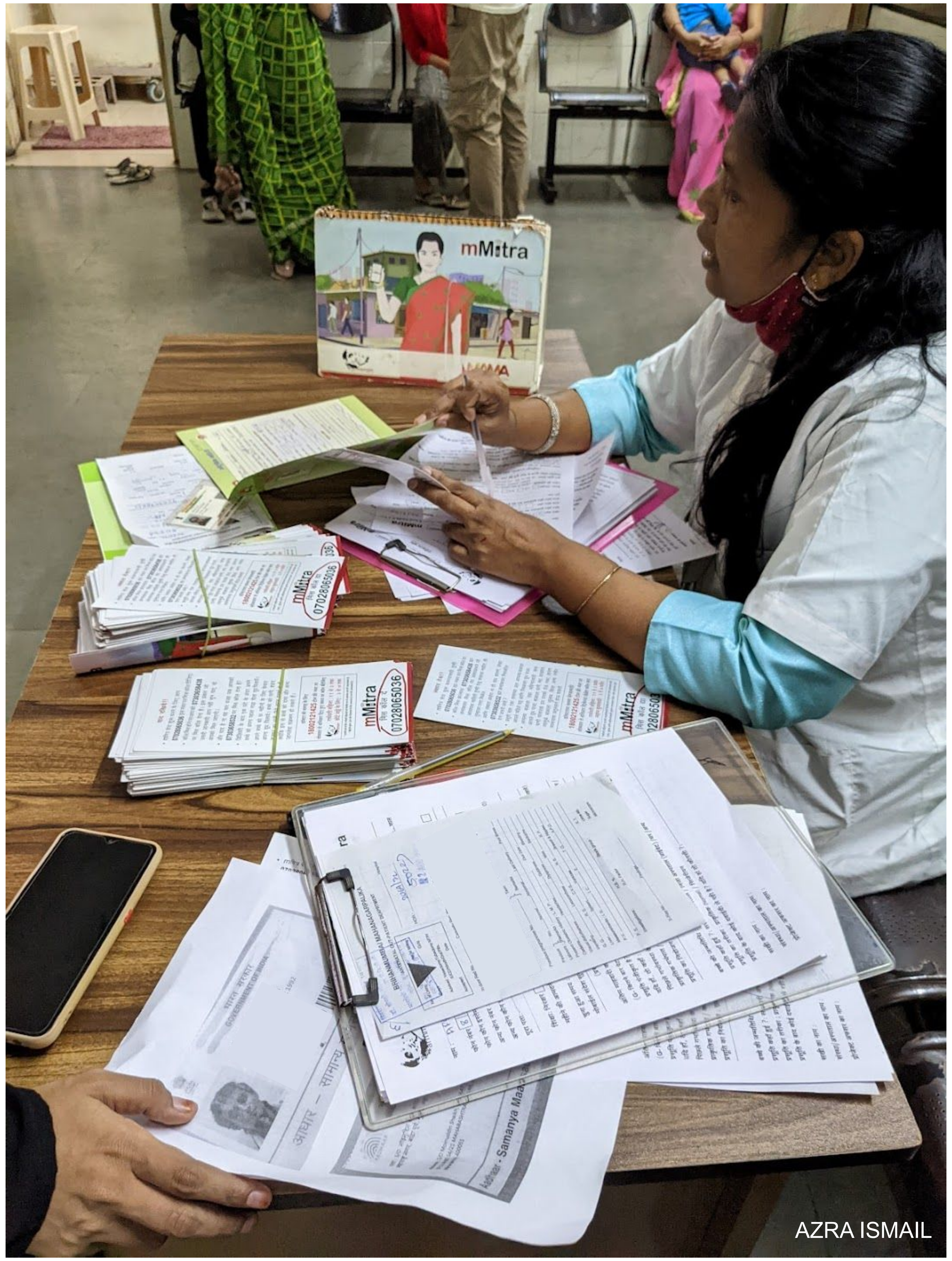
WANG*, VERMA*, MATE, SHAH, TANEJA, MADHIWALLA, HEGDE, AND TAMBE. SCALABLE DECISION-FOCUSED LEARNING IN RESTLESS MULTI-ARMED BANDITS WITH APPLICATION TO MATERNAL AND CHILD HEALTH. AAAI 2023.



RQ1 What are key design decisions when implementing AI in public health at a large scale?

RQ2 What are the metrics by which the success of such a system may be evaluated?

RQ3 How do these metrics connect to notions of health equity and algorithmic fairness?

