Activity Tracking *in vivo*

Rúben Gouveia
Madeira-ITI
Funchal, Portugal
rubahfgouveia@gmail.com

Evangelos Karapanos
Cyprus University of Technology
Limassol, Cyprus
e.karapanos@gmail.com

Marc Hassenzahl
University of Siegen
Siegen, Germany
marc.hassenzahl@uni-siegen.de

ABSTRACT
While recent research has emphasized the importance of understanding the lived experience of personal tracking, very little is known about the everyday coordination between tracker use and the surrounding environment. We combine behavioral data from trackers with video recordings from wearable cameras, in an attempt to understand how usage unfolds in daily life and how it is shaped by the context of use. We recorded twelve participants' daily use of activity trackers, collecting and analyzing 244 incidents where activity trackers were used. Among our findings, tracker use was strongly driven by reflection and learning-in action, contrasting the traditional view that learning is one of deep exploration, following the collection of data on behaviors. We leverage on these insights and propose three directions for the design of activity trackers: *facilitating learning through glances*, *providing normative feedback* and *facilitating micro-plans*.

Author Keywords
Physical Activity Tracking; Personal Informatics;

ACM Classification Keywords
H.5.2. User Interfaces: Evaluation/Methodology.

INTRODUCTION
Over recent years, physical activity trackers have received an upsurge of interest both in research and practice. Consumer interest in commercially available devices has tripled over the last couple of years [45]. Ownership rates followed similar trends, with one in every two U.S adults claiming to own, or have owned, an activity tracker [44]. This trend is accompanied by a rhetoric about the potential health benefits gained from the use of these devices. Individuals have been found to walk more [9], lose weight [2] and feel more in control of their behaviors [8] when consistently monitoring their step count. These benefits seem to prevail over months or years of continued monitoring [2,50].

CHI 2018, April 21–26, 2018, Montreal, QC, Canada

ACM ISBN 978-1-4503-5620-6/18/04...$15.00
https://doi.org/10.1145/3173574.3173936

However, more critical research repeatedly pointed out the complexity of tracking as a social practice and called for a deeper understanding of how trackers become a part of people's everyday life [see 16,18,47]. For instance, our understanding of self-tracking practices has moved beyond the conventional vision of trackers as mediators of change [10,47]. Trackers are used to understand routines, learn something out of interest or simply have fun and satisfy curiosity, as opposed to a stricter regulation of behaviors. Activity tracking happens alongside other daily activities. Users consult their trackers to gain momentary insights in-situ, when involved in an activity, as opposed to the conventional idea of deep, retrospective explorations of own data [23,47].

Unfortunately, most of the research highlighting the complexity of activity tracking as social practice relied on self-report data, gathered either through interviews or online surveys. Typically, participants are asked to recount typical use patterns and resulting experiences. These reports, of course, suffer from potential recall and social biases. For example, the interplay between technology and the particular context of use may be lost when studies solely focus on self-report [35].

In this paper, we report on an *in vivo* study of activity tracking. We provided 12 individuals with wearable cameras and monitored two days in their lives with tracking. We combined these recordings with behavioral data from trackers as well as interviews, providing us with a detailed view on how trackers are used in everyday life.

In the remainder of the paper, we will first provide an overview of empirical studies of activity tracking. We identified three methodological paradigms: the study of activity tracking *in the wild*, *in everyday life* and *in vivo*. Second, we describe a number of practices that surround the use of activity trackers. Most notably, we find tracking to be driven by reflection and *learning-in-action* rather than by learning through retrospective, deep exploration. Third, we leverage these findings and propose three directions for the future design of activity trackers: *facilitating learning through glances*, *providing normative feedback on goal accomplishment*, and *facilitating micro-plans*.

BACKGROUND
In this section, we discuss three paradigms for the inquiry of activity tracking: in the wild, in everyday life, and in vivo.

