"Who is running it?" Towards Equitable AI Deployment in Home Care Work

Ian René Solano-Kamaiko
Cornell Tech
New York, New York, USA
irs24@cornell.edu

Melissa Tan
Cornell Tech
New York, New York, USA
mrt96@cornell.edu

Joy Ming
Information Science
Cornell
Ithaca, New York, USA
jming@infosci.cornell.edu

Ariel C. Avgar
ILR School
Cornell University
Ithaca, New York, USA
aca27@cornell.edu

Aditya Vashistha
Cornell University
Ithaca, New York, USA
adityav@cornell.edu

Madeline Sterling
Division of General Internal Medicine
Weill Cornell Medicine
New York, New York, USA
mrs9012@med.cornell.edu

Nicola Dell
Jacobs Institute
Cornell Tech
New York, New York, USA
nixdell@cornell.edu

Abstract

We present a qualitative study that investigates the implications of current and near-future AI deployment for home care workers (HCWs), an overlooked group of frontline healthcare workers. Through interviews with 22 HCWs, care agency staff, and worker advocates, we find that HCWs do not understand how AI works, how their data can be used, or why AI systems might retain their information. HCWs are unaware that AI is already being utilized in their work, primarily via algorithmic shift-matching systems adopted by agencies. Participants detail the risks AI poses in sensitive care settings for HCWs, patients, and agencies, including threats to workers' autonomy and livelihoods, and express concerns that workers will be held accountable for AI mistakes, with the burden of proving AI's decisions incorrect falling on them. Considering these risks, participants advocate for new regulations and democratic governance structures that protect workers and control AI deployment in home care work.

CCS Concepts

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

Keywords

Artificial intelligence, AI, responsible AI, home health care, frontline work, low-wage work, labor, equity.

ACM Reference Format:
Ian René Solano-Kamaiko, Melissa Tan, Joy Ming, Ariel C. Avgar, Aditya Vashistha, Madeline Sterling, and Nicola Dell. 2025. "Who is running it?" Towards Equitable AI Deployment in Home Care Work. In *CHI Conference on Human Factors in Computing Systems (CHI '25), April 26–May 01, 2025, Yokohama, Japan.* ACM, New York, NY, USA, 19 pages. https://doi.org/10.1145/3706598.3713850

1 Introduction

Artificial Intelligence (AI) systems are rapidly transforming the lives of frontline workers in a wide range of domains, with AI often marketed as being capable of making smarter, more efficient, and more objective decisions compared to humans [51, 60]. Our research is situated in the complex and sensitive domain of home health care work, where there is significant interest in AI's potential to improve efficiency and reduce costs, possibly helping to ameliorate the current caregiving crises in many countries, including the United States (U.S.) [6, 66], Japan [58], the United Kingdom [36], and China [118]. These crises are caused by aging populations, with a growing number of older adults requiring assistance from a limited pool of paid, professional home care workers (HCWs) to support their health needs and enable them to age in their own homes [81, 110]. In the U.S., where our work is situated, the rising demand for home care services makes HCWs one of the fastest-growing sectors of the workforce, providing care for approximately 48 million Americans [84, 111].

Despite their crucial role in healthcare, research has shown that HCWs—mostly women from racial and ethnic minorities [84]—face low wages [57, 101], are undervalued by the healthcare system [55, 116], receive insufficient training and recognition [112], and often work in isolation [92, 114]. Compounding these issues, workplace technologies tend to focus on monitoring HCWs' labor for compliance (e.g., via GPS-enforced visit verification) and often reduce their autonomy over their work and personal data [70, 87].

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.
CHI '25, Yokohama, Japan
© 2025 Copyright held by the owner/author(s). Publication rights licensed to ACM.
ACM ISBN 979-8-4007-1394-1/25/04
https://doi.org/10.1145/3706598.3713850

Amidst these challenges, emerging AI technologies are poised to revolutionize the home health care ecosystem [66], promising substantial gains in efficiency and cost savings through automation in staffing and retention, scheduling and coordination, compliance, patient health prediction, worker performance tracking, and more [24]. The integration of these technologies into home care work systems will undoubtedly have implications and consequences—intended and unintended—that impact the livelihood and wellbeing of HCWs and their patients. Although current trends indicate that HCWs' work will increasingly be assigned, monitored, and evaluated using AI, there is limited understanding of HCWs' and other stakeholders' knowledge of AI, its current use in their work, the potential benefits and risks, and their preferences regarding data collection, governance, and accountability.

To better understand the implications of current and near-future AI deployment in home care work, we conducted a qualitative study involving semi-structured interviews with 22 participants, including HCWs, care agency staff, and worker advocates. Our findings make three key contributions. First, we show that AI tools are already being used in home care, providing efficiency gains for agencies, but these systems may compromise human care work by failing to account for important factors like empathy, personality, and compassion. Second, we identify challenges to equitable AI deployment in home care. Participants were concerned about fairness and discrimination due to HCWs' intersecting identities, the potential for AI to increase invisible labor and isolation, and the risk of exacerbating existing power imbalances. Third, we surface stakeholders' desires for new structures that enable human-centered, democratic governance of AI and discuss the need for standardized guidelines around AI use in home care.

Our research makes progress towards addressing a significant gap in current AI discussions by centering the perspectives of low-wage, frontline workers, whose voices are seldom heard in conversations about AI's impact on their professions. Our findings may thus help shape how organizations oversee and manage AI deployment in other low-wage work settings beyond home care.

2 Background and Related Work

2.1 AI and Low-wage Workers

As AI pervades the systems and processes governing work across various domains, it is essential to understand its risks and benefits for workers, especially low-wage frontline workers who are expected to integrate AI tools into their jobs. Although workers in some domains are understandably concerned about AI replacing their jobs [20, 106], there are many contexts—such as home care—where workers are unlikely to be fully replaced by AI. However, human jobs will undoubtedly be assigned, optimized, monitored, and evaluated via AI [31, 76], and workers will be required to learn and operate AI-driven tools [37, 56, 121].

A small number of studies have explored frontline workers' experiences with AI in high-stakes settings. Kuo et al. [71] examined frontline workers' concerns about using an algorithmic decision support tool for allocating scarce resources to unhoused people, finding that even without AI knowledge, workers could provide critical feedback on AI design and deployment. Kawakami et al. [65] investigated frontline workers' practices using AI-based decision support tools in child welfare, showing how workers' use of these tools was impacted by organizational pressures and incentives. Okolo et al. [90, 91] examined frontline workers' perceptions of AI-enabled health applications in India, highlighting the potential for overreliance on AI. To mitigate these challenges, Solano-Kamaiko et al. [109] proposed interactive, explainable tools that enabled frontline workers to improve their understanding of AI.

Collectively, these studies highlight the growing need to better understand frontline workers' knowledge of AI, their requirements for AI literacy and training [27, 62], how they can be empowered to contest AI decisions [61, 80], and how they can actively participate in developing work practices that effectively combine human and AI capabilities [59]. It is also important to understand how organizations make decisions to adopt AI tools that impact workers. Kawakami et al. [63] suggest that power relations between stakeholder groups (e.g., workers versus agency leaders) influence the practices of decision-makers who shape workers' AI experiences.

To this literature, we contribute a study examining AI deployment in home health care work in the U.S.—a high-stakes but understudied domain impacting millions of people [118]. Specifically, we analyze how AI may impact HCWs, a marginalized group of low-wage workers who have less power than other stakeholders in the ecosystem [12, 73].

2.2 AI in Institutional Care Facilities

Our work focuses on home-based care work, which provides essential support to older adults, enabling them to age in their own homes. While home-based care differs from institutional care settings (e.g., residential care), there is value in drawing insights from prior research in other long-term care environments.

A growing body of work examines the potential roles of AI technologies in institutional care facilities, such as nursing homes and residential care homes. Much of this research investigates the design of robots to assist with day-to-day care tasks [25, 26, 35, 98, 99, 119, 122, 124]. For example, Carros et al. [25] examined the perceptions of older adults, care workers, and managers regarding the use of a humanoid robot to support physical activity and cognitive training for older adults in a residential care facility, and how this robotic system might assist institutional care workers with daily tasks [26]. Findings from these studies suggest that, while humanoid robots in formal care facilities can help patients, they still require human moderation and have a limited impact on reducing caregiver workload [25, 26].

Beyond day-to-day care tasks, research has examined how AI-powered tools in long-term care facilities may burden care workers by subjecting them to large amounts of "data work", which is required to make these systems operable [118]. This includes manually producing, inputting, editing, and updating data, as well as contextualizing, communicating, and sharing data among stakeholders. Unfortunately, much of this work remains "invisible, undervalued, unpaid, and unacknowledged by healthcare companies and managers" [118].

In addition to burdening workers, research has also highlighted how AI-driven technologies might impact care facility residents. For example, Neves et al. [85] conducted interviews with staff, advocates, and AI developers to investigate how stakeholders' biases (e.g., ageism) might manifest in AI systems. Their findings suggest that, despite participants' best intentions, they exhibited bias against older adults' perceived inability or lack of interest in emerging technologies.

Our study extends this literature by examining the current and potential roles of AI in a distinct and understudied care context: home-based care. Unlike institutional care facilities or residential care homes, the goal of home-based care is to support older adults in aging in place—*in their own homes*. As such, the workforce at the heart of our study—HCWs—operate in a fundamentally different work environment from those in long-term care facilities.

HCWs are a highly distributed workforce, often working alone in patients' homes, isolated from their peers and supervisors [92, 112, 114]. This isolation means they are generally disconnected from the larger patient care team, working with limited oversight, support, and few opportunities for mentorship or training. Moreover, working in patients' homes constitutes an intensely intimate work environment, in which HCWs often have little control and less power than the patients they serve, their patients' families, clinicians, or other stakeholders. These factors may exacerbate concerns around AI ethics, fairness, trust, safety, and other critical issues, underscoring the urgency of examining the implications of AI deployment in this sensitive work environment.

2.3 AI in Home-Based Care

Beyond institutional care facilities, researchers have begun exploring whether AI systems could assist older adults as they age-in-place, either autonomously (i.e., absent caregivers) [19, 34, 46] or with the support of family caregivers [29, 126]. For example, Chang et al. [29] investigated older adults' willingness to adopt AI agents that autonomously perform care tasks (e.g., monitoring health, providing reminders, etc.) and communicate with other systems or people. The study also explored how these agents might evolve over time, shifting from supporting the older adult to assisting family caregivers as cognitive health declines. Participants responded positively to the idea of such agents, particularly if they could help reduce the burden on family caregivers.

Closest to our work, two studies explored the potential for AI-driven technologies to assist paid formal HCWs. Bartle et al. [11] examined the potential for commercially-available voice assistants (e.g., Amazon Alexa) to support HCWs' jobs in patients' homes by assisting with a variety of tasks including step-by-step medical assistance, task reminders, and more [11]. Their findings highlight the challenges of centering HCWs as primary users of these technologies, since they are deployed in patients' homes. A follow-up study then explored whether tailoring the physical appearance of the voice assistant device could improve its acceptability as a work tool for HCWs [10]. Although a promising approach, the study's findings highlighted concerns about HCWs' lack of power and the potential for in-home technologies to be used to surveil both workers and patients. These findings suggest that emerging AI solutions in home care may have unintended negative consequences that harm HCWs' and patients' safety, privacy, and autonomy.

Our research offers a broader perspective. Instead of focusing on a specific AI-driven device (e.g., a voice assistant) or only on day-to-day care tasks, we examine the landscape of current and near-future AI deployment across home care work contexts. This includes exploring the often conflicting perspectives and experiences of HCWs working in patients' homes, agency staff involved in operational and administrative functions, and worker advocates lobbying for improved working conditions and workforce recognition.

Beyond day-to-day care in patients' homes, there is growing interest in how AI might transform home care agency operations and logistics, leading to improved efficiency and cost savings. For example, algorithms have been proposed to match patients' home care needs with available services [28, 45, 79, 102]. Commercial tools are also actively marketed to home care agencies. For example, ShiftMatch.AI [23], developed by CareConnect [22], is promoted as an AI-powered shift management solution that automates aspects of HCW training and compliance, patient–HCW matching, shift scheduling and coordination, and more.

However, there is limited knowledge about HCWs' or other stakeholders' understanding of AI, the decision-making processes agencies use for purchasing and adopting these tools, and the governance and data management practices envisioned by stakeholders. Additionally, there is uncertainty about contestability and accountability mechanisms, and how to prevent AI tools from reinforcing the systematic deprioritization of HCWs' needs and perspectives, which could harm HCWs and patients. Our paper takes an important step toward answering these questions by analyzing the perspectives of HCWs, agency staff, and worker advocates regarding AI in these sensitive contexts. We explore potential benefits and risks of AI use and highlight areas where new oversight structures may be required to protect HCWs, patients, and other stakeholders.

