

# “This is eye opening:” Raising Awareness of Home Care Workers’ Health and Wellbeing via Activity Tracking

IAN RENÉ SOLANO-KAMAICO, Cornell Tech, United States

MELISSA TAN, Cornell Tech, United States

IRENE YANG, Cornell Tech, United States

KEXIN CHENG, Cornell Tech, United States

RONICA PERAMSETTY, Weill Cornell Medicine, United States

MICHELLE SHUM, Weill Cornell Medicine, United States

YANIRA ESCAMILLA, 1199SEIU Training and Employment Funds, United States

ARIEL C. AVGAR, Cornell University, United States

MADELINE STERLING, Weill Cornell Medicine, United States

ADITYA VASHISTHA, Cornell University, United States

NICOLA DELL, Cornell Tech, United States

Home care workers (HCWs) are an important group of frontline workers that deliver essential at-home care services to enable older adults to age in place. Despite their importance in patient care, research has shown that HCWs are an overlooked and undervalued workforce: HCWs work in isolated conditions, are paid low wages, experience high levels of stress and burnout, and more. As a result, despite being motivated to try and be healthy, this essential workforce suffers from poor physical and mental health outcomes. This paper combines data from focus groups, interviews, and a month-long field study with HCWs to investigate the feasibility and utility of using activity tracking devices to provide HCWs with fine-grained awareness and insights into daily activities that affect their health and wellbeing. We explore HCWs’ reactions to both their individual and collective data, discussing their efforts towards positive behavior change, but also highlighting systemic and occupational factors that may limit HCWs’ agency and control over their own activities. Finally, we discuss the potential for HCWs’ collective data to raise awareness about their working conditions and provide data-driven evidence to aid advocacy efforts towards improved policies, better wages, or greater protections for this vital workforce.

CCS Concepts: • **Human-centered computing** → **Empirical studies in ubiquitous and mobile computing**; **Information visualization**; • **Applied computing** → **Health informatics**.

Additional Key Words and Phrases: worker wellbeing, home health care, home care, frontline work, low-wage work, data governance, data advocacy, activity tracker, passive sensing, personal sensing.

## ACM Reference Format:

Ian René Solano-Kamaiko, Melissa Tan, Irene Yang, Kexin Cheng, Ronica Peramsetty, Michelle Shum, Yanira Escamilla, Ariel C. Avgar, Madeline Sterling, Aditya Vashistha, and Nicola Dell. 2025. “This is eye opening:” Raising Awareness of Home Care Workers’ Health and Wellbeing via Activity Tracking. In *CSCW Conference on Computer-Supported Cooperative Work and Social Computing (CSCW ’25)*, October 18–October 22, 2025, Bergen, Norway. ACM, New York, NY, USA, 26 pages. <https://doi.org/10.1145/nnnnnnn.nnnnnnn>

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](mailto:permissions@acm.org).

*CSCW ’25, October 18–October 22, 2025, Bergen, Norway*

© 2025 Copyright held by the owner/author(s). Publication rights licensed to ACM.

ACM ISBN 978-x-xxxx-xxxx-x/YY/MM...\$15.00

<https://doi.org/10.1145/nnnnnnn.nnnnnnn>

## 1 INTRODUCTION

Home care workers (HCWs) are an essential frontline workforce—primarily women from racial and ethnic minorities [71]—who provide life-changing care that enables an ever-growing number of older adults to remain at home and age in place [61, 91, 92]. However, despite HCWs' important role in healthcare delivery and patients' reliance on their services, research has shown they are an overlooked and undervalued workforce who face numerous challenges: they perform physically and mentally exhausting tasks [23, 65], often for long hours while working in isolation [75, 94], and receive low wages with little recognition and few opportunities for career advancement [46, 67, 84]. As a result, HCWs experience high levels of stress and work-related injuries [30], high job turnover rates [67], labor-induced burnout [23], and poor physical and mental health outcomes [23, 30, 67, 94]. These findings suggest a need for research and interventions aimed at supporting and improving HCWs' health.

Encouragingly, research shows that HCWs are motivated to remain healthy—driven in part by their desire to care for others and their work with sick patients—but they require support and resources to help them do so. [23]. Along these lines, prior work has called out the potential benefits of personal goal-setting and behavioral self-monitoring, especially in addressing HCWs' challenges around inadequate sleep, sufficient physical activity, and healthy nutrition [23, 74].

In other contexts, researchers have investigated the role of passive sensing devices, including consumer wearables (e.g., Fitbit [4]), in monitoring and supporting individuals' health and wellbeing, with sleep and physical activity (i.e., step count) recognized as key metrics for observing health-related outcomes [33, 72, 88]. These devices track personal data, offering users insights into their health and behavior [10, 72, 96], and studies have begun to examine their potential to enhance workers' wellbeing and productivity in workplace settings [10, 96]. Our research complements these efforts by investigating the feasibility and utility of providing HCWs with fine-grained awareness and insights into their daily activity levels, particularly sleep and physical exercise, both individually and within a community of peers.

First, we conducted focus groups with 12 HCWs to discover if and how activity trackers might be appropriate and useful, particularly in light of HCWs' sensitive and complex work environments. We discovered that HCWs were enthusiastic about the potential for tracking devices to increase their awareness of their health and wellbeing, both as individuals and as a collective of workers. They also expressed a willingness to share personal data with peers, employers, and advocacy organizations to aid broader advocacy efforts. They identified that wristband devices were most appropriate since they would be discreet and not interfere with HCWs' day-to-day tasks, which involve constant use of their hands and frequent hand washing.

Building on these insights, we conducted a field study in which we gave 17 HCWs Fitbit Charge 6 devices and asked them to use the devices for four weeks, with weekly reminders to reflect on their sleep and activity levels. We decided to track sleep and activity levels because they have been widely studied in relation to health and wellbeing [33, 38, 39, 62, 70, 72, 88], and are particularly relevant to HCWs, who, for example, have advocated against 24-hour shifts that negatively impact sleep quality [73]. Additionally, sleep and activity data can be passively collected, reducing data collection friction and minimizing participant errors, and are easy to understand and visually communicate to HCWs. At the end of the four weeks, we collected HCWs' data and used it to generate personalized visualizations for each participant that showed their activities in relation to (1) United States (U.S.) recommended health standards, and (2) the broader group of peer participants. We then conducted interviews with participants to explore their perspectives on this empirical data, including as an individual blending complex work and personal lives, among a group of distributed peers, and as a community trying to advocate for improved working conditions.

HCWs discussed how wearing tracking devices increased their awareness of their sleep and activity, with many describing the data as “*eye-opening*” and “*a wake-up alarm*”. Although many participants met recommended standards for physical activity, primarily driven by the demands of their frenetic and stressful work and home lives, most participants did not receive adequate sleep.

Participants described how reflecting on their data motivated them to try and change their daily habits in ways that might improve their health and wellbeing, such as by limiting television and phone use before bed. However, our findings also highlight how systemic and occupational factors, including power differentials governing their relationships with their patients and employers, may fundamentally limit HCWs' agency and control over their own schedules and activities.

Reflecting on HCWs' data as a group of peers, many participants drew comfort in realizing that they were “*not alone*” and “*all going through the same thing*”. They were eager to share their activity data more broadly in the hopes that it might help other HCWs, including via improved training programs or friendly competition among workers. They also saw potential for HCWs' collective data to play a role in raising awareness about their poor working conditions, providing data-driven evidence to help their union or labor advocates push for new policies, better wages, or greater protections for this precarious workforce.

We close by discussing the broader implications of our research, including the importance of centering HCWs' perspectives and experiences rather than one-size-fits-all health metrics that may not represent HCWs' realities. We highlight opportunities for workers' empirical activity data to add new layers to peer support and peer coaching programs, helping to support HCWs and mitigate systemic challenges such as worker isolation. Finally, we discuss opportunities for HCWs' collective data to raise awareness and amplify broader efforts to advocate for improved wages and working conditions for this low-wage, marginalized workforce.

## 2 RELATED WORK

### 2.1 Personal Informatics and Tracking Devices in Health and Workplace Wellbeing

The rise of digital devices that utilize passive sensing to enable fine-grained tracking of people's health and activity data (e.g., Apple Watch [2], Fitbit [4], and Oura Ring [7]) has inspired much CSCW and HCI research that investigates the potential for these devices to support both individuals' and communities' health and wellbeing [33, 52, 70, 72, 88]. For example, in the healthcare domain, a rich body of work studies the needs and experiences of patients and clinicians with wearables, including people with chronic conditions [52, 88] and older adults [20, 47]. Other work has examined how these devices might be integrated into broader healthcare systems and networks of care [72, 89], facilitating enhanced communication between patients and clinicians [72].

Beyond studying how these devices might help people manage their personal health, a cluster of studies has examined their utility in workplace settings. For example, tracking devices have been deployed to investigate the wellbeing and productivity of factory workers [41], medical residents and other healthcare professionals [10, 13], students [96], and information or knowledge workers [50, 63]. Close to our context, a few studies have explored the use of tracking devices by HCWs. For example, Muckell et al. [69] focused on mitigating the risk of injury to direct care workers caused by improper lifting of patients in an assisted living facility. During the COVID-19 pandemic, researchers also explored using tracking devices to aid early detection and reduce transmission of the virus among HCWs [11, 25]. Although related, much of this work primarily focused on monitoring HCWs, rather than actively supporting them.

Along these lines, research has discussed challenges around the use of tracking devices as workplace wellbeing technologies, particularly due to the sociotechnical context in which they operate and the often decontextualized nature of the data they collect [24, 27, 45, 60]. To address these issues,

Holten Møller et al. [45] proposed “collective sensemaking” as a strategy for workers to situate and contextualize the data by encouraging them to reflect on and annotate the data collected. However, while “collective sensemaking” could serve as a mitigating measure, other researchers, such as Maltseva [60], have shown that, in workplace settings, supposedly supportive technologies could inadvertently increase individuals’ emotional labor, dehumanizing and objectifying workers by treating them as “resources” rather than people. Additionally, privacy and security concerns have been raised around collecting workers’ data en masse, which might exacerbate workplace surveillance and monitoring [10, 24, 51]. Studies have also questioned whether workers can genuinely consent to these devices given existing power imbalances [24, 37, 66]. Our work contributes to this discourse by exploring workers’ reactions to tracking devices deployed in a novel and high-stakes context—home health care—involving a precarious and marginalized workforce of HCWs.

## 2.2 Sociocultural Aspects of Personal Informatics and Tracking Devices

Research has also called attention to the sociocultural dimensions of personal informatics and tracking devices, citing how these tools exist as part of a social practice [14, 26, 54, 58]. In particular, prior work contends that the notion of a quantified self [59] exists within the social, cultural, and political dimensions of society and emphasizes the importance of exploring how social factors such as power, gender, class, race, ethnicity, and other characteristics impact people’s lives [14, 26, 54, 58].

Furthermore, scholars have argued that health management, even when self-directed, is an inherently social process impacted by an individual’s personal relationships and broader sociocultural contexts [32, 38, 39, 57, 70]. For example, Murnane et al. [70] explored the use of self-tracking devices for mental health management, providing empirical and theoretical support for how these devices could better align with users’ interpersonal needs, values, and social experiences. Other work focused on sharing personal data from self-tracking devices with social networks [39] and on local community displays [38] to help promote physical activity and strengthen social relationships.