Activity tracking in the wild

Early studies of activity tracking often entailed the design, development and field trial of a novel research prototype. Driven by a theoretical concern, their goal was to assess the efficacy and user acceptance of the prototypes and their underlying design strategies. For instance, Consolvo and colleagues explored how mobile technology can motivate physical activity through social influence [13], goal-setting [38] and glanceable displays [14]. In [14], for instance, they designed *UbiFit*, a mobile application to provide feedback on one's physical activity through a glanceable, stylized representation on the background of a mobile phone, and employed it in a study with three experimental conditions to assess its impact on activity. More recent work has helped to untangle the design space of glanceable displays through the iterative design and analysis of twenty-one concepts of glanceable physical activity feedback [22]. Four of those concepts had been further prototyped and deployed in a comparative month-long study, inquiring into how users engaged with each prototype, the immediate impact on physical activity, and users' perceptions.

In the wild studies have been, and still are, instrumental to the development of the field. They move evaluation out of the lab, enabling the evaluation of novel technological systems in natural settings. Through quasi-experimental setups, and mixed-method approaches, they provide early insights both on which strategies work best, as well as why they work. However, these studies are limited in a number of ways. First, due to the complexity of the trial, and the technological limitations imposed by the maturity of the prototype, these studies are small in sample size and duration, typically involving 5 to 30 participants over a duration of 3 weeks to 3 months [51]. Second, participants are typically given a prototype, rather than purchasing a product on their own, and are incentivized to use the prototype for the duration of the study, which reduces the ecological validity of the study. Third, studies often featured a specific set of users with an already appropriate level of 'readiness' for change [33]. As a result, while these studies are extremely useful as efficacy evaluation of different design strategies [29], they have limited predictive power over the adoption and use of a tracker in 'real-life'.

The study of activity tracking in everyday life

With the widespread adoption of commercial activity trackers, researchers have increasingly shifted attention to the study of peoples' real-life practices emerging from owning and using a tracker. The focus of respective studies is not on the effectiveness and the efficiency of the technologies, but on how users appropriate those technologies, and how adoption, or non-adoption, is shaped by the context of use. Researchers produced models of how people use self-tracking tools informed by qualitative inquiry [16, 32]; investigated how people lapse and abandon these devices [29]; explored the ability of trackers to align with users' motivations and desires [25, 28]; and investigated tracking practices in everyday life [10,18,47] and in specific contexts, such as the workplace [11].

Most of the studies have been qualitative in nature, relying on users' self-reports, either through interviews or online surveys. For instance, Fritz et al. [18] interviewed 30 participants who purchased a tracker of their own volition and used it from 3 to 54 months. Their study revealed how the practices that surround long-term tracking were different from those of early adoption, and how non-beneficial practices were afforded by the design of the technology, such as "number fishing" which turned exercise from a meaningful intrinsic endeavor into an extrinsically-rewarded activity. Rooksby et al. [47] interviewed 22 people two times, separated by a month, and found five different motives for tracker use, from directive, to documentary and diagnostic tracking. Karapanos et al. [28] used a psychological needs framework to inquire into memorable experiences of 133 users through an online survey. Their study highlighted that tracking has a nuanced social component, from the sense belonging and social support provided through the online communities, to the stronger more direct social exchange among family members, when they purchased a tracker for a relative and joined in their efforts towards a better, healthier self.

Some studies leveraged the value of *secondary data*. For instance, Clawson et al. [12] analyzed 1600 advertisements of personal health tracking technologies on craigslist and found that individuals often abandon these, not due to technologies' failure, but often because they achieved their goal (e.g., lost weight), they desired an upgrade to a newer model, or because of unanticipated changes in their life (e.g. surgery). Choe et al. [10] analyzed video-recordings of Quantified Self talks and found that individuals often had a specific, personal, health-related goal, such as finding triggers for an allergy or the right drug dosage.

Other quantitative studies logged users' activities and interactions with the tracker in everyday life. For instance, Gouveia et al. [21] monitored the engagement of 256 users with an activity tracker called *Habito,* and its impact on users' physical activity over a period of ten months. They found that users rarely look back at their performance data. Over 70% of the interaction had been *glances*: brief, 5-sec sessions where users called the app to check how much they had walked so far without any further interaction. In addition, they found that current physical activity trackers work only for people in intermediary stages of behavior change (i.e., contemplation, preparation). Those displayed an adoption rate of 56%, contrary to that of 20% for people being in the remaining stages (i.e., precontemplation, action or maintenance). Moreover, contrary to a common assumption in personal informatics literature and Goal-Setting Theory [34], only 30% of users set their own daily step goal, while 80% of users who did so, never updated the goal again. Similarly, Meyer et al. [36] analyzed the behavioral data of 104 activity tracker users, over 14,413 days of use and found periodic breaks, lasting from a couple of hours to a couple of days, to be the norm in the use of activity trackers. They identified different patterns for activity tracker use such as try-and-drop, slow-starter, experimenter, hop-on hop-off, intermittent and power user.