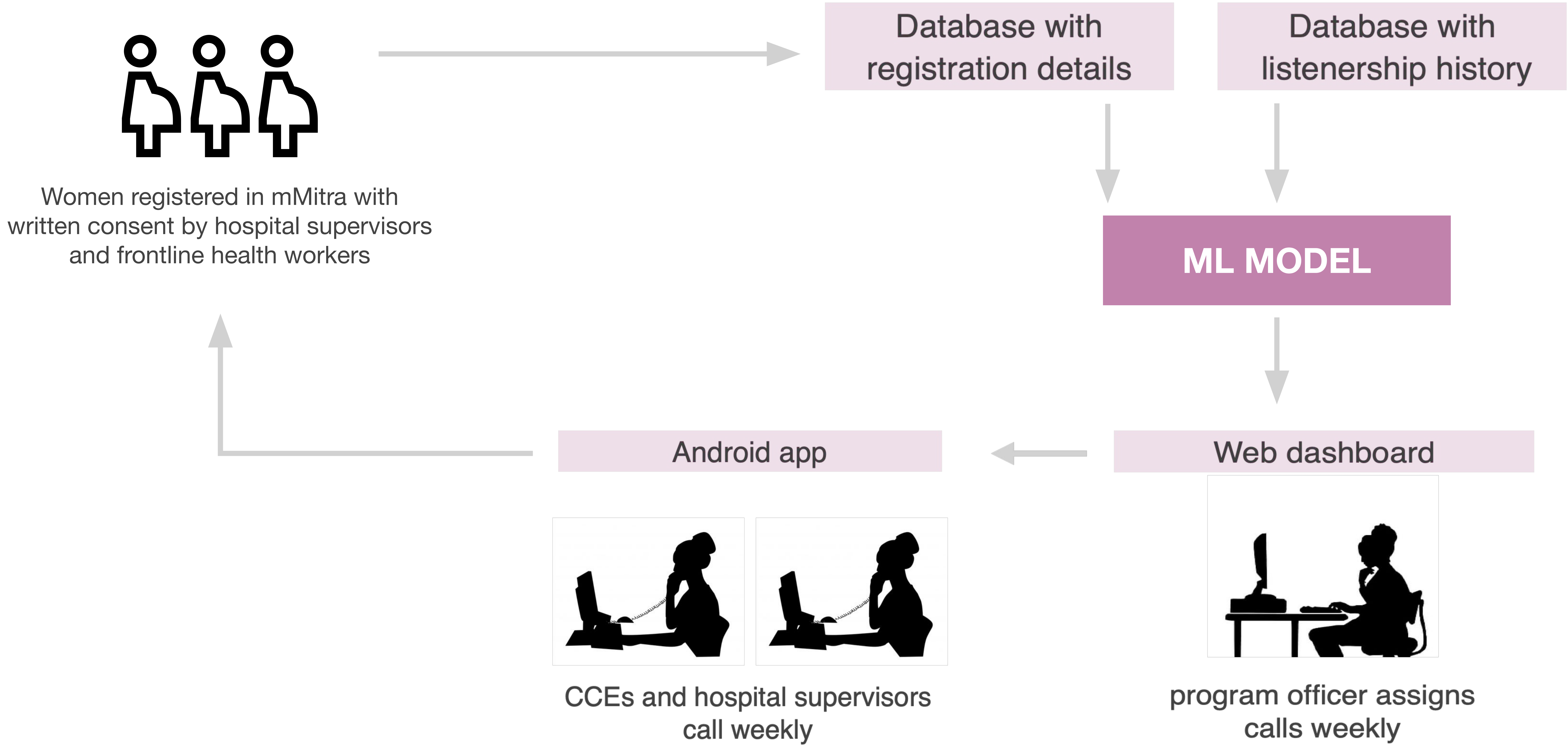


METHODS

Ethnographic research in Mumbai over three months including observations, interviews, and focus groups,

around AI integration in a call-based maternal and child health program (mMitra),

with Call Center Executives (CCEs), hospital supervisors, program officers, and ML developers.



Women registered in mMitra with written consent by hospital supervisors and frontline health workers
Database with registration details
Database with listenership history
ML MODEL
Web dashboard
program officer assigns calls weekly
Android app
CCEs and hospital supervisors call weekly

Where and how to introduce AI?


AZRA ISMAIL

ARMMAN introduced AI in the background to preserve human interaction on the calls,

during which workers motivated beneficiaries and addressed barriers in listening to mMitra.

"For the AI program, they told us that those beneficiaries [women] who are listening less, we need to call them and convince them to listen to the calls."

— Kusum, CCE

Who to target with AI?

The organizations weighed indicators like caste, religion, income, and education,

tried to balance fairness towards communities and workers, and

prioritize women with miscarriages, abortions, child death.

"The lady's husband picked up the call, and I started telling him about the mMitra service, and he said—'Madam, I want to stop the calls.' When I asked him why, he said that his wife had passed away while delivering their child. So he was very upset. But our [mMitra] calls had still been going to him because it was his number..."

— Leena, Hospital Supervisor

How to evaluate AI performance?

Various stakeholders had different metrics for program success (prediction accuracy, call pick-up rate, call outcomes),

and design decisions could shape performance on these metrics.