Particularly relevant to our research, Martin-Hammond and Purnell [62] studied how personal informatics can increase awareness of health behaviors to motivate behavior change among Black Americans. The study focused on a walking program designed to reduce heart health disparities in African American and other marginalized communities and utilized self-tracking as a tool to engage participants in healthy behaviors [62]. Participants felt the program was beneficial and remained engaged in part because of the program’s structure, which “fostered community building through shared knowledge and experiences and the use of historical context” [62]. Our work builds on these notions via a study that situates HCWs at the center of a complex sociotechnical ecosystem, consisting of multiple stakeholder groups, to understand HCWs’ positionalities, experiences, and perceptions around using tracking devices to raise awareness of their health and wellbeing.

## 2.3 Research Context: Home Health Care Work

Our study contributes to a growing body of CSCW research that seeks to understand the complex, multi-stakeholder work environments in home health care [22, 48, 49, 64] and support the precarious and essential workforce that drives the home care industry [48, 65, 79, 81]. As the U.S. population ages [9], a growing number of adults depend on HCWs to help them remain in their homes and age-in-place [61, 91]. This rising demand for home care services makes HCWs one of the fastest-growing sectors of the U.S. workforce, providing care for more than 48 million Americans [71, 92]. However, although HCWs are essential caregivers, research has shown they are an overlooked and undervalued segment of the healthcare workforce [43, 65, 95].

HCWs—a term that includes personal care aides, home health aides, and certified nursing assistants—are formal, paid caregivers who provide life-changing care for patients who often have chronic conditions, including heart disease, dementia, Alzheimer’s disease, or others. Their

work is situated in patients' homes, where HCWs may assist with personal care and activities of daily living (e.g., dressing, bathing, cleaning, cooking, etc.), medically-oriented care (e.g., monitoring medication, vital signs, physical activity, fluid intake, etc.), out-of-home logistics (e.g., doctor visits, shopping, etc.), and other responsibilities [82]. 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 [95].

Research suggests that HCWs—who are predominantly women from racial and ethnic minority backgrounds [71]—face a multitude of challenges. They typically work long hours for low wages [23, 46, 67, 84], within work environments that are highly intimate and geographically separated from the larger patient care team, leading to worker isolation and invisibility [65, 75, 94]. They do not receive adequate training or recognition for their contributions to patient care [75, 80, 94], and may encounter job safety hazards, harassment, or increased risk of work-related injuries due to the nature of their jobs [30]. As a result, HCWs experience high levels of stress and job turnover rates [67], labor-induced burnout [23], and poor physical and mental healthcare outcomes [23, 30, 67].

To ameliorate these challenges, there are growing calls for research to explore how to better care for these caregivers [23, 36] who themselves have expressed a strong desire to be healthy [23], both so that they are able to help others and due to their proximity to illness. More broadly, researchers and practitioners have created initiatives that seek to advocate for improved working conditions and protections for workers, such as the “No More 24” [73] campaign that seeks to end harmful practices where HCWs are expected to work 24-hour shifts, while only being paid for 13 hours, and pushing for new policies such as the Fair Pay for Home Care initiative [1].

Towards these goals, research has begun to explore ways to advocate for HCWs, including ensuring they are paid the wages they are due [64]. Other efforts have designed peer support programs [74, 80, 81] that incorporate topics such as worker safety, health, wellbeing, and social support. Our research complements these efforts by providing an empirical study tracking HCWs' activity data, which could offer concrete insights to raise awareness and amplify advocacy efforts. We explore HCWs perspectives on this empirical data, including as an individual blending complex work and personal lives, among a group of distributed peers, and as a community trying to advocate for improved working conditions.

## 2.4 Researcher positionality

Our US-based research team consists of eight women and three men with diverse academic backgrounds, spanning medicine, public health, and computer and information science. Our team possesses many years of experience working with HCWs, and underserved communities more broadly, and we have collaborated with our worker-union partner organization for the past six years. We are motivated to elevate, uplift, and advocate for the home care workforce in ways that improve their wellbeing and lead to greater recognition and respect for these essential workers. That said, none of our team has personal experience as a HCW and our education, cultural backgrounds, and socioeconomic status may have placed us in an uneven power dynamic with our participants, who were almost all women of color working within a marginalized workforce [40].

## 3 FOCUS GROUPS EXPLORING HCWS' PERCEPTIONS OF TRACKING DEVICES

Before deploying tracking devices with HCWs' in their sensitive work environments, it is important to first understand workers' willingness and enthusiasm to track their health and wellbeing data, as well as what devices might be appropriate and usable in their work and lives. Thus, we began by conducting initial focus groups that sought to answer three key questions:

- Do HCWs think tracking their health and wellbeing would be useful?

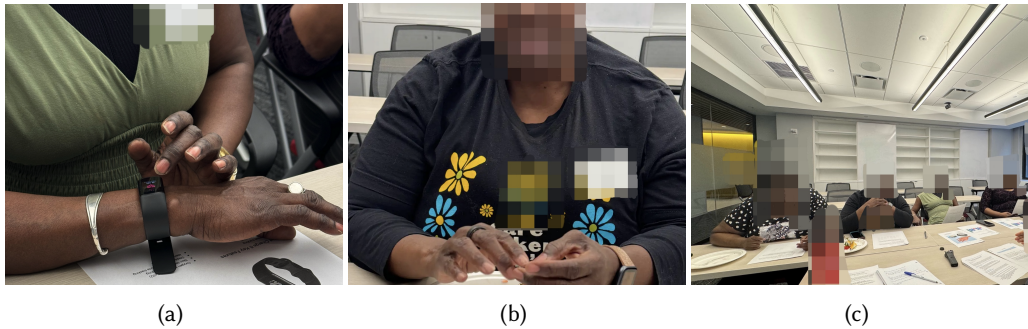


Fig. 1. Focus group participants trying on and interacting with (a) the Fitbit Charge 6 wristband and (b) the Oura ring; (c) shows the larger focus group setup.

- Would HCWs' be willing to track and share their data with others?
- What kinds of tracking devices might be appropriate for home care contexts?

### 3.1 Methodology

**3.1.1 Recruitment and Participants.** To recruit HCWs, we partnered with a large healthcare union that provides workforce training and education programs for thousands of HCWs in a major U.S. city. A union staff member reached out to HCWs who had previously expressed interest in union activities and offered them the opportunity to participate. Our inclusion criteria were: 18 years or older, English-speaking, smartphone owners (iOS or Android), and employed as formal, paid HCWs. Potential participants were informed that their decision to participate (or not) would not affect their relationship with the union or their employer. We recruited a total of 12 HCWs (see Table 1), a sample size we deemed to be sufficient to answer our initial focus group research questions. One participant was male and 11 were female, which reflects the heavily gendered HCW workforce.

**3.1.2 Focus Group Procedure.** We conducted three focus groups, each with four participants. The focus groups took place in-person at the union headquarters, which was recommended by union staff as a convenient location for participants. Each focus group involved two researchers: one researcher facilitated the discussion, asking questions based on our semi-structured interview guide, while the other provided support by taking notes and pictures, distributing materials, and operating the recording devices.

Prior to participating, all participants read and signed an informed consent form that included consent to audio record the sessions. The focus groups then began with a brief introduction to our research and a reminder that we would be capturing audio, photos, and note-taking.

As shown in Figure 1 we asked participants in the focus groups to try-on and interact with two tracking devices with different physical form factors: a wristband (Fitbit Charge 6 [35]) and a ring (Oura Ring [76]), representing two prevalent and different categories of consumer tracking devices currently on the market. Participants interacted with each device, examining how they functioned, the materials they were made of, and, in the case of the Fitbit, interacting with the wristband by swiping the display, exploring various features, and viewing data on the wristband interface. In addition to the devices, we provided printouts showing the types of data these devices collect.

After interacting with the devices and reviewing the data they collect, we discussed participants' initial perceptions of the devices, including their thoughts on the form factors, features offered, data collected (e.g., sleep and activity data), whether the devices might be useful, and any anticipated concerns. We also presented and discussed hypothetical data collection and sharing scenarios

that explored different levels of data privacy, including collecting and sharing (1) identifiable data (i.e., tied to a specific individual's name), (2) anonymized individual-level data, and (3) aggregate, group-level data. Upon completion of the focus groups, participants were given a \$25 giftcard.

**3.1.3 Data Collection and Analysis.** Our data consisted of approximately three hours of audio recordings that were transcribed, along with interview notes. We analyzed our data via structural coding [29], an established qualitative coding method where data is coded deductively based on known research questions or topics. In our case, we utilized our research questions and focus group topics as structural codes, and a member of the research team deductively analyzed and organized the data into discrete narrative segments that answered these known questions and topics. As a result, our findings are also organized around the three key questions we sought to answer.

## 3.2 Focus Group Findings

**3.2.1 Do HCWs think tracking their health and wellbeing would be useful?** HCWs were generally familiar with personal tracking devices, with participants having personal experience with them, either as their own device ( $n=2$ ) or that of a family member, friend, or patient. Participants were enthusiastic about the information provided by these devices increasing their awareness of their own health and wellbeing and helping them reflect on their own lives. For example, HCWs were conscious that they were not sleeping enough: *"I work at night, I get no sleep, I have no life"* (P12). They perceived that the information collected via the device might be useful for understanding their sleep patterns and making improvements. HCWs were similarly enthusiastic that activity tracking might help to establish clear and achievable goals and provide them with greater transparency into their daily exercise. HCWs noted that knowing their activity could help them better optimize their busy schedules and understand how much activity they were getting:

*"As a woman, you don't have time [for exercise]. You have to go home, you have to take care of your kids, you know ... it's better sometimes to get physical activity from walking, between times."* (P6)

HCWs thought that both sleep and activity data could be useful for documenting their circumstances to help advocate for systemic change. For example, HCWs felt that having empirical documentation of their lack of sleep could potentially be used to argue for increases in wages, changes in labor conditions, and fair implementations of existing laws:

*"We are the least paid, least respected of healthcare workers. ... it's like you don't matter. We are part of the ladder. We are the bottom ... This profession [HCWs] don't sleep. ... So if my information is being taken, they can assess the information and ... it could help. Maybe overnight shifts, we are going to pay you extra amount. And because of that I'm not going to take any extra job. I'll be able to sleep and my brain will relax and my system will work. Because if you don't sleep, you get so frustrated, you get tired, you get weak, you can't think straight, you do things that you forget, you are not supposed to do. So, I think for me, I would be willing to give any useful information that will help myself, my coworkers, and my patients."* (P11)

**3.2.2 Would HCWs' be willing to track and share their information?** HCWs were generally comfortable with the idea of both tracking and sharing their data. For example, P1 said *"They can track me, I have nothing to hide. I feel comfortable"*. That said, we did discover some variation in participants' preferences for who the data might be shared with. Of the 12 focus group participants, eight said they were comfortable sharing all their data with their peers, agency employers, unions, and advocacy organizations. However, four participants expressed concerns about the potential for their data to affect their current or future employment:

*“I would not like my employer to know about my activity level. Even when I apply for jobs, they ask, ‘how do you feel’ but I don’t know their motives. Why they are asking these questions.” (P7)*

Participants were also concerned about agencies potentially using activity data as proxies for health or labor monitoring, and that their hours might be cut or additional hurdles imposed by their agency employers. HCWs’ comfort also oscillated regarding sharing their sleep data with agency employers. For example, P1 emphatically stated *“I don’t care! They know we don’t sleep!”*, while others were more cautious and wanted to know how agencies might use their data.