Studies of activity tracking in everyday life advanced our understanding of how trackers are embedded and appropriated in users' routines. Due to their inexpensive format, qualitative studies based on interviews, surveys and secondary data, have inquired into the long-term adoption of and experiences with activity trackers, while quantitative, interaction logging studies provided a more realistic picture of how people actually engage with trackers, through the behavioral observation of many users, who acquired the trackers of their own volition, and used them over prolonged periods of time.

However, these studies are limited as well. As most of the studies rely on self-reports, asking people to retrospect on typical use patterns may suffer from recall bias [24]. Insights on actual behaviors and experiences are likely to be forgotten, overlooked, or avoided. While quantitative behavioral studies provide a more accurate picture of users' interactions, they provide an only limited understanding of the context that surround its use and the motives that drive it. For instance, while Gouveia's et al. [21] study classified users' engagements with trackers into *glance*, *review* and *engage* sessions, based on the duration of the usage session and the actions taken (e.g., whether users checked historical data), it provided limited understanding of users' goals within each usage session and the reasons that led them to check the tracker. As argued by McMillan et al. [35], "the coordination between technology and the surrounding environment of use may be lost when studies as solely focused on self-reported [and remote observation] methods."

The study of activity tracking in vivo

Motivated by the limitation of self-reports and remote observational studies of activity tracking, researchers turned to the use of video methods and direct, in-situ observation of users' interactions with activity trackers.

Patel and O'Kane [40], for instance, combined participant observation with interviews, to better understand how individuals use technology while exercising at the gym. Participants were asked to verbalize their thoughts and feelings while engaging with technology during a workout regime (e.g. engaging with the display of a treadmill or an activity tracker), while observed by a researcher. Similarly, Gorm and Shklovski combined participant observation with semi-structured interviews to better understand how trackers were used within a step-count campaign in the workplace. The first author participated in participants' "*work meetings, sat at a desk allocated to her in the open office space alongside the employees, joined in the lunch breaks, department meetings and Friday breakfasts, and generally partook in the daily life of the office during 12 workdays*" [23, p.151]. By using an in-situ approach, both studies provided insights into how trackers were used in these specific contexts.

While these studies are prime examples of in-situ inquiry, shadowing an individual over the course of a full day seems infeasible and may constrain how interactions with technology naturally occur [40]. One solution is the approach taken by Gorm et al [24]. They used a participant-driven photo elicitation method. Twenty-five novice users of trackers took photos of their "private" self-tracking experiences over the course of five months. Participants were instructed to take photos of events or experiences they felt were related to their activity tracking and send them via e-mail to the first author once a week and to include one or two sentences describing the photo or any thoughts they might like to share. Participants further reflected on their pictures in a follow-up interview, explaining why they took a certain photo. One of the identified limitations was the long follow-up time of interviews (in some cases, pictures were analyzed nearly 5 months after having been taken), as some participants had difficulties to recall the reasons that led them to capture a certain picture. Moreover, this method is limited in the sense it only highlights practices that are chosen to be shared by users, and in that they provide only a limited snapshot.

To counter for those limitations, Brown et al. [7] proposed the use of video methods in the study of mobile technology in everyday life. Mondada [37], for instance, used video-recordings to understand how phone calls unroll in work settings. Individuals were found to engage in *multi-activities* during calls, which could be interrupted, suspended, accelerated or perturbed by incoming calls. McMillan et al. [35] used video recording to understand how the use of the mobile phone becomes integrated into ongoing activities (e.g. how maps are used for route-finding), while Pizza et al. [42] examined how different features offered by smartwatches (e.g. time, notifications, activity tracking) were used in users' daily lives. Video methods offer naturalistic, visual perspectives on the use of technology as data are collected in-situ [37]. Moreover, these video logs may be revisited [26], thus creating the conditions for more precise recall of activities of interest, and allowing researchers and participants to become aware of aspects that might have been overlooked.