2.4 Research Context: Home Health Care Work

We now provide essential background on the home care work context within which our research is situated. HCWs (including personal care aides, home health aides, and certified nursing assistants) are formal, paid caregivers who work long hours providing at-home care for patients with serious illnesses such as heart disease, dementia, Alzheimer's disease, and more. Their work is situated in patients' homes, where HCWs often assist with personal care and activities of daily living (e.g., dressing, bathing, cooking, etc.), medically-oriented care (e.g., monitoring medication, vital signs, fluid intake, etc.), out-of-home logistics (e.g., doctor visits, shopping, etc.), and other responsibilities [100]. The work is challenging and unpredictable, requiring a complex mix of physical and emotional labor as HCWs respond to patients' changing moods, needs, and emergency situations [116].

In our context, HCWs are employed by home care agencies, who largely receive funding from public institutions (i.e., Medicare and Medicaid) [47]. These agencies are responsible for conducting background checks and ensuring HCWs have completed required training. Eligible HCWs are then assigned to work shifts, via a complex matching process that, in theory, should optimally balance the HCW's availability, qualifications, geographic location, etc., with the patient's needs and location [50], while also prioritizing long-term continuity of care (i.e., matching the same HCW with the same patient) [8, 113]. On the job, HCWs report to an agency coordinator, who manages their daily work, and a supervising nurse who periodically (e.g., every few months) visits patients' homes to triage symptoms and provide medically-oriented care [115].

Although demand for HCWs is growing and patients increasingly rely on their services, research has shown that HCWs are an overlooked and undervalued segment of the healthcare workforce who face numerous challenges [55, 116]. HCWs, who are predominantly women from racial and ethnic minorities [84], are paid low wages [57, 101], do not receive sufficient training or recognition [112], and operate day-to-day in isolation [92, 114], without the ability to observe and learn from peers or be mentored by supervisors. As a result, this workforce suffers from high levels of stress, burnout, on-the-job injuries, and high job turnover rates [30, 40, 52, 77], made worse during the COVID-19 pandemic [92, 117]. Moreover, HCWs' current workplace technologies are hard to use and largely revolve around monitoring HCWs' labor for compliance (e.g., via GPS-enforced visit verification) [70, 88], reducing HCWs' autonomy over their work and data [70, 87].

HCI scholarship has begun to examine how technology could improve the complex landscape of paid home health care work. Recognizing the challenges faced by HCWs, Tseng et al. [120] used design provocations to explore whether technology might improve equity for workers. They found that designing for equity requires paying attention to structural problems, such as HCWs' lack of power, in addition to their stated needs. In another line of work, Poon et al. investigated the peer support needs of isolated HCWs [94] and designed computer-mediated peer support programs [95], delivered by peer coaches [93], which encouraged HCWs to collectively reflect on their experiences and build shared identity with their peers. We extend this work by examining how emerging AI technologies might improve equity for HCWs and/or exacerbate their burdens.

3 Methods

We conducted a qualitative study, consisting of semi-structured interviews with 22 HCWs, agency staff, and worker advocates. The interviews took place between June and August 2024. All study methods were IRB-approved.

3.1 Recruitment and Participants

To recruit HCWs, we partnered with a labor-management division of a large health care union in the U.S., whose goal is to deliver training programs that provide HCWs with skill-building and professional development opportunities. We posted flyers at our partner's offices that encouraged participants to contact our team. A staff member also reached out to HCWs who were engaged in other training programs and offered them the opportunity to participate. Participants needed to be employed as HCWs, speak English, and be 18 years or older; prior knowledge of AI was not required.

To recruit agency staff and worker advocates, we sent emails advertising the study to a range of home care agencies and worker advocacy organizations. Interested participants were encouraged to respond to our email and schedule an interview time. We also used snowball sampling, asking participants to connect us with other relevant staff at their agency/organization who might be interested in our study. Participants needed to be currently engaged in the home care ecosystem, speak English, and be 18 years or older; again, prior knowledge of AI was not required.

We recruited 22 participants (see Table 1): 11 HCWs, eight agency staff from three agencies, and three worker advocates, all from different organizations, whose jobs involve advocating for improved working conditions and recognition for the home care workforce. Participants ranged in age from 29 to 68 years and had an average of 12.3 years of experience in home care.

3.2 Interview procedure

Our interviews used a common interview script for all participant groups, with minor wording differences in questions to accommodate participants' varying roles. Interviews lasted 60 minutes, were semi-structured, and were conducted over Zoom, which enabled us to accommodate participants' varied work schedules and geographic locations. Prior to the interview, participants were sent a consent form to read and sign. The interview session then began with an overview of the study's goals, after which we reviewed the consent form, answered any questions, and confirmed participants' consent. We explained that the study was voluntary and that participants could refuse to answer questions or stop the interview at any time without forfeiting compensation. We also reassured participants that they did not need prior knowledge of AI.

The rest of the interview proceeded in three parts (see Appendix A). First, we sought an understanding of participants' occupational backgrounds and prior experiences working in home care. We also asked them to explain their current understanding of AI. Second, we used two fictional vignettes (discussed below) to explore participants' perceptions of the potential benefits and risks posed by AI in home care work, their thoughts on data collection and usage by AI systems, and their opinions on trust and safety. Third, we engaged participants in a general discussion about current and potential issues related to AI use in home care, including handling of AI system mistakes, resolution of conflicts between AI and human workers, and governance, regulation, and control of AI tools. Interviews were audio-recorded with participants' consent. All participants were given a $25 USD gift card as a token of appreciation.

Vignettes. One challenge in conducting our multi-stakeholder study was ensuring that discussions with different stakeholder groups, who possess varied backgrounds and experiences, were based on a realistic understanding of how AI tools might be deployed in home care work. To achieve this, we grounded our interviews in real examples of AI tools currently marketed for home care contexts [23, 107]. We created two fictional vignettes, each consisting of a short story that suggested possible scenarios for AI tools in home care (Table 2). We carefully worded our vignettes to encourage balanced discussions on the potential benefits, risks, challenges, and tensions associated with AI use.

The vignettes depict AI systems deployed at various points within the home care ecosystem. The first vignette is based on a tool that claims to offer "transformational value for agencies" through AI-powered shift management. In this scenario, an administrator uses the tool to streamline agency operations, including matching HCWs with patients. The second vignette is based on a tool marketed as an "always-on virtual care assessment through 100% audio technology …requiring no human engagement". In

Table 1: Demographic details of study participants (n=22). In the column on AI knowledge, *No Knowledge* means participants have no understanding or awareness of the basic principles of AI; they cannot identify AI-driven technologies. *Low Knowledge* means participants have a basic awareness of AI technologies but limited encounters and understanding of how AI works or is applied. They recognize popular examples such as Google Maps, ChatGPT, or Amazon Alexa. *Moderate Knowledge* means participants understand key concepts of AI technologies and are able to identify the applications of AI deployments. They understand that AI uses data for training to improve its accuracy.

Workers

ID	Role	Age	Gender	Education	Experience (years)	Knowledge of AI	Tech Usage
W1	HCW	68	Female	Some College	16	Low Knowledge	Phone
W2	HCW	57	Female	Master's Degree	7	No Knowledge	Phone
W3	HCW	50	Female	Some College	7	Low Knowledge	Phone
W4	HCW	33	Female	High School Diploma	7	Low Knowledge	Phone
W5	HCW	42	Female	Associate's Degree	11	Low Knowledge	Phone
W6	HCW	39	Female	Bachelor's Degree	7	Low Knowledge	Phone
W7	HCW	64	Female	Associate's Degree	34	Low Knowledge	Phone
W8	HCW	29	Female	Bachelor's Degree	4	Low Knowledge	Phone
W9	HCW	29	Male	Some College	4	Low Knowledge	Phone
W10	HCW	52	Female	Master's Degree	5	Low Knowledge	None
W11	HCW	49	Female	Some College	12	Low Knowledge	Phone

Agencies

ID	Role	Age	Gender	Education	Experience (years)	Knowledge of AI	Tech Usage
A1	Client Services Manager	42	Male	Bachelor's Degree	7	Low Knowledge	Phone, Computer
A2	Senior Vice President	55	Male	Master's Degree	30	Moderate Knowledge	Phone, Computer
A3	Vice President	45	Female	Master's Degree	20	Moderate Knowledge	Phone, Computer
A4	Director	44	Male	Bachelor's Degree	16	Moderate Knowledge	Phone, Computer
A5	Director	50	Female	Master's Degree	9	Moderate Knowledge	Phone, Computer
A6	Vice President	37	Male	Bachelor's Degree	6	Moderate Knowledge	Phone, Computer
A7	Nurse Manager	66	Female	Bachelor's Degree	14	Low Knowledge	Phone, Computer
A8	Compliance Officer	40	Male	Bachelor's Degree	16	Moderate Knowledge	Computer

Worker advocates

ID	Role	Age	Gender	Education	Experience (years)	Knowledge of AI	Tech Usage
V1	Executive Director	61	Female	Some College	30	Moderate Knowledge	Phone, Computer, iPad
V2	Coordinator	36	Female	Professional Doctorate	3	Moderate Knowledge	Phone, Computer, iPad
V3	Lead Organizer	36	Female	Master's Degree	5	Moderate Knowledge	Phone, Computer

this vignette, AI is used in the patient's home, where microphones placed throughout the house monitor patient-caregiver interactions and make predictions. All participants were presented with both vignettes. After each vignette, we asked questions to elicit participants' perceptions.

3.3 Data Analysis

Our data consisted of 18 hours of audio-recorded data and interview notes. Recordings were transcribed using NoScribe [43], an open-source, locally-run, AI-based tool. After transcription, we cleaned each transcript by listening to the recording, correcting errors, and redacting potentially identifying information (e.g., names).

After preparing the data, we followed Kuckartz's [69] three-stage process for qualitative data analysis. Our process involved (1) structural coding of high-level topics; (2) inductive generation of sub-codes within these categories; and (3) thematic analysis within and across categories. Structural coding is a first round qualitative coding method where data is coded deductively based on known research questions or topics [39]. In our case, the interviews were organized around a set of five key areas that our interviews sought to explore, including (1) knowledge of AI, (2) data collection, usage, and retention, (3) trust and safety, (4) accountability, and (5) governance. Our structural coding involved multiple passes over our data in which we tagged pieces of text using codes that corresponded to these topics. Then, we inductively analyzed the data within each topic, employing open coding to develop a comprehensive understanding of the data and sub-codes making up each topic. This resulted in a total of 34 sub-codes (e.g., prior experience using AI, willing to share data, trust human opinion over AI). After generating sub-codes, we used Braun & Clarke's thematic analysis [18] to cluster related codes into salient themes across our five key topic areas (see Table 3). Throughout our analysis, we used a collaborative qualitative approach [103] to ensure consistency in the coding through researcher agreement.

3.4 Positionality

We acknowledge that our research is influenced by our own experiences, identities, and motivations [41, 78, 105]. Our team consists of multidisciplinary researchers from a U.S. academic institution, including four women and three men with backgrounds in computer

Table 2: Fictional vignettes we created based on real examples of AI tools [23, 107] marketed for home care contexts.

Vignette 1 *Imagine Suzie is a home care agency administrator. Her job is to match and manage multiple home care workers and patients. Her agency recently decided to use an AI tool called PairMe to help her match home care workers with patients. PairMe looks at a lot of information about the agency's business goals, home care workers, and patients. Using all this information PairMe makes a prediction. PairMe suggests Suzie pair Mary, a home care worker employed by the agency, with a patient in Upper Manhattan who was previously working with a different care worker.*
Vignette 2 *John has recently been diagnosed with Alzheimer's Disease. He needs support throughout the day, yet often resists care, expressing anger and frustration with his caregiver Maria. John also often does not recognize Maria. The home care agency that Maria works for recently started using an AI tool called HearMe to better understand what is happening in patients' homes. HearMe uses audio speakers and microphones like Amazon Alexa and mobile phones to record audio in a patient's home. HearMe analyzes the audio to detect information like signs of distress, conflict, happiness, or other important information. In this case, HearMe alerted the agency staff that John is having intense interactions with Maria around the time she arrives every morning. HearMe also detects that John typically resists care during the morning but later in the afternoon, he tends to have more positive interactions with Maria. Based on this information, HearMe suggests shifting more challenging care activities to the afternoon when John tends to be less resistant. It also suggests that the agency give Maria extra training.*

and information science, labor relations, health, and medicine. We are all currently based in the U.S., but possess diverse and multicultural identities, including Latinx, Asian, and white researchers. Our motivation for conducting this study is to contribute knowledge and insights that might minimize the risks of AI for HCWs and ensure the equitable distribution of benefits to this marginalized workforce. Our team possesses years of experience conducting community-engaged research with HCWs. However, none of us have lived experience as a HCW and our positioning as researchers interested in AI may have influenced participants' responses.

4 Findings

Table 3 provides a high-level summary of our findings, organized around five key topic areas chosen to explore different facets of AI deployment, with each topic further structured around themes that emerged during thematic analysis. First, we explore participants' knowledge of AI and how it is currently deployed in home care (Section 4.1). We then examine participants' perceptions around how AI systems might collect, use, and retain home care data (Section 4.2). Next, we discuss how participants trust AI to make fair and objective decisions, despite being aware of risks AI systems may pose for HCWs, patients, and agencies (Section 4.3). We then unpack considerations around who may be held accountable for AI-driven decisions, mistakes, and the responsible usage of these tools (Section 4.4), before discussing participants' desires for new policies and governance structures to regulate AI deployment in these sensitive contexts (Section 4.5).