HCWs were interested in sharing their data with their coworkers and building peer support initiatives through this shared knowledge. That said, one HCW said they would prefer to share anonymized data with their coworkers. Finally, HCWs also noted that the personal health benefits for workers might justify the potential for invasive tracking by agency employers:

*“For me personally, I don’t see a problem [with the device tracking me] because for me it’s like not [that] personal information. ... I’m diabetic, I have high blood pressure. For me in tracking this information, it’s an assistance to my daily way of living ... it’s a help more than to say ‘oh they are listening to everything you are saying or they are hearing what you are doing.’ That would be more invasive. But like, these things, for me personally, are more on a health basis.” (P3)*

**3.2.3 What kinds of tracking devices might be appropriate for home care contexts?** When we asked HCWs what devices might fit into their work environments, there was clear and emphatic consensus that a wristband (such as the Fitbit Charge 6) was more appropriate than a ring (i.e., Oura ring).

HCWs pointed out that the wristband was simpler and more discrete. It also enabled them to see their data and receive feedback directly on their wrist, while the Oura ring required looking at a connected app on their phone, which would be negatively perceived in their work environment: *“Especially if you are at work, a patient is going to be like ‘she’s on her phone’” (P3).*

Other HCWs noted that *“the watch is more pragmatic” (P6)* and said it would interfere less with their day-to-day work, which involved constant use of their hands and frequent hand washing. They also raised concerns regarding the durability of the ring and the increased likelihood of it being lost due to its small size, leading P8 to note that they *“would never choose the ring”*. Finally, one participant said that wearing rings was not allowed or otherwise restricted in her religion and so she would not be able to wear a ring.

## 4 FIELD STUDY DEPLOYING TRACKING DEVICES WITH HCWS

The focus group findings suggested that HCWs saw potential benefits of tracking devices for both their individual health and wellbeing, as well as a collective of workers sharing data. Building on these insights, we conducted a four-week field study with 17 HCWs, during which we deployed tracking devices. Based on our focus group findings, we selected the Fitbit Charge 6 wristband as the tracking device for the study.

### 4.1 Methodology

**4.1.1 Recruitment and Participants.** We recruited participants through our healthcare union partners, using the same inclusion criteria as in the focus groups. We initially targeted a sample size of 20 HCWs, which we deemed to be sufficiently large to answer our research questions and also feasible given the duration of the study, potential burden on participants, and the financial cost of purchasing the Fitbit devices. To expand the sample beyond the original 12 focus group participants, a union staff member again reached out to HCWs visiting the union headquarters for other programs and offered them the opportunity to participate. This approach led to the recruitment of



Table 1. Demographic details of study participants (n=20). Three focus group participants did not provide demographic data and are marked “Unknown” in the table. The term “device experience” refers to whether participants had any prior experience using self-tracking devices.

| ID  | Age | Gender  | Race/Ethnicity         | Education          | Experience (years) | Participation | Device Experience |
|-----|-----|---------|------------------------|--------------------|--------------------|---------------|-------------------|
| P1  | –   | Unknown | Unknown                | Unknown            | Unknown            | Focus groups  | Unknown           |
| P2  | –   | Unknown | Unknown                | Unknown            | Unknown            | Focus groups  | Unknown           |
| P3  | –   | Unknown | Unknown                | Unknown            | Unknown            | Focus groups  | Unknown           |
| P4  | 68  | Female  | Black/African American | Some College       | 16                 | Both          | No                |
| P5  | 65  | Female  | Hispanic or Latinx     | Associate's Degree | 21                 | Both          | No                |
| P6  | 57  | Female  | Black/African American | Master's Degree    | 7                  | Both          | No                |
| P7  | 50  | Female  | Black/African American | Some College       | 7                  | Both          | No                |
| P8  | 58  | Female  | Black/African American | College Degree     | 12                 | Both          | Yes               |
| P9  | 61  | Female  | Black/African American | College Degree     | 19                 | Both          | Yes               |
| P10 | 33  | Female  | Black/African American | High School        | 7                  | Both          | No                |
| P11 | 42  | Female  | Black/African American | Associate's Degree | 11                 | Both          | No                |
| P12 | 44  | Male    | Black/African American | Master's Degree    | 8                  | Both          | No                |
| P13 | 64  | Female  | Hispanic or Latinx     | Associate's Degree | 34                 | Field study   | No                |
| P14 | 52  | Female  | Hispanic or Latinx     | Associate's Degree | 6                  | Field study   | No                |
| P15 | 29  | Female  | Black/African American | College Degree     | 4                  | Field study   | No                |
| P16 | 29  | Male    | Hispanic or Latinx     | Some College       | 4                  | Field study   | Yes               |
| P17 | 39  | Female  | Hispanic or Latinx     | High School        | 10                 | Field study   | No                |
| P18 | 37  | Female  | Black/African American | College Degree     | 5                  | Field study   | No                |
| P19 | 49  | Female  | Black/African American | College Degree     | 15                 | Field study   | No                |
| P20 | 50  | Female  | White                  | High School        | 11                 | Field study   | Yes               |

eight additional HCWs, complementing the initial 12 focus group participants. Ultimately, three focus group participants chose not to participate in the field study (which we attribute to natural attrition), leaving an eventual sample size of 17 participants: nine who participated in both the focus group and field study, and eight who only participated in the field study.

Table 1 provides participants' demographic information. Two participants identified as male and 15 as female. Most HCWs were people of color with 11 identifying as Black or African American, five as Hispanic or Latinx, and one as White. Participants ranged in age from 29 to 68 years old, with an average of 11.6 years of experience working as a HCW. Four participants had prior experience with self-tracking devices such as Apple or Android Smartwatches. All participants worked for home care agencies providing services to patients, with 14 working full-time and three working part-time.

**4.1.2 Field study procedure.** We began by onboarding participants through a one-hour, one-on-one, in-person session. The session started with an introduction to the research team and an overview of the study procedures, including a review of study timeline, key participant tasks, the types of data we would collect, and the data collection process. Participants were then asked to read and sign a written consent form if they agreed to participate. The consent form, approved by our university IRB, outlined the use of activity tracking devices for data collection, the associated risks, and the study limitations on data collection: restricting it to relevant information (sleep and activity data) and only data from the four-week study period. It also explained privacy and confidentiality measures for safeguarding participant data. Additionally, during this process, a researcher was available to answer any questions about the consent form or the study.

Upon receiving consent, we asked participants to respond to demographic, technological, and occupational questions. During the onboarding process, the research team walked participants through step-by-step instructions to get the device up and running. We also highlighted key features for participants to focus on during the field study including activity and sleep tracking on both the wristband and in the accompanying Fitbit mobile application. After onboarding and creating their

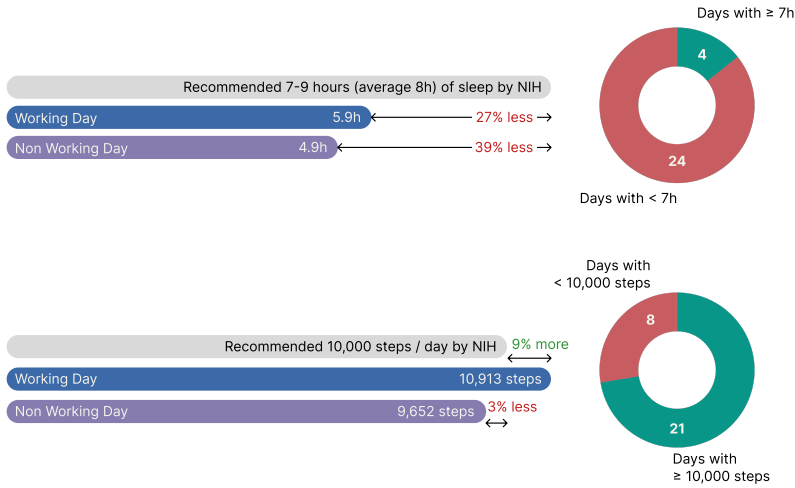


Fig. 2. Example visualizations we showed to participants depicting their average sleep and activity compared to NIH recommendations. This image represents an example of what participant P12 saw in our interview.

Fitbit accounts, we guided participants through an authentication and authorization process to allow the research team to remotely access participant data via the Fitbit API [3].

We asked participants to wear the Fitbit wristband continuously throughout the day (24 hours per day) for the next four weeks to capture the most complete picture of their personal data, including both during their work and personal life. We recommended removing the device for charging during periods of limited activity, such as while bathing. Participants were also encouraged to frequently review their data (focusing on sleep and steps), not only through the wristband display but also in the accompanying mobile application, which included a variety of out-of-the-box visualizations and insights. During this time, the research team remotely contacted participants weekly via SMS, their preferred method of contact. These messages reminded participants to wear the wristband and review the mobile application data daily. These weekly communications also provided participants with a way to contact the research team if issues or questions arose.

After the four-week field study period, we used the Fitbit API to collect participants' data and, for each participant, we developed personalized insights and visualizations based on their data. One set of visualizations showed their progress towards NIH-recommended standards for sleep and activity (see Figure 2 for an example). The other set of visualizations showed their average sleep and activity levels throughout the study in relation to the broader group of 17 participants (see Figure 3 for an example). These visualizations were substantially different from those offered via the Fitbit mobile application, featuring minimal, pared-down designs that also incorporated NIH recommendations and information from other participants. The goal of utilizing these artifacts was to facilitate concrete conversations about participants' real data in relation to a group of peers.

After preparing the visualizations, we conducted individual, in-person, hour-long interviews with participants in which we asked about their experiences with the device, preferences for data collection and sharing, and reflections on knowledge and insights from the data. After reviewing their experiences, we showed participants the visualizations we had prepared for them and discussed their reactions and insights to the visualizations (see Figures 2 and 3). We requested that participants think-aloud when reflecting on these artifacts [21]. Participants received a \$25 giftcard for sharing

| Rank | Participant | Average Sleep (hours) | Rank | Participant | Average Activity (steps) |
|------|-------------|-----------------------|------|-------------|--------------------------|
| 1    | P7          | 7.4                   | 1    | P10         | 20,528                   |
| 2    | P10         | 7.3                   | 2    | P20         | 13,024                   |
| 3    | P17         | 7.2                   | 3    | P16         | 12,980                   |
| 4    | P4          | 6.6                   | 4    | P5          | 12,683                   |
| 5    | P5          | 6.6                   | 5    | P13         | 11,928                   |
| 6    | P19         | 6.6                   | 6    | P6          | 11,680                   |
| 7    | P13         | 6.5                   | 7    | P14         | 11,133                   |
| 8    | P15         | 6.4                   | 8    | P12         | 10,739                   |
| 9    | P14         | 6.1                   | 9    | P11         | 10,262                   |
| 10   | P20         | 6.1                   | 10   | P15         | 9,212                    |
| 11   | P9          | 5.9                   | 11   | P19         | 9,063                    |
| 12   | P6          | 5.8                   | 12   | P8          | 7,935                    |
| 13   | P11         | 5.8                   | 13   | P18         | 7,863                    |
| 14   | P8          | 5.8                   | 14   | P9          | 7,133                    |
| 15   | P12         | 5.7                   | 15   | P17         | 7,026                    |
| 16   | P18         | 5.6                   | 16   | P7          | 6,867                    |
| 17   | P16         | 5.4                   | 17   | P4          | 3,855                    |

Fig. 3. Example visualizations we showed to participants depicting their sleep and activity levels in relation to the broader group of 17 study participants. This image represents an example of what participant P12 saw in our interview.

four weeks of data with our research team, another \$25 giftcard for participating in an interview at the end of the study, and were allowed to keep the Fitbit device after the study concluded.