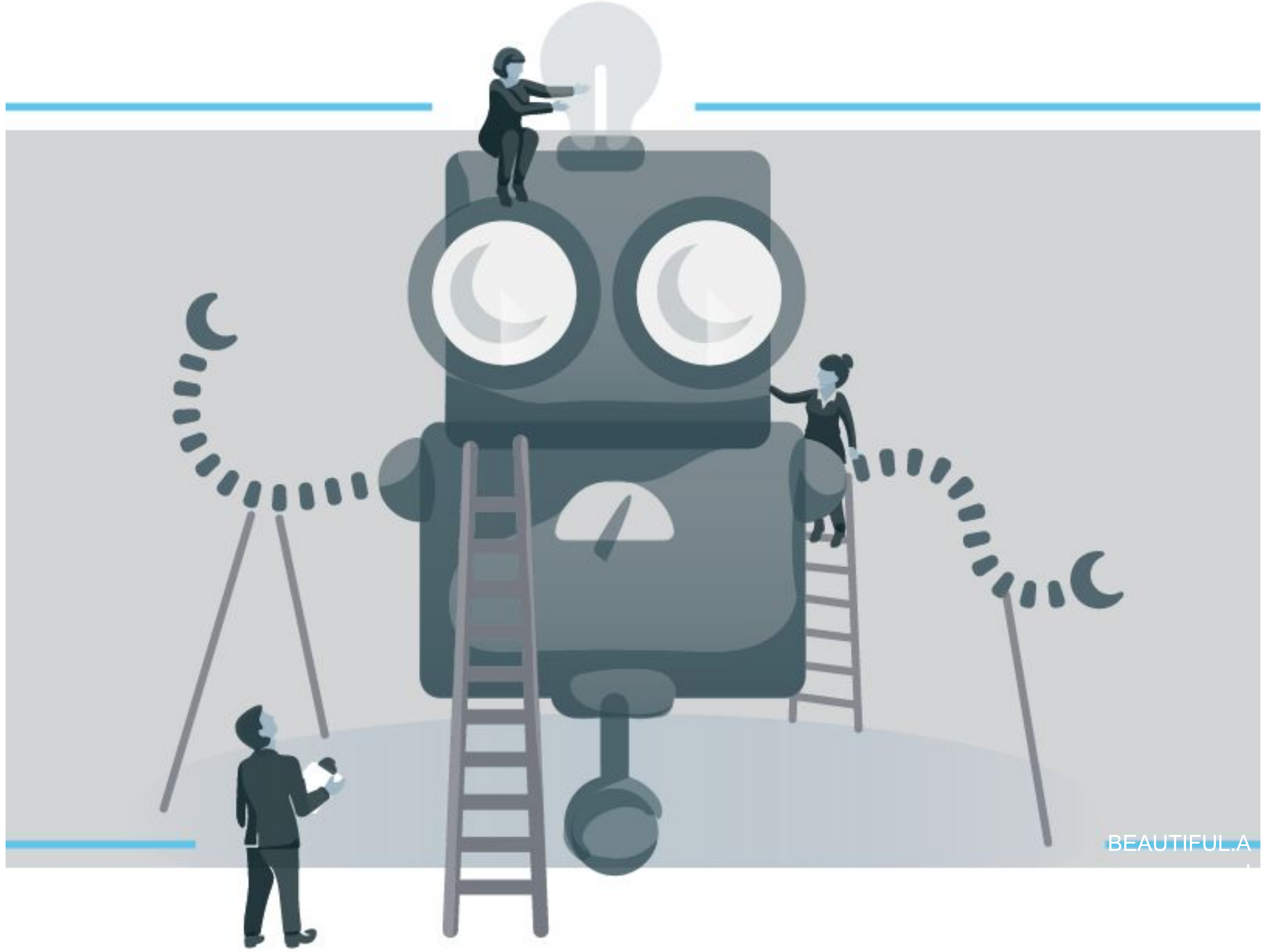
"I am looking at how many women are prevented from falling out of the program. That would be my success rate…

If she is not interested in listening to the call, or if she's not listening to the calls because she does not have network in her house, then it [AI] is not going to help."