4.1 Knowledge of AI and its use in home care

As a starting point, we sought to understand participants' current knowledge of AI and its use in their work. Key themes that emerged from this exploration include: (1) HCWs have limited knowledge of AI and were unaware that AI is already used in their work; (2) AI tools are already deployed and providing efficiency gains for home care agencies; and (3) the use of AI may lead to agencies prioritizing efficiency at the cost of human care.

HCWs have limited knowledge of AI and were unaware that AI is already used in their work. We found that HCWs possessed little knowledge of AI. For example, when asked what AI was, W8 said, *"It's a computer program, I guess."* W5 elaborated, *"I don't really know much, but I know it's like a computer based something. It's the big information from surroundings and put it together to make a meaning to something."* Four HCWs mentioned using AI tools outside of their work, including for education; W11 said, *"I've tried ChatGPT to do my homework."*

For their part, agency staff and worker advocates had a greater understanding of AI compared to HCWs, often mentioning LLM-based tools they read about online:

> *"AI is when a computer is trying to answer a question or complete a task in a way that a human brain might...I guess my mind goes straight to, like . . . OpenAI and ChatGPT and Microsoft Copilot . . . I guess any, like, text prediction thing."* (V2)

Worryingly, when we probed HCWs' knowledge of AI tools currently deployed in home care, we found that HCWs were generally unaware that AI tools were already deployed in home care work. Instead, they did not know whether the applications they used for work incorporated AI or if any aspects of their work were already being optimized by AI. Only one HCW mentioned that their agency was already using AI for shift matching.

AI tools are already providing efficiency gains for home care agencies. By contrast, agency participants were generally able to explain how AI was already being used by their agency. The most common use was the same as our first vignette, shift matching: *"So we're basically using a tool like this already . . . We have a tool that matches the workers and the shifts. It does definitely help"* (A6). At least six agency participants worked for agencies that were already using AI-driven shift matching tools and perceived these tools as

Table 3: Summary of the main findings and themes from our analysis.

Topic		Themes
4.1	Knowledge of AI and its use in home care work	HCWs have limited knowledge of AI and were unaware that AI is already used in their work. AI tools are already providing efficiency gains for home care agencies. Using AI risks prioritizing efficiency at the cost of human care.
4.2	Perceptions around data collection, usage, and retention	HCWs do not understand why AI systems would collect or retain their information. Agency participants are not aware of current data collection or sharing agreements. Maintaining data accuracy and freshness will be costly and require substantial human labor.
4.3	Opinions on AI trust and safety	AI is perceived to be objective and may provide insights beyond what is perceptible by humans. HCWs do not want to know details of how AI works, but want assurances it is operating fairly. AI might exacerbate existing inequities and create invisible work for HCWs. AI may pose new risks for patients and agencies.
4.4	Accountability for AI's decisions and mistakes	Mistakes made by AI systems could have negative repercussions for HCWs. Agencies will be held responsible but have limited capacity to manage AI. Clinicians and technology companies may have a role in AI accountability.
4.5	Desires for governance and regulation of AI in home care work	Participants want standardized guidance and regulation of AI in home care work. Participants want democratic governance approaches that involve all stakeholders.

providing greater operational efficiency, making shift supervisors' work easier. They discussed how supervisors initially resisted the technology, but have come to embrace it:

> *"All of our staff who use it, love it. And if there's something wrong with it, they all go crazy and say, 'it's not working. We need it back. We need it to work.' … when we first started using it, there was a lot of skepticism but now they've all gotten used to it, they're all like, 'I can't do without it.'"* (A4)

In addition to shift matching, agency participants mentioned that their organizations used AI for several other purposes, including predictive analytics—such as identifying patients at high risk for certain problems to help guide subsequent interventions. For the most part, agency participants suggested that AI was most appropriate for processes such as *"visit verification and clerical and administrative functions"* (A2).

Beyond operational and administrative functions, participants were not aware of AI tools currently deployed in patients' homes. That said, V3 stated that they had heard of an AI-enabled tool designed to support patients in the home: *"it's a stuffed animal used as comfort companion, that you can talk to … it will learn things about you and you can have conversations with them."* Despite this observation, none of the participants we spoke to knew of any AI tools deployed for direct use by HCWs (such as in Vignette 2) and were skeptical of using AI in these sensitive environments.

Using AI risks prioritizing efficiency at the cost of human care. Although agency participants generally agreed that using AI for tasks like shift matching was efficient and saved their agencies time and money, they also expressed concerns around its use. A2 explained that it worked well as long as HCWs "fit" into what the tool expected: *"it has its limitations. It doesn't capture the whole universe. It captures people that fit squarely into whatever parameters you've set."* HCW participants elaborated, describing how their patient or shift matches seemed to prioritize minimum geographic distance between HCWs' and patients' homes, without accounting for, for example, ease of access to public transit or HCWs who commute from locations other than their home (e.g., another patient or their child's school). Beyond these pragmatic limitations, agency participants were also wary of how AI deployment may exacerbate existing systemic problems prevalent in home care work. For example, A2 explained how AI might result in less contact between HCWs and agencies, further isolating this already highly distributed and isolated workforce [112]:

> *"We already don't supervise [HCWs] nearly as much as you would normally supervise a person who does this kind of work. And it's not because we don't want to, it's because we don't have to. The state has very minimal requirements around supervision … it's a bad system already … and while these [AI] solutions are great and they're meaningful and their intent is great, it's just another way for [HCWs] to become less and less attached and engaged with the agency."* (A2)

Participants also worried that current AI tools, for example for shift matching, do not take important factors like empathy, personality, compassion, and intelligence into account when matching HCWs with patients:

> *"It's sometimes being a little discriminatory against somebody . . . you end up not matching a perfectly capable HCW with a [patient] that might benefit. [The AI] has basic things. Oh, she uses a Hoyer lift. She knows how to do CPR, things like that. But you're . . . missing the person and the intelligence and the compassion. These HCWs have such compassion, and they would encourage a severely overweight person, because they might have had something in their life that leads them into home care like that."* (A7)

In light of these concerns, participants felt strongly that humans should remain involved in work processes, because *"this is a very human industry, we're caring for people"* (A1). A6 elaborated, *"you cannot take the human element out completely, because there are subtleties . . . you need certain elements of emotional intelligence, and that's something I don't think AI has developed."*

4.2 Perceptions around data collection, usage, and retention

Next, we investigated participants' opinions around how AI systems deployed in home care might collect, use, and retain information. Key themes from our analysis suggest that: (1) HCWs do not understand why AI systems would collect or retain their information; (2) agency staff were more aware that data is needed to train AI models, but were not aware of any existing data collection or sharing agreements; and (3) participants perceived that maintaining data accuracy and freshness will be a costly endeavor that requires substantial human labor.

HCWs do not understand why AI systems would collect or retain their information. In line with their limited knowledge of AI, we found that HCWs did not understand the concept that AI systems would need to collect large amounts of data to train AI models. As such, HCWs struggled to grasp how the input of data into an AI tool is critical for improving its accuracy. For example, when we asked HCWs how they would feel about sharing their data to improve the AI system, W6 responded, *"Those are my personal information. So I just feel that the information should be for only me. So why would they want to use it? What do they want to use it for?"*

Further, when we asked about data retention, we discovered that HCWs felt strongly that if they stopped working for an agency, their data should be removed from any AI systems the agency used. They struggled to conceive of how their data might live on indefinitely as part of these tools: *"I'm no longer working with you. If you need improvement, use one of your workers"* (W11). Instead, HCWs expected that any data collected about them or their patients would be responsibly destroyed when a HCWs' employment ended or if the patients were no longer receiving services.

For their part, worker advocates reinforced that HCWs should be able to know if, and how, their data is used by any AI system, and have the ability to remove it. V2 shared how technology companies and agencies should *"be transparent with people about what is saved . . . and who has it. If [AI] was collecting information about me, I would want to know, like, are you going to sell it? Sell my email address or something, I'd really like to know that."* V1 went further, asking *"Can you burn personal data? Like, wipe it off completely. No record."*

Agency participants are not aware of current data collection or sharing agreements. In contrast to HCWs, we found that agency participants, who typically knew more about how AI worked, were aware that data would be needed to train AI systems. That said, they were not aware of any current policies or data agreements between the agencies that purchased AI tools and the technology companies that developed them:

> *"Do you know if or to what extent [tech companies] are using the data to improve their systems? I don't. We don't know the data agreements . . . but they're not actually using it to, like, train their systems or those sorts of things? If they are I wouldn't know that."* (A2)

Outside of AI tools, agency staff were aware of policies that mandated retention of data for compliance and posterity purposes. For example A8, who works as an agency compliance officer, mentioned that the current industry expectation is for agencies *"to store all data for at least seven years. It's just a requirement for us. And so, whether we have the hard copies or a digital copy in the system, we have to maintain it."*

Moreover, although agency participants empathized with HCWs desires to have their data removed from AI systems, they pointed out that as part of their labor contract, HCWs had consented to relinquish control over their data:

> *"I'd like to think that I control my data. I'd like to say, you know, this is my information about me. However, there's fine print everywhere that we don't read. So when you're joining a job and you're saying, 'okay, I accept this offer', the fine print in that offer, whether stated or unstated, is that I am agreeing to follow the rules and regulations, policies, procedures of this company. And in that is data retention."* (A3)

That said, agency participants expressed concerns about not fully understanding how data collected by technology companies might be stored and shared. They were particularly worried about data leakage, questioning if, and how, their organizations' data would be protected from competitors: *"There's a growing concern among all the licensed providers that use these technologies that the sharing of information across [agencies] is sensitive . . . especially when they do things like recruiting as a service. Like, how are you recruiting for one agency and not the other?"* (A2).

Maintaining data accuracy and freshness will be costly and require substantial human labor. Beyond collecting and using data to train AI models in the first place, participants worried about the potential human labor that would be required to ensure the system keeps generating viable outcomes. Specifically, keeping the data used by the AI system accurate and up-to-date was viewed as an immense and potentially costly challenge, especially because, as V1 put it, *"in the healthcare system, we're all stretched so thin . . . there isn't something that exists, unless we create it."* Drawing on their experience implementing prior, non-AI applications in home health care, A7 explained:

> *“All the administrative costs of keeping this up to date. Who’s monitoring all of this? . . . Hundreds of person hours to manually input every single HCW, every single patient, every single calendar, because people change hours all the time . . . It’s only as accurate as you make it . . . there’s thousands of HCWs. There’s only a couple hundred supervisors. So they have a huge cohort every day of patients and HCWs. You would need people that are very tech savvy, and able to pull the right information to pull the reports.”* (A7)

Participants were aware that such challenges may impact any technology deployed by their agency, both AI and non-AI, and that the issues were not necessarily something that could be addressed by AI systems. They discussed how triaging these issues starts further up the operational pipeline and is more related to the agency’s systems and processes: *“When we hear that I’m not going back to this patient because I’m allergic to cats. That is data entry on our part. So we’re able to identify [that] it’s not a caregiver, it’s not a patient, it’s not AI, it’s not the system. It is our own operational issue of missing something”* (A3).

4.3 Opinions on AI trust and safety

Beyond how AI systems might collect, use, and retain data, we were interested in exploring participants’ trust in AI and their opinions around its potential impact on their work and lives. Key themes that emerged from this exploration include: (1) participants perceived AI to be objective and capable of providing insights beyond human perception; (2) HCWs did not want to know the technical details of AI but sought assurances that it operates fairly; (3) participants were worried that AI could exacerbate existing inequities and create invisible work for HCWs; and (4) participants believed AI could introduce new risks for both patients and agencies.

AI is perceived to be objective and may provide insights beyond what is perceptible by humans. When we asked participants if they would trust the decisions made by an AI system, we found that 20 out of 22 participants had not previously thought about the need to consider whether an AI tool could be trusted or not; instead, they assumed that if it delivered results, it could be trusted. As A6 said, *“We’re already using it, so obviously, we trust it.”* However, when we probed further, asking participants how they would determine if the decisions made by AI tools were the *right* ones, A2 responded: *“Oh we would have no idea.”*

Agency staff further perceived that AI tools would operate fairly, discussing how AI-driven systems added a layer of objectivity and visibility to decision making processes. They felt that decisions made by AI systems seemed more merit-based and free of human bias: *“I think the biggest benefit is that [HCWs] see visibility into everything that we have available. Rather than them thinking, ‘your work goes to your favorites and I’m not one of your favorites”’* (A2).