Despite the premise of video methods, according to the authors' knowledge, such methods have not been employed in the study of activity tracking yet.

AN IN VIVO STUDY OF ACTIVITY TRACKING

Participants

Twelve individuals were recruited in the study (5 female, 7 male, median age=28, min=21, max=41). They had all been using an activity tracker already for a minimum of 4 months (max=14, median=7 months). Our goal was to understand the practices surrounding these devices even after months of use. All participants were Portuguese. Nine had a full-time job, three were students.

Table 1. Summary of participant information

	Device	Months of use	Age	Gender	Occupation	Stage of behavior change	Daily step goal
P1	HR	9	33	M	Professor	Action	12,500
P2	HR	6	30	F	Teacher	Main.	18,000
P3	HR	4	23	F	Usability	Prep.	9,000
P4	HR	5	26	M	Research	Cont.	8,800
P5	HR	7	31	M	Security	Main.	15.000
P6	HR	5	22	M	Student	Cont.	12,000
P7	HR	8	29	F	Retail	Main.	13,000
P8	Flex	14	41	M	Lawyer	Main.	11,500
P9	Flex	7	25	M	Student	Prep.	15,000
P10	Flex	10	38	M	Designer	Prep.	8,500
P11	Flex	4	24	F	Student	Prep.	11,000
P12	Flex	6	21	F	Designer	Main.	12,000

The recruitment took place through local mailing lists and social media. We limited our search to *Fitbit* users to facilitate the comparison among participants' practices. However, we included two different versions from the same brand, varying considerably in features. Seven participants owned a *Fitbi*t *Charge HR* and five a *Fitbit Flex*. *Fitbit Flex* displays users' step count through five LEDs, each lighting up for achieving 20% of a daily walking goal. *Fitbit Charge HR* displays a wider range of metrics on users' physical activity – i.e. numerical step count, heart rate, caloric count, distance and floors, as well as the time and notifications on incoming calls. Users navigate through these metrics by tapping the *Charge HR*, or clicking on a side button (as seen in Figure 1). All *HR* users had the time as their primary watch face – having to click, or tap on their device to see physical activity feedback. These distinctions are taken into account when interpreting the results of our study. Both devices offer more elaborate feedback on physical activity, such as visualizations of one's step and sleep data over time, through a mobile and web application. Our analysis is constrained to the use of the wristband. We focused on the wristband, as prior work has shown that tracker usage is confined to short interactions [21], where users check their current activity levels with no further exploration of data.

We did not sample for participants with specific levels of physical activity or fitness and health goals. However, in line with previous research [21], we measured participants' stage of behavior change towards physical activity [43] in an attempt to understand how individuals' commitment to exercise influenced their use practices. As expected, our recruitment was biased towards physically active people: six out of twelve were in advanced stages of behavior change (i.e. action and maintenance), with the remaining in the intermediate stages (i.e. contemplation and preparation). Most set a higher daily walking goal than the 10K steps that are typically suggested by medical practitioners [49] (median = 12,000). All participants were rewarded with a 40€ voucher for taking part in the study.

Figure 1. Fitbit Flex (left), Fitbit Charge HR (right)

Method

Our study consisted of two phases: *a recording* and a *reconstruction* phase.

Recording phase

Throughout the recording phase, participants carried a *Xiaomi Yi* wearable camera and a bag, containing an external battery bank, allowing for up to 8 hours of video recording. The camera was mounted vertically, slightly above the chest of the participant. This setting allowed us to capture participants' interactions with their tracker, as well as the environment (see Figure 2).

Figure 2. Participants wore a camera during two days, providing insights into how tracker use unfolds in daily life

The first author conducted a meeting with all participants, in which he introduced them to the study apparatus. Participants were given a camera and asked to record on two days for eight hours, between 9am and 5pm. Participants were told to turn the camera off when they felt they needed privacy. They were free to choose the day in which they wanted to start recording. At the end of each day, the researcher met them to collect the recordings and to discuss any technical problems. Due to technical issues, two participants were only able to record approximately six hours of footage on their second day of recording.