— Gavin, Program Staff

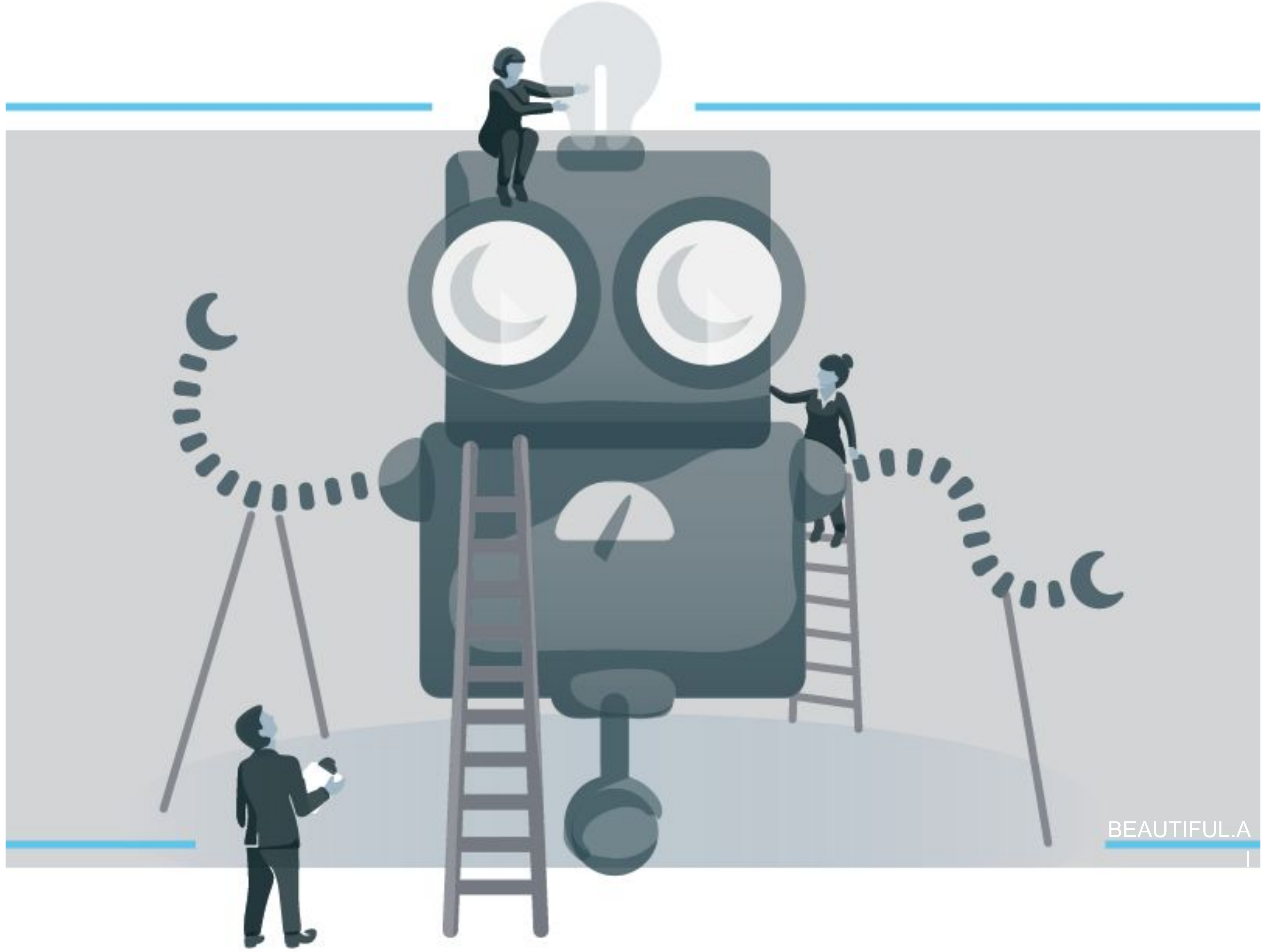
TAKEAWAYS

CONFIGURING HUMAN-AI SYSTEMS



TAKEAWAYS

CONFIGURING HUMAN-AI SYSTEMS



Organizations can think about why, where, and how AI should be integrated, and

leverage AI's role as a probe and diagnoser of health equity concerns.

AI developers can contextualize understanding of fairness and model success.

Microsoft Research

Study 1
—
Data Pipelines in ML

Study 2
—
ML for Resource Allocation

Study 3
—
Chatbot Codesign for Care Work

MOTIVATION

AZRA ISMAIL

High data collection burden for workers, impacts caregiving

How can we reduce the burden of work and improve care?

Existing heavy use of WhatsApp in work, potential for conversational agents

ISMAIL, YADAV, GUPTA, DABAS, SINGH, KUMAR. IMAGINING CARING FUTURES FOR FRONTLINE HEALTH WORK. ACM CSCW 2022.

ISMAIL & KUMAR. ENGAGING SOLIDARITY IN DATA COLLECTION PRACTICES FOR COMMUNITY HEALTH. ACM CSCW 2018.

ISMAIL & KUMAR. EMPOWERMENT ON THE MARGINS: THE ONLINE EXPERIENCES OF COMMUNITY HEALTH WORKERS. ACM CHI 2019.

METHODS

Developed a WhatsApp chatbot prototype in Hindi called Sehat Sakhi, and

conducted remote interviews and think aloud sessions and recorded chat logs

with health workers in urban Delhi and rural Haryana.

DISCUSSION PROMPT

You are working at a deep tech startup building “AI” (but really just using computer vision) to detect risk of lung cancer from radiology images.

What are some questions to ask before building the AI? (5 min)

How can you address these concerns? (5 min)

How can you evaluate if you have addressed these concerns? (5 min)

Recent article about such a system:

https://news.mit.edu/2023/ai-model-can-detect-future-lung-cancer-0120

What to take away from today

1. Start asking questions!
2. Think about how AI can fit in into existing processes rather than making humans accommodate AI
3. Understand that trust is earned, and that learning is a big a component of how people work with systems

I AM RECRUITING!

Reach out if you are interested in the design of AI systems that can enable health equity!