For their part, HCWs saw potential for AI systems to provide objective evidence of their hard work and professionalism. For example, seven HCWs expressed that AI-driven systems might offer their employers greater transparency into what happens in patients’ homes and might help arbitrate conflicts between patients and workers: *“they would know what’s going on with both the HCW and the patient. So there’s no miscommunication, making up stories and stuff like that”* (W8). All 11 HCWs stated a willingness to have their work monitored, expressing confidence that any surveillance would affirm their professionalism and dedication. As W6 said, *“there’s nothing to hide. I’m there to do my work professionally. So, even if it records my audio and whatever I say to clients and things I’m doing, I’m fine with it.”*

Agency participants also saw value in AI tools providing seemingly objective evidence of incidents in the home, which could be helpful for HCWs facing mistreatment from patients or their families: *“Being recorded is a bona fide absolute, like as close to gospel testimony that we’re going to get from someone when they file a complaint or report something about a patient”* (A2). Furthermore, agency participants felt that AI-enabled monitoring systems could help identify HCWs facing challenges with patients, including abuse, who might be afraid to report such issues. A1, who is responsible for addressing client complaints, told us, *“[the AI] could also help us provide more support for workers that are going through challenges and not voicing their challenges to us.”* By providing such support, participants saw the potential for AI tools to help balance power asymmetries between patients, workers, and agencies.

We also found that HCWs perceived AI tools might offer benefits beyond the functionality of currently deployed tools or our fictional vignettes. For instance, W6 anticipated that an AI tool could provide feedback on its decisions that could help them learn and improve:

> *“It would . . . help me to know what to do next. If I wasn’t chosen in a particular case, I would know the reason I wasn’t chosen and the next thing to do. What steps can I take and what can I do to make myself a better candidate, and to make myself available whenever I have the next opportunity to be chosen.”* (W6)

Agency participants also thought AI tools could offer valuable insights into on-the-ground situations that might be imperceptible for humans, such as helping to ameliorate potential blind spots for overworked shift supervisors:

> *“For us, more information is better, right? Like having the ability to process and identify things that maybe AI would know that we wouldn’t . . . we’re so busy in the trenches of the day-to-day operations. When we say, ‘hey, you know what? You’ve had six people resign or leave their patient on this one street.’ And for us, it’s like, maybe that street is just not safe . . . And I think for a supervisor, it’s just constant churn and burn. I have to find another HCW. Not that maybe this area or this street is unsafe.”* (A3)

HCWs do not want to know details of how AI works, but want assurances it is operating fairly. Although participants thought AI systems might provide new insights that help HCWs and agencies, they generally agreed that HCWs would not want or need to know technical details or the ins and outs of how AI systems make decisions. In fact, HCWs assumed they would likely be ill-equipped to understand an AI system’s outcomes and said they would thus rely on their agency to explain: *“I would not be able to understand what the machine did . . . because it’s not a person . . . so I would just resort to asking the agency”* (W3). In line with these findings, agency participants were skeptical that HCWs, who are already overburdened, would want to understand the inner workings of an AI system:

> *"I don't think that [HCWs] have the interest in understanding how the technology works, like if you ask 'do you want to know how this works?' they'll be like 'no I just want to know what it does.' Don't tell me more than I need to know . . . I just want to know that it's being distributed in an equitable and a fair way."* (A2)

This quote reflects what we observed from participants, a desire for HCWs to be assured that decisions made by AI systems are fair and equitable. HCWs further emphasized that they would want to know they had been fairly evaluated or considered for work opportunities: *"I just want to know if it considered me"* (W8).

AI might exacerbate existing inequities and create invisible work for HCWs. Participants also recognized the risk that AI systems might reinforce the current status quo, where HCWs have less authority and voice compared to other stakeholders. For example, participants were quick to highlight how HCWs have little control over their employment conditions. Consequently, if agencies decided to incorporate AI tools into HCWs' workflows, workers would likely have little choice but to comply. W3 stated *"if my agency tells me that we're going to put the AI in your patient's home, I cannot say no. I just go for it and learn how to use it."*

Moreover, participants raised concerns that introducing new AI systems into HCWs' workflows might create additional burdens, such as the need to learn and operate a new technology, troubleshoot problems, coordinate technical support, and handle the consequences of technical failures. Much of this additional work might fall into the category of 'invisible work' [83, 118], in that it would likely be additional labor HCWs are expected to perform that goes unnoticed and uncompensated. Participants highlighted challenges from previous technology rollouts, such as recent electronic visit verification systems that require HCWs to clock in and out using GPS-enforced applications [87]. V1 described:

> *"I know that HCWs don't like to be tracked from when the electronic visit verification went into effect. It was a really heavy lift to get people to not feel like they were just being watched all the time. And they don't trust it because oftentimes, it's wrong. It doesn't go through right. It messes up their paychecks. So I think there'd be some concern about, 'could this AI make a choice that negatively affects me?'"*

HCWs further worried that agencies might not believe them when conflicts with patients arise: *"when the patient's family says something about your work, [the agency] believes more in the patient's family than you. That's the problem. And this can happen with AI"* (W2). Participants also stressed that the introduction of any new technologies or AI tools should be accompanied by training and communication that enables HCWs to clearly understand the system's goals. For example, communication would be needed to elucidate the system's goal of ultimately improving patient care, rather than punishing HCWs' for poor performance: *"We don't want to be punitive and I think that's a lot of the ways that our HCWs feel . . . it's really how we communicate and let them know it's a way for us to improve care and ensure we're providing reliable services"* (A1).

AI may pose new risks for patients and agencies. In addition to posing risks for HCWs, participants were also concerned that AI monitoring tools might present risks for patients if they misinterpret nuanced interactions, particularly for those who suffer from complex conditions such as Alzheimer's disease or dementia:

> *"We've had HCWs actually call and say, I need to be removed. Can I step out? He's [the client] so violent this morning . . . So you worry that this [AI tool] would actually be used against the [patient] . . . the family doesn't want him to go to a nursing home because he has one outburst or maybe two . . . You know, because AI has said, 'oh, you're a violent man. You're a violent person.' Not that, you know, he's so exasperated because he wants to go to the bathroom but doesn't remember where it is. So he's so upset. He doesn't know what to do. So he lashes out at the HCW."* (A7)

Agencies were also wary of the risks associated with AI and the data it collects. Specifically, they worried that a disgruntled patient, patient's family, or HCW might be able to cause reputational harm by, for example, inappropriately sharing sensitive data collected by an AI system. A2 explained, *"there's got to be a way in which the agency's practices are safeguarded . . . I would be worried that somebody could have a bad experience at an agency and there's enough data to for somebody to take that and do a lot of reputational harm."* In line with these concerns, V1 worried about the amount of data that might be collected about people and who would keep it and control it: *"the general push back [against AI] . . . at least from the team that I work with is, this shared personal information, where does it go? And who finds that out?"*

4.4 Accountability for AI's decisions and mistakes

Given the potential for AI-driven decisions to have negative consequences for HCWs, patients, and other stakeholders, we explored participants' views on accountability for these decisions, including any errors. Overall, we found a consensus among participants that while humans should work in collaboration with AI systems, AI is ultimately just a tool, and humans should be responsible for final decisions. However, participants had varying perspectives on who should be held accountable and suffer the resulting consequences when things go awry. The key themes we uncovered suggest: (1) mistakes made by AI systems could have negative repercussions for HCWs; (2) agencies will be held responsible for AI's mistakes, but have limited capacity to manage AI; and (3) clinicians and technology companies may have a role in helping address AI mistakes.

Mistakes made by AI systems could have negative repercussions for HCWs. A common concern among participants was that HCWs would be the ones to suffer if AI systems make mistakes. At least five HCWs perceived that they would be blamed for mistakes made by AI systems. One HCW thought this should be the case, as they were the ones accepting any suggestions made by AI: *"I think it will be my fault because [the AI system] is only giving me suggestions and I am the person who decides to do that suggestion or* *not. So I will blame myself"* (W9). Other HCWs thought it would be unfair if they were blamed for mistakes made by AI systems, worrying that being held accountable might lead to loss of income and employment: *"So now [the AI] makes a mistake and us humans are getting blamed for their mistake. I'm losing my job, nobody wants to wanna hire me"* (W11).

A7 worried that data collected by AI systems might be used against HCWs, suggesting a need for legislative protections to safeguard them from liability: *"Legally, you would worry that it would be used to prosecute a HCW. You know, families get very indignant that the HCW is not doing the best job for their family member . . . So you worry that this would be used against her, make her lose her livelihood, make her lose her job."*

Rather than attempt to handle mistakes themselves, seven HCWs said they would seek guidance from their agencies about what to do if an AI system made an error: *"I just gonna let my agency know that there was a mistake on what the AI is telling me to do . . . And from there, they will try to see what they can do to solve the problem"* (W3). Agency participants also felt that the correct course of action would be for HCWs to report disagreements they have with AI decisions to the agency. Two agency participants repeated some variation of an internal mantra: *"observe, record, and report"* (A8) and believed *"it's [HCWs'] responsibility to communicate with [the agency] about any discrepancies."* However, HCWs were quick to point out that when making a report to their agency, the agency's default assumption would likely be that the AI decision is correct, and the burden of proof would fall to HCWs to show otherwise.

Agencies will be held responsible but have limited capacity to manage AI. Beyond the repercussions for HCWs, both HCWs and agency participants felt that agencies would be responsible for decisions made by AI, since they procure and deploy these tools: *"Who's responsible when you rely on technology? I guess you can blame the AI but ultimately it's the agency's responsibility to ensure these things don't happen"* (A8). Similar to HCWs, agency participants worried that the automatic assumption would be that AI decisions are correct and it would be up to the agency to prove otherwise:

> *"Things would have to go for review and . . . policies written in favor of the provider more than the AI. I worry that we already have 'the customer's always right', we don't need now to have ['the AI is always right'] and it's up to the agency to disprove it. I don't think that's a great way to think about it."* (A7)

Worker advocates also voiced concerns about agencies being stretched too thin and lacking the capacity to properly manage AI deployments. For example, when asked who should be responsible for keeping data safe and secure, V1 responded, *"I would not say agencies. They cannot do anything right. They just don't have the capacity. They run at such a small margin . . . there would be no motivation for them to spend extra money to keep somebody safe."*

Clinicians and technology companies may have a role in AI accountability. Another suggestion was that clinicians might be best positioned to arbitrate AI recommendations, since they presumably knew more about the patient's plan of care and medical conditions. W3 suggested, *"I think that it's the nurse's job. Because she's the one who . . . makes the care plan. So she knows what the patient needs, how to take care of him."*

Finally, participants thought that technology companies should assume at least some responsibility for the AI systems they create. Specifically, participants felt that, given their domain expertise, technology companies were uniquely positioned to appropriately address issues such as stakeholder training, responsible data warehousing, and correcting AI mistakes. W6 explained, *"technology companies work hand in hand to invent AI . . . they know more about AI . . . so they should be held responsible."* Alternatively, participants thought an approach that ensures cooperation between home care agencies and technology companies may be best, given their different roles. To this effect, W11 stated *"I think the agency should be responsible for getting the training from the technology company and then train their workers."*

4.5 Desires for governance and regulation of AI in home care work

Finally, we examined participants' opinions on potential governance structures for AI in home care work. Key themes show that participants: (1) want standardized guidance and regulation for AI tools used in home care settings; and (2) strongly prefer democratic approaches to AI governance that involve all stakeholders.

Participants want standardized guidance and regulation of AI in home care work. Home care work, especially for agency-employed HCWs like those in our study, is a highly-regulated environment. There are several existing laws that codify important aspects of home care provision, including HIPAA [7], which protects patients' private health information, and compliance with Electronic Visit Verification [82] that is mandated for Medicaid-funded services. Similarly, participants saw a need for formal regulations that codify AI usage guidelines and liability procedures into law. For example, A8 stated, *"I can see policymakers and the government officials being very involved . . . to ensure that, they're [agencies] following all the regulations, all the laws, because it could be easy to violate HIPAA if you're not prepared."* Worker advocates agreed, including V1, who added:

> *"There should be serious discussions and potential policies or laws, maybe in the National Labor Relations Act or the National Labor Relations Board. [AI] can affect workplaces as well as conditions of work so this [needs to be] reviewed. People need to be held to a standard and . . . watch [AI] and constantly review that it's working as intended and that negative consequences are addressed immediately if there are any."*

For their part, HCWs wanted standardized guidance and structures that clearly established the responsibilities of both AI systems and HCWs. W6 felt that such structures were essential to ameliorate any conflicts between AI and human beings: *"yeah, there will surely be a lot of conflicts. It should be managed in the sense that it's all about structure. AI should be structured on what specific things to do. And humans should know what they are supposed to do."*

As part of creating established regulations, worker advocates stressed the importance of transparent rules and definitions, including specifying standards that need to be met and ensuring compliance. They also described a need for regulations that allow HCWs and patients to opt-out of being required to use AI in their work or to receive care. Knowing that digital technologies may lead to unintended consequences, participants emphasized the importance of establishing pathways for people to pursue algorithmic recourse, especially if they felt an AI system was discriminating against them:

> *"I think the regulations should definitely help with definitions . . . if it's appropriate to wipe data from the system. . . . I think the government should say, 'well, when we say 'wipe the system' you have to meet this standard' . . . I hear about discrimination and AI taking on the biases we already have. So . . . I would like to ensure that people have recourse if they feel that the tools are unfairly discriminating against them."* (V2)

Participants want democratic governance approaches that involve all stakeholders. In light of participants' desires for clear regulations and structures governing AI use in home health care, we explored their thoughts on who should control decisions, such as which AI systems are procured and deployed in home care work. To the best of our participants' knowledge, agencies currently have full control over the AI tools that they choose to purchase, with AI systems not currently differentiated from any other technology product procured for agency operations. Participants were also unaware of any processes in place for agencies to assess the trust, safety, or fairness of AI tools prior to adoption. That said, participants mentioned that they were not privy to the details of any contracts signed or data sharing agreements in place, and thus did not know if any such agreements existed.

