Class in the Health and Personal Informatics Research and Design Space

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In this literature review in progress, we investigate how socioeconomic class shows up in wearables deployment studies. We identify how class cultures are embedded in the design of wearable studies and technology, and reflect on the nuances of class embeddedness by investigating how time, activity type, compensation, and other study requirements characterize the wearables study populations, and the activity affordances of the wearable devices themselves. Within the larger literature review, we will entangle with these nuances as they apply to larger class dimensions and provide points of reflection from a class conscious perspective.

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

Additional Key Words and Phrases: personal informatics, physical activity, wearables, socioeconomic class

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1 INTRODUCTION

In the last decade and a half, personal informatics as both a discipline and design tool(s) has seen steady growth in interest [5]. In both commercial, computing, and medical spaces alike, there has been a development of tools which can be used to help people understand some area of individual personal information. And although 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) and general health data, and the "wearables" which directly track this data via automated sensors. In this work in progress, we present a literature review of HCI and Medical wearables research and its relationship to the "class" dimension (as it relates to the systemic and cultural phenomenon). When describing class as the underlying motivator for this study, class is not only used in the literal sense, as in the capital that an individual holds as both an independent person and as part of a group of people with similar monetary 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. Class is an especially important distinction as it has intersectional and non-linear relationships with other important social considerations such as race,gender, and education, and largely rendered "invisible" in the context of societal cultural measurements [22].

As wearables have started to gain more traction as potentially crucial technologies for at-home non-clinical care (in the medical context), and as supplements for personal fitness and wellness tracking, there are tangible health (and design) implications at stake [29]. All of the papers reviewed came from two existing corpus' of HCI and Medical venue studies [4, 6]. Studies met the inclusion criteria if they focused on the deployment of tracking devices (mobile and desktop based applications were excluded), were conducted no earlier than 2005, and aimed to provide novel design improvements or modifications of PA wearable devices. The intent of the completed review, is to contribute an understanding of how the health and HCI research literature considers dimensions of class. Ultimately, we aim to

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Table 1. Study Length

Length of Study	**Medical**	**HCI**
<=5 weeks	1	2
6-10 weeks	5	7
>=11 weeks	4	3
>=24 weeks	4	1

Table 2. Activity Type Figures

Activity Metric	**Number of Studies**
Step count / walking	21
Flexible Tracking Evaluation Metric(s)	6

Table 3. Compensation Figures

Compensation Type	**Number of Papers**			
Cash	5*	$100	3	$10-25
Gifting Wearables	2			
Payment Not Acknowledged	15			
Gift Cards	1	$100	2	$10-15

expand on works which examine the experiences of low-SES persons in tracking their personal fitness, as investigated in studies such as [24].

2 METHODS AND FINDINGS

From an investigation of the literature, we developed a few class centered dimensions, two of which will be discussed in the next section. Below are findings which encompass a variety of smaller class adjacent themes which will be evaluated within those larger dimensions.

The first theme surrounds the average study length by discipline. These figures can be found in Table 1. There were also varying PA time requirements (list not exhaustive) where participants were to: participate in PA less than or equal to an hour a week [1, 13], more than two hours a week [11, 19, 23], or wear devices at least 10 hrs a day or during all waking hours [8, 9, 12, 16, 21, 27].

The second, surrounds the primary activity type participants were both required to participate in, and the data that researchers analyzed. We considered all papers which evaluated movements related to walking as step count activity. These figures are represented in Table 2. One study [17] which provided wearables to participants, did not have any predetermined activity requirements. In addition, there were other general study participation requirements which included (list not exhaustive), interviews [3, 7, 10, 14, 15, 21, 24, 25], group PA sessions [1, 13], educational sessions [2], existing patterns [18, 20, 23, 25], reflective activities [1, 10, 15], and personal training sessions [27].

The third class implication is compensation. When cash payments were reported, payment ranged from 10 euros at the lowest, to twenty to twenty five dollars, at the most consistent rate. More consistently, participant compensation was not acknowledged. It is also important to note that the outlier one hundred dollar payments were provided by the same set of researchers. These figures are represented in Table 3.

3 DISCUSSION AND CONCLUSION

The figures highlighted above are directly tied to mechanisms of socioeconomic class, but they are not explicitly regarded as aligning as such in the development of wearables studies and the design of those technologies. We highlight two bucketed dimensions from which to evaluate them: time and activity type.

The time dimension engages the findings on time related entities such as length of study, physical activity time, travel time, and other calculable time data such, labor and compensation. Time shows up in all facets of human civility and is inherent to the ideals of the late capitalism of the last few decades [26] and also to the capacity for one to both participate in a wearables study (the actions aligned to create data descriptions), and the systemic circumstances of time within which these studies exist. In evaluating the papers, time is often represented as a calculation useful solely for understanding the most optimal "way" to collect data for the research study. Time then appears to be seen as an entity manipulable by the research team, a calculation for the potential for data, and not necessarily as an experience which is largely predicated on both systemic and social realities. These choices are troublesome because they do not interrogate the myriad ways that time and its sub-dimensions limit (or expand) ones experiences, depending on socio-economic class positioning [26]. Therefore, due to the "necessities" of time locked data unique to wearables research, this poses several conflicts in the inclusion of lower-socioeconomic persons.

The activity type dimension surrounds the type of activities that are heralded as useful for tracking.From our evaluation, we have found that the most common activity centered in wearables studies, is by and large step count and other leisure related activities. This focus on step counting is also heavily reflected in wearable tracking capabilities, as there are difficulties in tracking exercises which don't necessarily increase heart rate (e.g. yoga, strength training) or have "easily tracked movement" [28]. With the focus on step count as the centralized activity for which the other physical activity frameworks are founded, there is a continued narrowing of physical activity as existing in a single context. We emphasize that there is a need to diversify the thought processes behind what (activities), where (spatial and occupational), and subsequently how, physical activity can be tracked.

All in all, there are cultural assumptions which limit the complexities of physical health data tracking and potentially aid in the reinforcement of who has access to actively participate in personal physical health knowledge. In the completed review we will inquire more deeply, from the lens' outlined in the earlier sections, how these assumptions occur, and introduce more critical analytic dimensions and their implications.

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