Socioeconomic Class in Physical Activity Wearables Research and Design

Whitney-Jocelyn Kouaho
wkouaho@uci.edu
University of California, Irvine
Irvine, California, USA

Daniel A. Epstein
University of California, Irvine
Irvine, California, USA

ABSTRACT

Wearable technology for physical activity promotion is a frequent research topic within HCI and health, and researchers have documented that much of our knowledge is sourced from understanding the needs of populations from college educated, racially privileged, Western backgrounds. However socioeconomic class, a core component for how people perceive physical activity, wearables, and even wearable studies, has not often been contended with. In this critical discussion of the literature, incorporating examples from over 30 deployment studies involving wearables and over 70 other related works, we investigate how socioeconomic class shows up in study design and identify how class cultures are embedded in the design of wearable technology. We hypothesize that common study components related to time and activity type engenders high SES class cultures and ultimately risk creating intervention generated inequalities. We discuss the implications of ignoring class such as further perpetuating inequities in subsequent waves of wearable device maturity.

CCS CONCEPTS

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

KEYWORDS

personal informatics, physical activity, wearables, socioeconomic class

ACM Reference Format:
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 (CHI '24), May 11–16, 2024, Honolulu, HI, USA.* ACM, New York, NY, USA, 15 pages. https://doi.org/10.1145/3613904.3642789

1 INTRODUCTION

In the last decade and a half, personal informatics as a discipline, and wearables as design tools, have seen steady growth in interest in commercial, computing, and medical spaces alike. Though the personal informatics tag does not necessarily signify specific data content to be tracked, by and large a most common association is with physical activity (PA), sleep, and bio-signals such as heart rate [33]. The wearable devices which track this data via automated sensors are increasingly gaining traction, with upwards of 490 million units shipped in 2022 alone [70]. Research done in this space broach a wide variety of pain points ranging from aesthetics [24, 54], long term adherence [23, 73, 119], and use patterns [25, 34, 49, 107], to outpatient tracking [14, 79, 86], wellness [22, 47], and more. However, although there is a large diversity of applications for research, the same cannot be said for the research populations at the center of these studies.

In personal informatics research and design, by and large there is a pattern of centering privileged and homogeneous participant groups such as 'WEIRD' participants (Western, Educated, Industrialized, Rich, and Democratic) [85], ignoring the needs of people with disabilities (e.g., wheelchair users) [16], and presuming that people desire subjective well-being goals like weight loss [109]. This limited focus creates a gap in understanding because it limits the generalization of findings, and even more-so, the predominant narrative for how people use these systems, and how we should go about designing personal informatics systems, then becomes invariably based on the experiences of the dominant population. Although researchers have frequently mentioned limitations in population demographics [85], not many personal informatics studies have directly investigated research limitations with *socioeconomic status (SES)* as a primary dimension. As this is a discipline which is predicated on learning personal patterns and optimizing collected data, by excluding class as a use variable, we are losing crucial considerations for wearables device design, and ultimately, worsening health disparities.

Social class in particular is an important metric because it is one of the determining factors for how one can move through the world, comes to understand themselves, their status' and social norms [28]. And it is widely reported that SES is a determinant for health access and outcomes, with poor health outcomes being most prevalent amongst persons of lower socioeconomic status [128]. Due to socioeconomic realities such as a lack of, or limited access, to proper health resources and education, medical discrimination, or even the prevalence of geopolitical discrimination such as food deserts [129], persons of a low SES positionality are most susceptible to obesity [74] or other illnesses like heart disease [72, 102]. There also exist correlations between SES and exercise decisions, sleep patterns, and other general health outcomes [91, 122]. All of these factors relate to data points which are centered in the design of wearables devices (heart rate, physical activity, food, and sleep tracking, etc.). Ultimately, as wearables have been proposed as a technology intervention for managing health and well-being [138], there are tangible health (and design) implications at stake. As we move toward an era where an increased number of healthcare

CHI '24, May 11–16, 2024, Honolulu, HI, USA

ACM ISBN 979-8-4007-0330-0/24/05
https://doi.org/10.1145/3613904.3642789

systems and workplace programs develop close partnerships with consumer wearable companies, which has already begun [82], we will potentially begin to see healthcare tracking interventions that were designed with voices which do not adequately address diverse population needs. This is an unfortunately common trend among digital health interventions, which pose a risk of creating intervention generated inequalities [127].

In systematically reviewing the mobile health (mHealth) literature in HCI, Stowell et al. explicitly point out that *"there is a need for research that teases apart the broad categ[ory] of 'low-SES'... to identify how mHealth tools can effectively address the needs of diverse subgroups"* [116]. We begin to answer this call by examining how wearables, as an example of mHealth technology, intersect with the needs of low-SES groups.

In this paper, we present a critical discussion regarding HCI and Medical wearables studies and how they interact with, or come to understand socioeconomic class (culturally and fiscally), in the style of an argument or opinion contribution [135]. Our goal in discussing this literature was to get an understanding of how socioeconomic class cultures are/or are not engendered in our design of wearables studies and the development of design recommendations for the space. To achieve this, we evaluated common research study design choices related to time subjectivity and activity type, and postulate on theories on class, time, and identity. We draw specific examples of how time and activity type are characterized from over 30 HCI and Medical deployment studies of novel or commercial wearable devices, with additional insight around class trends from over 70 other studies involving wearables. We use these examples to frame critical perspectives regarding how study decisions endemic to our discipline can impact how class shows up overtly and covertly both in the design features of wearable technology and the class diversity of the study populations.

From this critical discussion, we contend:

- There should be a more focused entanglement with socioeconomic class as a framework for understanding research design outcomes. Without doing so, we incite a missed opportunity for understanding the way socioeconomic cultures and politics color the way we interpret and even come to collect health data.
- Time based requirements which are central to wearables studies can be population limiting. Unique adherence components like device wear time, physical activity requirements, study length, and other more hidden work, require extensive effort on the part of the participant. Therefore, working class populations who have less discretionary time and who are more susceptible to time based disruptions, could be less likely to be able to participate in our research studies.
- Physical activity types available on devices are indicative of middle and higher socioeconomic class cultures. We find that the emphasis on leisure-based activities such as walking, both reduces the value individuals of low-SES background can derive from wearables, as well as underestimates the level of activity of people who do manual labor.

Beyond pointing out the ways in which class shows up as an invisible metric and the limits of study and technology affordances, we provide a few suggestions for moving the field forward. First, we suggest that strategies frequently leveraged in clinical trials, such as periodic incentives, could be adapted to increase participation of socioeconomically disadvantaged groups. We also suggest that a move away from analysis techniques that require adherence to wearing a device, and more toward a holistic understanding of non-use, can provide opportunities to more deeply understand how efficacy is impacted by class. We finally point to intersections between class and wearables use which warrant deeper investigation in HCI, such as understanding needs and opportunities for wearables to support the manual labor workforce toward their physical activity goals.

2 THEORIES ON CLASS

Our understanding of class builds on socio-temporal, intersectional, and time centered theoretical contributions. We first describe those trends before examining how they relate to wearables studies.

2.1 Time, Labour, and Culture As Modes of Contention

We will frame class, and the accompanying discussion, in two ways. First, we will examine socioeconomic class as it relates to the actual state of one's earnings and associated labor. We base this on a categorization that places income, educational attainment, and occupation on a scale [5, 60]. Therefore, where socioeconomic status, 'SES', is notated, we refer to this materiality of socioeconomic class. We frame the discussion in this way in order to dispel societal limitations or lack thereof, for people by SES and what this means for their potential capacity to engage in common constructions of wearables research studies. In this case, SES is used to describe trends in access, sorted by the range of literal capital that an individual holds as both an independent person and as part of a group of people in similar conditions.

Class is also represented as a multi-layered cultural and material concept which encompasses the way people maneuver through "society", and the way that "society", interacts with them, as both an extension of their ownership of capital, and the subsequent positionalities which are created as a result of these temporalities. We broadly ruminate on the way "cultures" are understood and how they are directly associated within the broader social status for which they are either enticed or shunned (or something in between), and how these same understandings of a specific "culture" can be translated to other similar contexts [13], p18. Therefore, we view class positionality as one significant factor for how people come to participate and understand culture, inspired by frameworks in [13, 88, 105].

We employ these social class distinctions because they are far-spreading, and even exist within circumstances which on the surface may seem universal. By example, something as unassuming as the music genre one primarily listens to or is most familiar with, is directly tied to the social and economic background of the listener [125]. The distinction between SES, and class as a culture, serves to offer a more complex conversation about the multiplicities of class and how it impacts the way we interact with research and physical activity.

2.2 Why is Class Important?

Socioeconomic class is one identity marker which we can use to understand more vividly how one experiences the world at all phases, including psychologically and socially [78]. Therefore, although there are a few competing interests which help to contextualize why class is such a crucial metric for evaluation, we choose to focus on two which are especially complex, the first is *culture*.

Culturally, there are unique beliefs and practices that are generally imbued by social class. These core beliefs can impact how persons from particular socioeconomic class backgrounds navigate their identities, and engage with the world and systems which are not indicative of their class. For example, those from the middle class are said to champion active independence, personal delegation, and adopt a self-starter view on life [29, 108, 114]. In these cases, the self is the pillar. On the other hand, what is central to working class survival is community building and interdependence [114], which can make it harder for working class persons to assimilate into conditions which promote middle to upper class behaviors, such as the corporate workplace [114]. As personal informatics is largely founded on observations from users with access to discretionary income, time and higher education [19], the cultural foundation of device and research design is largely indicative of high-SES perspectives.

The second is *time*. Time is another analysis element for understanding the relationship between societal dimensions such as health outcomes, as socioeconomic class has correlations to how time is boxed and valued [106]. One's access to "discretionary time", periods of time where one is free to determine how to use it, largely becomes unstable the lower the income [46]. Lower income workers are more likely to face difficult labor conditions like irregular work schedules or being beholden to practices such as "just in time scheduling" [50]. Just in time scheduling is a practice of providing shift hours on short notice, often fluctuating by week. This poses difficulties for scheduling important events, child care, medical visits, etc. and places persons in a state of constant time instability [50]. Such class conditions are transmutable and are even considerable factors for whether one engages in regular exercise, with those who are time poor less likely to participate in physical activity [110] or self report health status' [106]. These realities can also influence research participation, which we will further explore within the unique context of wearables intervention studies.

2.3 Class and HCI

The HCI research community is seeing an increasingly non-white, working class HCI audience [35, 116, 137]. As a result, some research has emphasized a need to consider *identity* in the process, such as race, education, and gender in technology design [103]. In the greater HCI research community, there have been a few efforts to contend with socioeconomic class. Although this is not an exhaustive list, class has served as an analysis tool in evaluating family technology use and monitoring differences by SES and ethnicity [40], how unhoused teens engage with information technology [136], hiring [20, 21], and labor [76] by socioeconomic class. In many instances, socioeconomic class is used as an inter-sectional boundary for a larger formula which usually includes race and gender. For example, in reviewing the impact of mHealth technologies on vulnerable populations in the U.S., Stowell et al. consider vulnerable groups to be of low-SES, racial/ethnic minorities, and/or individuals with disabilities [116].

In other cases, the conversation on class and research studies transgresses tangentially, particularly through considering participant compensation. In these instances, researchers from other disciplines have conducted comprehensive literature reviews on common compensation reporting metrics, evaluated the ethical implications of these patterns, and express a desire for the development of purported best methods [68, 71, 90]. Therefore, the conversation largely is centered on establishing transparency on compensation practices and the line between coercion and incentive. Mainly class is circumvented and the emphasis is more so on replicability of research projects and the ethical implications of non-reporting for the larger research space, such as in this systematic review of how participant compensation is reported (in HCI) by Pater et al. [92]. What is missing notably, is a nuanced exchange about how current class standing and class cultures affect someones agency to participate in a study dependent on the compensation structures that are in place.