**4.1.3 Data Collection and Analysis.** Our study generated both qualitative and quantitative research data. We collected participants' Fitbit data, consisting of 187 JSON files that contained a variety of data regarding participants' activity, calories, distance, heart rate, sleep, and steps. We ingested the data in Jupyter Notebooks, applied exploratory data analysis methods, and generated data visualizations for the reflection interviews. We also incorporated auxiliary data such as participants' work schedules from our onboarding interviews to develop richer, more insightful takeaways.

We also collected approximately 17 hours of audio-recorded interview data. The audio recordings were professionally transcribed using NoScribe [31], 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. To analyze the data, we used inductive thematic analysis [17]. Four authors engaged in open coding of the transcripts. We first coded one interview together, generating a baseline set of codes. Next, we chose a different interview to code separately, as two teams of two, and met to organize, reconcile, and merge coding conflicts. Subsequently, we separately coded the remaining 15 interviews, meeting regularly to discuss code additions, disagreements, ambiguities, and to iteratively refine the codes. Prolonged engagement with the data helped us establish credibility and reduce coding biases. This process resulted in a total of 57 codes. We then performed affinity diagramming to synthesize the codes into high-level themes that shape our findings.

Table 2. Participants’ average sleep durations (in hours) over the four-week study period.

| Rank | Participant | Average sleep |
|------|-------------|---------------|
| 1    | P7          | 7.38          |
| 2    | P10         | 7.30          |
| 3    | P17         | 7.15          |
| 4    | P4          | 6.59          |
| 5    | P5          | 6.58          |
| 6    | P19         | 6.55          |
| 7    | P13         | 6.46          |
| 8    | P15         | 6.36          |
| 9    | P14         | 6.13          |
| 10   | P20         | 6.09          |
| 11   | P9          | 5.87          |
| 12   | P6          | 5.82          |
| 13   | P11         | 5.79          |
| 14   | P8          | 5.75          |
| 15   | P12         | 5.74          |
| 16   | P18         | 5.64          |
| 17   | P16         | 5.40          |

Table 3. Participants’ average activity levels (in steps) over the four-week study period.

| Rank | Participant | Average activity |
|------|-------------|------------------|
| 1    | P10         | 20,528           |
| 2    | P20         | 13,024           |
| 3    | P16         | 12,980           |
| 4    | P5          | 12,683           |
| 5    | P13         | 11,928           |
| 6    | P6          | 11,680           |
| 7    | P14         | 11,133           |
| 8    | P12         | 10,739           |
| 9    | P11         | 10,262           |
| 10   | P15         | 9,212            |
| 11   | P19         | 9,063            |
| 12   | P8          | 7,935            |
| 13   | P18         | 7,863            |
| 14   | P9          | 7,133            |
| 15   | P17         | 7,026            |
| 16   | P7          | 6,867            |
| 17   | P4          | 3,855            |

## 5 FIELD STUDY FINDINGS

When we analyzed the Fitbit data collected from participants, we discovered that only one participant, P10, had average sleep and activity levels aligned with the recommended NIH standards for healthy adults. As Table 2 indicates, the majority of participants (82%) received less than the recommended seven hours of sleep per day [6]. In contrast, as shown in Table 3, nine participants (53%) walked 10,000 steps or more—a commonly cited health metric [5]—and 13 participants (76%) walked more than 7,500 steps a day, which research suggests can provide significant health benefits [5].

In the rest of this section, we contextualize the data we collected from participants with their observations and reflections on their own and others’ data. We begin by examining HCWs’ awareness and understanding of their own sleep and activity levels (Section 5.1), including their efforts to make positive changes during the study. We next describe the limits they faced in changing their behavior due to the nature of their work (Section 5.2). We then describe more collective perspectives of these data collected across the group of participants, including HCWs’ perspectives in relation to a group of peers (Section 5.3) and how this collective data could be used more broadly to advocate for them (Section 5.4).

### 5.1 Tracking sleep and activity improved HCWs’ awareness and encouraged reflection

HCWs expressed strong interest in learning more about their health and wellbeing. Four participants indicated that they were already aware of issues, such as a lack of sleep, even before our study. Others shared that they had a history of chronic medical conditions, including diabetes and hypertension. In line with prior work [23], participants described being highly motivated to maintain their health, emphasizing the need to be in good health to deliver high-quality care. As one participant noted, “...because we don’t [get] adequate sleep, then I would say we are going to perform below [standard]. Not necessarily, but we have to look at reality” (P8).

While participants had a general awareness of certain aspects of their wellbeing, they reported that the activity tracker greatly enhanced their understanding of their own health. HCWs expressed

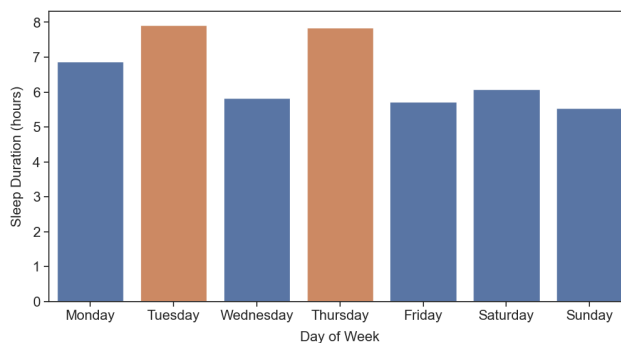


Fig. 4. Average sleep duration (in hours) for each day of the week during the four-week study for participant P19. Orange indicates days when P19's work schedule allowed them to sleep more.

surprise when they saw the detailed data on their activities. For example, P8 said, *"This is eye opening ... Especially the sleep. Yeah, I thought I was a good sleeper."* Similarly, P13 described:

*"It was a wake up alarm ... because I was wrong. I was always thinking that I sleep good. ... it made me realize that sometimes, I said, 'I want to go to sleep. I need to sleep.' And I [was thinking] so much that I needed to sleep that I don't sleep."* (P13)

As this quote suggests, HCWs were not only unaware of the amount of sleep they were getting but also struggled to fall asleep. Despite their desire for rest, often HCWs experienced sleep-related anxieties, which could be linked to heightened anxiety levels throughout the day [8]. This can create a cyclical pattern: anxiety can disrupt sleep, and poor sleep can in turn exacerbate anxiety [8].

For participants, the tracking data provided a detailed way to reflect on their experiences and understand how their work and home lifestyle impacted aspects like sleep. For example, P19 reflected on their sleep patterns in relation to their work schedule:

*"So I realize now that the days that I actually don't work in the morning, which is Tuesdays and Thursdays, ... those are the days when I slept longer. Because ... when I don't have to go to work Tuesday morning and Thursday morning, you know, I might get six, seven hours as I get it before I get up late to go to work."*

This observation was supported by P19's data (see Figure 4). In the figure, we show P19's average sleep duration, in hours, for each day of the week over our four-week study period. The bars highlighted in orange represent Tuesdays and Thursdays, which P19 identified as days when they got more sleep since they do not work in the morning. In contrast, the blue bars indicate the days when P19 begins work in the morning. The bar chart clearly illustrates the difference in sleep duration between days with morning starts (blue) and days with later starts (orange).

We also found that a number of HCWs were unaware of the amount of physical activity they were doing. After reviewing the table with participants' activity levels (see Figure 2), P8 remarked:

*"I know some of us wasn't even thinking on this level that we walk so much for these jobs. We just do what we're asked to do without even thinking of the consequences ... but you have to say, do I need to do something different? Is this an advantage or disadvantage for me? I know the walking is an advantage for me because it makes me feel good. So I'll be walking. ... I don't work like a regular HCW ... But when I think about [others], they're doing like eight, 12 hours a day."*

Here, P8 offers a thoughtful reflection on the data. Although this participant expressed enthusiasm about maintaining their walking habits, they also questioned whether all these steps are truly

beneficial for workers. In fact, they suggested that it might indicate the opposite —highlighting just how long and exhausting some HCWs' jobs can be.

Participants explained how their increased awareness led to changes in behavior. HCWs reported that their heightened awareness of sleep encouraged them to adopt healthier habits, such as limiting television and phone use, adjusting bedtime and wake-up times, and incorporating relaxation techniques like warm showers and listening to calming music. For instance, when asked about changes made to improve sleep, P17 said:

*"When I was seeing that I had four hours sleep, I said 'oh my god, I have to sleep today'. ... I need to relax, take a shower, and calm down. Try to rest more without electronics, close my eyes ... I was listening to music too."*

When considering how to make changes, participants noted that reflecting on their own activity data had a motivating effect. For example, P7 described the device as an "invisible coach" that encouraged them to stay active: "You know, walking is an activity that [can] help you with your health ... and the Fitbit is like a booster ... like an invisible coach there to say 'you can do it, go ahead, keep going.'" However, participants found that changing activity levels (step count) was often easier than changing sleep patterns. For example, participants such as P10 described how their increased awareness from the activity tracker helped them adjust their daily habits, which sometimes also included encouraging their patients to be more active as well:

*"Yes, I did something different. Usually, I go to work by train and after take the bus. But instead ... I walk at least for 30 to 40 minutes to take the train ... And then whenever I get off, instead [of] the bus, ... I walk all the way. ... Whenever I'm at work, sometimes when ... I'm free, I ask the patient to walk a little bit in the hallway. I go back and forth, back and forth, back and forth."*

By contrast, P11 noted that making changes to their sleep patterns was more challenging, as the study intervention did not alter their existing circumstances:

*"Yeah, for the steps I walk around a lot. So that one wasn't an issue. But the sleep, sometimes I can't help it for now because I work overnight. And when I come home during the day, sometimes I don't really sleep good. And sometimes I go to school as well. So for the sleep, there's not much I can do for now. But the exercise, sometimes when I see that [device feedback] I try to run around my house."*

Reflecting this sentiment, others expressed skepticism about their ability to make improvements due to the demands of their jobs. For instance, P15 said "I do wanna sleep more, but I don't know if I can." In the next section, we discuss how HCWs' ability to make lifestyle changes may be limited.