Participants expressed concerns about treating AI the same as other digital tools. They questioned whether agencies could adequately and safely maintain, manage, and deploy AI systems, and responsibly handle the data they collect:

> *"Who is running it? Like, home care agencies have such high turnover, and it's not only at the caregiver level, it's also at management and coordinator levels, people don't stay. I would wonder about their capacity and their ability to manage something like that."* (V1)

Instead, all 22 participants expressed a desire for more democratic approaches to AI control and governance. Worker advocates suggested that worker unions, of which many agency-employed HCWs are members, would provide a better nexus of control to ensure workers' voices are considered. Others, such as HCWs, said: *"I think [all] parties should come on board and decide . . . the policymakers, the agencies, the family members . . . they should come on board to decide and see the opinion of the people"* (W5). In general, participants felt that it would be beneficial for representatives from all key stakeholder groups to come together and collectively make decisions, with oversight from government agencies:

> *"I think it's a combination, right? I think it's not just home care agencies but also managed care organizations . . . client services . . . nurses . . . I can see policymakers and government officials being very involved . . . the Department of Health, Department of Labor. There should be some kind of involvement from [government] to ensure that [agencies] are following all the regulations."* (A8)

5 Discussion

At a high level, our findings suggest that the home care industry is at a critical juncture with respect to AI deployment. In this section, we discuss some of the broader challenges facing equitable AI deployment in light of our findings, including concerns about fairness and discrimination given HCWs' intersecting identities, the potential for AI to increase HCWs' invisible work and isolation, and the risk of exacerbating existing power asymmetries (Section 5.1). We then highlight opportunities and challenges for the development of equitable structures for AI governance in home care (Section 5.2). Finally, we discuss opportunities to equip frontline workers such as HCWs with critical AI knowledge via stakeholder-first responsible AI literacy efforts (Section 5.3).

5.1 Challenges to Equitable AI Development and Deployment in Home Care Work

Our study shows that AI tools are already integrated into home care work processes, particularly for tasks like matching HCWs with patients and work shifts. As participants pointed out, the potential efficiency gains offered by AI are enormous for home care, an industry that is increasingly burdened by labor shortages and growing demands for care [68, 74]. Moreover, we observed stakeholders assuming that, since these tools demonstrably improve efficiency for agencies, they are trustworthy, although participants acknowledged they have no idea if these tools are operating fairly.

These findings are concerning because algorithmic rankers, comparable to the system in Vignette 1 (Table 2), can, and often do, discriminate against people who possess the exact demographic characteristics of most HCWs in our context [84]: women, people of color, immigrants, and those with other marginalized identities [16, 44, 86, 96, 125]. Similarly, research has shown that automated speech recognition systems, like the tool in Vignette 2, show disparities in their performance based on race [67], language [13], and ethnicity-related dialects [123]. While participants saw risks that AI systems might reinforce the current status quo, they were, for the most part, unaware of AI's potential to reproduce racism, sexism, and other forms of discrimination.

In addition, participants mostly judged the benefits of these deployed tools by the efficiency gains for *agencies*: being able to fill shifts or find replacements quickly. Few participants considered if, or how, these efficiency gains might negatively impact HCWs, such as by reducing their working hours and thus their income. This would be especially harmful given that nearly a quarter of HCWs live below the poverty line [84, 114]. These findings indicate the need for future research into the design of new AI auditing structures. Such structures should enable stakeholders in frontline work contexts—including technology companies, employers, workers, and others—to identify *who* benefits from potential AI-driven savings and suggest ways to equitably distribute any benefits.

Our findings also suggest that introducing AI tools into HCWs' workflows may lead to additional labor for HCWs, who will need to learn, maintain, and troubleshoot these tools. Much of this may be "invisible work", a well-documented structural problem in home care [83]. HCWs' working conditions may amplify these burdens since HCWs largely operate in isolation [101], meaning there are no witnesses to vouch for them or to help identify and correct errors made by AI systems, resulting in workers likely having little recourse to challenge AI outputs.

Corroborating these findings, prior literature has also shown how marginalized groups may be required to navigate and correct flawed AI systems, consuming excessive amounts of time and exacerbating social and economic inequalities [32]. Further, when existing discrimination is reproduced and amplified by AI systems, it is likely to be seen as the authoritative, neutral, and objective product of sophisticated technology [32, 48].

More broadly, our findings reinforce research narratives around the risks posed by significant power asymmetries between those with the resources to design and deploy AI systems (technology companies and agency employers) and those who are tracked, ranked, and assessed by these systems (HCWs and patients). In short, research suggests that those who possess less structural power are most at risk of harm from biased and exclusionary AI [33, 38, 104, 127].

This literature suggests that, when things go awry, the risks and liabilities introduced by AI systems are likely to fall on the most vulnerable stakeholders: HCWs and patients. Indeed, our participants felt that mistakes made by AI systems could lead to high-stakes consequences for HCWs, including loss of income and employment, a devastating proposal for workers already existing on the margins. We also heard concerns about how patients might lose their eligibility for home care services or be forced into more restrictive environments, an outcome antithetical to the values offered by home care. As we discuss next, these findings clearly point to an urgent need for new policies and frameworks that actively safeguard the interests and livelihoods of vulnerable stakeholders in the home care ecosystem.

5.2 The Need for Equitable AI Governance Structures

Our participants vocalized clear desires for established regulations and operating procedures to ensure equitable and responsible usage of AI in home care work. Our findings show that current approaches involve agencies treating AI systems the same as other software products used for agency operations. However, AI tools have important differences from conventional computer programs that follow predetermined instructions. To name a few, their decisions are non-deterministic, their rationale is opaque, their output lacks explanation, and they can learn and adapt by identifying patterns in large amounts of data. These complexities suggest a need for new regulatory structures that account for AI's differences from conventional software solutions.

Outside of home care contexts, AI regulation and governance is a hotly contested topic. Recent years have seen the introduction of sweeping policies and guidelines, many of which aim to enshrine human-centricity as a core tenet for AI governance structures [108]. Examples include the Artificial Intelligence Act (AIA) [3], Ethics Guidelines for Trustworthy AI [2], and General Data Protection Regulation (GDPR) [4] in the European Union (EU), along with the AI Bill of Rights [1] in the United States. By design, these policies are broad in scope and top-down in nature; they intentionally lack implementation details needed to operationalize AI governance mechanisms in industries like home care. However, this means there are large gaps between the policies available and the immediate needs of stakeholders in frontline work contexts like home care.

At the same time, current discourse around AI governance occurs largely between highly educated and privileged knowledge workers. One example is Meta's "Open Loop", a consortium of technology companies and policymakers working to develop governance frameworks and discuss regulatory best practices [5]. It is rare for such debates to include the voices or perspectives of non-AI experts or working-class people. By contrast, our participants wanted democratic governance structures that afforded all stakeholder groups meaningful input in the development of AI policies that govern their work.

In line with our participants' preferences, recent scholarship has called for moving away from hierarchical, top-down AI governance and decision-making processes to more participatory or collective approaches [21, 108]. For example, prior work suggests that stakeholder participation in the development of AI governance structures could help balance differing interests and lead to more responsible AI [17, 64, 75], with some viewing participatory approaches as "essential to understanding and adequately representing the needs, desires and perspectives of historically marginalized communities" [14], such as HCWs. On the other hand, critiques of participatory approaches point out that these methods may impose an epistemic burden on stakeholders to possess sufficient knowledge of AI systems [54]. Worse, participation may be co-opted by those with ulterior motives to claim legitimacy, providing stakeholders with a false sense of power rather than actual power [9].

Thus, participatory approaches to developing AI governance structures will need to be constructed with care to ensure they center problems and potential solutions from the perspectives of stakeholders who are not only on the margins but whose voices are critically excluded in current discourse on AI governance [53, 54] (i.e., patients and HCWs). This will involve establishing long-term, trusting relationships between stakeholders, developing processes that carefully account for the burdens and schedules of historically marginalized groups, and providing inclusive and accessible means for discussing AI processes, workflows, and implications.

Another intriguing avenue for future exploration of AI governance structures that aligns well with our participants' perspectives is the idea of data cooperatives, a type of platform cooperative characterized by democratic governance, collective ownership, and equitable data practices [15, 21, 97]. Data cooperatives support the premise that ordinary people require "political and epistemic power in order to challenge current algorithmic use and to expand the field of authority over algorithmic governance beyond legislatures, courts, agencies, and private industry" [89].

Of course, running a successful data cooperative would require both resources and capacity — both of which our findings suggest may be in short supply in home care contexts. Certainly, our participants worried that agencies may have neither the capacity nor the incentives to equitably govern such infrastructure. However, as our participants noted, the presence of strong worker unions and advocacy organizations in home care presents promising opportunities for these groups to play a role in establishing and running data cooperatives that benefit HCWs.

A key strength of these ideas—both participatory approaches and data cooperatives—is that they involve stakeholders. We now discuss a corresponding challenge in pursuing these approaches: ensuring stakeholders possess the requisite AI knowledge to effectively and responsibly deliberate on AI governance structures.

5.3 The Need for Stakeholder-First AI Literacy and Education

Our findings show that AI tools are already impacting home care work processes, highlighting the growing role of AI in this sensitive work environment. At the same time, we saw worrying discrepancies in AI knowledge among stakeholder groups. Compared to HCWs, agency participants possessed greater knowledge of AI, were more aware of ongoing AI implementation, and had a better understanding of data usage and retention policies. HCWs, on the other hand, generally did not understand how AI works, how their data could be used, or why AI systems might retain their information.

This lack of critical AI understanding limits HCWs' abilities to correctly identify and challenge AI systems. It also hampers HCWs' capacity to provide informed consent to participate in the use of AI systems—as operators of AI tools or as data subjects who contribute their information. Informed consent means that "data subjects should have the ability to exercise a real and genuine choice; consent is 'specific' and 'informed' when it is intelligible, referring clearly and precisely to the full scope, purposes, and consequences of the data processing" [4, 49]. This is at odds with our findings, which suggested that HCWs have little control over their employment conditions, often having no choice but to comply with the introduction of new technologies or risk losing their jobs. At the same time, we saw that many HCWs were willing to learn about AI and use it in their work, corroborating research in other contexts in which frontline workers similarly expressed a desire for knowledge and training around AI literacy [72, 90, 109].

The question, then, is what do HCWs or other frontline workers *need* to know about AI to be effective operators of AI tools, able to meaningfully consent, contest AI decisions, and contribute to participatory processes and democratic governance structures (as envisioned in Section 5.2). Drawing on recent scholarship by Domínguez Figaredo and Stoyanovich [42], we see potential for future AI education programs for HCWs that incorporate a stakeholder-first approach to responsible AI literacy. Instead of focusing AI literacy on the technology itself, the stakeholder-first approach shifts the emphasis from the content to be learned to the contexts in which AI systems are applied. This approach helps workers better understand and reason about the implications of AI in their specific contexts, without requiring programming knowledge [42]. Of course, AI literacy efforts alone will not fully address the aforementioned structural power imbalances. Nevertheless, improving epistemic parity among stakeholder groups, particularly HCWs, may serve as a significant first step toward informed consent and clearer accountability efforts, enabling more equitable deployment of AI in these sensitive work contexts.

5.4 Limitations

Our investigation has several limitations. We conducted a small-scale, qualitative study in one large city in the United States. Further research is needed to understand how our findings might generalize to larger samples and other locales, including rural and non-US settings. Our participants were drawn from three key stakeholder groups; future work is needed to capture perspectives of other stakeholders, including patients and families, clinicians, technology companies, policymakers, and others. Finally, our study has limitations inherent to qualitative interviews, such as potential recall bias. Further research could utilize ethnographic methods or field studies to examine real AI deployments in situ.

6 Conclusion

As AI is integrated into frontline work across various sectors, it is crucial to understand its benefits and risks for low-wage frontline workers, whose voices are seldom heard in discussions about AI's impact on their occupations. This paper investigates the implications of current and near-future AI deployment in home health care work. We show that AI is already being used in this sensitive context, resulting in efficiency gains for agencies that may come at the cost of human care. We highlight several challenges to equitable AI deployment in home care work, including concerns about fairness and discrimination given HCWs' intersecting identities, the potential for AI to increase their invisible work and isolation, and the risk of exacerbating existing power asymmetries. We discuss opportunities for developing equitable AI governance structures and emphasize the need to equip frontline workers, such as HCWs, with critical AI knowledge via stakeholder-first responsible AI literacy efforts. Lastly, our findings underscore the urgent need for the HCI community to consider how AI tools can support low-wage frontline workers—enhancing their work, agency, and power.