Within the personal informatics discipline, there has been entanglement with socioeconomic class, but these studies tend to be the minority, with many saying as much. For example, of 83 mHealth interventions targeted towards vulnerable populations, like low-SES individuals, Stowell et al. identify just two which leverage wearable fitness trackers [116]. Similarly, Huh et al. identified just 13 papers which identify barriers and facilitators to adoption of consumer health informatics technology by underserved populations, of which *most* examined patient-facing portals or educational tools, rather than wearables [58].

There have been studies which more directly provoke our target populations and their perspectives on general wearable use. For example, Holko et al. [57] conducted a survey study of patients of federally qualified health centers around the U.S., where they learn that most participants positively answered the question, *"whether participants would like a fitness tracker"*. Some of those who did not reasoned that it was because they did not find trackers to be helpful, among other reasons like not being able to commit to daily use, a lack of knowledge, and general disinterest.

There are also a few intervention studies which lie at the intersection of wearables and class. Take for example, this 2019 study by Saksono et al., where the objective was to understand how families can reflect on past fitness tracker activity data to support future physical activity. What makes this paper particularly unique, is both that the families studied were from low-SES backgrounds (alongside being racial minorities), and had family histories of obesity [100]. Another paper, also by Saksono et al., describes a two month wearable deployment study conducted with families in *"low-SES neighborhoods"* from a North-Eastern city in the U.S. [99]. The primary data analysis focuses on the social, emotional, and environmental relationships between PA and wearables use choices. These two studies offer a glimpse into tracking as a community effort.

Similarly, Cruz et al. [26] describe an interview study conducted with economically disadvantaged, minoritized participants, living in *"high crime"* areas. The purpose of the study was to probe their perceptions of wearables device use, and notably they found that participants emphasized neighborhood walkability and vulnerability to crime as contention points for investigation, similar to meditations in the 2018 and 2019 papers by Saksono et al. [26, 99, 100].

While these lines of research have helped introduce class and race perspectives to personal informatics and HCI more broadly, there is space for an even more expansive view on class, which discusses other more granular influences on device use and study participation. We add to this literature and this conversation by discussing some of the reasons for *how* the way we design our studies contributes to this critical lack. We surface a more nuanced perspective which regards class as more than a fiscal and access measurement, but also as a phenomenon which has temporal and cultural dimensions. This is a necessary junction to address in order to provoke a critical discussion about what this may mean for the field, the data that we collect, and the knowledge we produce.

3 APPROACH TO UNDERSTANDING TRENDS IN THE WEARABLES LITERATURE

In support of understanding how the wearables literature contends with aspects of socioeconomic class, our aim is not to identify or prescribe a systematic and holistic account of the HCI and Health research discipline. Rather, our goal is to identify key areas which should be considered zones where socioeconomic class has potential crucial bearing on study population, participation outcomes, and general device use. In doing so, we aim to follow Erete et al.'s call on the HCI community to be self-reflective of how we go about interacting with participants when designing around margins like class [35].

This paper is formed in alignment with the style of argument or opinion papers within HCI which have attempted to self-critique and observe trends [135]. One such relevant example is Fit4Life, by Purpura et al. [93], where authors argue that there is pressing need to rethink persuasive technology (PT) frameworks – challenging the prevailing sentiment regarding behavior change in the PT field. In another example of a critical reflection pieces, Hekler et al. [55] describe avenues for intertwining behavioral theory with the design and research of "behavior change technologies". The authors construct an analysis on what we can assume is an observation of behavioral technology literature, intermixed with their previous knowledge of social science behavioral theory, but in lieu of pulling from large bodies of literature, they discuss their observations using single papers as the examples. Similarly, other authors use examples from a rich literature field to critique research practices around various topics such as sustainability [30], critical design [9] or gender [65]. Although the topics are different, what makes these papers similar is that the authors are interested in providing critical perspectives on a subject within HCI, often about research methods and research focus, through highlighting trends, engaging with theory, observing potential implications, and offering suggestions. Our methods are inspired by these kinds of contributions. We invite future work to systematically examine how the research literature on wearables has entangled with aspects of SES and class, such as trying to estimate the average amount of time required to participate in an intervention given study procedures and physical activity expectations.

3.1 Process for Engaging Examples

Regardless, although our goal was not to systematically analyze the literature, we *did* have a procedure for collecting and documenting examples to base our engagement. The basis of this procedure is in alignment with Rapid Reviews, which aim to be structured and rigorous but are not exhaustive of all relevant literature [52]. We began with an initial search of the ACM digital library for the keywords *"personal informatics"*, and *"physical activity"* for full papers published between January 2015 and December 31, 2022. The purpose of this initial search was to develop our inclusion and exclusion criteria, and to finalize a consistent rubric of data points for which we would base our analysis.

3.1.1 *Inclusion Criteria.*
From this initial search which elicited 292 results, we read 12 of the top most cited papers to help us create the following inclusion criteria:

- Studies should have deployed physical devices *for a period of time*, with a focused intent on the lived experience of wearable use. Interview, survey, and lab studies were therefore excluded as they did not rely on the deployment of novel or commercial wearables.
- Studies which *solely* discussed mobile or desktop 'wearable' applications were excluded. Take this 10 month in the wild study of "Habito", a self-developed Google Play mobile application, by Gouveia et al. [49] which we initially read for the review. It was excluded as it did not describe a deployment and it did not involve a physical tracker. As mobile application sensing is mainly supported through GPS tracking and accelerometer sensing, accuracy is often contingent on the phones relative position on the body, thereby limiting best use case to walking, running, or the like [64]. As our dialogue will already center this step count phenomenon, our perspective can still be used to entangle with the realities of mobile app, sensing based tracking applications.
- Studies had to have a central focus on physical activity, therefore any which primarily focused on other tracking domains like sleep tracking or food tracking were outside of scope. This is because the relationship between SES, access, and sleep, or some other tracking focus, is vastly different enough that the central considerations should be addressed independently. For example, a food study with economically disadvantaged participants may bring forth a different focus in dimension due to implications of barriers like food deserts, which would not necessarily hold the same criticality or perspective in a dialogue on sleep or physical activity. However, studies which assessed behavior change, weight loss, or psychiatric outcomes, for example, were included if the actionable procedure for *assessing* and *achieving* these goals was physical activity in conjunction with tracker use. We see examination of class dimensions around other tracking goals as a valuable opportunity for future work.
- Studies should have been published 2015 or later. This date range is in alignment with development maturity of wearable sensing technology and general public interest. For example, the first Apple Watch was released in April 2015 and in that same time frame, Fitbit had largely moved from producing clip-worn to wrist-worn devices. Thus, our date criteria only excluded a few

potentially relevant studies, as most studies we observed pre-2015 involved mobile wearables, like in the case of UbiFit garden [24].

- Only full papers were included, published abstracts, works in progress, or others of similar persuasion, were excluded.

3.1.2 Assessment Rubric. After establishing these criteria from the initial search of the ACM library, we developed a rubric for gathering objective information about a personal informatics study and its components. By assessing each with the same rubric, we were able to get a more stable view of areas where socioeconomic differences could prove important for study and design outcomes. We began each paper review with a short annotation of the overall objective of the study and other contextual information, and then we assessed the following themes:

- The first bucket, *Recruitment*, consisted of two questions, *"From where/how are participants acquired?"*, and *"What are the requirements for selection?"* Our hope was to contextualize participant demographics, especially in cases where such information was not directly reported. This choice was supported by literature [126] which suggests that inclusion and exclusion criteria, alongside recruitment methods [61, 77], can help to indicate participant background. For example, exclusion criteria on the basis of one's access to technology, can be indicative of a participants educational background or socioeconomic class [123]. Ultimately, although the data was collected, our findings on recruitment were excluded from the centralized focus of our paper as it is already often discussed as a point of contention for representation and inclusivity in studies like [126].
- The second bucket, *Device* consisted of a multi-layered response mechanism with the high level question: *"Did the participant possess a wearable device prior to study participation?"* Supplemental questions were triggered dependent on the yes or no response. If yes, we evaluated this in context with that studies' goals and participant data (if available). If no, we were interested in whether the devices were provided by the research team, purchased for the study by the participant, or acquired by some other means. For example, if the research team provided the wearables, the supplemental question would be *"At the conclusion of the study, who keeps the device?"* With these lines of inquiry, we hoped to trace whether there was consistency in how devices were acquired, as we were aware of studies where devices were given wearables as compensation, as well as as studies where participants were required to have their own devices for enrollment. As we were not sure of the prevalence of either, this line of questioning was crucial for establishing more context on prevalence. Furthermore, we hoped to get a more implicit view of participant demographic and/or level of access or other such subtle, yet important data. These two *Device* and *Recruitment* were particularly useful for contextualizing participant demographics in studies where such data was not *explicitly* reported.
- The last buckets were *Compensation, Time,* and *Activity*. With *Compensation*, the high level question, *"Are participants compensated, if so, how?"*, fed into lower level answers which we used to report compensation type, amount, and any other relevant data such as periodic incentives. We also used this data to compliment the device section, in determining whether the device was the compensation. The *Time* bucket was used to collect exact information on study length and physical activity time adherence. We were interested in how long a study lasted and how long participants were to participate in daily (or weekly, dependent on study adherence requirements) physical activity. If a study did not quantify physical activity adherence, that was noted. Lastly, we traced the type of activities that participants were expected to perform and the evaluation criteria for the goal of a study within the *Activity* theme. For example, we highlighted whether participants were instructed to track steps through walking or to track other activities, say swimming. We also took note of studies where physical activity adherence was up to individual participant discretion. We generally also held space for 'miscellaneous' text descriptions for any other important details which could provide further context to the above themes, and/or help us to get a more complete understanding on how researchers used the data they collected.

After we finalized our rubric, we removed any papers from our initial search of the ACM which did not meet the criteria, and collected the final batch of papers from an existing corpus of HCI and Medical venue studies, and a repository of peer-reviewed publications which discussed the use of Fitbit devices hosted by Fitabase [36]. The personal informatics paper browser [32] companion to the Epstein et al. systematic review of the personal informatics literature [33], was attractive because it includes around 500 papers pulled from ACM, IEEE Xplore, and PubMed, with the keywords *"self-tracking"*, *"personal tracking"*, *"quantified self"*, and *"personal informatics"*, among other criteria. As this repository only included papers published 2019 and earlier, we engaged with Fitabase repository for papers published until May 2023.

We characterize our discussion with more than 30 papers within these criteria and color the work with more than 70 other related personal informatics works. Although the corpus is not comprehensive of the entire physical activity wearable space, we already have ample confidence to believe that the central basis of this discussion, **that the space is lacking in low SES participation and design considerations which include them**, is both valid and myriad as there have been studies (as outlined earlier) which discuss the existence of shortcomings of our discipline in that regard.

4 CHARACTERIZING CLASS IN WEARABLE STUDIES

Our research team comes into the paper with two respective knowledge points. One researcher came to the topic with a rich understanding of the sociotechnical literature on class, race, and gender, and how these realities color technology use and design. The other came in with a decade of experience designing and deploying HCI studies in personal informatics leveraging wearables, but with limited exposure to the literature which discusses the impacts of class on technology use. Collaboratively, over the course of reading and discussing the literature described above, the two researchers developed a shared understanding of the aspects of class typically ignored by wearables research, including many ways in which the researcher with prior experience designing and deploying for wearables had ignored class in their prior studies.