AZRA ISMAIL

Assistant Professor, Biomedical Informatics,

Emory University

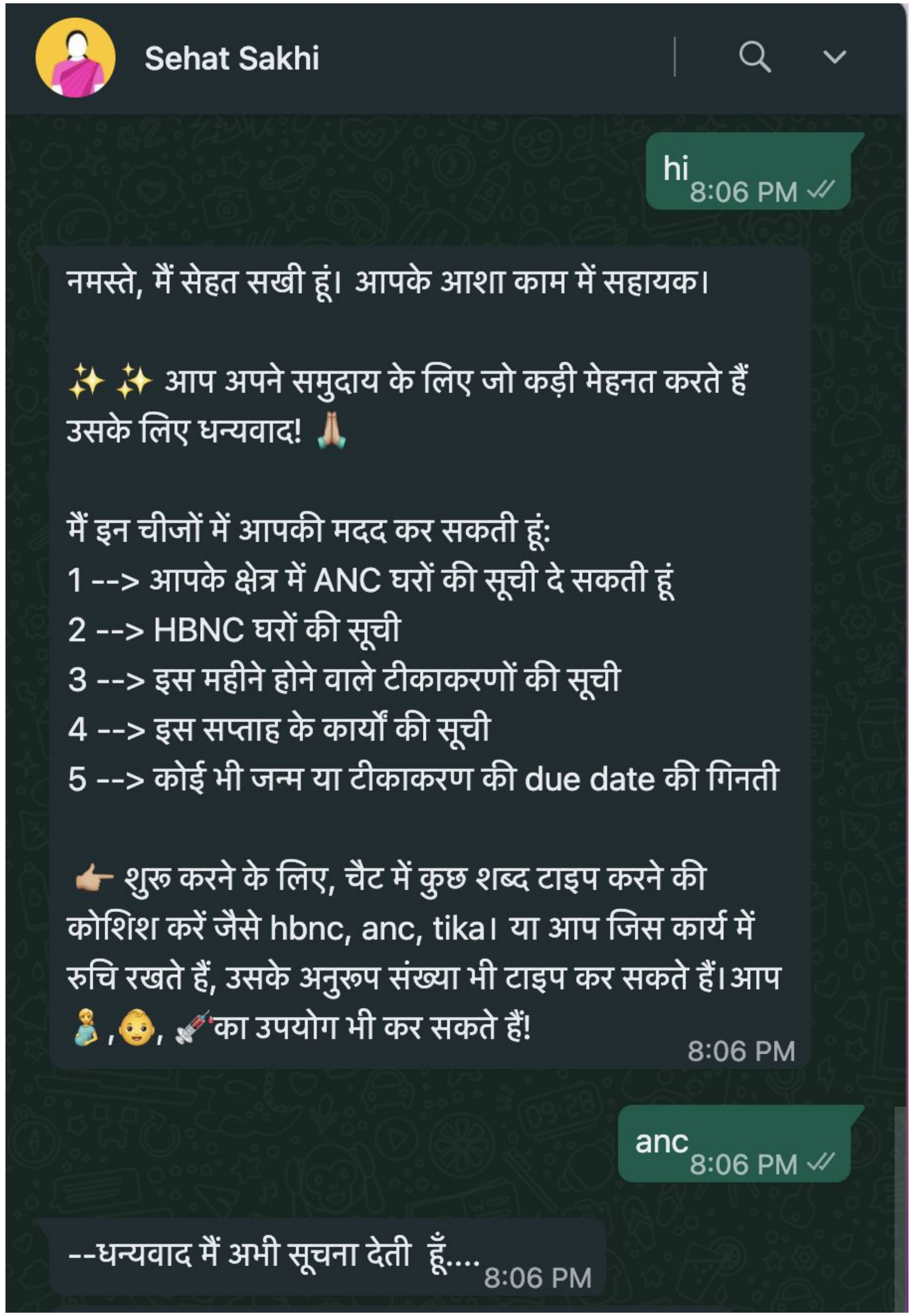
https://www.azraismail.me/

azra.ismail@emory.edu

RQ1 How do health workers perceive and interact with conversational agents?

RQ2 How might conversational agents support work tasks while centering worker control and agency?

RQ3 How might their design account for gendered digital access and literacies, and social dynamics with communities as well as supervisors?