## 5.2 HCWs' agency and control to make changes may be limited

HCWs reported that their health and wellbeing are significantly influenced by social determinants beyond their control, complicating their ability to make desired health-related changes. For example, participants who worked overnight shifts mentioned that their sleep was largely dictated by the demands of their cases. P12 highlighted this challenge by saying:

*"Some patients, you put them to bed, then you can go to bed as well. And I know some patients, they don't sleep at all."*

This quote shows the limited control HCWs have over their sleep schedules. Additionally, participants shared how when working they needed to constantly remain watchful, attending to patients' needs, and staying alert in case of an emergency. HCWs felt this level of hyper-vigilance impacted their ability to relax, negatively affecting their sleep during overnight shifts, which goes against some city guidelines for 24-hour shifts [73].

HCWs also recognized some of the challenges that resulted from non-traditional work schedules. Because their work was subject to constant change, these volatile work schedules resulted in HCWs finding it difficult to get adequate sleep even on days when they were not working, as their bodies were continually in flux. P7 expressed this difficulty, stating *“I wanted to do about eight, nine hours, as people do, but I’m not able to because my body doesn’t get used to that.”* Others elaborated on these sentiments, underscoring how challenging it was to self-regulate and maintain a consistent sleep schedule. P11 said:

*“The one thing I noticed about the overnight ... you get a little sleep over there ... So when you get home, you don’t feel like sleeping anymore. By the time you feel like sleeping, it’s time to get back to work and [then] the entire day you didn’t sleep.”*

HCWs also expressed how the blurred boundaries between work and personal life impacted their sleep, with participants noting that some patients were particularly demanding, often contacting them outside of work hours. For instance, P19 remarked: *“Sometimes you go to work, the patients stress you out. You’re home, they’re calling you. And [you wonder] why we not sleeping?”* These issues were exacerbated by the fact that HCWs are typically low-wage workers with little social standing [23, 42, 95]. As a result, HCWs felt unable to advocate for their personal needs due to power imbalances with patients and agencies, fearing reprisal or a lack of institutional support.

Given their low pay and limited recognition [23, 65], participants viewed home care work as a temporary role and aspired to pursue better career opportunities. As a result, at least 10 HCWs were actively pursuing higher education to enhance their professional skills and career prospects, particularly in health-related fields like nursing. However, this aspiration and effort brought its own challenges, with HCWs finding it difficult to balance school, work, and personal life:

*“Once I’m at home, I want to catch up [on] my assignments and currently I’m doing my internship as well. So it’s a lot for me ... and I still have to keep up with my personal life, my kids, my husband. ... So I think those are the things that contribute to going to bed late at home.”* (P18)

Other HCWs said their work schedules, specifically working night shifts, were driven by their need to attend classes during the day: *“I go to school, that’s why I choose to work overnight”* (P11).

Beyond school, HCWs often worked long days and weeks with minimal time off due to financial pressures. During the limited time they did have off, HCWs felt their personal lives were subsumed by various responsibilities. For example, P12 described how their sleep was hampered on their days off as they tried to make the most of their time with family. They elaborated:

*“I stay home with my children and my wife. So most times we stay up late. ... we go out, we come back and talk, we watch movies, and [do stuff with] the kids ... So sometimes before we go to bed to sleep, it takes a long ... time, but it’s my off day, but you know, it’s overtaken by activities.”*

Lastly, we found that where HCWs live significantly impacted both their sleep and activity levels. Due to financial constraints, HCWs lived on the outskirts of the city, where long commutes were necessary when work was not available nearby. These long commutes left them with little time for sleep and other activities. In contrast, HCWs living in more urban areas reported that they often walked around their neighborhoods or to church on Sundays for extra exercise, which helped boost their activity levels. However, this was not the case for HCWs who lived in more suburban, car-dependent areas, where access to public transit and amenities were limited. For example, P8 noted that they recently moved to a more pedestrian-friendly area closer to both church and work:

*“I walk every Sunday morning from my house to church. ... I am now walking from my house to church because I moved from [redacted]. I’m now in [redacted]. So I’m pretty*

*much close to church and I'm pretty much close to my job. I'm pretty much close to the bus stop. So I walk."*

Overall, these insights illustrate the challenging balancing act that HCWs face as they juggle responsibilities related to their patients, school, agencies, children, and spouses, leaving them with limited time, resources, and ability to manage their own health and wellbeing.

### 5.3 Reflections on HCWs' collective activity data as a group of peers

In addition to reflecting on their personal data, HCWs derived a lot of value from reflecting on the data of their peer group. They often expressed the value of engaging in communal reciprocity, noting that access to others' data helped contextualize and validate their own experiences. For instance, P11 found it *"very helpful because I see that we are all going through the same thing and I think we can do something about it."* Similarly, P15 expressed: *"it gives you an idea that you're not alone in this."* This observation is significant, as the highly distributed nature of the workforce often leaves HCWs feeling isolated from one another and the larger care team [65, 75, 94]. In line with these quotes, some participants referenced their experiences in union-based peer support groups. They believed that incorporating these data could enhance those efforts by fostering solidarity among workers, allowing them to reflect on their shared experiences.

Others, like P12, found the data motivating and compared the tables of participants' data to a sports tournament bracket:

*"This is live data that was collected. So they didn't make it up. I believe this data. And from what I have seen, I think I need to improve on my sleep, because it's like this is a league and you are at the bottom, ... you're not meeting up for the Champions League."*

While P12's sentiment may initially seem competitive, they echoed similar feelings expressed by other participants, suggesting that the bracket serves as a way to: *"see you're not alone, right?"* This highlights a desire among participants to connect and interact with other HCWs to support each other's activity goals through these empirical data and dialogue.

HCWs also expressed empathy for each other's experiences, noting how patients' care needs and demands can significantly impact their activity levels. They explained that some patients held dehumanizing views of HCWs, seeing them as "resources" to be managed, which often kept workers constantly on the move. P19 expressed:

*"I know that when you go to work, [with] certain patients, you can't take a break. You can't sit. Cause they think you're part of the slave trade and there are particular patients that they are of the opinion that you don't take a break when you come. I had a patient, she made sure that there was no chair in her house for you to sit. So when you get there, you were constantly on your feet doing something and she will send you to the store to purchase something [and then] send you to take it back. ... So, you know, some of these other [HCWs], I do understand their activity. ... [It] depends on the patient that they have."*

They also showed a keen interest in learning more about the demographic information, job roles, and personal lives of HCWs that were at either end of the sleep and activity spectrum. This curiosity seemed to stem from a desire to identify role models whose habits they could emulate, as well as to understand the specific challenges faced by those struggling on the other end of the spectrum. For instance, P9 said: *"you will want to know what they did, especially the first one. What's she doing to make those steps? If she goes to a gym?"* This interest highlights a communal drive among HCWs to learn from one another and make positive improvements in their own lives. By gaining insights into the circumstances and strategies of their peers, participants felt they could better navigate their own challenges and work towards healthier routines.



Additionally, HCWs viewed sharing their data and creating shared data repositories as highly beneficial for the workforce. When asked about potential concerns regarding data sharing, HCWs expressed little to no hesitation in sharing anonymized data with other HCWs. P12 explained:

*“Oh, I am very comfortable for this information to be shared. ... I would be happy if people learn through my experience or through [the] data that was collected from me, if my coworkers ... will also participate and encourage themselves to partake in doing anything that will improve their heads. ... For me personally, I have seen where I am now, and it's also gonna make me know what to do next, so that I feel better as well ... it's not taken for my own detriment, but it's taken in order to improve the heads of community, the heads of individuals here in the United States. So, especially the home care workers, I would like it to be shared or be used.”*

Similar to our findings in Section 3.2, all (n=17) HCWs were willing to share their data, although a small minority (n=5) expressed some reservations regarding potential misuse; any concerns were not directed at their peers but rather on how agency employers might use these devices to surveil and penalize workers who do not comply with their policies. For example, at least three workers mentioned being concerned that these devices could be used by their agencies to monitor daily movements, including instances of sitting down or resting on the job. They felt that employers might not fully appreciate the context of their work, such as when they are sitting and waiting in a doctor's office for a patient to return, or when a patient is asleep at home.

#### 5.4 Collective data sharing could raise awareness and aid advocacy efforts

Beyond peer support, HCWs believed that their data, combined with that of others, could help raise awareness among agency employers, unions, labor advocates, policy makers, and the general public, potentially driving larger systemic changes. For instance, HCWs like P6 were strongly in favor of sharing their data to improve their labor conditions, stating: *“If we share it with our agency, they can know our living conditions. Maybe they can help us to improve our life ... for example, advocate for us with the union, ... to have [a] better salary from the government, something like that.”* While workers such as P6 felt labor improvements needed to be done by their agency in concert with outside entities such as unions and governments, other HCWs felt as though their agencies could make impactful changes with the aggregate data at hand:

*“As an agency, they should see this and realize that even if 60% of home care workers keep themselves healthy, the other 40% is under that. They should say we need to improve it. Let's put a gym for free ... and then for them to be able to improve their work activity.”* (P16)

Beyond amenities, other participants suggested that their agencies should incorporate these data into ongoing education and training programs to better address HCWs' needs:

*“In our agencies, every three months or six months, depending on the agency, we go for in-service ... they give you information about health and how to improve your health ... I think it [would] be nice if this particular data can be provided for them so that they can use that opportunity to let their workers know ... because it's gonna be a kind of awareness. Because some people don't know about this.”* (P12)

P12's suggestion is intriguing, indicating that a lack of health-related awareness may be negatively affecting workers. Efforts like the one suggested could provide useful data for agencies or unions to engage with. Data-sharing opportunities might enable workers to actively discuss their data, discuss potential challenges, share positive habits, and more. Furthermore, it may be helpful for

agency employers or unions to be privy to these conversions, as they may help to build empathy for workers' conditions.

HCWs consistently highlighted the impact of low-wage labor on their health and wellbeing. Participants felt compelled to take on multiple jobs and work long hours for little pay just to make ends meet. P4 captured the paradox faced by HCWs nearing retirement, pointing out the troubling irony that the physical demands of their work often leave their health and wellbeing compromised so that they themselves require supportive services, like home care, which are often unaffordable for them. For these reasons, P4 and others believed the collective data could be useful in advocating for wage increases and improved labor conditions:

*"Yeah, we're doing a lot. And that's why we are fighting. We not compensated enough for what we do. And I guess if we were given, say, like good hours to work, you won't have to be running for two agencies. You work with one agency and at the end of your shift, you go home, you can relax and be able to take care of yourself. But because you have bills to pay, you have a family to look after, you have yourself to look after. You just got to be hustling, scrambling. And that is breaking us down. Many of us, when we finish this home care, when we meet the age of retirement, we don't got [money] to put in to get [our own] assistance in the home [and] your body's worn."*

Additionally, HCWs emphasized the importance of having empirical datasets that include information on their sleep patterns. They discussed the difficulties of working overnight shifts and the challenge of getting adequate sleep. They believed that the aggregated data could help substantiate workers' claims and reveal patterns of labor violations. P6 expressed:

*"If you don't sleep, you have to report it to the agency. ... And sometimes you report it, to the agency and they think you're lying. And it's going to make you lazy to report it every time. You know, when you're working with a client, the client doesn't sleep the night and they keep calling you over to their bed to help them. And if you don't go, the next day they're going to call the agency and they tell them, they [the agency] put you out. So to avoid that, you have to suffer to accept it and continue working."* (P6)

Figure 5 further illustrates the impact of working nights. In this box-and-whiskers diagram we show P20's sleep duration distributions, in hours, for each day of the week during the four-week study period. Each individual plot in the diagram shows the distribution of P20's sleep duration data for that particular day, with the bottom whisker line representing the minimum sleep duration, the middle line representing the median sleep duration, and the top line representing the maximum sleep duration. The white dot in the middle of each plot represents P20's average (mean) sleep for that day of the week. In the diagram, we can clearly see that P20 has a much more erratic sleep schedule, indicated by the larger variance in plots, on Fridays, Saturdays, and Sundays, which correspond to the days they work overnight.