Informed by our respective experiences in the topic, we do not intend for our critical discussion to be systematic, as it is nearly intractable to identify and label every HCI and Medical wearable intervention study. We bring up specific examples of research studies as examples of trends that we have observed in the field, rather than critiques on the researchers or the methodology of any particular study. Thus, from our analysis, we have identified two larger dimensions, *Time* and *Activity Type*, for which we consider how class can inform the use and design of wearable tracking technology. We will wrap up our observations of how class has been contended with in wearables studies by pointing to positive examples of papers which effectively contend (in some manner) with our pain points.

4.1 Time

In this section, we will discuss time as a dimension of concern, which will be the basis of our later discussion. The following variables are areas of concern both independently and in relation to each other. This means that although the variables have their own impacts on study participation, they coexist functionally within the larger structure of the intervention study. We evaluate four distinct areas in which time, as it exists as an entity of SES, can impact participation in wearables intervention studies:

- **Length of Study**: We evaluate the longitudinal dimensions of intervention studies.
- **PA (Time) Requirements**: We analyze how researchers design physical activity adherence.
- **Hidden Work**: We contextualize potential hidden work resulting from study participation.
- **Compensation**: We identify trends in how participants are compensated or otherwise incentivized for enrolling in intervention studies.

4.1.1 Length of Study. HCI researchers have often questioned the necessary study length to abide by when a new technology is being deployed or tested for efficacy [66, 67]. It's not uncommon for wearables intervention studies to be long, many studies can be more or less anywhere between six weeks [18, 39, 131, 132], ten to twelve weeks [87], or even five months or more [53, 62]. Some studies such as Nyrop et al. [86] allow varying weeks in intervention, dependent on participant needs or health status such as week in cancer treatment. Long studies are not unique to wearable intervention studies, and the HCI research community regularly discusses the merits of long-term deployments towards answering certain kinds of research questions [67]. However, study length is particularly notable in the space of PA wearables because of how much these studies emphasize adherence, or sustained engagement with the device and the intervention over its course [119]. More unique to wearables, researchers can directly monitor this adherence through the use of a device. Often as a result, adherence itself is a common evaluation goal with studies frequently comparing level of engagement of an intervention to a baseline condition, wear time and steps taken. Although this is not an exhaustive list, we observe that adherence is a common study goal, used to evaluate or measure device abandonment [73], change in weight [15, 62, 97], changes in PA participation time [132], PA reflection, and others.

Additionally, we sometimes observe an increase in participation expectation over the duration of the study such as in Thorndike et al. [121]. In another example, Abrantes et al. [1], there was a 4,500 step a day goal at the onset of the study, accompanied by a 500-step increase by week in intervention. In other cases, certain time points also elicited non-PA activities such as interviews.

4.1.2 PA Time Responsibilities. Within wearables studies, participants typically have time responsibilities related to their participation, including wear time or the completion of PA for a certain duration. The time burdens of participation therefore extend beyond direct contact with the researchers. These timed physical activity requirements are in addition to other study responsibilities typical of field deployments such as interviews, daily diarying, capturing video, photo, or audio, group activities, and more. What is more unique to wearables is that these expectations often span a great portion of the intervention (e.g., continuous or near-continuous monitoring), as opposed to ad-hoc interaction with the intervention decided on by the participant. For example, a mobile app intervention might encourage or require daily use, but when to engage is typically at the discretion of the participant and the engagement is relatively brief.

With device deployments, often there are expectations for participants to engage in a timed minimum of PA. An example of a timed PA requirement could be 250 minutes of PA a week [97] or no more than 300 [131]. Typically, the expectation is that participants would adhere to this requirement daily or weekly and in some studies such as Losina et al. [75], participants who increased minutes could gain a ten dollars a week incentive.

There also sometimes exist device usage and wear requirements, where participants are required to wear the Fitbit all day or during waking hours, [42, 43, 62, 87, 121]. In some cases, researchers only consider a valid wear day one where a participant wears the device for a specified amount of time, for example more than eight hours [1]. This means that for the days which participants did not have the device on for the specified minimum, the wearable data was not included in the overall analysis. While exclusion of certain days may not (or may) impact their overall participation adherence or eligibility for compensation, they reduce the impact that participants who face time burdens can have on our understanding of people's use of wearables.

4.1.3 Hidden work. There are also invisible labors attached to timed PA responsibilities and study adherence in general. Hidden or invisible work relates to labor that is made invisible under the pretense of a larger, more direct labor activity [112], it is the work that one is invariably inducted to enact as an effect of some larger labor context. Hidden *work* in this context, is the unintended impact of, unexpected modification to, or unannounced consequences of, participation in a wearables intervention study. Essentially, we look to the components of a study which may not be immediately obvious as being characteristic of labor, or time burdening.

There are dozens of areas where invisible labors can manifest in an intervention study. An example of a smaller scale invisible labor is the charging and maintenance of a wearables device. A few Apple Watch models for example require a charge after 18 hours of use [3], which has been discussed as a reason for lapsing in use [34]. For a study which requires a minimum wear time, this means users are expected to maintain and charge the device daily. While other wearable devices might have longer battery life, like multiple days, the hidden labor may not be lessened but become less periodic. Additionally, even if one were to use a sensing app on their phone, mobile phone sensing applications tend to drain phone batteries more quickly, which requires more charging than usual [80]. Hidden labor can even exist in the travel and transportation to facilities for PA, in the adjustment of child care, or even in the warm up, cool down, and recovery from physical activity.

4.1.4 Compensation. It is not necessarily surprising that there is a considerable lack of compensation reporting in studies of wearables, considering that in a systematic review of HCI *"user"* studies, Pater et al. found that nearly 85% of papers did not report compensation [92]. In that paper, they discuss a need to investigate compensation structures in order to standardize compensation practices. However, what is interesting about wearables studies, generally, when figures are reported it was unclear whether the compensation was determined based on effort or time. Even more so, the compensation structure of wearable deployment studies is more complex because the decisions and implications of compensation go even more in hand with other design choices like study length and adherence. Devices introduce an interesting dichotomy because in theory, they are a type of compensation which could prove beneficial beyond the study.

Unsurprisingly, in our search, researchers either do not report compensation structures or have unclear language surrounding it. Whether this indicates that participants were not compensated, or they were, but the figures are unreported, is unclear. Some studies solely compensate participants with the wearables devices themselves. In these cases, where participants were provided wearables for study use, only two explicitly reported that participants were *"gifted"* the devices[73, 79]. In other scenarios, participants purchased the devices for study use but were not otherwise compensated [98]. Thus, regardless of a participants intent or capability to use a wearables device, this is their sole material incentive. When cash or gift card figures were reported, payments are typically under thirty dollars [75, 81]. A small part of studies like [18] participants were compensated over 50 dollars. And of the studies conducted in conversation with low-SES participants [99, 100], they were compensated at an outlier rate of one hundred dollars.

4.2 Activity Type

The activity type dimension surrounds the type of activities that are centered in intervention studies and wearables device tracking generally. Within this section, we will investigate the current trends in wearables study activity types mainly:

- **Activities Assessed**: We meditate on the common PA types which studies emphasize adherence.
- **Detection Capability**: We gather varied insight into device detection accuracy as conveyed in academic and industry research studies.
- **Workplace and Sedentary Labor Contexts**: We report common circumstances for labor contexts of intervention studies.

4.2.1 Activities Assessed. Studies have primarily analyzed step count or walking over other forms of PA. Although a few studies have a more fluid requirement for participants, allowing them to engage in PA as they see fit [48, 73], its fairly common for step count data to be a primary point of analysis [39, 42, 63, 73, 75, 79, 98–100, 121, 132]. In a few cases, walking is a secondary point of analysis, with the intervention being a supplemental tool for achieving a more primary goal like weight loss [15, 62]. Additionally, similar to PA minutes, some studies define step count goals for participants such as 10,000 steps a day [18, 97].

4.2.2 Detection Accuracy. Within wearables marketing [2, 37, 89], there is a collected effort to emphasize the tracker's unique capability to collect data which one could not aggregate (as effectively) on their own. However, the proficiency at which wearables can track different forms of PA has come into question as there are difficulties in accurately tracking exercises which do not necessarily increase heart rate or have "easily tracked movement" [134]. Therefore, of the activities which can be tracked, some are not supported as effectively as others [69], because the quality of the movements are more challenging to identify from these sensors. Activities which are closer to those which share similar mechanics to walking, are more likely to be included in the automatic list of tracked activities, and also easier to track, such as being on a stair climber or running. On the research side, advances in human activity recognition have suggested that wearables could be further used for detection of other activities involving arm or hand movements, like jumping jacks or sit-ups [83], with frequent efforts to improve accuracy and diversify capabilities.

In some studies where researchers relay participants' observations on the efficacy and/or feasibility of step counting, we regularly observe sentiments regarding detection accuracy. For example, in Cruz et al. [26], they note participant perceptions that their material reality did not afford the safe accommodation of (leisure) walking in the place that is presumed to be most convenient: the home (neighborhood). Others, in accessibility literature [16], found that there are significant challenges in wearable tracking for individuals who do not have the capability to take steps. As wearables are accelerometer based and usually wrist or hand worn for the purpose of step counting, the general sensor type and overall activity sensing proficiency proved impractical as there was not clarity on whether pushing is accounted for on wearables.

In a 2008 study by Consolvo et al. [24] they contend that the more diverse activity tracking affordances available, the more users engaged in diverse activities. Even so, although there are more options today for participants to select different activities, they are still calculated within the framework of step count. Thus, regardless of being able to support multiple kinds of activities [25], goal setting and achievement are still translated to step count equivalents. This was a point of concern for some users in Cauchard et al. [18] who desired to track other PA activities but were discouraged because the device reinforced step counting. Some research even expressed participant perceptions on the devices focus on step counting [23, 47, 54, 73, 107]. Therefore to best optimize device use, many felt they had to change their activities to encourage step counting or find ways to manipulate the wearable into detecting the motions from the non-step activity they were partaking in.

Although these use cases do not represent identical issues, they call into question the perceived ease of access of step counting and even its accuracy. Here, you have different communities who without inspecting their potential commonalities in background, bring extra thoughts about the way in which wearables fit into their lives. Their perspectives on the surface seem different, but ultimately the sentiments are similar, in that although they are interested in engaging with the tool, the material shortcomings of the sensing (cannot calculate wheelchair movements accurately) or the design considerations (centering leisure walking as a PA metric) does not allow for them to do so optimally.

4.2.3 Workplace and Sedentary Labor Contexts. There is a research focus in personal informatics where intervention studies are done in workplace settings, with participants recruited from a work site usually to observe PA behavior change. This is understandable as workplace wellness programs are common and often associated with insurance or company gifts [22]. However, of the papers written in these settings, its not atypical for them to be in sedentary work environments [18, 24, 47, 48, 75, 121], or with sedentary students in college [81]. In these settings, researchers look to team building and incentives, in addition to the device, as a mechanism for inspiring an increase of PA.

Yet it is also important to note that we did not find any workplace studies performed in manual labor environments. From our vantage point, there is not a large consideration for physical activity done in manual labor. Contexts which could provide unique insights into activity tracking, such as forklifting, package handling, waitressing, construction work, and other jobs which employ physical labor tend not to be the focus of the literature, despite the working class being the majority of workers in the U.S. [45]. An employee who carries hundreds of pounds of woodstock a day or heavy luggage at the airport, is participating in physical activity but if we are to inspect the activities highlighted by Fitbit or Apple Watch, these are not explicitly found. This has socioeconomic implications, as persons of a lower socioeconomic class are more likely to partake in occupation based physical activity then all other groups [10].

4.3 Positive Examples from the Literature

Amidst the critique, we did find studies where researchers centered class perspectives as part of recruitment, analysis, or framing of participant experiences. These examples are undoubtedly not the only papers which center class perspectives, but are rather exemplars we believe are worth holding up as ways that researchers can contend with class as they design studies and report on findings.