Design of Sehat Sakhi

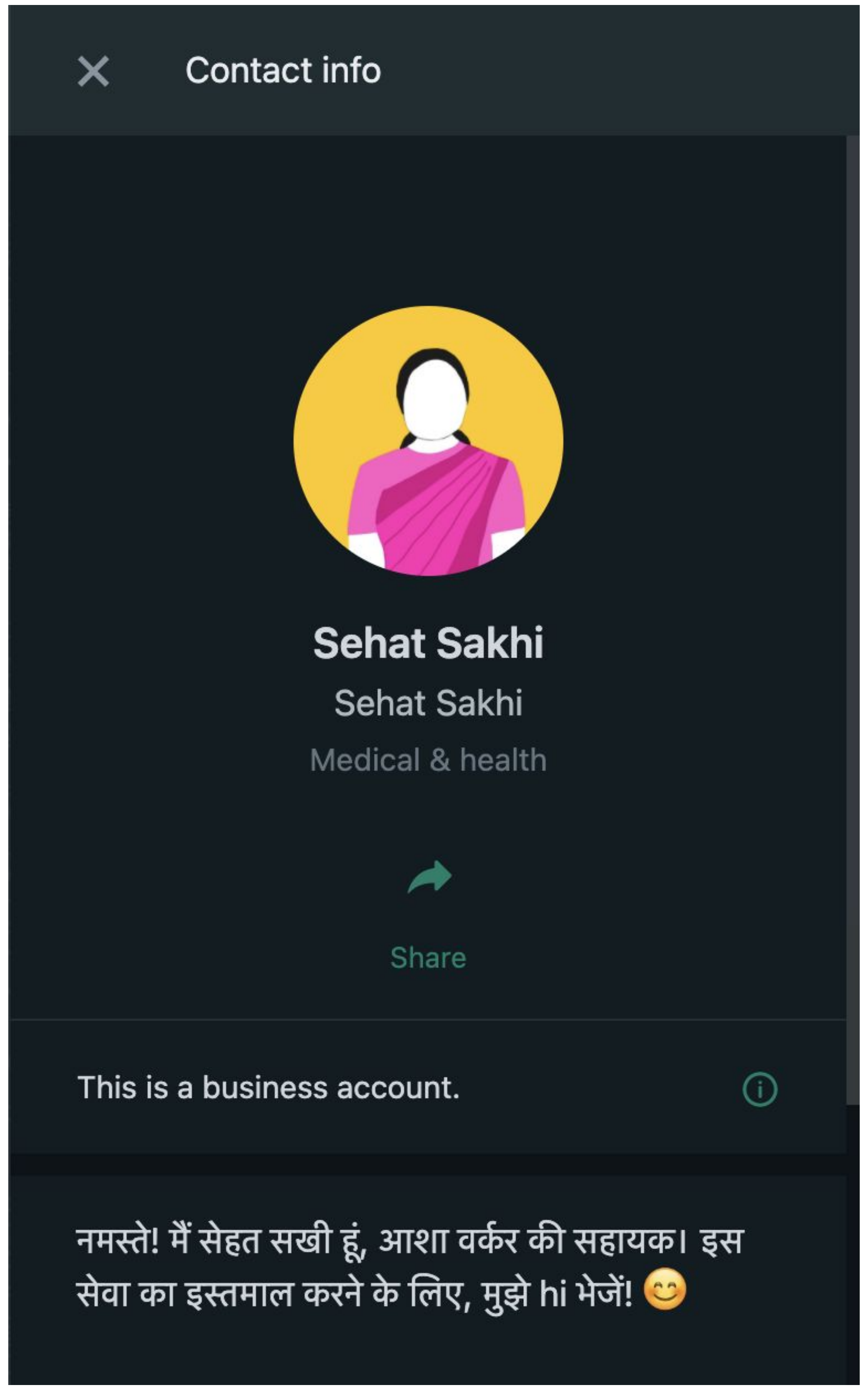
Sehat Sakhi: Namaste, I am Sehat Sakhi. I'm here to help with your ASHA tasks.

✨ ✨ Thank you for all the hard work you do for your community! 🙏

I can help you in the following tasks:
1 --> get list of upcoming ANC visits in your area
2 --> get list of upcoming HBNC visits
3 --> list of tasks due this month
4 --> list of tasks due this week
5 --> calculate date of birth or immunization dates

👉 To start, please type the number next to the work task that you are interested in. Or you can try typing some words like Imp, tika, anc, hbnc, week or 🤰, 👶, 💉 emojis.

Making sense of conversational agents



ASHA workers were tech savvy and learned over time, and

mostly had transactional interactions with the chatbot despite anthropomorphization.

"It's basically a computerised system, right? I think I've heard of it before."

— Farida, ASHA

Balancing agency and scaffolding

ASHAs modeled chatbot interactions on existing interactions with humans on WhatsApp,