Lastly, in contrast to P6's optimism that agencies would improve working conditions based on the collective data, participants also noted the lack of incentives for agency employers to implement positive changes for their labor force. For example, P19, reflecting on agency dynamics, saying: *"They want what they want when they want it. So they don't care if you don't sleep as long as they get the job done."* Other HCWs, like P9, expressed uncertainty about how their agency might actually use the data to improve workers' wellbeing, stating:

*"I'm trying to figure out what they would use it for ... I don't know. I don't think they even have time, because simple things, they don't even have solutions [for] ... So I don't think they have time to check anything anyway, unless they hire somebody who could be on a computer and watching it. They don't have time to do that."*

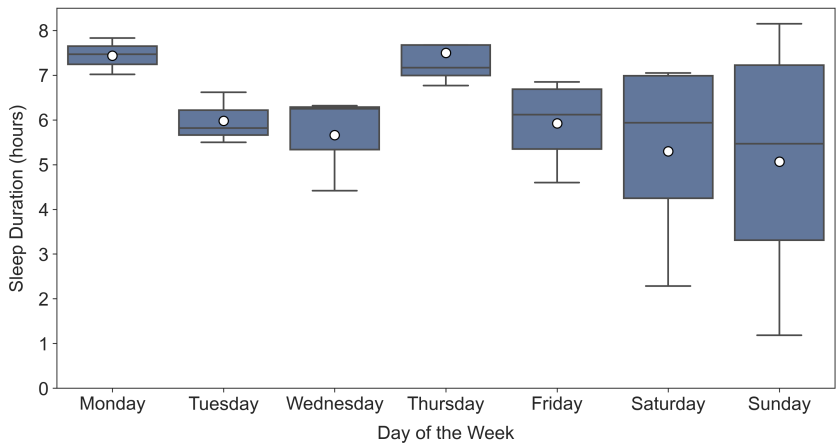


Fig. 5. Distribution of P20’s sleep duration (in hours) for each day of the week during the four-week study period. Fridays, Saturdays, and Sundays correspond to the days that P20 worked overnight. The larger plot variance on these days indicates that P20 sleep was more variable.

While opinions about agencies taking action on the collective data were mixed, HCWs felt that sharing this information with unions could be impactful. HCWs felt that unions, with their advocacy-oriented focus and ongoing labor initiatives, were well positioned to use these aggregated data to identify patterns of labor violations and push for systemic changes. They felt that empirical evidence of sleep deprivation, long working hours, and physical strain could provide unions with concrete evidence to advocate for better labor conditions, fair compensation, and improved regulations. HCWs, such as P6, who have participated in prior advocacy efforts expressed that this collective data might strengthen their bargaining power in negotiations: *“They can use it maybe to try to advocate, like behind the union. Advocate the government to increase our pay”*.

6 DISCUSSION

Our findings provide real data collected from a marginalized group of low-wage workers that show how, despite being highly motivated to be healthy, HCWs must juggle complex responsibilities related to their patients, agencies, school, and families, leaving them with limited time, resources, and ability to manage their own health and wellbeing. In the face of these challenges, HCWs found it useful and motivating to reflect on their own data, felt less alone when reflecting on the data contributed by a group of distributed peers, and saw how the data could raise awareness and help them advocate for improved working conditions. Here, we synthesize these findings to discuss (1) the importance of centering HCWs’ perspectives and experiences rather than health metrics, (2) implications for peer support programs and reducing worker isolation, and (3) opportunities to support broader HCW advocacy efforts via data sharing.

6.1 Centering HCWs’ perspectives and experiences rather than health metrics

Our study uses passive sensing devices to track activities relevant to the health and wellbeing of a low-wage, marginalized workforce [65, 77, 93], who have traditionally been overlooked in discussions on workplace wellbeing. At a high-level, participants found the data collected during the study to be “eye opening” (P8). We saw that, on the one hand, many participants do not

meet recommended guidelines for adequate sleep [6]; on the other, most participants did reach recommended guidelines of taking at least 10,000 steps per day [5].

To interpret this data holistically, we adopt a stance that seeks to avoid the risks of data empiricism [53], and instead aim to evaluate these data within the context they were collected—centering HCWs’ experiences and perspectives. To achieve this, we build on research by Maltseva [60], who emphasize a need to create space for reflective engagement with workplace tracking data, and Holten Møller et al. [45], who propose “collective sensemaking” as a means for workers to situate and contextualize the data by asking workers to reflect and expound on the data collected. In our study, we sought to create space for HCWs to reflect on their data and their peers’ data, thereby situating and contextualizing their experiences.

In doing so, we see that while recommended sleep and activity metrics may add some clarity into HCWs’ experiences, viewed in isolation, they may be an oversimplification of workers’ experiences. For example, (P7), who had some of the best sleep patterns, explained that this resulted from not currently having full-time work. Although this provided more time for sleep, it negatively impacted the HCW’s wages, causing financial stress and anxiety. Likewise, our findings suggest that simply walking 10,000 steps per day does not necessarily indicate HCWs have healthy activity levels. Instead, HCWs’ elevated activity levels were often a result of strenuous labor conditions, being required to work multiple jobs, and struggling to balance complex work and family responsibilities, rather than a reflection of healthy daily exercise. These findings emphasize the importance of centering the perspectives and experiences of workers when interpreting device usage and the data these devices collect, particularly with regard to “one-size-fits-all” population health metrics.

Moreover, our findings caution against assuming individual workers should be solely responsible for changing their behavior to improve their health and wellbeing. Prior work on passive sensing for health and wellbeing has focused on, for example, office workers [83], students [68], or patients [72], who may all be able to carve out time and opportunities in their daily schedules to exercise or sleep more. In contrast, our findings suggest that, due to systemic barriers and structural power imbalances, HCWs may not have the agency or control over their own schedules required to change their day-to-day activities in ways that improve their health and wellbeing.

Thus, to support HCWs in improving their health and wellbeing, we need approaches that empower them to both reflect and make changes, while also leveraging their collective data to strengthen efforts to address systemic barriers. Along these lines, we next discuss ways for HCWs’ activity data to support existing programs aimed at reducing HCWs’ isolation through peer support and coaching (Section 6.2), followed by opportunities for utilizing collective data to aid broader advocacy efforts for this marginalized workforce (Section 6.3).

## 6.2 Implications for peer support and reducing HCW isolation

Our findings underscore the importance of extending health and wellbeing efforts beyond the individual. For participants, reflecting on data collected from a group of distributed peers helped contextualize and validate their own lived experiences, fostering a sense of togetherness and solidarity. When reviewing their peers’ information, HCWs expressed camaraderie, felt less isolated, and empathized with other workers. They found the collective data offered a useful representation of the tensions and challenges within the workforce, and saw opportunities for communal reciprocity, driven by the belief that their contributions could enhance the overall wellbeing of the workforce. This sense of shared purpose motivated participants to support their peers through data sharing.

These findings align with prior research that emphasizes the value of incorporating social aspects, such as data sharing in self-tracking, to enhance health awareness, motivate positive behavior change, and strengthen social relationships and community [32, 38, 39, 57, 62, 70]. We also expand this literature by highlighting the nuanced sociocultural dimensions of activity tracking within

an understudied workforce—HCWs—and propose future avenues for integrating this data into ongoing efforts to improve HCWs' health and wellbeing.

One practical way for HCWs' collective data to benefit the workforce could be via integration into existing peer support efforts that aim to reduce worker isolation—a well-documented practice [65, 75, 94]—and strengthen community ties. Prior work has developed computer-mediated peer support programs [74, 80, 81] that engage with topics such as worker safety, health, wellbeing, and social support. We see opportunities for our research to bolster and expand these efforts; to date, peer support programs such as those developed by Olson et al. [74] and Poon et al. [78] have relied exclusively on HCWs' self-reported stories of experiences or behaviors. Collective data from activity trackers when added as a layer can help HCWs articulate the challenges they face, concretize their recounted experiences, and add nuances. Moreover, the empirical data could guide those who design peer support programs to more precisely ground discussion topics and activities based on HCWs' collective experiences.

Future work could further investigate how to integrate HCWs' activity data into peer coaching programs, which has shown promise in improving HCWs' health and wellbeing [12, 87]. Peer coaching is a distinctive type of coaching and mentorship where two peers typically work together to achieve common goals. In this non-competitive relationship, peers provide performance feedback, support one-another via reflection and skills building, and work together to solve problems [12, 87]. Future research could explore whether integrating activity tracking data into peer coaching might help workers provide more precise performance feedback, facilitate reflections on opportunities and challenges, and better identify possible avenues to improve workers' health and wellbeing.

### 6.3 Opportunities to support HCW advocacy efforts via data sharing

Throughout our study, participants vocalized clear desires to use their activity data to raise awareness and advocate for systemic changes. HCWs were willing to share their data with peers, agencies, labor unions, researchers, policymakers, and others if it might help them achieve goals such as improved wages or better working conditions. Of course, making tangible progress towards these goals is immensely challenging. For example, most HCWs in our context are employed by home care agencies that are primarily funded by public agencies such as Medicare and Medicaid [36]. As a result, enacting changes, including wage increases, requires policy-based initiatives.

Within this complex landscape, collective data from HCWs can bolster existing efforts to advocate for the home care workforce. For example, worker unions and other advocacy organizations are actively fighting for new policies such as Fair Pay for Home Care, which aims to grow the HCW workforce by promoting livable wages and stabilizing employment [1]. In addition, highly relevant to HCWs' poor sleep levels, the No More 24 [73] campaign seeks to end the harmful practice of requiring HCWs to work 24-hour shifts, in which HCWs work for 24 hours but are only paid for 13 hours under the premise that they receive at least five hours of uninterrupted sleep and other breaks during those shifts. Our research suggests that tracking HCWs' activities may be a viable way to generate data-driven evidence about HCWs' sleep patterns and sleep quality, combined with worker-centered reflections that contextualize these data, that might be hard for policymakers to ignore and that could bolster the arguments made by labor unions and other advocacy organizations.

At the same time, any efforts to track workers' activities should exercise caution. Prior work has raised concerns regarding workers' abilities to provide informed consent, particularly given the power asymmetries within workforces [24, 37, 66]. Researchers have also underscored the need for enhanced privacy and security considerations and the importance of using these tools to empower workers and increase awareness, rather than as a means of monitoring and surveillance [10, 24, 51].