As mentioned earlier, Saksono et al. [99, 100] do much work in terms of low-SES demographic inclusivity and perspective centering. Noteworthy examples from these works include describing class-specific challenges associated with use of wearables, such as neighborhood walkability. These studies were also at the high end of financial compensation for study participation, which helps offset the time expectations of the studies. An interview study by Niess et al. [85], examined differences (and similarities) in perspective between *"Western, Educated, Industrialised, Rich, Democratic (WEIRD)"* fitness tracker users from America and Europe, and those of Arab Egyptian ethnicity and nationality. Their decision to contrast Egyptian participants was in direct response to the distinct lack of non-western voices in the common lexicon of fitness tracker related research. They found notable differences in perspectives between the two groups regarding varying topics related to fitness tracker use, notably about the prioritization of specific metrics. Studies like these which make demographic a central part of analysis, make it much easier to trace the subjectivity of user experience in data findings because we can contextualize interactions within the lines of our participants independent experiences, and those of larger socio-cultural significance.

In another case, frequent support and communication with participants was a central part of a deployment study by Abrantes et al. [1] with women both enrolled in an alcohol and drug partial program and also managing depression. Aligning with recommendations around how to engage with running studies with marginalized populations [35], researcher support helped maintain and build rapport with the women. Researchers conducted phone sessions, held a pre-study informational coaching session on resources, device use, and best practices for incorporating study requirements into their daily lives. There were also 30 minute, bi-weekly, in-study phone calls to discuss participants PA and device use and other counseling topics, and to generally provide assistance as needed. This form of focused study design is more in line with an SES-conscious practice, designed to help overcome barriers around long term retention and low technology literacy. However, there exists a tension in that the frequency of these check-ins may introduce further time requirements related to participation, which may not align with other needs of low-SES individuals. As it is unclear the SES of these participants, we cannot further extrapolate these tensions.

Although few and far between, some researchers reported participant yearly salary, like in this workplace study by Wentz et al. [131], and Saksono et al. [100] where they reported class based demographic inclusion criteria (less than $21,979 annually). It is more often that studies described participant *occupations,* by listing or summarizing them (such as in a table [18]) or explicitly stating that participants engaged in sedentary work practices [47]. while studies predominantly understood the needs of sedentary workers who work 9-5 jobs, reporting this context is helpful for surfacing the availability of PA as a leisure activity and participant access to discretionary time. Additionally when salary or income is provided, there is useful context which is produced. For example, high salary could suggest the opportunity to purchase the equipment needed for certain types of physical activities, and suggests that high study compensation may not be needed for sustained engagement.

Lastly, there were a few studies which contained unique research metrics that differed from numerical data, such as this study by Miragall et al. [81] where *"enjoyment"* of PA participation was a secondary analysis. Among early commercial wearables, the now-defunct Nike+ Fuel Band used a unique measure of *"Fuel"* to abstractly refer to exercise as measured across different kinds of activities, rather than translating sensor data to *"Steps"* [133]. While perhaps less human-interpretable, this measure had the advantage of being scalable to different kinds of activities.

5 DISCUSSION

In the previous section we examined intervention trends on *Time* and *Activity Type*. With *Time*, we discussed study length, PA time requirements, hidden work, and compensation correlating both with typical study adherence guidelines and with activity type. With *Activity Type*, we reflected on the cultural contexts which tracking is usually situated and how design choices affect perceptions of device capability. From our evaluation, we surface that a common activity centered in wearables studies is by and large step count.

In the following sections, we will explore the implications of these findings on the inclusion of socioeconomically disadvantaged users and provide suggestions for future considerations.

5.1 Implications of Time and Participation on Lower Socio-Economic Persons

A study's length does not necessarily hold the brunt of the burden for the current socioeconomic landscape of HCI studies. Longitudinal studies are not necessarily more burdensome than others simply by their nature of being longer in length. It is the content of the study which determines the relative burden of participation. These participation time burdens cannot only affect inclusivity but also retention. By and large a consistent narrative surrounding low study participation of persons from economically disadvantaged or ethnic minority groups are about difficulties in recruitment and mistrust of researchers by community members [101]. Although it is true that persons who are of a lower SES are often missing from the health research populations as a result of siloed recruitment strategies, it is also important to note that with successful inclusively design, attrition rates can be improved such as in [118]. However, not much of the HCI intervention research domain focuses on the retention of said populations, or even the development of research studies which account for complex life circumstances.

The latter, retention, is a crucial piece of the puzzle in regards to longitudinal studies. In general, researchers have had trouble with attrition for community members who are low-SES due to instability in life conditions. This could be due to something as innocuous on the surface as a change of contact information, systemic such as a lack of agency to free time, or ultimately personal, like the prioritization of normal day to day responsibilities [12, 118]. In clinical trials which are also longitudinal in nature, researchers working with low-SES populations note drop offs by week, with trouble maintaining contact as time goes on [12, 118]. Although these studies were done in the general medical context, some of the reasons for attrition directly correlate to time, which is a variable wearable intervention studies are founded upon (PA, wear time).

In a multi-month studies where participants are given a wearable device to track daily or weekly data, in addition to other specified study requests, a participant must have access to discretionary time. Our studies are long, require increased effort, and the introduction, or increasing, of physical activity. These sorts of study requirements can prove more significantly impractical for working class persons, as often times their labor is within the margin of the rest or leisure of white collar workers. This impedes upon one's ability to have true agency on their schedules [105], p66, and in the context of wearables studies, this could limit their ability to fully engage with recruitment processes or study requirements. In many cases, working class people spend their free time sedentary as due to the physical demands of their occupations [94], this means that it is not rare for working class persons to feel the *"materialization"* of labor on their physical bodies [105], p70. Therefore, if we frame physical activity as a thing which must be done in our free time, we must account for the nuances of leisure time. And it is not that there is an inherent disinterest from members of these communities, as underrepresented populations tend to have the same amount of interest in participation as the common study demographics, and in some instances even more [56].

What is true, however, is that in the case of low-SES populations whose class positionalities most directly necessitate extensive time to generate money and resources for their immediate survival, the trade-off for participation looms more potently. Study components such as forms of low cash, *"experience"* based, or other types of compensation (e.g., a gifted wearable), can be deterrents to joining or completing a research study for low-SES communities – assuming that the study recruitment methods even reach them. We suspect that even if participation presents potential greater benefit, these benefits may not be sufficient enough to justify accommodation within the material conditions of one's day-to-day reality. We hypothesize that if a household does not readily have access to discretionary funding, the advantage for partaking in a months long study cannot solely be for altruism. Low compensation is a trade off people from higher SES backgrounds can choose to make.

5.2 Implications of Activity Type on Wearables Design

Traditionally, wearables leverage a mixture of accelerometers and heart rate sensors for detection [8, 69, 120] as the advent of wearables device design included a focused effort to introduce pedometer based tracking. Therefore, step count as the central tracking measurement for wearables is connected to the history of pedometers in the early 2000's conceptualizations of personal informatics. In that era of wearables research, pedometers were the chosen tracking devices due to their perceived usability and purported ease for tracking walking movements. Yet, as early as 2008, [25] researchers expressed the shortcomings of sensing with pedometers and suggested the need for either improvement of the apparatus or for the development of new devices to create a more comprehensive PA tracking foundation.

Today, researchers and commercial agents alike continue to hail walking (step counting) for its diversity of engagement cases [14] and its low barrier to entry [104]. Within this framework, 10,000 steps is widely advertised as the metric by which a healthy person should strive for daily. This step count goal is said to provide benefits such as improved cardiovascular health, mental health, potential weight loss, and weight management, among other things [124]. However, the legitimacy of the 10,000 step a day metric has also been countered. In some spaces [84, 96], it has been argued that steps a day as low as 4,400, or a few thousand steps over, provide nearly the same benefits as the 10,000. In time metrics, 30 minutes a day of exercise is considered to be enough for a healthy adult to support much of the same things that 10,000 steps a day is purported to provide [11]. Yet, what these figures signify are more than suggestions for health improvement, they embody a larger sociopolitical dynamic.

There are three ways we choose to evaluate step count, and subsequently step count goals, as engendering middle and upper class cultures. The first, calls into question step counting as a reflection of health literacy. The second, surrounds centering physical activity as leisure. The third, unpacks how focusing on step count limits device use.

First, daily step count goals are not necessarily common knowledge. In wellness culture and the popular lexicon of fitness tracking, they float around freely as these communities are largely evocative of middle to upper class lifestyles and cultures which are more likely to have a higher health literacy [115]. However, what appears to be common knowledge, is not so common when investigating health education and awareness. In thinking of personal health and how ones behavior impacts it, although not exhaustive, this literacy is more likely to be lacking in lower SES and minoritized contexts and can affect information recall, [6], mortality [117], increased hospital admission [7], and general health outcomes.

In Wardle [130], a UK study performed on personal perceptions regarding different health related topics such as leisure PA, life expectancy, dietary choices, amongst other things, they found associations between lower socioeconomic status and a reduced awareness for how ones lifestyle choices affects their overall health. They also found a significant portion of working class individuals were often very present in mind and behavior, not often thinking of the future. When contending with devices such as wearables which center behavior change and reflection, one's capacity to understand the significance of the data and the behavior change that should go alongside it, is crucial. Thus, when a participant is presented with a step count total, or a heart rate number, how do they begin to interpret what this means for their health? Researchers such as Saksono et al. [100] and Lazar et al. [73], discuss participants' limited capacity to reflect on the usefulness of the unprocessed data collected which then makes it difficult to decide next steps.

In designing tracking technology which requires that participants interpret data on their own volition, this brings forth disparities in who can optimize device data. And in the case where devices are used in the medical context, as mentioned earlier, there exist correlations between limited health literacy and information recall. Information/Instructional recall is important for sufficiently understanding and following physician suggestion.

Secondly, low-SES groups are less likely to participate in leisure based physical activity [44, 110], but this does not mean that persons of a lower socioeconomic class are necessarily largely sedentary [111]. According to Besser & Dannenberg [11], the working class living in urban areas are more likely to walk for transportation more than 30 minutes a day, in addition to being most likely to participate in workplace PA [27]. The framing of PA outside of these contexts marks a shift from the previous century where PA was largely defined as a work related activity [113]. We suggest that by framing step count as the activity for which all activities are based, we are creating a limited frame by which a user can develop a broad understanding of their physical activity patterns and habits.

Additionally, we also note that more modern commercial wearable devices often include detection capabilities for other kinds of PA including swimming, biking, rowing, diving, and golf [4, 41]. While research studies on PA wearables tend not to center these, we note that many of these activities have particularly high requirements with regards to equipment (e.g., a bike or elliptical, a rowing machine, golf clubs) and physical space (e.g., to a swimming pool, a golf course) which result in these activities not permeating across class cultures. This is another barrier for low-SES persons as participation in specific sports types changes by socioeconomic class, with high SES persons significantly more likely to play in racquet based and club based sports due to the relative cost participation [31, 95]. Disparities also exists by youth sport [59]. The investment of resources that are going into detecting these activity types and designing complete and compelling experiences around them, points to a deepening reinforcement of wearables serving leisure purposes and favoring individual versus community-based activities. While it is hard to explicitly prescribe detection capabilities which would be beneficial to low-SES individuals, some recreational exercise activities with low indices of inequality include strength training [95]. Beyond these, as we discuss later, we see a particular need to consider detection of activities associated with manual labor.