had different synchronous and asynchronous interaction,

had to deal with interruptions during their interactions, and

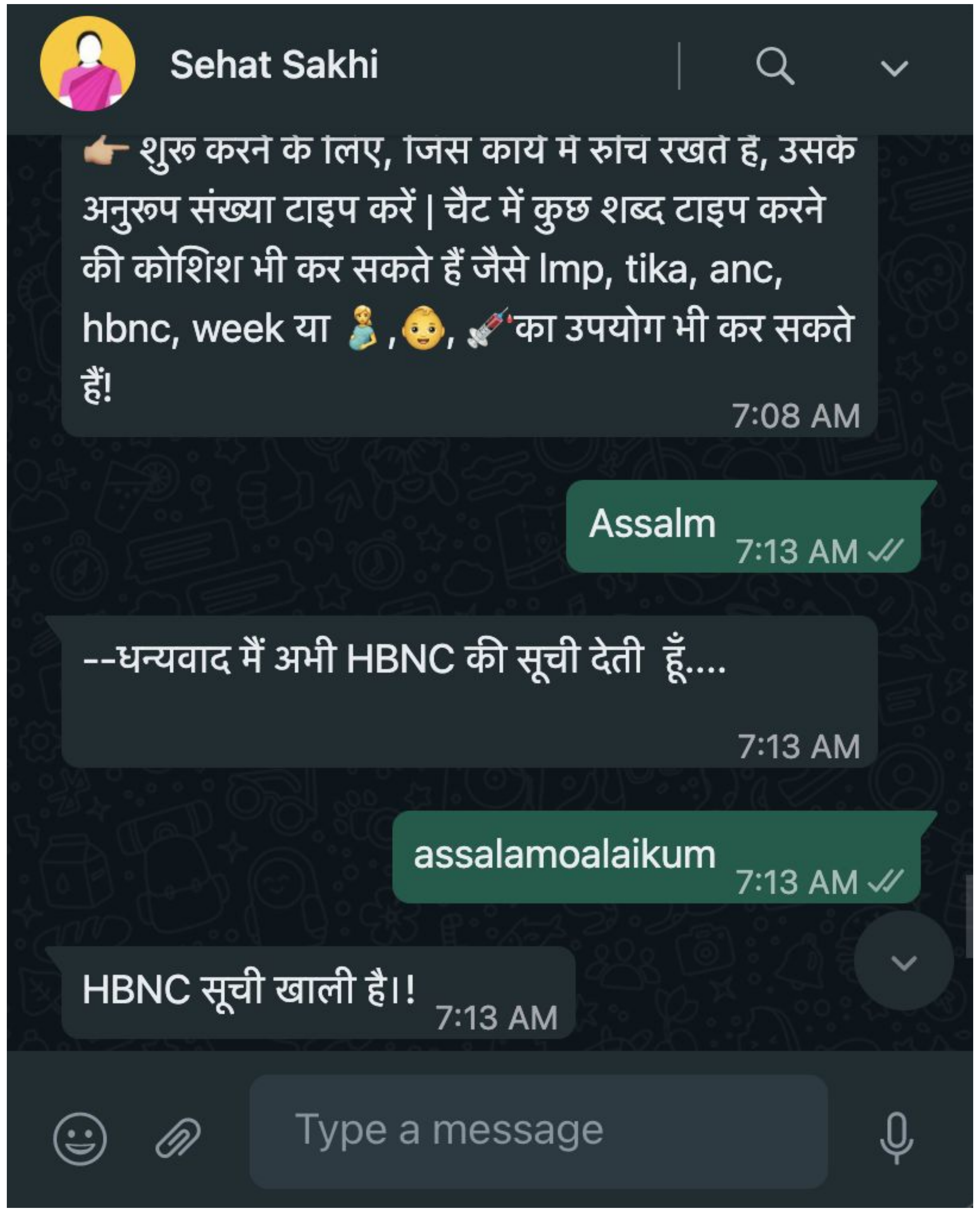
their onboarding experience was shaped by digital literacies.

"Oh, so now what should I do?

Why isn't it accepting this input?"

— Alia, ASHA

Dealing with system failures



ASHA workers were impatient when waiting for chatbot responses, and

contextualised language expressions by ASHAs were not understood by the chatbot.

ASHA Maryam: Assalm

Sehat Sakhi: Thank you, I will get the HBNC list in a moment

ASHA Maryam: assalamoalaikum

Sehat Sakhi: The HBNC list is empty!

TAKEAWAYS

TOWARDS WORKER-CENTERED DESIGN

ML developers need to balance scaffolding and agency for users,

consider how learning shapes interaction, and

account for diverse language use and digital literacies.

Next step is to evaluate long-term impact on time spent on and quality of data and care work.

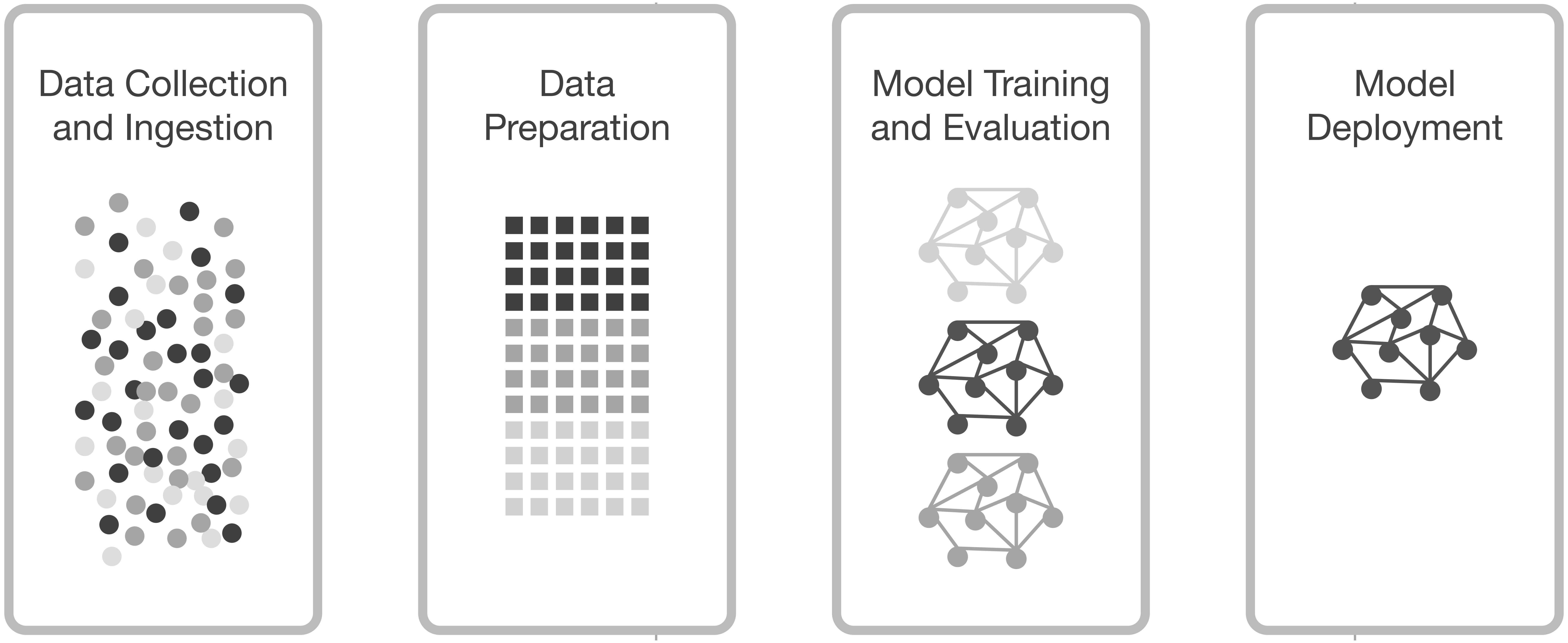
RQ. How might we integrate AI with care in public health?