One potential way to navigate these concerns might be to establish worker-owned data cooperatives: platform cooperatives characterized by democratic governance, collective ownership, and

equitable data practices [16, 18]. Data cooperatives grant members control over their data through data sovereignty, allowing workers to enter, access, share, and delete their own information at any time [55]. By facilitating equitable data access and enabling appropriate sharing, these cooperatives can “generate significant economic, social, and environmental benefits for their members and the wider community” [18]. We see opportunities for future work that explores, for example, how HCWs’ activity data such as those collected via our study might serve as a pipeline for channeling HCWs’ information into a worker-owned data cooperative for use in advocacy efforts.

Moreover, as the home care industry increasingly faces the impacts of algorithmic systems and AI [19, 34, 56, 85, 90], workers’ data has become a crucial commodity for technology companies and other organizations seeking to build systems that rely on large amounts of workers’ data [44, 86]. Historically, low-wage workers, like HCWs, have been excluded from participating in conversations about how these technologies impact their jobs [15]. One way for workers to ensure participation is by controlling access to and usage of their own data, and data cooperatives may play a key role in facilitating this reality. Based on our work, we envision labor unions and advocacy organizations to be well positioned to play an organizational role in establishing and maintaining data cooperatives that might benefit HCWs. Future work might thus explore how to responsibly share and manage HCWs’ collective data in ways that center workers’ needs, experiences, and perspectives.

## 6.4 Limitations

Our study has a number of limitations. First, we conducted a small-scale, empirical study in a single geographic location—a large city in the U.S. Further research is needed to assess how our findings might generalize to larger, more diverse samples and other settings, including rural and non-U.S. contexts. Additionally, a longitudinal study would be valuable to explore how participants’ experiences evolve over time. Our study also focused on passively tracked data, such as sleep and step count, which represents only one aspect of participants’ health and wellbeing. Active tracking methods, like journaling, could provide richer, more contextual information and encourage deeper self-reflection. Finally, employing journaling or remotely distributed surveys could also help reduce participant response bias, which is a known limitation of qualitative interviews due to the researchers’ positionality [28].

## REFERENCES

- [1] 2022. Fair Pay for Home Care - 1199SEIU. <https://fairpayforhomecareworkers.org/>. Accessed: 2022-7-15.
- [2] 2024. Apple Watch — apple.com. <https://www.apple.com/watch/>. [Accessed 14-10-2024].
- [3] 2024. Fitbit Development: Web API — dev.fitbit.com. <https://dev.fitbit.com/build/reference/web-api/>. [Accessed 16-10-2024].
- [4] 2024. Fitbit Official Site for Activity Trackers & More — store.google.com. [https://store.google.com/category/watches\\_trackers?hl=en-US](https://store.google.com/category/watches_trackers?hl=en-US). [Accessed 14-10-2024].
- [5] 2024. How many steps for better health? — nih.gov. <https://www.nih.gov/news-events/nih-research-matters/how-many-steps-better-health>. [Accessed 23-10-2024].
- [6] 2024. How much sleep do you need? | NIH MedlinePlus Magazine — magazine.medlineplus.gov. <https://magazine.medlineplus.gov/article/how-much-sleep-do-you-need>. [Accessed 23-10-2024].
- [7] 2024. Oura Ring. Smart Ring for Fitness, Stress, Sleep & Health. — ouraring.com. <https://ouraring.com/>. [Accessed 14-10-2024].
- [8] 2024. Sleep Anxiety: What It Is, Causes, Symptoms & Treatment — my.clevelandclinic.org. <https://my.clevelandclinic.org/health/diseases/21543-sleep-anxiety>. [Accessed 27-10-2024].
- [9] 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/>
- [10] Daniel A Adler, Emily Tseng, Khatiya C Moon, John Q Young, John M Kane, Emanuel Moss, David C Mohr, and Tanzeem Choudhury. 2022. Burnout and the quantified workplace: Tensions around personal sensing interventions for stress in resident physicians. *Proceedings of the ACM on Human-computer Interaction* 6, CSCW2 (2022), 1–48.

- [11] Alejandro Aguado-García, América Arroyo-Valerio, Galileo Escobedo, Nallely Bueno-Hernández, P V Olguín-Rodríguez, Markus F Müller, José Damián Carrillo-Ruiz, and Gustavo Martínez-Mekler. 2023. Opportune warning of COVID-19 in a Mexican health care worker cohort: Discrete beta distribution entropy of smartwatch physiological records. *Biomed. Signal Process. Control* 84 (July 2023), 104975.
- [12] Hasanat Alamgir, Sharla Drebit, Helen Guiyun Li, Catherine Kidd, Helen Tam, and Catherine Fast. 2011. Peer coaching and mentoring: a new model of educational intervention for safe patient handling in health care. *American journal of industrial medicine* 54, 8 (2011), 609–617.
- [13] Milica Barac, Samantha Scaletty, Leslie C Hassett, Ashley Stillwell, Paul E Croarkin, Mohit Chauhan, Sherry Chesak, William V Bobo, Arjun P Athreya, and Liselotte N Dyrbye. 2024. Wearable Technologies for Detecting Burnout and Well-Being in Health Care Professionals: Scoping Review. *Journal of medical Internet research* 26 (2024), e50253.
- [14] Karthik S Bhat and Neha Kumar. 2020. Sociocultural dimensions of tracking health and taking care. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW2 (2020), 1–24.
- [15] 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.
- [16] Alessandro Blasimme, Effy Vayena, and Ernst Hafen. 2018. Democratizing health research through data cooperatives. *Philosophy & Technology* 31 (2018), 473–479.
- [17] G Braun. 1977. Using thematic analysis in psychology. *Using thematic analysis in psychology* 3, 10 (Oct. 1977), 77–83.
- [18] Michael Max Bühler, Igor Calzada, Isabel Cane, Thorsten Jelinek, Astha Kapoor, Morshed Mannan, Sameer Mehta, Vijay Mookerjee, 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.
- [19] Safa Chabouh, Adnen El-Amraoui, Soudes 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.
- [20] Ranganathan Chandrasekaran, Vipanchi Katthula, and Evangelos Moustakas. 2021. Too old for technology? Use of wearable healthcare devices by older adults and their willingness to share health data with providers. *Health Informatics J.* 27, 4 (2021), 14604582211058073.
- [21] Elizabeth Charters. 2003. The use of think-aloud methods in qualitative research an introduction to think-aloud methods. *Brock Education Journal* 12, 2 (2003).
- [22] Josh Cherian, Samantha Ray, Thomas Mernar, Paul Taele, Helen Mach, Jung In Koh, Ping Ye, and Tracy Hammond. 2024. A Step Toward Better Care: Understanding What Caregivers and Residents in Assisted Living Facilities Value in Health Monitoring Systems. *Proceedings of the ACM on Human-Computer Interaction* 8, CSCW1 (2024), 1–29.
- [23] Jacklyn Cho, Brittany Toffey, Ariel Silva, Ariel Shalev, Monika Safford, Erica Phillips, Ann Lee, Faith Wiggins, Elissa Kozlov, Emma Tsui, Nicola Dell, Ariel Avgar, Susan Andrea, and Madeline Sterling. 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 (02 2023). <https://doi.org/10.1111/1475-6773.14147>
- [24] 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.
- [25] Caroline A Clingan, Manasa Dittakavi, Michelle Rozwadowski, Kristen N Gilley, Christine R Cislo, Jenny Barabas, Erin Sandford, Mary Olesnavich, Christopher Flora, Jonathan Tyler, et al. 2021. Monitoring health care workers at risk for COVID-19 using wearable sensors and smartphone technology: Protocol for an observational mHealth study. *JMIR research protocols* 10, 5 (2021), e29562.
- [26] Stefany Cruz, Claire Lu, Mara Ulloa, Alexander Redding, Josiah Hester, and Maia Jacobs. 2024. Perceptions of Wearable Health Tools Post the COVID-19 Emergency in Low-Income Latin Communities: Qualitative Study. *JMIR mHealth and uHealth* 12 (2024), e50826.
- [27] Vedant Das Swain, Lan Gao, Abhirup Mondal, Gregory D Abowd, and Munmun De Choudhury. 2024. Sensible and Sensitive AI for Worker Wellbeing: Factors that Inform Adoption and Resistance for Information Workers. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24, Article 104)*. Association for Computing Machinery, New York, NY, USA, 1–30.
- [28] Nicola Dell, Vidya Vaidyanathan, Indrani Medhi, Edward Cutrell, and William Thies. 2012. "Yours is better!" participant response bias in HCI. In *Proceedings of the sigchi conference on human factors in computing systems*. 1321–1330.
- [29] Delve, L Ho, and A Limpaecher. 2020. *How To Do Structural Coding*. Retrieved October 15, 2024 from <https://delvetool.com/blog/structuralcoding>
- [30] Margaret A Denton, İşk 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.
- [31] Kai Dröge. 2024. *NoScribe*. Retrieved July 3, 2024 from <https://github.com/kaixxx/noScribe>