5.3 Broader Implications of Ignoring Class in Wearable Studies

A clear intent of our critical discussion is to argue for researchers to more consciously consider class when designing wearable studies for physical activity promotion. We can speculate on a variety of reasons as to why there may not be a focused effort on people of lower socioeconomic background in studies of wearables. It could be that researchers have tried to reach communities but have not been able to due to various historical reasons such as mistrust of researchers. However, HCI researchers have written about suggested best practices [35, 126, 127] for navigating the recruitment of these hard-to-reach populations. It could be that because personal informatics is often associated with middle class wellness, there is a belief that economically disadvantaged people do not have interest in using wearables. However, studies have found that these groups are more interested in device use than not [57]. There are many other concerns or limitations that may prevent researchers from considering class in their studies, some legitimate. Even so, as part of arguing for greater consideration, we further unpack the short- and long-term consequences of ignoring class in wearables studies.

As wearables become more entrenched in the patient process and become even more ubiquitous within the technological ecosystem, there is incredible potential for researchers in the space to create and perpetuate Intervention Generated Inequalities (IGIs) [127]. Veinot et al. discuss that health technology interventions can generate inequality if they are *"more accessible to, adopted more frequently by, adhered to more closely by, or more effective in socioeconomically advantaged groups such as those with more resources or education"* [127]. Our critical discussion surfaces that the wearable, when designed with the goal of physical activity promotion, is well on the way to generating inequality. Veinot et al. [127] label four distinct areas through which inequalities can precipitate: access, adoption, adherence, and effectiveness. Our critical discussion particularly surfaces that low-SES individuals might face barriers to adherence stemming from time-based expectations, and poor effectiveness rooted in limitations surrounding activity type.

What is specifically unique about the potential for wearables to cause IGIs, is that in addition to being the intervention in health promotion, both in our studies and in the wild, the devices themselves are often used to measure the success of other interventions. For example, ownership of a wearable is the first stage of the intervention, the use of that wearable to promote some part of ones health, is the second stage. This means that owning a device is an intervention in and of itself and having access to personal data could provide another level of knowledge that cannot be necessarily obtained without it. **In leveraging the use of a wearable as an outcome measure for research, we are deepening our understanding for how to support health promotion – but for people of high-SES background.** Therefore, if the device as it stands is not useful or usable by economically disadvantaged groups, they are now missing out on health interventions which could have otherwise been leveraged. Or worse, our research could perpetuate that a novel health intervention is beneficial, while missing out on the context that this benefit only exists for high-SES individuals.

We have arguably reached the first wave of technological maturity of wearables. **As subsequent waves of the technology come into center, it will become even harder to play catch-up in designing wearables which fit the needs of lower-class individuals.** The possibilities for the next generation of mass scale medical technology could be with tracking devices [138] but without sincere contemplation now, we will be forced to reform later. If we do not instead attack the problem in its relative technological infancy, there could be yet another generation of people at risk of being further victim to health disparities because of their socioeconomic backgrounds. As devices mature, the way we conduct our studies, analyze our data, and disseminate findings, will continue to place people of low SES at another significant disadvantage to which they already are.

6 MOVING FORWARD

The barriers to intervention study participation for persons who are economically disadvantaged could be mitigated through the thoughtful design of more equitable studies. There are some easier and more practical adaptations we can consider introducing, which have been proven to be effective in establishing high retention rates for economically disadvantaged research populations. One such example is the periodic incentive [12, 38, 118]. Retention of low SES participants of clinical trials is more likely to be higher in cases where researchers provide small incentives to study participants. Small incentives like groceries and gift cards or cash bonuses, are useful for enhancing motivation, increasing health visits, and generally improving study adherence. In addition, these incentives are not by their nature necessarily coercive [51]. Incentives are only a part of the larger piece of inclusive design where successful retention of low-SES populations necessitates that researchers intentionally create an environment concerned with building community, constant communication and feedback, and an overall concerted desire to learn the needs of the population [118, 126]. Additionally, the use of incentives is not new to personal informatics as it has been used in intervention studies [75], but its application for retention of low-SES populations could be explored more.

Other more difficult solutions can be reframed in the way we analyze data and come to accept adherence. Expectations such as a minimum of eight hours of wear time severely limit the comprehensive understanding of in-the-wild use of wearables devices and privileges certain behaviors. By framing the research analysis around meeting certain number thresholds, we are missing out on gaining a more layered analysis on the non-quantifiable circumstances of any individuals PA/tracking data. Thus, participant tracking patterns such as those related to non-use, prove opportunistic for a deeper interrogation of the efficacy of a wearable intervention. There's more to the story than step count numbers as observed by [79, 86] and we see an opportunity to reflect on which requirements are most necessary for understanding design needs.

We recognize that these time based issues exist both within the wearables study experience and independent of it. We acknowledge that there are systemic limitations that can affect one's ability to participate and that as researchers we cannot necessarily control all of the institutional barriers that exist in timed dimensions. However, we can investigate how our own processes and practices (further) burden participants and reflect on how to engage these analyses in developing new frameworks.

In regards to activity type, we point to expanding frameworks on how physical activity can be conducted and researched. Although there is concerted advertising of tracking capabilities as being comprehensive of ones exercise reality, it is crucial that we take into active consideration other manners by which one can be physically active, aside from step count. Through the placement of fitness trackers in *wellness culture*, we are missing out on designing technology which is illustrative of a broader PA reality. One of the key instances for design consideration should be the manual workplace.

Looking to the manual labor work-forces to understand how labor and PA correlate could be fruitful as there is a bevy of obtainable knowledge regarding PA as it functions within the larger socio-temporal reality of a workplace. Through this workplace broadening, we place ourselves in a position to better understand how this form of PA impacts groups and individuals' perceptions of their own health, their behavior change goals, and whether or how they see technology supporting those goals. Situating studies in this context could even help to inspire new ways of sensing movement on an engineering level, such as recognizing when heavy objects are lifted or repetitive motions undertaken. Such considerations might require radically rethinking the physical design of wearables to account for what might be detectable via different sensing modalities. For example, e-textiles or smart clothing [17], like gloves, might be better suited for detecting the repetitive lifting of heavy boxes. Advancing these sorts of sensing techniques could go a long way towards increasing the utility of physical activity wearables across class. However, creating distinct class-correlated wearable devices, separated by labor contexts, has the potential to reinforce some of the more cultural divides surrounding class cultures. Regardless, we see these questions as useful for HCI's activity recognition community to contend with.

Finally, we call on the community to report participant demographics, specifically salary. By keeping these data figures out of reported demographics, we are placing SES as an invisible data piece. If we are not identifying the *source of the voices* that support our findings, we risk continuing to make socioeconomic class a neutral data point. It is not enough to report salary only when we are working with vulnerable populations and doing so implies that anything outside of that socioeconomic reality is the norm. Additionally, when perspectives of low-SES individuals are not a part of a study, we encourage the community to reflect on what aspects of the findings may or may not apply to that demographic (e.g., in a Limitations section). It is also not enough to not engage with the implications of the perspectives of the economically advantaged in their lived-in experiences with the study and device. We implore the field to engage with these concepts, and at a minimum, report the salaries of their participants so we have a more complete picture of who design implications might apply to.

All in all, much like any instances of cultural entrenchment, patterns and habits over time are presumed to be natural and thus become more of a de-facto representation of naturalistic realism, rather than patterns and techniques which were created and through some process of assimilation, never delineated from [13]. This implies a systemic reality of our discipline which by design extends into a mode of replication of societal realities during study making, which can be limiting. In the grand scheme of wearables research, there must be an opening for a broader conceptualization of how it looks to collect participant physical activity data which takes into serious consideration the complexities attached to such data.

7 CONCLUSION

After critically reviewing literature on wearables interventions, we find that class in both the capital and cultural sense is often largely ignored as a pivotal metric of the self. We offer an analysis of areas where low-SES class barriers are possibly overlooked, and we do this though the lens of two primary dimensions with bearing on SES outcomes, *Time* and *Activity type*. We contribute suggestions for the prevention of the continued perpetuation of inequities in these sorts of interventions. Ultimately, we implore the field to consider this dialogue and reflect on the conversation as it applies to your own personal work. We see opportunities for researchers involved in all stages of the wearables creation and evaluation process, ranging from those focused on activity recognition, to those using wearables as a tool for measuring health outcomes of an intervention, and anything in between, to participate in this reflection.

ACKNOWLEDGMENTS

We thank Paul Dourish, Anne Marie Piper, and WISH 2023 attendees for their feedback on early drafts of this work. This work was partially supported by the National Science Foundation under award IIS-2237389. The content is solely the responsibility of the authors and does not necessarily represent the official views of the funding organizations.

REFERENCES

[1] Ana M. Abrantes, Claire E. Blevins, Cynthia L. Battle, Jennifer P. Read, Alan L. Gordon, and Michael D. Stein. 2017. Developing a Fitbit-supported lifestyle physical activity intervention for depressed alcohol dependent women. *Journal of Substance Abuse Treatment* 80 (2017), 88–97. https://doi.org/10.1016/j.jsat.2017.07.006
[2] Apple. 2024. Apple Watch. Retrieved February 20, 2024 from https://www.apple.com/watch/
[3] Apple. 2024. Apple Watch Battery. Retrieved February 20, 2024 from https://www.apple.com/watch/battery/
[4] Apple. 2024. Workout types on Apple Watch. Retrieved February 20, 2024 from https://support.apple.com/en-us/HT207934
[5] American Psychological Association. 2022. Socioeconomic Status. https://www.apa.org/topics/socioeconomic-status
[6] Brian J. Ayotte, Jason C. Allaire, and Hayden Bosworth. 2009. The associations of patient demographic characteristics and Health Information Recall: The Mediating Role of Health Literacy. *Aging, Neuropsychology, and Cognition* 16, 4 (2009), 419–432. https://doi.org/10.1080/13825580902741336
[7] David W. Baker, Julie A. Gazmararian, Mark V. Williams, Tracy Scott, Ruth M. Parker, Diane Green, Junling Ren, and Jennifer Peel. 2002. Functional Health Literacy and the risk of hospital admission among Medicare managed care enrollees. *American Journal of Public Health* 92, 8 (2002), 1278–1283. https://doi.org/10.2105/ajph.92.8.1278
[8] Ling Bao and Stephen S. Intille. 2004. Activity recognition from user-annotated acceleration data. *Lecture Notes in Computer Science* (2004), 1–17. https://doi.org/10.1007/978-3-540-24646-6_1
[9] Jeffrey Bardzell and Shaowen Bardzell. 2013. What is "critical" about critical design? *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (2013). https://doi.org/10.1145/2470654.2466451
[10] Marielle A Beenackers, Carlijn BM Kamphuis, Katrina Giskes, Johannes Brug, Anton E Kunst, Alex Burdorf, and Frank J van Lenthe. 2012. Socioeconomic inequalities in occupational, leisure-time, and transport related physical activity among European Adults: A systematic review. *International Journal of Behavioral Nutrition and Physical Activity* 9, 1 (Sep 2012), 116. https://doi.org/10.1186/1479-5868-9-116
[11] L. Besser and A. Dannenberg. 2005. Walking to public transit: Steps to help meet physical activity recommendations. *American Journal of Preventive Medicine* 29, 4 (2005), 273–280. https://doi.org/10.1016/j.amepre.2005.06.010
[12] Billie Bonevski, Madeleine Randell, Chris Paul, Kathy Chapman, Laura Twyman, Jamie Bryant, Irena Brozek, and Clare Hughes. 2014. Reaching the hard-to-reach: A systematic review of strategies for improving health and medical research with socially disadvantaged groups. *BMC Medical Research Methodology* 14, 1 (2014). https://doi.org/10.1186/1471-2288-14-42
[13] Pierre Bourdieu. 1984. *Distinction: A social critique of the judgement of taste: Pierre Bourdieu.* Harvard University press.
[14] Dena M. Bravata, Crystal Smith-Spangler, Vandana Sundaram, Allison L. Gienger, Nancy Lin, Robyn Lewis, Christopher D. Stave, Ingram Olkin, and John R. Sirard. 2007. Using pedometers to increase physical activity and improve health. *JAMA* 298, 19 (2007), 2296. https://doi.org/10.1001/jama.298.19.2296
[15] Justin C Brown, Rachel L Yung, Anita Gobbie-Hurder, Laura Shockro, Keelin O'Connor, Nancy Campbell, Jocelyn Kasper, Erica L Mayer, Sara M Tolaney, Ann H Partridge, et al. 2018. Randomized trial of a clinic-based weight loss intervention in cancer survivors. *Journal of Cancer Survivorship* 12 (2018), 186–195.
[16] Patrick Carrington, Kevin Chang, Helena Mentis, and Amy Hurst. 2015. "but, I don't take steps". *Proceedings of the 17th International ACM SIGACCESS Conference on Computers and Accessibility - ASSETS '15* (Oct 2015). https://doi.org/10.1145/2700648.2809845
[17] Lina M Castano and Alison B Flatau. 2014. Smart fabric sensors and e-textile technologies: a review. *Smart Materials and structures* 23, 5 (2014), 053001.
[18] Jessica R Cauchard, Jeremy Frey, Octavia Zahrt, Krister Johnson, Alia Crum, and James A Landay. 2019. The positive impact of push vs pull progress feedback: a 6-week activity tracking study in the wild. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 3, 3 (2019), 1–23.
[19] Eun Kyoung Choe, Nicole B. Lee, Bongshin Lee, Wanda Pratt, and Julie A. Kientz. 2014. Understanding quantified-selfers' practices in collecting and exploring personal data. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (2014). https://doi.org/10.1145/2556288.2557372
[20] Phoebe K. Chua, Hillary Abraham, and Melissa Mazmanian. 2021. Playing the Hiring Game: Class-Based Emotional Experiences and Tactics in Elite Hiring. *Proc. ACM Hum.-Comput. Interact.* 5, CSCW2, Article 392 (oct 2021), 27 pages. https://doi.org/10.1145/3479536
[21] Phoebe K. Chua and Melissa Mazmanian. 2022. The Substance of Style: How Social Class-Based Styles of Interpersonal Interaction Shape Hiring Assessments at Large Technology Companies. *Proc. ACM Hum.-Comput. Interact.* 6, CSCW2, Article 464 (nov 2022), 22 pages. https://doi.org/10.1145/3555565
[22] Chia-Fang Chung, Nanna Gorm, Irina A. Shklovski, and Sean Munson. 2017. Finding the right fit. *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (2017). https://doi.org/10.1145/3025453.3025510
[23] James Clawson, Jessica A Pater, Andrew D Miller, Elizabeth D Mynatt, and Lena Mamykina. 2015. No longer wearing: investigating the abandonment of personal health-tracking technologies on craigslist. In *Proceedings of the*