INTEGRATING WITH

data flows and practices

organizational structures and goals

care workflows



FUTURE WORK

AI & Health Equity

Future of Care Work

Human-AI Collaboration

FUTURE WORK

AI & Health Equity

Future of Care Work

Human-AI Collaboration

How do we empower community data ownership and voice in AI interventions?

How can we take an intersectional perspective when targeting equity with AI?

FUTURE WORK

AI & Health Equity

Future of Care Work

Human-AI Collaboration

How do we center worker agency and control, particularly in decision-support tools?

What is the impact of AI tools on the work burden and quality of care?

FUTURE WORK

AI & Health Equity

Future of Care Work

Human-AI Collaboration

How can AI strengthen informal and formal caregiving networks?

How might we design AI systems that align with language use, particularly in diverse cultural settings?

FUTURE WORK

AI & Health Equity

Future of Care Work

Human-AI Collaboration

PROPOSED R01 GRANT

Design and evaluation of ML-based risk assessment to address racial disparities in maternal care

Motivation

2-3x maternal mortality among Black women in the US (3.3x in GA, highest in the country).
ML has been proposed to identify women that need further intervention.

Aim 1

Develop ML algorithms and causal inference models to predict pregnancy complications and estimate effects of potential health or social interventions

Aim 2

Develop interface to present risk assessment and suggested intervention to care providers and patients

Aim 3

Evaluate impact of providing risk assessment on decision-making and racial bias in care provision

Aim 4

Evaluate patient trust in risk assessment and effect on behavior change

SERVICE AND COMMUNITY-BUILDING

THANK YOU






NEHA KUMAR

SHAOWEN BARDZELL

MICHAEL BEST

ANDREA PARKER

THOMAS PLOETZ

PUSHPENDRA SINGH

THANK YOU

KARTHIK BHAT

CAMILLE HARRIS

NAVEENA KARUSALA

SACHIN PENDSE

VISHAL SHARMA

ANUPRIYA TULI

MARISOL WONG-VILLACRES

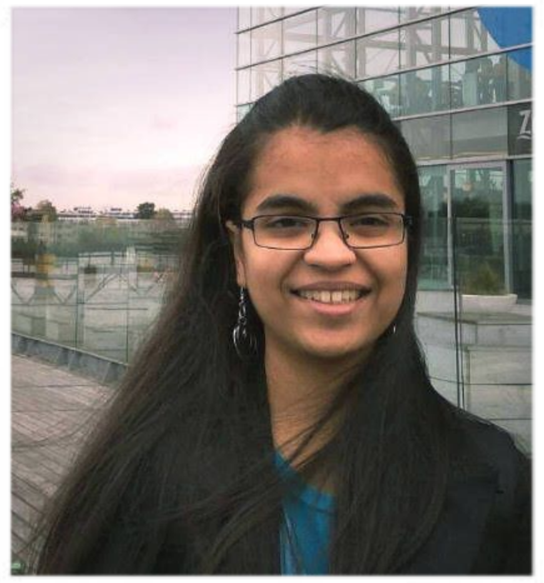
THANK YOU













POOJITA GARG

NEHA MADHIWALLA

MOHIT JAIN

DEEPIKA YADAV

NITHYA SAMBASIVAN

DIVY THAKKAR

ROSA ARRIAGA

KIRTI DABAS

MEGHNA GUPTA

RAJESH CHANDWANI

HAYLEY EVANS

PRERNA RAVI

SAMYUKTA SHERUGAR