- [32] Daniel A Epstein, Bradley H Jacobson, Elizabeth Bales, David W McDonald, and Sean A Munson. 2015. From" nobody cares" to" way to go!" A Design Framework for Social Sharing in Personal Informatics. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*. 1622–1636.
- [33] Shan Feng, Matti Mäntymäki, Amandeep Dhir, and Hannu Salmela. 2021. How self-tracking and the quantified self promote health and well-being: systematic review. *Journal of Medical Internet Research* 23, 9 (2021), e25171.
- [34] Christian Fikar and Patrick Hirsch. 2017. Home health care routing and scheduling: A review. *Computers & Operations Research* 77 (2017), 86–95.
- [35] Fitbit 2024. Premium Fitness Tracker | Shop Fitbit Charge 6. <https://www.fitbit.com/global/us/products/trackers/charge6> (Accessed on 2024-06-27).
- [36] Emily Franzosa, Emma K Tsui, and Sherry Baron. 2019. "Who's caring for us?": Understanding and addressing the effects of emotional labor on home health aides' well-being. *The Gerontologist* 59, 6 (2019), 1055–1064.
- [37] Alexandra Giannopoulou. 2020. Algorithmic Systems: The Consent Is in the Detail? (2020).
- [38] Daniel Gooch, Blaine A Price, Anna Klis-Davies, and Julie Webb. 2021. A design exploration of health-related community displays. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW1 (2021), 1–22.
- [39] Xinning Gui, Yu Chen, Clara Caldeira, Dan Xiao, and Yunan Chen. 2017. When fitness meets social networks: Investigating fitness tracking and social practices on werun. In *Proceedings of the 2017 CHI conference on human factors in computing systems*. 1647–1659.
- [40] Donna Haraway. 2020. Situated knowledges: The science question in feminism and the privilege of partial perspective. In *Feminist theory reader*. Routledge, 303–310.
- [41] Päivi Heikkilä, Anita Honka, Eija Kaasinen, and Kaisa Väänänen. 2021. Quantified factory worker: field study of a web application supporting work well-being and productivity. *Cognition, Technology & Work* 23, 4 (2021), 831–846.
- [42] Melissa Yanez Hernandez, Elizabeth Fong-Chy Kuo, Yefrenia Henriquez Taveras, Ann Lee, Aida Ramos, Joanna Ringel, Susan Andreae, Emma Tsui, Monika M Safford, Ariel C Avgar, et al. 2024. Mental Health and Well-Being Among Home Health Aides. *JAMA Network Open* 7, 6 (2024), e2415234–e2415234.
- [43] 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.
- [44] Linda F Hogle. 2016. Data-intensive resourcing in healthcare. *BioSocieties* 11 (2016), 372–393.
- [45] Naja Holten Møller, Gina Neff, Jakob Grue Simonsen, Jonas Christoffer Villumsen, and Pernille Bjørn. 2021. Can workplace tracking ever empower? Collective sensemaking for the responsible use of sensor data at work. *Proceedings of the ACM on human-computer interaction* 5, GROUP (2021), 1–21.
- [46] 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.
- [47] Rui Hu, Hieu Pham, Philipp Buluscheck, and Daniel Gatica-Perez. 2017. Elderly People Living Alone: Detecting Home Visits with Ambient and Wearable Sensing. In *Proceedings of the 2nd International Workshop on Multimedia for Personal Health and Health Care (MMHealth '17)*. Association for Computing Machinery, New York, NY, USA, 85–88.
- [48] Azra Ismail, Deepika Yadav, Meghna Gupta, Kirti Dabas, Pushpendra Singh, and Neha Kumar. 2022. Imagining caring futures for frontline health work. *Proceedings of the ACM on Human-Computer Interaction* 6, CSCW2 (2022), 1–30.
- [49] Naveena Karusala, Azra Ismail, Karthik S Bhat, Aakash Gautam, Sachin R Pendse, Neha Kumar, Richard Anderson, Madeline Balaam, Shaowen Bardzell, Nicola J Bidwell, et al. 2021. The future of care work: towards a radical politics of care in CSCW research and practice. In *Companion Publication of the 2021 Conference on Computer Supported Cooperative Work and Social Computing*. 338–342.
- [50] Harmanpreet Kaur, Alex C Williams, Daniel McDuff, Mary Czerwinski, Jaime Teevan, and Shamsi T Iqbal. 2020. Optimizing for happiness and productivity: Modeling opportune moments for transitions and breaks at work. In *Proceedings of the 2020 CHI conference on human factors in computing systems*. 1–15.
- [51] Anna Kawakami, Shreya Chowdhary, Shamsi T Iqbal, Q Vera Liao, Alexandra Olteanu, Jina Suh, and Koustuv Saha. 2023. Sensing wellbeing in the workplace, why and for whom? envisioning impacts with organizational stakeholders. *Proceedings of the ACM on Human-Computer Interaction* 7, CSCW2 (2023), 1–33.
- [52] Rachel Keys, Paul Marshall, Graham Stuart, and Aisling Ann O'Kane. 2024. "I think it saved me. I think it saved my heart": The Complex Journey From Self-Tracking With Wearables To Diagnosis. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24, Article 138)*. Association for Computing Machinery, New York, NY, USA, 1–15.
- [53] Rob Kitchin. 2014. Big Data, new epistemologies and paradigm shifts. *Big data & society* 1, 1 (2014), 2053951714528481.
- [54] Whitney-Jocelyn Kouaho and Daniel A Epstein. 2024. Socioeconomic Class in Physical Activity Wearables Research and Design. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–15.
- [55] Romy Lauer, Sebastian Merkel, Jennifer Bosompem, Henrike Langer, Peter Naeve, Benjamin Hertent, Anja Burmann, Horst Christian Vollmar, Ina Otte, and Coop4Health. NRW Consortium Brand Angela Brand Helmut Clemens Timo



- Geller Simon Hinzmann Alice Huhnt Jönne Kerstan Leah Venne Julien. 2024. (Data-) Cooperatives in health and social care: a scoping review. *Journal of Public Health* (2024), 1–19.
- [56] Meiyang Lin, Lijun Ma, and Chengshuo Ying. 2021. Matching daily home health-care demands with supply in service-sharing platforms. *Transportation Research Part E: Logistics and Transportation Review* 145 (2021), 102177.
- [57] Xi Lu, Yunan Chen, and Daniel A Epstein. 2021. A model of socially sustained self-tracking for food and diet. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW2 (2021), 1–32.
- [58] Deborah Lupton. 2014. Self-tracking cultures: towards a sociology of personal informatics. In *Proceedings of the 26th Australian computer-human interaction conference on designing futures: The future of design*. 77–86.
- [59] D Lupton. 2016. The quantified self. *Polity* (2016).
- [60] Kateryna Maltseva. 2020. Wearables in the workplace: The brave new world of employee engagement. *Business Horizons* 63, 4 (2020), 493–505.
- [61] 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.
- [62] Aqueasha Martin-Hammond and Tanjala S Purnell. 2022. Bridging community, history, and culture in personal informatics tools: Insights from an existing community-based heart health intervention for Black Americans. *Proceedings of the ACM on Human-Computer Interaction* 6, GROUP (2022), 1–23.
- [63] Akhil Mathur, Marc Van den Broeck, Geert Vanderhulst, Afra Mashhadi, and Fahim Kawsar. 2015. Tiny habits in the giant enterprise: understanding the dynamics of a quantified workplace. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. 577–588.
- [64] Joy Ming, Dana Gong, Chit Sum Eunice Ngai, Madeline Sterling, Aditya Vashistha, and Nicola Dell. 2024. Wage Theft and Technology in the Home Care Context. *Proceedings of the ACM on Human-Computer Interaction* 8, CSCW1 (2024), 1–30.
- [65] 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 (April 2023), 1–21.
- [66] Phoebe Moore and Lukasz Piwek. 2017. Regulating wellbeing in the brave new quantified workplace. *Employee Relations* 39, 3 (2017), 308–316.
- [67] Lisa Morris. 2009. Quits and job changes among home care workers in Maine: The role of wages, hours, and benefits. *The Gerontologist* 49, 5 (2009), 635–650.
- [68] Mehrab Bin Morshed, Koustuv Saha, Richard Li, Sidney K D'Mello, Munmun De Choudhury, Gregory D Abowd, and Thomas Plötz. 2019. Prediction of mood instability with passive sensing. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 3, 3 (2019), 1–21.
- [69] Jonathan Muckell, Yuchi Young, and Mitch Leventhal. 2017. A wearable motion tracking system to reduce direct care worker injuries: An exploratory study. In *Proceedings of the 2017 International Conference on Digital Health*. 202–206.
- [70] Elizabeth L Murnane, Tara G Walker, Beck Tench, Stephen Volda, and Jaime Snyder. 2018. Personal informatics in interpersonal contexts: towards the design of technology that supports the social ecologies of long-term mental health management. *Proceedings of the ACM on Human-Computer Interaction* 2, CSCW (2018), 1–27.
- [71] 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/>
- [72] Ada Ng, Rachel Kornfield, Stephen M Schueller, Alyson K Zalta, Michael Brennan, and Madhu Reddy. 2019. Provider perspectives on integrating sensor-captured patient-generated data in mental health care. *Proceedings of the ACM on human-computer interaction* 3, CSCW (2019), 1–25.
- [73] No More 24! 2024. Abolish modern-day slavery! No more 24-hour workdays! <https://nomore24.org/>. Accessed: 2024-4-12.
- [74] Ryan Olson, Diane Elliot, Jennifer Hess, Sharon Thompson, Kristy Luther, Brad Wipfli, Robert Wright, and Annie Mancini Buckmaster. 2014. The COMMUNITY of Practice And Safety Support (COMPASS) total worker health™ study among home care workers: study protocol for a randomized controlled trial. *Trials* 15 (2014), 1–13.
- [75] Zainab Totah Osakwe, Jennel C Osborne, Tonya Samuel, Gabriella Bianco, Amarilis Céspedes, Michelle Odum, 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.
- [76] Oura Ring 2024. Oura Ring. Smart Ring for Fitness, Stress, Sleep & Health. <https://ouraring.com> (Accessed on 2024-06-27).
- [77] Sanjay Pinto, Chenjuan Ma, Faith Wiggins, Sarah Ecker, Michael Obodai, and Madeline Sterling. 2022. Forgotten front line: understanding the needs of unionized home health aides in downstate New York during the COVID-19 pandemic. *New Solutions: A Journal of Environmental and Occupational Health Policy* 31, 4 (2022), 460–468.

- [78] 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 (CHI '23, Article 414)*. Association for Computing Machinery, New York, NY, USA, 1–18.
- [79] 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. *Proc. ACM Hum.-Comput. Interact.* 5, CSCW2 (Oct. 2021), 1–32.
- [80] 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. *Proc. ACM Hum.-Comput. Interact.* 5, CSCW2 (Oct. 2021), 1–32.
- [81] 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. *Proc. ACM Hum.-Comput. Interact.* 7, CSCW1 (April 2023), 1–35.
- [82] 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.
- [83] Xipei Ren, Bin Yu, Yuan Lu, and Aarnout Brombacher. 2018. Exploring cooperative fitness tracking to encourage physical activity among office workers. *Proceedings of the ACM on Human-Computer Interaction* 2, CSCW (2018), 1–20.
- [84] 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.
- [85] María I Restrepo, Louis-Martin Rousseau, and Jonathan Vallée. 2020. Home healthcare integrated staffing and scheduling. *Omega* 95 (2020), 102057.
- [86] J Warren Salmon, Stephen L Thompson, J Warren Salmon, and Stephen L Thompson. 2021. Big data: information technology as control over the profession of medicine. *The Corporatization of American Health Care: The Rise of Corporate Hegemony and the Loss of Professional Autonomy* (2021), 181–254.
- [87] Heidi Schwellnus and Heather Carnahan. 2014. Peer-coaching with health care professionals: what is the current status of the literature and what are the key components necessary in peer-coaching? A scoping review. *Medical Teacher* 36, 1 (2014), 38–46.
- [88] Yasaman S Sefidgar, Carla L Castillo, Shaan Chopra, Liwei Jiang, Tae Jones, Anant Mittal, Hyeyoung Ryu, Jessica Schroeder, Allison Cole, Natalia Murinova, Sean A Munson, and James Fogarty. 2024. MigraineTracker: Examining Patient Experiences with Goal-Directed Self-Tracking for a Chronic Health Condition. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24, Article 129)*. Association for Computing Machinery, New York, NY, USA, 1–19.
- [89] Matthew Smuck, Charles A Odonkor, Jonathan K Wilt, Nicolas Schmidt, and Michael A Swiernik. 2021. The emerging clinical role of wearables: factors for successful implementation in healthcare. *NPJ Digit Med* 4, 1 (March 2021), 45.
- [90] 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. (2025).
- [91] 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>
- [92] MR Sterling and AL Shaw. 2019. Sharing the care—a patient and her caregivers. *JAMA Internal Medicine* 179, 12 (2019), 1617.
- [93] 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.
- [94] 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.
- [95] 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.
- [96] Camellia Zakaria, Rajesh Balan, and Youngki Lee. 2019. StressMon: scalable detection of perceived stress and depression using passive sensing of changes in work routines and group interactions. *Proceedings of the ACM on human-computer interaction* 3, CSCW (2019), 1–29.