2015 ACM international joint conference on pervasive and ubiquitous computing. 647–658.

[24] Sunny Consolvo, Predrag Klasnja, David W McDonald, Daniel Avrahami, Jon Froehlich, Louis LeGrand, Ryan Libby, Keith Mosher, and James A Landay. 2008. Flowers or a robot army? Encouraging awareness & activity with personal, mobile displays. In *Proceedings of the 10th international conference on Ubiquitous computing*. 54–63.

[25] Sunny Consolvo, David W. McDonald, Tammy Toscos, Mike Y. Chen, Jon Froehlich, Beverly Harrison, Predrag Klasnja, Anthony LaMarca, Louis LeGrand, Ryan Libby, Ian Smith, and James A. Landay. 2008. Activity Sensing in the Wild: A Field Trial of Ubifit Garden *(CHI '08)*. Association for Computing Machinery, New York, NY, USA, 1797–1806. https://doi.org/10.1145/1357054.1357335

[26] Stefany Cruz, Alexander Redding, Connie W. Chau, Claire Lu, Julia Persche, Josiah Hester, and Maia Jacobs. 2023. Equityware: Co-designing wearables with and for low income communities in the U.S. *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (2023). https://doi.org/10.1145/3544548.3580980

[27] Rachel Cusatis and Dana Garbarski. 2019. Different domains of physical activity: The role of Leisure, housework/care work, and paid work in socioeconomic differences in reported physical activity. *SSM - Population Health* 7 (Apr 2019), 100387. https://doi.org/10.1016/j.ssmph.2019.100387

[28] Tori DeAngelis. 2015. Class differences. https://www.apa.org/monitor/2015/02/class-differences

[29] Andrea Dittmann. 2017. Understanding social class as culture. https://behavioralscientist.org/understanding-social-class-as-culture/

[30] Paul Dourish. 2010. HCI and Environmental Sustainability. *Proceedings of the 8th ACM Conference on Designing Interactive Systems* (2010). https://doi.org/10.1145/1858171.1858173

[31] Rochelle M Eime, Jack T Harvey, Melinda J Craike, Caroline M Symons, and Warren R Payne. 2013. Family support and ease of access link socio-economic status and Sports Club membership in adolescent girls: A mediation study. *International Journal of Behavioral Nutrition and Physical Activity* 10, 1 (Apr 2013), 50. https://doi.org/10.1186/1479-5868-10-50

[32] Daniel A. Epstein. 2023. Personal Informatics Paper browser. http://personal-informatics.depstein.net/

[33] Daniel A Epstein, Clara Caldeira, Mayara Costa Figueiredo, Xi Lu, Lucas M Silva, Lucretia Williams, Jong Ho Lee, Qingyang Li, Simran Ahuja, Qiuer Chen, et al. 2020. Mapping and taking stock of the personal informatics literature. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 4, 4 (2020), 1–38.

[34] Daniel A. Epstein, An Ping, James Fogarty, and Sean A. Munson. 2015. A Lived Informatics Model of Personal Informatics. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (Osaka, Japan) *(UbiComp '15)*. Association for Computing Machinery, New York, NY, USA, 731–742. https://doi.org/10.1145/2750858.2804250

[35] Sheena Erete, Aarti Israni, and Tawanna Dillahunt. 2018. An intersectional approach to designing in the margins. *Interactions* 25, 3 (2018), 66–69. https://doi.org/10.1145/3194349

[36] Fitabase. 2023. Fitabase Research Library. https://www.fitabase.com/research-library/

[37] Fitbit. 2024. Fitbit. Retrieved February 20, 2024 from https://www.fitbit.com/global/us/home

[38] Diann E. Gaalema, Rebecca J. Elliott, Patrick D. Savage, Jason L. Rengo, Alex Y. Cutler, Irene Pericot-Valverde, Jeffrey S. Priest, Donald S. Shepard, Stephen T. Higgins, and Philip A. Ades. 2019. Financial incentives to increase cardiac rehabilitation participation among low-socioeconomic status patients. *JACC: Heart Failure* 7, 7 (2019), 537–546. https://doi.org/10.1016/j.jchf.2018.12.008

[39] Andrew Garbett, David Chatting, Gerard Wilkinson, Clement Lee, and Ahmed Kharrufa. 2018. ThinkActive: designing for pseudonymous activity tracking in the classroom. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. 1–13.

[40] Radhika Garg and Subhasree Sengupta. 2019. "When You Can Do It, Why Can't I?": Racial and Socioeconomic Differences in Family Technology Use and Non-Use. *Proc. ACM Hum.-Comput. Interact.* 3, CSCW, Article 63 (nov 2019), 22 pages. https://doi.org/10.1145/3359165

[41] Garmin. 2024. Activity Profile Options on vívo and Venu Watches. Retrieved February 20, 2024 from https://support.garmin.com/en-US/?faq=srpP0JRZAj8ffbOMoTgNU7

[42] Nancy M Gell, Kristin W Grover, Morgan Humble, Michelle Sexton, and Kim Dittus. 2017. Efficacy, feasibility, and acceptability of a novel technology-based intervention to support physical activity in cancer survivors. *Supportive Care in Cancer* 25 (2017), 1291–1300.

[43] Nancy M Gell, Kristin W Grover, Liliane Savard, and Kim Dittus. 2020. Outcomes of a text message, Fitbit, and coaching intervention on physical activity maintenance among cancer survivors: a randomized control pilot trial. *Journal of Cancer Survivorship* 14 (2020), 80–88.

[44] Christopher Gidlow, Lynne Halley Johnston, Diane Crone, Naomi Ellis, and David James. 2006. A systematic review of the relationship between socio-economic position and physical activity. *Health Education Journal* 65, 4 (2006), 338–367. https://doi.org/10.1177/0017896906069378

[45] Aurelia Glass. 2022. What policymakers need to know about today's working class. https://www.americanprogress.org/article/what-policymakers-need-to-know-about-todays-working-class/

[46] Lonnie Golden. 2015. Irregular work scheduling and its consequences. https://www.epi.org/publication/irregular-work-scheduling-and-its-consequences/

[47] Nanna Gorm and Irina Shklovski. 2016. Steps, Choices and Moral Accounting: Observations from a Step-Counting Campaign in the Workplace. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing (CSCW '16)*. Association for Computing Machinery, New York, NY, USA, 148–159. https://doi.org/10.1145/2818048.2819944

[48] Nanna Gorm and Irina Shklovski. 2017. Participant driven photo elicitation for understanding activity tracking: Benefits and limitations. In *Proceedings of the 2017 ACM conference on computer supported cooperative work and social computing*. 1350–1361.

[49] Rúben Gouveia, Evangelos Karapanos, and Marc Hassenzahl. 2015. How do we engage with activity trackers? *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (2015). https://doi.org/10.1145/2750858.2804290

[50] Katherine Guyot and Richard V. Reeves. 2022. Unpredictable work hours and volatile incomes are long-term risks for American workers. https://www.brookings.edu/articles/unpredictable-work-hours-and-volatile-incomes-are-long-term-risks-for-american-workers/

[51] Scott D. Halpern, Marzana Chowdhury, Brian Bayes, Elizabeth Cooney, Brian L. Hitsman, Robert A. Schnoll, Su Fen Lubitz, Celine Reyes, Mitesh S. Patel, S. Ryan Greysen, and et al. 2021. Effectiveness and ethics of incentives for research participation. *JAMA Internal Medicine* 181, 11 (2021), 1479. https://doi.org/10.1001/jamainternmed.2021.5450

[52] Candyce Hamel, Alan Michaud, Micere Thuku, Becky Skidmore, Adrienne Stevens, Barbara Nussbaumer-Streit, and Chantelle Garritty. 2021. Defining rapid reviews: a systematic scoping review and thematic analysis of definitions and defining characteristics of rapid reviews. *Journal of Clinical Epidemiology* 129 (2021), 74–85.

[53] Sarah J Hardcastle, Ruth Jiménez-Castuera, Chloe Maxwell-Smith, Max K Bulsara, and Dana Hince. 2020. Fitbit wear-time and patterns of activity in cancer survivors throughout a physical activity intervention and follow-up: Exploratory analysis from a randomised controlled trial. *PLoS One* 15, 10 (2020), e0240967.

[54] Daniel Harrison, Paul Marshall, Nadia Bianchi-Berthouze, and Jon Bird. 2015. Activity tracking. *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (2015). https://doi.org/10.1145/2750858.2805832

[55] Eric B. Hekler, Predrag Klasnja, Jon E. Froehlich, and Matthew P. Buman. 2013. Mind the theoretical gap. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (2013). https://doi.org/10.1145/2470654.2466452

[56] Alex Helman and Kirsten Bibbins-Domingo. 2022. *Barriers to Representation of Underrepresented and Excluded Populations in Clinical Research National Academies of Sciences, Engineering, and Medicine. 2022. Improving Representation in Clinical Trials and Research: Building Research Equity for Women and Underrepresented Groups. Washington, DC: The National Academies Press. https://doi.org/10.17226/26479.* National Academies Press, 75–106.