Acknowledgments

We are grateful for the valuable contributions made by all our study participants and the partner organizations that made these connections possible. This work was funded in part by a grant from the Innovation Resource Center for Human Resources (IRC4HR), the CAROW Initiative on Home Care Work, and a Google Cyber NYC award. We thank them for their generous support.

References

[1] 2024. Blueprint for an AI Bill of Rights | OSTP | The White House — whitehouse.gov. https://www.whitehouse.gov/ostp/ai-bill-of-rights/. [Accessed 03-09-2024].

[2] 2024. Ethics guidelines for trustworthy AI — digital-strategy.ec.europa.eu. https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai. [Accessed 03-09-2024].

[3] 2024. EU Artificial Intelligence Act | Up-to-date developments and analyses of the EU AI Act — artificialintelligenceact.eu. https://artificialintelligenceact.eu/. [Accessed 03-09-2024].

[4] 2024. General Data Protection Regulation (GDPR) Compliance Guidelines — gdpr.eu. https://gdpr.eu/. [Accessed 03-09-2024].

[5] 2024. Introducing Open Loop, a global program bridging tech and policy innovation — ai.meta.com. https://ai.meta.com/blog/introducing-open-loop-a-global-program-bridging-tech-and-policy-innovation/. [Accessed 06-09-2024].

[6] AARP and National Alliance for Caregiving. 2020. *Caregiving in the United States 2020*. Retrieved August 3, 2024 from https://www.caregiving.org/research/caregiving-in-the-us/caregiving-in-the-us-2020/

[7] Accountability Act. 1996. Health insurance portability and accountability act of 1996. *Public law* 104 (1996), 191.

[8] Oluwasegun P Akinyelure, Calvin L Colvin, Madeline R Sterling, Monika M Safford, Paul Muntner, Lisandro D Colantonio, and Lisa M Kern. 2022. Frailty, gaps in care coordination, and preventable adverse events. *BMC geriatrics* 22, 1 (2022), 476.

[9] Sherry R Arnstein. 1969. A ladder of citizen participation. *Journal of the American Institute of planners* 35, 4 (1969), 216–224.

[10] Vince Bartle, Liam Albright, and Nicola Dell. 2023. "This machine is for the aides": tailoring voice assistant design to home health care work. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems.* 1–19.

[11] Vince Bartle, Janice Lyu, Freesoul El Shabazz-Thompson, Yunmin Oh, Angela Anqi Chen, Yu-Jan Chang, Kenneth Holstein, and Nicola Dell. 2022. “A second voice”: Investigating opportunities and challenges for interactive voice assistants to support home health aides. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems.* 1–17.

[12] Mara Bensson-Ravunniarath, Joanna Bryan Ringel, Ariel Avgar, Faith Wiggins, Ann Lee, Margaret V McDonald, Lourdes R Guerrero, John Kallas, Geoffrey Gusoff, Megan Shen, et al. 2023. Having a say matters: the association between home health aides’ voice and job satisfaction. *Risk Management and Healthcare Policy* (2023), 1791–1800.

[13] Laurent Besacier, Etienne Barnard, Alexey Karpov, and Tanja Schultz. 2014. Automatic speech recognition for under-resourced languages: A survey. *Speech communication* 56 (2014), 85–100.

[14] Abeba Birhane, William Isaac, Vinodkumar Prabhakaran, Mark Diaz, Madeleine Clare Elish, Iason Gabriel, and Shakir Mohamed. 2022. Power to the people? Opportunities and challenges for participatory AI. In *Proceedings of the 2nd ACM Conference on Equity and Access in Algorithms, Mechanisms, and Optimization.* 1–8.

[15] Alessandro Blasimme, Effy Vayena, and Ernst Hafen. 2018. Democratizing health research through data cooperatives. *Philosophy & Technology* 31 (2018), 473–479.

[16] Miranda Bogen and Aaron Rieke. 2018. Help wanted: An examination of hiring algorithms, equity, and bias. *Upturn, December* 7 (2018).

[17] Elizabeth Bondi, Lily Xu, Diana Acosta-Navas, and Jackson A Killian. 2021. Envisioning communities: a participatory approach towards AI for social good. In *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society.* 425–436.

[18] Virginia Braun and Victoria Clarke. 2012. Thematic analysis. In *APA handbook of research methods in psychology, Vol 2: Research designs: Quantitative, qualitative, neuropsychological, and biological.* American Psychological Association, Washington, 57–71. http://dx.doi.org/10.1037/13620-004

[19] Robin N Brewer. 2022. “If Alexa knew the state I was in, it would cry”: Older Adults’ Perspectives of Voice Assistants for Health. In *CHI Conference on Human Factors in Computing Systems Extended Abstracts.* 1–8.

[20] Erik Brynjolfsson and Tom Mitchell. 2017. What can machine learning do? Workforce implications. *Science* 358, 6370 (2017), 1530–1534.

[21] Michael Max Bühler, Igor Calzada, Isabel Cane, Thorsten Jelinek, Astha Kapoor, Morshed Mannan, Sameer Mehta, Vijay Mookerje, Konrad Nübel, Alex Pentland, et al. 2023. Unlocking the power of digital commons: Data cooperatives as a pathway for data sovereign, innovative and equitable digital communities. *Digital* 3, 3 (2023), 146–171.

[22] CareConnect. 2024. . Retrieved August 3, 2024 from https://careconnectmobile.com

[23] CareConnect. 2024. *ShiftMatch.AI.* Retrieved August 3, 2024 from https://careconnectmobile.com/for-agencies/

[24] CareTap. 2023. *The Future Of Artificial Intelligence In Home Care Software.* Retrieved August 16, 2024 from https://caretap.net/blog/future-artificial-intelligence-home-care-software/

[25] Felix Carros, Johanna Meurer, Diana Löffler, David Unbehaun, Sarah Matthies, Inga Koch, Rainer Wieching, Dave Randall, Marc Hassenzahl, and Volker Wulf. 2020. Exploring human-robot interaction with the elderly: results from a ten-week case study in a care home. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems.* 1–12.

[26] Felix Carros, Isabel Schwaninger, Adrian Preussner, Dave Randall, Rainer Wieching, Geraldine Fitzpatrick, and Volker Wulf. 2022. Care workers making use of robots: results of a three-month study on human-robot interaction within a care home. In *Proceedings of the 2022 CHI conference on human factors in computing systems.* 1–15.

[27] Dilek Cetindamar, Kirsty Kitto, Mengjia Wu, Yi Zhang, Babak Abedin, and Simon Knight. 2022. Explicating AI literacy of employees at digital workplaces. *IEEE transactions on engineering management* 71 (2022), 810–823.

[28] Safa Chabouh, Adnen El-Amraoui, Sondes Hammami, and Hanen Bouchriha. 2023. A systematic review of the home health care planning literature: emerging trends and future research directions. *Decision Analytics Journal* 7 (2023), 100215.

[29] Mai Lee Chang, Alicia Lee, Nara Han, Anna Huang, Hugo Simão, Samantha Reig, Abdullah Ubed Mohammad Ali, Rebekah Martinez, Neeta M Khanuja, John Zimmerman, et al. 2024. Dynamic Agent Affiliation: Who Should the AI Agent Work for in the Older Adult’s Care Network?. In *Proceedings of the 2024 ACM Designing Interactive Systems Conference.* 1774–1788.

[30] Jacklyn Cho, Brittany Toffey, Ariel F Silva, Ariel Shalev, Monika M Safford, Erica Phillips, Ann Lee, Faith Wiggins, Elissa Kozlov, Emma K Tsui, et al. 2023. To care for them, we need to take care of ourselves: A qualitative study on the health of home health aides. *Health Services Research* 58, 3 (2023), 697–704.

[31] Shreya Chowdhary, Anna Kawakami, Mary L Gray, Jina Suh, Alexandra Olteanu, and Koustuv Saha. 2023. Can Workers Meaningfully Consent to Workplace Wellbeing Technologies?. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency (FAccT ’23).* Association for Computing Machinery, New York, NY, USA, 569–582. https://doi.org/10.1145/3593013.3594023

[32] Nelson Colón Vargas. 2024. Exploiting the margin: How capitalism fuels AI at the expense of minoritized groups. *AI and Ethics* (2024), 1–6.

[33] Kate Crawford. 2021. The Atlas of AI: Power, Politics, and the Planetary Costs of Artificial Intelligence.

[34] Andrea Cuadra, Jessica Bethune, Rony Krell, Alexa Lempel, Katrin Hänsel, Armin Shahrokni, Deborah Estrin, and Nicola Dell. 2023. Designing Voice-First Ambient Interfaces to Support Aging in Place. In *Proceedings of the 2023 ACM Designing Interactive Systems Conference.* 2189–2205.

[35] Torbjørn S Dahl and Maged N Kamel Boulos. 2013. Robots in health and social care: A complementary technology to home care and telehealthcare? *Robotics* 3, 1 (2013), 1–21.

[36] T Dann. 2014. Global elderly care in crisis. *The Lancet* 383, 9921 (2014), 927.

[37] David De Cremer and Garry Kasparov. 2021. AI should augment human intelligence, not replace it. *Harvard Business Review* 18, 1 (2021).

[38] David De Cremer, Devesh Narayanan, Andreas Deppeler, Mahak Nagpal, and Jack McGuire. 2022. The road to a human-centred digital society: opportunities, challenges and responsibilities for humans in the age of machines. *AI and Ethics* 2, 4 (2022), 579–583.

[39] Delve, L Ho, and A Limpaecher. 2020. *How To Do Structural Coding.* Retrieved August 3, 2024 from https://delvetool.com/blog/structuralcoding

[40] Margaret A Denton, Işk Urla Zeytinoğlu, and Sharon Davies. 2002. Working in clients’ homes: the impact on the mental health and well-being of visiting home care workers. *Home health care services quarterly* 21, 1 (2002), 1–27.

[41] 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.* 656–671.

[42] Daniel Domínguez Figaredo and Julia Stoyanovich. 2023. Responsible AI literacy: A stakeholder-first approach. *Big Data & Society* 10, 2 (2023), 20539517231219958.

[43] Kai Dröge. 2024. *NoScribe.* Retrieved July 3, 2024 from https://github.com/kaixxx/noScribe

[44] Virginia Eubanks. 2018. *Automating inequality: How high-tech tools profile, police, and punish the poor.* St. Martin’s Press.

[45] Christian Fikar and Patrick Hirsch. 2017. Home health care routing and scheduling: A review. *Computers & Operations Research* 77 (2017), 86–95.

[46] Jodi Forlizzi, Carl DiSalvo, and Francine Gemperle. 2004. Assistive robotics and an ecology of elders living independently in their homes. *Human–Computer Interaction* 19, 1-2 (2004), 25–59.

[47] Emily Franzosa, Tamar Wyte-Lake, Emma K Tsui, Jennifer M Reckrey, and Madeline R Sterling. 2022. Essential but excluded: building disaster preparedness capacity for home health care workers and home care agencies. *Journal of the American Medical Directors Association* 23, 12 (2022), 1990–1996.

[48] Allison Gardner. 2022. Responsibility, recourse, and redress: A focus on the three R’s of AI ethics. *IEEE Technology and Society Magazine* 41, 2 (2022), 84–89.

[49] Alexandra Giannopoulou. 2020. Algorithmic systems: the consent is in the detail? *Internet Policy Review* 9, 1 (2020).

[50] Xuran Gong, Na Geng, Yanran Zhu, Andrea Matta, and Ettore Lanzarone. 2020. A matheuristic approach for the home care scheduling problem with chargeable overtime and preference matching. *IEEE Transactions on Automation Science and Engineering* 18, 1 (2020), 282–298.

[51] Katja Grace, John Salvatier, Allan Dafoe, Baobao Zhang, and Owain Evans. 2018. When will AI exceed human performance? Evidence from AI experts. *Journal of Artificial Intelligence Research* 62 (2018), 729–754.

[52] Jennifer A Gray-Stanley and Naoko Muramatsu. 2011. Work stress, burnout, and social and personal resources among direct care workers. *Research in developmental disabilities* 32, 3 (2011), 1065–1074.

[53] Jean Hardy, Caitlin Geier, Stefani Vargas, Riley Doll, and Amy Lyn Howard. 2022. LGBTQ futures and participatory design: Investigating visibility, community, and the future of future workshops. *Proceedings of the ACM on Human-Computer Interaction* 6, CSCW2 (2022), 1–25.

[54] Christina Harrington, Sheena Erete, and Anne Marie Piper. 2019. Deconstructing community-based collaborative design: Towards more equitable participatory design engagements. *Proceedings of the ACM on human-computer interaction* 3, CSCW (2019), 1–25.

[55] Sarah J Hewko, Sarah L Cooper, Hanhmi Huynh, Trish L Spiwek, Heather L Carleton, Shawna Reid, and Greta G Cummings. 2015. Invisible no more: a scoping review of the health care aide workforce literature. *BMC nursing* 14 (2015), 1–17.

[56] John Howard. 2019. Artificial intelligence: Implications for the future of work. *American journal of industrial medicine* 62, 11 (2019), 917–926.

[57] Candace Howes. 2015. Home care: The fastest growing low-wage industry. In *New Labor Forum*, Vol. 24. SAGE Publications Sage CA: Los Angeles, CA, 98–105.

[58] Hiroo Ide, Naonori Kodate, Sayuri Suwa, Mayuko Tsujimura, Atsuko Shimamura, Mina Ishimaru, and Wenwei Yu. 2021. The ageing 'care crisis' in Japan: is there a role for robotics-based solutions? *International Journal of Care and Caring* 5, 1 (2021), 165–171.

[59] Akanksha Jaiswal, C Joe Arun, and Arup Varma. 2023. Rebooting employees: Upskilling for artificial intelligence in multinational corporations. In *Artificial Intelligence and International HRM*. Routledge, 114–143.

[60] Mohammad Hossein Jarrahi. 2018. Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business horizons* 61, 4 (2018), 577–586.

[61] Naveena Karusala, Sohini Upadhyay, Rajesh Veeraraghavan, and Krzysztof Z. Gajos. 2024. Understanding Contestability on the Margins: Implications for the Design of Algorithmic Decision-making in Public Services. In *Proceedings of the CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '24)*. Association for Computing Machinery, New York, NY, USA, Article 478, 16 pages. https://doi.org/10.1145/3613904.3641898

[62] Magnus Høholt Kaspersen, Line Have Musaeus, Karl-Emil Kjær Bilstrup, Marianne Graves Petersen, Ole Sejer Iversen, Christian Dindler, and Peter Dalsgaard. 2024. From Primary Education to Premium Workforce: Drawing on K-12 Approaches for Developing AI Literacy. In *Proceedings of the CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '24)*. Association for Computing Machinery, New York, NY, USA, Article 268, 16 pages. https://doi.org/10.1145/3613904.3642607

[63] Anna Kawakami, Amanda Coston, Hoda Heidari, Kenneth Holstein, and Haiyi Zhu. 2024. Studying Up Public Sector AI: How Networks of Power Relations Shape Agency Decisions Around AI Design and Use. arXiv:2405.12458 [cs.HC]

[64] Anna Kawakami, Amanda Coston, Haiyi Zhu, Hoda Heidari, and Kenneth Holstein. 2024. The Situate AI Guidebook: Co-Designing a Toolkit to Support Multi-Stakeholder, Early-stage Deliberations Around Public Sector AI Proposals. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–22.

[65] Anna Kawakami, Venkatesh Sivaraman, Hao-Fei Cheng, Logan Stapleton, Yanghuidi Cheng, Diana Qing, Adam Perer, Zhiwei Steven Wu, Haiyi Zhu, and Kenneth Holstein. 2022. Improving Human-AI Partnerships in Child Welfare: Understanding Worker Practices, Challenges, and Desires for Algorithmic Decision Support. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (New Orleans, LA, USA) *(CHI '22)*. Association for Computing Machinery, New York, NY, USA, Article 52, 18 pages. https://doi.org/10.1145/3491102.3517439

[66] Josh Klein. 2023. *The Coming AI Revolution in Home Care.* Retrieved August 16, 2024 from https://www.forbes.com/councils/forbesbusinesscouncil/2023/06/02/the-coming-ai-revolution-in-home-care/

[67] Allison Koenecke, Andrew Nam, Emily Lake, Joe Nudell, Minnie Quartey, Zion Mengesha, Connor Toups, John R Rickford, Dan Jurafsky, and Sharad Goel. 2020. Racial disparities in automated speech recognition. *Proceedings of the national academy of sciences* 117, 14 (2020), 7684–7689.

[68] Amanda R Kreider and Rachel M Werner. 2023. The home care workforce has not kept pace with growth in home and community-based services: Study examines the US home care workforce alongside the growth in home-and community-based services. *Health Affairs* 42, 5 (2023), 650–657.

[69] Udo Kuckartz. 2013. Three Basic Methods of Qualitative Text Analysis. In *Qualitative Text Analysis: A Guide to Methods, Practice & Using Software*, Udo Kuckartz (Ed.). SAGE Publications Ltd, London. http://dx.doi.org/10.4135/9781446288719

[70] Elizabeth Fong-Chy Kuo, Jacklyn Cho, Iredia Olaye, Diana Delgado, Nicola Dell, and Madeline R Sterling. 2022. Understanding the Technological Landscape of Home Health Aides: Scoping Literature Review and a Landscape Analysis of Existing mHealth Apps. *J Med Internet Res* 24, 11 (11 Nov 2022), e39997. https://doi.org/10.2196/39997

[71] Tzu-Sheng Kuo, Hong Shen, Jisoo Geum, Nev Jones, Jason I. Hong, Haiyi Zhu, and Kenneth Holstein. 2023. Understanding Frontline Workers' and Unhoused Individuals' Perspectives on AI Used in Homeless Services. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) *(CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 860, 17 pages. https://doi.org/10.1145/3544548.3580882

[72] Tzu-Sheng Kuo, Hong Shen, Jisoo Geum, Nev Jones, Jason I Hong, Haiyi Zhu, and Kenneth Holstein. 2023. Understanding Frontline Workers' and Unhoused Individuals' Perspectives on AI Used in Homeless Services. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–17.

[73] Djin Lai, Kristin G Cloyes, Margaret F Clayton, Katherine Doyon, Maija Reblin, Anna C Beck, and Lee Ellington. 2018. We're the eyes and the ears, but we don't have a voice: perspectives of hospice aides. *Journal of Hospice & Palliative Nursing* 20, 1 (2018), 47–54.

[74] Steven Landers, Elizabeth Madigan, Bruce Leff, Robert J Rosati, Barbara A McCann, Rodney Hornbake, Richard MacMillan, Kate Jones, Kathryn Bowles, Dawn Dowding, et al. 2016. The future of home health care: a strategic framework for optimizing value. *Home health care management & practice* 28, 4 (2016), 262–278.

[75] Min Kyung Lee, Daniel Kusbit, Anson Kahng, Ji Tae Kim, Xinran Yuan, Allissa Chan, Daniel See, Ritesh Noothigattu, Siheon Lee, Alexandros Psomas, et al. 2019. WeBuildAI: Participatory framework for algorithmic governance. *Proceedings of the ACM on human-computer interaction* 3, CSCW (2019), 1–35.

[76] Min Kyung Lee, Daniel Kusbit, Evan Metsky, and Laura Dabbish. 2015. Working with Machines: The Impact of Algorithmic and Data-Driven Management on Human Workers. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems* (Seoul, Republic of Korea) *(CHI '15)*. Association for Computing Machinery, New York, NY, USA, 1603–1612. https://doi.org/10.1145/2702123.2702548

[77] Samsik Lee and Gyeongrim Oh. 2023. Working conditions Affecting Home Care workers' stress and turnover intention. *Journal of Applied Gerontology* 42, 4 (2023), 717–727.

[78] Calvin A Liang, Sean A Munson, and Julie A Kientz. 2021. Embracing four tensions in human-computer interaction research with marginalized people. *ACM Transactions on Computer-Human Interaction (TOCHI)* 28, 2 (2021), 1–47.

[79] Meiyan Lin, Lijun Ma, and Chengshuo Ying. 2021. Matching daily home healthcare demands with supply in service-sharing platforms. *Transportation Research Part E: Logistics and Transportation Review* 145 (2021), 102177.

[80] Henrietta Lyons, Eduardo Velloso, and Tim Miller. 2021. Conceptualising Contestability: Perspectives on Contesting Algorithmic Decisions. *Proc. ACM Hum.-Comput. Interact.* 5, CSCW1, Article 106 (apr 2021), 25 pages. https://doi.org/10.1145/3449180

[81] Pia Markkanen, Margaret Quinn, Catherine Galligan, Stephanie Chalupka, Letitia Davis, and Angela Laramie. 2007. There's no place like home: a qualitative study of the working conditions of home health care providers. *Journal of Occupational and Environmental Medicine* 49, 3 (2007), 327–337.

[82] Medicaid.gov. 2016. *Electronic Visit Verification.* Retrieved September 4, 2024 from https://www.medicaid.gov/medicaid/home-community-based-services/guidance/electronic-visit-verification-evv/index.html

[83] Joy Ming, Elizabeth Kuo, Katie Go, Emily Tseng, John Kallas, Aditya Vashistha, Madeline Sterling, and Nicola Dell. 2023. "I Go Beyond and Beyond" Examining the Invisible Work of Home Health Aides. *Proc. ACM Hum.-Comput. Interact.* 7, CSCW1, Article 59 (apr 2023), 21 pages. https://doi.org/10.1145/3579492

[84] PHI National. 2023. Direct Care Workers in the United States: Key Facts 2023. Report. Retrieved June 11, 2024 from https://www.phinational.org/resource/direct-care-workers-in-the-united-states-key-facts-2023/

[85] Barbara Barbosa Neves, Alan Petersen, Mor Vered, Adrian Carter, and Maho Omori. 2023. Artificial intelligence in long-term care: Technological promise, aging anxieties, and sociotechnical ageism. *Journal of Applied Gerontology* 42, 6 (2023), 1274–1282.

[86] Safiya Umoja Noble. 2018. Algorithms of oppression: How search engines reinforce racism. In *Algorithms of oppression*. New York university press.

[87] Serena Oduro, Brittany Smith, and Alexandra Mateescu. 2021. Electronic Visit Verification: a guide to intersecting harms and policy consequences. (2021).

[88] Fabian Okeke, Emily Tseng, Benedetta Piantella, Mikaela Brown, Harveen Kaur, Madeline R Sterling, and Nicola Dell. 2019. Technology, home health care, and heart failure: a qualitative analysis with multiple stakeholders. In *Proceedings of the 2nd ACM SIGCAS Conference on Computing and Sustainable Societies*. 122–133.

[89] Ngozi Okidegbe. 2024. The Outsiders Of Algorithmic Governance. *Boston Univ. School of Law Research Paper Forthcoming* (2024).

[90] Chinasa T. Okolo, Dhruv Agarwal, Nicola Dell, and Aditya Vashistha. 2024. "If it is easy to understand then it will have value": Examining Perceptions of Explainable AI with Community Health Workers in Rural India. *Proc. ACM Hum.-Comput. Interact.* 8, CSCW1, Article 71 (apr 2024), 28 pages. https://doi.org/10.1145/3637348

[91] Chinasa T. Okolo, Srujana Kamath, Nicola Dell, and Aditya Vashistha. 2021. "It cannot do all of my work": Community Health Worker Perceptions of AI-Enabled Mobile Health Applications in Rural India. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, Article 701, 20 pages. https://doi.org/10.1145/3411764.3445420

[92] Zainab Toteh Osakwe, Jennel C Osborne, Tonya Samuel, Gabriella Bianco, Amarilis Céspedes, Michelle Odlum, and Ana Stefancic. 2021. All alone: A qualitative study of home health aides' experiences during the COVID-19 pandemic in New York. *American Journal of Infection Control* 49, 11 (2021), 1362–1368.

[93] Anthony Poon, Lourdes Guerrero, Julia Loughman, Matthew Luebke, Ann Lee, Madeline Sterling, and Nicola Dell. 2023. Designing for Peer-Led Critical Pedagogies in Computer-Mediated Support Groups for Home Care Workers. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–18.

[94] Anthony Poon, Vaidehi Hussain, Julia Loughman, Ariel C Avgar, Madeline Sterling, and Nicola Dell. 2021. Computer-mediated peer support needs of home care workers: emotional labor & the politics of professionalism. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW2 (2021), 1–32.

[95] Anthony Poon, Matthew Luebke, Julia Loughman, Ann Lee, Lourdes Guerrero, Madeline Sterling, and Nicola Dell. 2023. Computer-mediated sharing circles for intersectional peer support with home care workers. *Proceedings of the ACM on Human-Computer Interaction* 7, CSCW1 (2023), 1–35.

[96] Manish Raghavan, Solon Barocas, Jon Kleinberg, and Karen Levy. 2020. Mitigating bias in algorithmic hiring: Evaluating claims and practices. In *Proceedings of the 2020 conference on fairness, accountability, and transparency*. 469–481.

[97] Maria Elisabete Ramos, Ana Azevedo, Deolinda Meira, and Mariana Curado Malta. 2022. Cooperatives and the Use of Artificial Intelligence: A Critical View. *Sustainability* 15, 1 (2022), 329.

[98] Teemu Rantanen, Paula Lehto, Pertti Vuorinen, and Kirsi Coco. 2018. The adoption of care robots in home care—A survey on the attitudes of Finnish home care personnel. *Journal of clinical nursing* 27, 9-10 (2018), 1846–1859.

[99] Teemu Rantanen, Teppo Leppälahti, Jaakko Porokuokka, and Sari Heikkinen. 2020. Impacts of a care robotics project on finnish home care workers’ attitudes towards robots. *International Journal of Environmental Research and Public Health* 17, 19 (2020), 7176.