[57] Michelle Holko, Tamara R. Litwin, Fatima Munoz, Katrina I. Theisz, Linda Salgin, Nancy Piper Jenks, Beverly W. Holmes, Pamelia Watson-McGee, Eboni Winford, and Yashoda Sharma. 2022. Wearable Fitness Tracker use in Federally Qualified Health Center Patients: Strategies to improve the health of all of US using Digital Health Devices. *npj Digital Medicine* 5, 1 (2022). https://doi.org/10.1038/s41746-022-00593-x

[58] Jina Huh, Jejo Koola, Alejandro Contreras, Alanah KP Castillo, Melissa Ruiz, Keely G Tedone, Melissa Yakuta, and Melody K Schiaffino. 2018. Consumer health informatics adoption among underserved populations: thinking beyond the digital divide. *Yearbook of medical informatics* 27, 01 (2018), 146–155.

[59] Aspen Institute. 2022. Retrieved February 20, 2024 from https://projectplay.org/youth-sports/facts/challenges

[60] National Cancer Institute. 2023. Socioeconomic Status. https://www.cancer.gov/publications/dictionaries/cancer-terms/def/socioeconomic-status

[61] Bradley E. Iott, Tiffany C. Veinot, Jimena Loveluck, Erin Kahle, Leon Golson, and Akilah Benton. 2018. Comparative analysis of recruitment strategies in a study of men who have sex with men (MSM) in Metropolitan Detroit. *AIDS and Behavior* 22, 7 (2018), 2296–2311. https://doi.org/10.1007/s10461-018-2071-z

[62] Rozmin Jiwani, Brittany Dennis, Chandler Bess, Siler Monk, Kylie Meyer, Jing Wang, and Sara Espinoza. 2021. Assessing acceptability and patient experience of a behavioral lifestyle intervention using fitbit technology in older adults to manage type 2 diabetes amid COVID-19 pandemic: A focus group study. *Geriatric Nursing* 42, 1 (2021), 57–64.

[63] Karyn O Jones, Snehal S Lopes, Claire Kelly, Ralph S Welsh, Liwei Chen, Mark Wilson, Meenu Jindal, Heidi Zinzow, Lingling Zhang, and Lu Shi. 2021. A

qualitative study on participants' experiences with a community-based mindful walking intervention and mobile device activity measurement. *Complementary Therapies in Medicine* 57 (2021), 102640.

[64] Maged N. Kamel Boulos and Stephen P. Yang. 2021. Mobile physical activity planning and tracking: A brief overview of current options and Desiderata for Future Solutions. *mHealth* 7 (Jan 2021), 13–13. https://doi.org/10.21037/mhealth.2020.01.01

[65] Os Keyes, Chandler May, and Annabelle Carrell. 2021. You keep using that word. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW1 (2021), 1–23. https://doi.org/10.1145/3449113

[66] Maria Kjærup, Mikael B. Skov, Peter Axel Nielsen, Jesper Kjeldskov, Jens Gerken, and Harald Reiterer. 2021. Longitudinal studies in HCI research: A review of Chi Publications from 1982–2019. *Human–Computer Interaction Series* (2021), 11–39. https://doi.org/10.1007/978-3-030-67322-2_2

[67] Predrag Klasnja, Sunny Consolvo, and Wanda Pratt. 2011. How to Evaluate Technologies for Health Behavior Change in HCI Research. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Vancouver, BC, Canada) *(CHI '11)*. Association for Computing Machinery, New York, NY, USA, 3063–3072. https://doi.org/10.1145/1978942.1979396

[68] Robert Klitzman, Ilene Albala, Joseph Siragusa, Kristen N. Nelson, and Paul S. Appelbaum. 2007. The reporting of monetary compensation in research articles. *Journal of Empirical Research on Human Research Ethics* 2, 4 (Dec 2007), 61–67. https://doi.org/10.1525/jer.2007.2.4.61

[69] Oscar D. Lara and Miguel A. Labrador. 2013. A Survey on Human Activity Recognition using Wearable Sensors. *IEEE Communications Surveys & Tutorials* 15, 3 (2013), 1192–1209. https://doi.org/10.1109/SURV.2012.110112.00192

[70] Federica Laricchia. 2023. Wearables shipments worldwide 2022. https://www.statista.com/statistics/437871/wearables-worldwide-shipments/

[71] Jessica Latterman and Jon F. Merz. 2001. How much are subjects paid to participate in research? *American Journal of Bioethics* 1, 2 (2001), 45–46. https://doi.org/10.1162/152651601300169040

[72] Claire A Lawson, Francesco Zaccardi, Iain Squire, Suping Ling, Melanie J Davies, Carolyn S Lam, Mamas A Mamas, Kamlesh Khunti, and Umesh T Kadam. 2019. 20-year trends in cause-specific heart failure outcomes by sex, socioeconomic status, and place of diagnosis: A population-based study. *The Lancet Public Health* 4, 8 (Aug 2019). https://doi.org/10.1016/s2468-2667(19)30108-2

[73] Amanda Lazar, Christian Koehler, Theresa Jean Tanenbaum, and David H Nguyen. 2015. Why we use and abandon smart devices. In *Proceedings of the 2015 ACM international joint conference on pervasive and ubiquitous computing*. 635–646.

[74] James A. Levine. 2011. Poverty and obesity in the U.S. *Diabetes* 60, 11 (Oct 2011), 2667–2668. https://doi.org/10.2337/db11-1118

[75] Elena Losina, Savannah R Smith, Ilana M Usiskin, Kristina M Klara, Griffin L Michl, Bhushan R Deshpande, Heidi Y Yang, Karen C Smith, Jamie E Collins, and Jeffrey N Katz. 2017. Implementation of a workplace intervention using financial rewards to promote adherence to physical activity guidelines: a feasibility study. *BMC public health* 17, 1 (2017), 1–9.

[76] Alex Jiahong Lu, Anna Gilhool, Joey Chiao-Yin Hsiao, and Tawanna R. Dillahunt. 2022. Emotional Labor in Everyday Resilience: Class-Based Experiences of Navigating Unemployment Amid the COVID-19 Pandemic in the U.S. *Proc. ACM Hum.-Comput. Interact.* 6, CSCW2, Article 388 (nov 2022), 27 pages. https://doi.org/10.1145/3555113

[77] Amy Maghera, Paul Kahlke, Amanda Lau, Yiye Zeng, Chris Hoskins, Tom Corbett, Donna Manca, Thierry Lacaze-Masmonteil, Denise Hemmings, and Piush Mandhane. 2014. You are how you recruit: A cohort and randomized controlled trial of recruitment strategies. *BMC Medical Research Methodology* 14, 1 (2014). https://doi.org/10.1186/1471-2288-14-111

[78] Antony S. Manstead. 2018. The psychology of social class: How socioeconomic status impacts thought, feelings, and behaviour. *British Journal of Social Psychology* 57, 2 (2018), 267–291. https://doi.org/10.1111/bjso.12251

[79] Helena M Mentis, Anita Komlodi, Katrina Schrader, Michael Phipps, Ann Gruber-Baldini, Karen Yarbrough, and Lisa Shulman. 2017. Crafting a view of self-tracking data in the clinical visit. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*. 5800–5812.

[80] Chulhong Min, Chungkuk Yoo, Inseok Hwang, Seungwoo Kang, Youngki Lee, Seungchul Lee, Pillsoon Park, Changhun Lee, Seungpyo Choi, and Junehwa Song. 2015. Sandra Helps You Learn. *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (2015). https://doi.org/10.1145/2750858.2807553

[81] Marta Miragall, Alejandro Domínguez-Rodríguez, Jessica Navarro, Ausiàs Cebolla, and Rosa M Baños. 2018. Increasing physical activity through an Internet-based motivational intervention supported by pedometers in a sample of sedentary students: A randomised controlled trial. *Psychology & health* 33, 4 (2018), 465–482.

[82] Kathryn Montgomery, Jeff Chester, and Katharina Kopp. 2018. Health wearables: Ensuring fairness, preventing discrimination, and promoting equity in an emerging internet-of-things environment. *Journal of Information Policy* 8 (2018), 34–77. https://doi.org/10.5325/jinfopoli.8.2018.0034

[83] Dan Morris, T Scott Saponas, Andrew Guillory, and Ilya Kelner. 2014. RecoFit: using a wearable sensor to find, recognize, and count repetitive exercises. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 3225–3234.

[84] Harvard Chan School News. 2021. Far fewer than 10,000 steps per day can boost health. Retrieved February 20, 2024 from https://www.hsph.harvard.edu/news/hsph-in-the-news/far-fewer-than-10000-steps-per-day-can-boost-health/

[85] Jasmin Niess, Paweł W. Woźniak, Yomna Abdelrahman, Passant ElAgroudy, Yasmeen Abdrabou, Caroline Eckerth, Sarah Diefenbach, and Kristina Knaving. 2021. 'I Don't Need a Goal': Attitudes and Practices in Fitness Tracking beyond WEIRD User Groups. Association for Computing Machinery. https://doi.org/10.1145/3447526.3472062

[86] KA Nyrop, AM Deal, SK Choi, CW Wagoner, JT Lee, A Wood, C Anders, LA Carey, EC Dees, TA Jolly, et al. 2018. Measuring and understanding adherence in a home-based exercise intervention during chemotherapy for early breast cancer. *Breast Cancer Research and Treatment* 168 (2018), 43–55.

[87] Maku Orleans-Pobee, Julia Browne, Kelsey Ludwig, Carrington Merritt, Claudio L Battaglini, L Fredrik Jarskog, Paschal Sheeran, and David L Penn. 2022. Physical Activity Can Enhance Life (PACE-Life): results from a 10-week walking intervention for individuals with schizophrenia spectrum disorders. *Journal of Mental Health* 31, 3 (2022), 357–365.

[88] Sherry B. Ortner. 2006. *New Jersey Dreaming Capital, culture, and the class of '58.* Duke Univ. Press.

[89] Oura. 2024. Oura Ring. Retrieved February 20, 2024 from https://ouraring.com/

[90] Mansi Pandya and Chetna Desai. 2013. Compensation in clinical research: The debate continues. *Perspectives in Clinical Research* 4, 1 (2013), 70. https://doi.org/10.4103/2229-3485.106394

[91] Nirav P Patel, Michael A Grandner, Dawei Xie, Charles C Branas, and Nalaka Gooneratne. 2010. "sleep disparity" in the population: Poor sleep quality is strongly associated with poverty and ethnicity. *BMC Public Health* 10, 1 (2010). https://doi.org/10.1186/1471-2458-10-475

[92] Jessica Pater, Amanda Coupe, Rachel Pfafman, Chanda Phelan, Tammy Toscos, and Maia Jacobs. 2021. Standardizing reporting of participant compensation in HCI: A systematic literature review and recommendations for the Field. *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (2021). https://doi.org/10.1145/3411764.3445734

[93] Stephen Purpura, Victoria Schwanda, Kaiton Williams, William Stubler, and Phoebe Sengers. 2011. Fit4life. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (2011). https://doi.org/10.1145/1978942.1979003

[94] Charlotte Lund Rasmussen, Dorothea Dumuid, Karel Hron, Nidhi Gupta, Marie Birk Jørgensen, Kirsten Nabe-Nielsen, and Andreas Holtermann. 2021. Day-to-day pattern of work and leisure time physical behaviours: Are low socioeconomic status adults couch potatoes or work warriors? *BMC Public Health* 21, 1 (2021). https://doi.org/10.1186/s12889-021-11409-0

[95] Viviane Richard, Giovanni Piumatti, Nick Pullen, Elsa Lorthe, Idris Guessous, Nicola Cantoreggi, and Silvia Stringhini. 2023. Socioeconomic inequalities in sport participation: Pattern per sport and time trends – a repeated cross-sectional study. *BMC Public Health* 23, 1 (2023). https://doi.org/10.1186/s12889-023-15650-7

[96] Michelle Rogers. 2023. Do you have to walk 10,000 steps a day? https://www.bluecrossnc.com/blog/healthy-living/fitness/walk-10000-steps-a-day

[97] Kathryn M Ross and Rena R Wing. 2016. Impact of newer self-monitoring technology and brief phone-based intervention on weight loss: a randomized pilot study. *Obesity* 24, 8 (2016), 1653–1659.