[100] Jennifer M Reckrey, Emma K Tsui, R Sean Morrison, Emma T Geduldig, Robyn I Stone, Katherine A Ornstein, and Alex D Federman. 2019. Beyond functional support: the range of health-related tasks performed in the home by paid caregivers in New York. *Health affairs* 38, 6 (2019), 927–933.

[101] Amanda Gray Rendón. 2022. A Case for Federal Labor Legislation to Protect Underpaid Home Care Workers. *AMA Journal of Ethics* 24, 9 (2022), 860–866.

[102] María I Restrepo, Louis-Martin Rousseau, and Jonathan Vallée. 2020. Home healthcare integrated staffing and scheduling. *Omega* 95 (2020), 102057.

[103] K Andrew R Richards and Michael A Hemphill. 2018. A Practical Guide to Collaborative Qualitative Data Analysis. *J. Teach. Phys. Educ.* 37, 2 (2018), 225–231.

[104] Rashida Richardson, Jason M Schultz, and Kate Crawford. 2019. Dirty data, bad predictions: How civil rights violations impact police data, predictive policing systems, and justice. *NYUL Rev. Online* 94 (2019), 15.

[105] Ari Schlesinger, W Keith Edwards, and Rebecca E Grinter. 2017. Intersectional HCI: Engaging identity through gender, race, and class. In *Proceedings of the 2017 CHI conference on human factors in computing systems*. 5412–5427.

[106] Alana Semuels. 2020. Millions of Americans have lost jobs in the pandemic—And robots and AI are replacing them faster than ever. *Time magazine* 6 (2020), 2020.

[107] Sensi.AI. 2024. *Sensi*. Retrieved August 3, 2024 from https://www.sensi.ai/

[108] Anton Sigfrids, Jaana Leikas, Henrikki Salo-Pöntinen, and Emmi Koskimies. 2023. Human-centricity in AI governance: A systemic approach. *Frontiers in artificial intelligence* 6 (2023), 976887.

[109] Ian René Solano-Kamaiko, Dibyendu Mishra, Nicola Dell, and Aditya Vashistha. 2024. Explorable Explainable AI: Improving AI Understanding for Community Health Workers in India. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–21.

[110] U.S. BUREAU OF LABOR STATISTICS. 2024. *Occupational Outlook Handbook: Home Health and Personal Care Aides*. Retrieved June 11, 2024 from https://www.bls.gov/ooh/healthcare/home-health-aides-and-personal-care-aides.htm

[111] MR Sterling and AL Shaw. 2019. Sharing the care—a patient and her caregivers. *JAMA Internal Medicine* 179, 12 (2019), 1617.

[112] Madeline R Sterling, Nicola Dell, Emily Tseng, Fabian Okeke, Jacklyn Cho, Benedetta Piantella, and Jonathan N Tobin. 2020. Home care workers caring for adults with heart failure need better access to training and technology: A role for implementation science. *Journal of clinical and translational science* 4, 3 (2020), 224–228.

[113] Madeline R Sterling, Jennifer Lau, Mangala Rajan, Monika M Safford, Oluwasegun Philip Akinyelure, and Lisa M Kern. 2023. Self-reported gaps in care coordination and preventable adverse outcomes among older adults receiving home health care. *Journal of the American Geriatrics Society* 71, 3 (2023), 810–820.

[114] Madeline R Sterling, Jia Li, Jacklyn Cho, Joanna Bryan Ringel, and Sharon R Silver. 2021. Prevalence and predictors of home health care workers’ general, physical, and mental health: Findings from the 2014–2018 behavioral risk factor surveillance system. *American Journal of Public Health* 111, 12 (2021), 2239–2250.

[115] Madeline R Sterling, Joanna Bryan Ringel, Barbara Riegel, Parag Goyal, Alicia I Arbaje, Kathryn H Bowles, Margaret V McDonald, and Lisa M Kern. 2023. Home health care workers’ interactions with medical providers, home care agencies, and family members for patients with heart failure. *The Journal of the American Board of Family Medicine* 36, 2 (2023), 369–375.

[116] Madeline R Sterling, Ariel F Silva, Peggy BK Leung, Amy L Shaw, Emma K Tsui, Christine D Jones, Laura Robbins, Yanira Escamilla, Ann Lee, Faith Wiggins, et al. 2018. “It’s Like They Forget That the Word ‘Health’Is in ‘Home Health Aide’”: Understanding the Perspectives of Home Care Workers Who Care for Adults With Heart Failure. *Journal of the American Heart Association* 7, 23 (2018), e010134.

[117] Madeline R Sterling, Emily Tseng, Anthony Poon, Jacklyn Cho, Ariel C Avgar, Lisa M Kern, Claire K Ankuda, and Nicola Dell. 2020. Experiences of home health care workers in New York City during the coronavirus disease 2019 pandemic: a qualitative analysis. *JAMA internal medicine* 180, 11 (2020), 1453–1459.

[118] Yuling Sun, Xiaojuan Ma, Silvia Lindtner, and Liang He. 2023. Data Work of Frontline Care Workers: Practices, Problems, and Opportunities in the Context of Data-Driven Long-Term Care. *Proceedings of the ACM on Human-Computer Interaction* 7, CSCW1 (2023), 1–28.

[119] Sayuri Suwa, Mayuko Tsujimura, Naonori Kodate, Sarah Donnelly, Helli Kitinoja, Jaakko Hallila, Marika Toivonen, Hiroo Ide, Camilla Bergman-Kärpijoki, Erika Takahashi, et al. 2020. Exploring perceptions toward home-care robots for older people in Finland, Ireland, and Japan: a comparative questionnaire study. *Archives of Gerontology and Geriatrics* 91 (2020), 104178.

[120] Emily Tseng, Fabian Okeke, Madeline Sterling, and Nicola Dell. 2020. "We can learn. Why not?": Designing Technologies to Engender Equity for Home Health Aides. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3313831.3376633

[121] Yan TU, Po HAO, and Lirong LONG. 2023. Job replacement or job transformation? Definition, consequences, and sources of technology-driven job insecurity. *Advances in Psychological Science* 31, 8 (2023), 1359.

[122] David Unbehaun, Konstantin Aal, Felix Carros, Rainer Wieching, and Volker Wulf. 2019. Creative and cognitive activities in social assistive robots and older adults: Results from an exploratory field study with Pepper. (2019).

[123] Alicia Beckford Wassink, Cady Gansen, and Isabel Bartholomew. 2022. Uneven success: automatic speech recognition and ethnicity-related dialects. *Speech Communication* 140 (2022), 50–70.

[124] Geng Yang, Zhibo Pang, M Jamal Deen, Mianxiong Dong, Yuan-Ting Zhang, Nigel Lovell, and Amir M Rahmani. 2020. Homecare robotic systems for healthcare 4.0: Visions and enabling technologies. *IEEE journal of biomedical and health informatics* 24, 9 (2020), 2535–2549.

[125] Ke Yang and Julia Stoyanovich. 2017. Measuring fairness in ranked outputs. In *Proceedings of the 29th international conference on scientific and statistical database management*. 1–6.

[126] Tamara Zubatiy, Kayci L Vickers, Niharika Mathur, and Elizabeth D Mynatt. 2021. Empowering dyads of older adults with mild cognitive impairment and their care partners using conversational agents. In *Proceedings of the 2021 CHI conference on human factors in computing systems*. 1–15.

[127] Shoshana Zuboff. 2015. Big other: surveillance capitalism and the prospects of an information civilization. *Journal of information technology* 30, 1 (2015), 75–89.

A Interview Protocol

A.1 Occupational Questions

- What is your job title?
  - How long have you been a [INSERT JOB TITLE]?
- Do you use a phone, computer, or other tech devices to do your job?
  - Can you tell me more about how you use tech or devices in your work?
  - What apps do you use?

A.2 Understanding of AI

- Have you heard of the term AI or artificial intelligence?
  - In your own words, can you explain what you think AI is? Can you give us some examples?
- Why don’t we go over a quick definition of AI together that way we are all on the same page:
  Let’s think of AI as a computer that can do things that normally require human intelligence, like making decisions by finding patterns in large amounts of information. For example, have you ever been recommended to tag specific people in your Facebook pictures? That is AI recognizing faces and suggesting that you tag your friend. It learns from user-uploaded pictures to improve its accuracy over time.

A.3 AI Scenarios

A.3.1 Vignette 1. Imagine Suzie is a home care agency administrator. Her job is to match and manage multiple home care workers and patients. Her agency recently decided to use an AI tool called PairMe to help her match home care workers with patients. PairMe looks at a lot of information about the agency's business goals, home care workers, and patients. Using all this information PairMe makes a prediction. PairMe suggests Suzie pair Mary, a home care worker employed by the agency, with a patient in Upper Manhattan who was previously working with a different care worker.

Benefits and Risks.

- What do you think could be some potential benefits of an AI shift matching tool like PairMe?
  - For Suzie, the admin?
  - For Mary, the worker?
  - For patients?
  - For the agency? And it's business goals?
- What do you think could be some potential problems or risks of an AI shift matching tool like PairMe?
  - For Suzie, the admin?
  - For Mary, the worker?
  - For patients?
  - For the agency? And it's business goals?

Trust and Safety.

- Would you trust AI to do a good job of shift matching?
  - What do you think is the most important information the AI should consider in making its decisions?
- How do you know if this shift matching tool is making the right decision?
  - For example, how would you know it selected the right care worker and patient match?
  - Would it help if the system described its rationale for how it made a decision? Why or why not?

Data Collection, Retention, and Use.

- Would you be comfortable sharing your information to help this AI make decisions?
  - For example, are you willing to share information such as your daily commute, qualifications, or language preferences?
  - Is there any information that you would be concerned about giving this AI tool or you think could be misused?
- If your employment were to end, what do you think should happen with your personal data that the AI system has collected on you?
- If a patient were to pass away, what do you think should happen with their data? For example, information on their illness, care needs, home location, or care schedule.

A.3.2 Vignette 2. John has recently been diagnosed with Alzheimer's Disease. He needs support throughout the day, yet often resists care, expressing anger and frustration with his caregiver Maria. John also often does not recognize Maria. The home care agency that Maria works for recently started using an AI tool called HearMe to better understand what is happening in patients' homes. HearMe uses audio speakers and microphones like Amazon Alexa and mobile phones to record audio in a patient's home. HearMe analyzes the audio to detect information like signs of distress, conflict, happiness, or other important information. In this case, HearMe alerted the agency staff that John is having intense interactions with Maria around the time she arrives every morning. HearMe also detects that John typically resists care during the morning but later in the afternoon, he tends to have more positive interactions with Maria. Based on this information, HearMe suggests shifting more challenging care activities to the afternoon when John tends to be less resistant. It also suggests that the agency give Maria extra training.

Benefits and Risks.

- What do you think could be some potential benefits of an AI monitoring tool like HearMe?
  - For Maria, the worker?
  - For John, the patient?
  - For the agency? And it's business goals?
- What do you think could be some potential problems or risks of an AI monitoring tool like HearMe?
  - For Maria, the worker?
  - For John, the patient?
  - For the agency? And it's business goals?
- Would you want an AI monitoring tool like this to be used in your work? Why or why not?

Trust and Safety.

- How would you know if the AI tool is making the right decision? For example, how would you know that the tool is correctly identifying conflict?
  - Would it be helpful if the system provided information about how it arrived at a decision? Why or why not?

Data Collection, Retention, and Use.

- Would you be comfortable sharing your information with these systems? For example, are you willing to let it record and analyze the audio conversations you have in a patient's home?
  - Can you think of ways that having such audio recordings might be beneficial for you?
  - Can you think of ways that the information recorded could cause problems for you?
  - Is there any information that you would be concerned about people having access to or that could be misused?
- If your employment were to end, what do you think should happen with the data the AI system has collected on you?
- If a patient were to pass away, what do you think should happen with their data? For example, their audio conversations or illnesses and care needs.

A.4 General Discussion

Accountability.

- Would you trust your own opinion or the AI more?
  - Do you think that your agency would agree?
- Would you want the option to opt out of using AI tools in your work?
  - Would you worry about getting "left behind" if you refuse to use AI tools?
- If you thought an AI system made a mistake, what do you think should happen?
  - For example, say an AI tool made a suggestion about caring for a patient that you thought was incorrect. What would you do?
  - Who should be responsible for the mistake?
  - Would you be comfortable reporting these mistakes? Why or why not?
  - How do you think conflicts between AI and humans should be handled?

Governance.

- Who should have the power to decide if an AI tool is used?
- Who should own or have control of the information collected by AI systems?
- Who should be responsible for keeping this information safe and secure?

- Who should be responsible for training you on these types of AI systems?

Wrap-up and Demographics.

- Aside from the examples we talked about, have you heard about AI systems at your job? If so, for what?
- Do you have any other thoughts about AI in home care?
- How old are you?
- What gender do you identify as?
- What’s the highest level of education that you have completed?
    - What did you study in school? [If applicable]