[98] Aubrianne E Rote. 2017. Physical activity intervention using Fitbits in an introductory college health course. *Health Education Journal* 76, 3 (2017), 337–348.

[99] Herman Saksono, Carmen Castaneda-Sceppa, Jessica Hoffman, Magy Seif El-Nasr, Vivien Morris, and Andrea G Parker. 2018. Family health promotion in low-SES neighborhoods: A two-month study of wearable activity tracking. In *Proceedings of the 2018 chi conference on human factors in computing systems*. 1–13.

[100] Herman Saksono, Carmen Castaneda-Sceppa, Jessica Hoffman, Magy Seif El-Nasr, Vivien Morris, and Andrea G Parker. 2019. Social reflections on fitness tracking data: A study with families in low-SES neighborhoods. In *Proceedings of the 2019 chi conference on human factors in computing systems*. 1–14.

[101] Darcell P. Scharff, Katherine J. Mathews, Pamela Jackson, Jonathan Hoffsuemmer, Emeobong Martin, and Dorothy Edwards. 2010. More than Tuskegee: Understanding mistrust about research participation. *Journal of Health Care for the Poor and Underserved* 21, 3 (Aug 2010), 879–897. https://doi.org/10.1353/hpu.0.0323

[102] Inge Schjødt, Søren P. Johnsen, Anna Strömberg, Nickolaj R. Kristensen, and Brian B. Løgstrup. 2019. Socioeconomic factors and clinical outcomes among patients with heartfailure in a universal health care system. *JACC: Heart Failure* 7, 9 (Sep 2019), 746–755. https://doi.org/10.1016/j.jchf.2019.06.003

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

[104] National Health Service. 2022. Walking for health. Retrieved February 20, 2024 from https://www.nhs.uk/live-well/exercise/running-and-aerobic-exercises/walking-for-health/

[105] Sarah Sharma. 2014. *In the meantime: Temporality and cultural politics*. Duke University Press.

[106] Anna Shcherbina, C. Mattsson, Daryl Waggott, Heidi Salisbury, Jeffrey Christle, Trevor Hastie, Matthew Wheeler, and Euan Ashley. 2017. Accuracy in wrist-worn, sensor-based measurements of heart rate and energy expenditure in a diverse cohort. *Journal of Personalized Medicine* 7, 2 (2017), 3. https://doi.org/10.3390/jpm7020003

[107] Patrick C Shih, Kyungsik Han, Erika Shehan Poole, Mary Beth Rosson, and John M Carroll. 2015. Use and adoption challenges of wearable activity trackers. *IConference 2015 proceedings* (2015).

[108] Beverley Skeggs. 2011. Imagining personhood differently: Person value and autonomist working-class value practices. *The Sociological Review* 59, 3 (Sep 2011), 496–513. https://doi.org/10.1111/j.1467-954x.2011.02018.x

[109] Katta Spiel, Fares Kayali, Louise Horvath, Michael Penkler, Sabine Harrer, Miguel Sicart, and Jessica Hammer. 2018. Fitter, happier, more productive? The normative ontology of fitness trackers. In *Extended abstracts of the 2018 CHI conference on human factors in computing systems*. 1–10.

[110] Jamie Spinney and Hugh Millward. 2010. Time and money: A new look at poverty and the barriers to physical activity in Canada. *Social Indicators Research* 99, 2 (2010), 341–356. https://doi.org/10.1007/s11205-010-9585-8

[111] Ragna Stalsberg and Arve Pedersen. 2018. Are differences in physical activity across socioeconomic groups associated with choice of physical activity variables to report? *International Journal of Environmental Research and Public Health* 15, 5 (2018), 922. https://doi.org/10.3390/ijerph15050922

[112] Susan Leigh Star and Anselm Strauss. 1999. Layers of silence, Arenas of Voice: The ecology of visible and invisible work. *Computer Supported Cooperative Work (CSCW)* 8, 1–2 (1999), 9–30. https://doi.org/10.1023/a:1008651105359

[113] Dirk Steinbach and Christine Graf. 2008. Leisure time physical activity and sedentariness. *Encyclopedia of Public Health* (2008), 849–851. https://doi.org/10.1007/978-1-4020-5614-7_1968

[114] Nicole M Stephens, Stephanie A Fryberg, and Hazel Rose Markus. 2012. *It's your choice: How the middle class model of independence disadvantages working class Americans*. Russell Sage Foundation, 87–88.

[115] Coraline Stormacq, Stephan Van den Broucke, and Jacqueline Wosinski. 2018. Does health literacy mediate the relationship between socioeconomic status and health disparities? Integrative Review. *Health Promotion International* 34, 5 (2018). https://doi.org/10.1093/heapro/day062

[116] Elizabeth Stowell, Mercedes C Lyson, Herman Saksono, Reneé C Wurth, Holly Jimison, Misha Pavel, and Andrea G Parker. 2018. Designing and evaluating mHealth interventions for vulnerable populations: A systematic review. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. 1–17.

[117] Rebecca L. Sudore, Kristine Yaffe, Suzanne Satterfield, Tamara B. Harris, Kala M. Mehta, Eleanor M. Simonsick, Anne B. Newman, Caterina Rosano, Ronica Rooks, Susan M. Rubin, and et al. 2006. Limited literacy and mortality in the elderly. *Journal of General Internal Medicine* 21, 8 (2006), 806–812. https://doi.org/10.1111/j.1525-1497.2006.00539.x

[118] Murad H. Taani, Bev Zabler, Michael Fendrich, and Rachel Schiffman. 2020. Lessons learned for recruitment and retention of low-income African Americans. *Contemporary Clinical Trials Communications* 17 (2020), 100533. https://doi.org/10.1016/j.conctc.2020.100533

[119] Lie Ming Tang, Jochen Meyer, Daniel A. Epstein, Kevin Bragg, Lina Engelen, Adrian Bauman, and Judy Kay. 2018. Defining adherence. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 1 (2018), 1–22. https://doi.org/10.1145/3191769

[120] Emmanuel Munguia Tapia, Stephen S. Intille, William Haskell, Kent Larson, Julie Wright, Abby King, and Robert Friedman. 2007. Real-Time Recognition of Physical Activities and Their Intensities Using Wireless Accelerometers and a Heart Rate Monitor. In *2007 11th IEEE International Symposium on Wearable Computers*. 37–40. https://doi.org/10.1109/ISWC.2007.4373774

[121] Anne N Thorndike, Sarah Mills, Lillian Sonnenberg, Deepak Palakshappa, Tian Gao, Cindy T Pau, and Susan Regan. 2014. Activity monitor intervention to promote physical activity of physicians-in-training: randomized controlled trial. *PloS one* 9, 6 (2014), e100251.

[122] Lianne M. Tomfohr, Sonia Ancoli-Israel, and Joel E. Dimsdale. 2010. Childhood socioeconomic status and race are associated with adult sleep. *Behavioral Sleep Medicine* 8, 4 (2010), 219–230. https://doi.org/10.1080/15402002.2010.509236

[123] Tammy Toscos, Michelle Drouin, Jessica Pater, Mindy Flanagan, Rachel Pfafman, and Michael J Mirro. 2019. Selection biases in technology-based intervention research: Patients' technology use relates to both demographic and health-related inequities. *Journal of the American Medical Informatics Association* 26, 8–9 (2019), 835–839. https://doi.org/10.1093/jamia/ocz058

[124] Catrine Tudor-Locke, Cora L Craig, Wendy J Brown, Stacy A Clemes, Katrien De Cocker, Billie Giles-Corti, Yoshiro Hatano, Shigeru Inoue, Sandra M Matsudo, Nanette Mutrie, et al. 2011. How many steps/day are enough? For adults. *International Journal of Behavioral Nutrition and Physical Activity* 8, 1 (2011), 1–17.

[125] Gerry Veenstra. 2015. Class position and musical tastes: A sing-off between the cultural omnivorism and Bourdieusian homology frameworks. *Canadian Review of Sociology/Revue canadienne de sociologie* 52, 2 (2015), 134–159. https://doi.org/10.1111/cars.12068

[126] Tiffany C. Veinot, Phillipa J. Clarke, Daniel M. Romero, Lorraine R. Buis, Tawanna R. Dillahunt, Vinod V.G. Vydiswaran, Ashley Beals, Lindsay Brown, Olivia Richards, Alicia Williamson, and et al. 2022. Equitable research praxis: A framework for health informatics methods. *Yearbook of Medical Informatics* 31, 01 (Aug 2022), 307–316. https://doi.org/10.1055/s-0042-1742542

[127] Tiffany C Veinot, Hannah Mitchell, and Jessica S Ancker. 2018. Good intentions are not enough: How informatics interventions can worsen inequality. *Journal of the American Medical Informatics Association* 25, 8 (2018), 1080–1088. https://doi.org/10.1093/jamia/ocy052

[128] Adam Wagstaff. 2002. Poverty and health sector inequalities. *Bulletin of the world health organization* 80 (2002), 97–105.

[129] Renee E. Walker, Christopher R. Keane, and Jessica G. Burke. 2010. Disparities and access to healthy food in the United States: A review of food deserts literature. *Health and Place* 16, 5 (2010), 876–884. https://doi.org/10.1016/j.healthplace.2010.04.013

[130] J Wardle. 2003. Socioeconomic differences in attitudes and beliefs about healthy lifestyles. *Journal of Epidemiology & Community Health* 57, 6 (2003), 440–443. https://doi.org/10.1136/jech.57.6.440

[131] Jennifer R. Wentz and Sonja Wilhelm Stanis. 2023. Physical activity and social comparison: The importance of group composition in an employee Fitbit Intervention. *Health Promotion Practice* (2023), 152483992311601. https://doi.org/10.1177/15248399231160152

[132] Maxine E Whelan, Francesca Denton, Claire LA Bourne, Andrew P Kingsnorth, Lauren B Sherar, Mark W Orme, and Dale W Esliger. 2021. A digital lifestyle behaviour change intervention for the prevention of type 2 diabetes: a qualitative study exploring intuitive engagement with real-time glucose and physical activity feedback. *BMC Public Health* 21 (2021), 1–11.

[133] Wikipedia. 2023. Nike+ Fuel Band. https://en.wikipedia.org/wiki/Nike%2B_FuelBand

[134] Kade Wilson. 2021. The science behind Fitbit: Do fitness trackers really work? https://badgerherald.com/news/2021/12/20/the-science-behind-fitbit-do-fitness-trackers-really-work/

[135] Jacob O Wobbrock and Julie A Kientz. 2016. Research contributions in human-computer interaction. *interactions* 23, 3 (2016), 38–44.

[136] Jill Palzkill Woelfer and David G. Hendry. 2010. Homeless young people's experiences with information systems. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (2010). https://doi.org/10.1145/1753326.1753520

[137] Sarita Yardi and Amy Bruckman. 2012. Income, race, and class. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (2012). https://doi.org/10.1145/2207676.2208716

[138] Ali K Yetisen, Juan Leonardo Martinez-Hurtado, Barış Ünal, Ali Khademhosseini, and Haider Butt. 2018. Wearables in medicine. *Advanced Materials* 30, 33 (2018), 1706910.