We edited the video footage and extracted incidents in which participants interacted with their activity trackers. We refer to those as *usage sessions*. A usage session was defined by the moment in which the user brought the tracker at eyesight, to the moment the participant lowered his arm to its original position (similarly to [42] and [22]). We also extracted the fifteen seconds preceding, and following a usage session, in an attempt to gain insights on the aspects that lead up to and followed each usage session. We logged the duration, time of occurrence and nature of use of the session – i.e. *where* a session took place, *who* was present and *what* feedback was checked during a session (as in [31]). Each daily footage was edited by at least two individuals, immediately after being collected. We found no incidents of participants removing their tracker, either temporarily or permanently, during the recording.

Finally, we collected, and analyzed participants' physical activity data during recording. Participants were asked to log into the *Fitbit API* and grant access to their step count data. We used the Fitbit Intraday API to collect minute-by-minute data of participants' step count, as well as the corresponding levels of intensity for each minute – sedentary, lightly active, moderately active and vigorously active (as described in [19]).

Reconstruction phase

On the third day, participants took part in an interview. Participants were presented with their usage sessions and asked to recall these moments, focusing on the reasons that led them to interact with their tracker and how they thought the surrounding environment (e.g. location, ongoing activity and people) shaped their action. Participants were also asked to describe what they were doing prior to interaction. Insights were attached to the corresponding usage session.

Inspired by the Day Reconstruction Method [27], we displayed usage sessions chronologically, featuring the time in which they unfolded. Prior work has found temporal cues, such as timestamps in pictures or videos, to assist in the recollection of events and prevent misjudgments, such as the temporal misplacement of such events [20]. Video footage supported a more specific recall of the moments in which participants engaged with their trackers [20] and allowed them to take the leading role in the interview and provide their own insights into how usage unfolded. Each interview lasted about of 40 minutes.

The analysis of interviews grows out of thematic analysis. Interviews were transcribed, coded and organized into emerging themes (closely following the phases of thematic analysis suggested in [6]). Iterative rounds of discussion and refinement were performed between authors, looking for salient themes from interviews and observations of usage sessions. The prevalence of each theme was measured by counting the number of occurrences in which a theme appeared in the reflections of a usage session.

FINDINGS AND DISCUSSION

Tracker use

We collected 184 hours and 15 minutes of footage from all participants. Each participant recorded about 15 hours of footage. Participants were found to interrupt recording during situations considered inappropriate and in which they did not feel comfortable in wearing the apparatus (e.g. in a bathroom or work meeting).

A total of 244 usage sessions were identified. 82% (201 of 244) referred to the *Fitbit HR*, while 18% referred to *Fitbit Flex* (43 of 244). Participants engaged with the *HR* (N=7) for a median of 1.8 times per hour (IQR=1.7-1.9), while they engaged with the *Flex* (N=5) for 0.6 times per hour (IQR=0.4-0.7). A Mann-Whitney test revealed a significantly higher frequency of engaging with the *HR* (Mann-Whitney U=0, p<.01) as compared to the *Flex*.

While *HR* owners were found to engage more frequently with their devices, this did not mean they checked their physical activity more often. We grouped each individual usage session with the *HR* into three distinct categories, regarding the feedback offered by this device: a) sessions in which participants checked the time and engaged no further, b) sessions in which participants checked physical activity feedback and the time, and c) sessions in which notifications on incoming phone calls were checked. We further logged the time spent within each of these screens. An overview of this data is displayed in Table 2.

Approximately half of the usage sessions with the *HR* were time checking, with no engagement with further feedback (102 of 201, 51%). Physical activity related feedback was checked in approximately one third of usage sessions (65 of 201, 32%), while 11% (22 of 201) were triggered by notifications from incoming phone calls. The screen was not visible in the remaining sessions (12 of 201, 6%).

Table 2. Hourly checking rates and duration for different types of feedback checking

	Fitbit HR		***Fitbit Flex***	
Tracker use	**Hourly checking rate (IQR)**	**Duration, in sec. (IQR)**	**Hourly checking rate (IQR)**	**Duration, in sec. (IQR)**
Time	0.9 (0.8-1.1)	2.1 (1.7-2.7)	-	-
Physical activity	0.6 (0.6-0.6)	4.9 (3.4-6.7)	0.6 (0.4-0.7)	2.8 (2.2-3.7)
Notifications	0.2 (0.1-0.3)	3.5 (2.4-4.1)	-	-

Physical activity checking, with the *HR*, was not an isolated practice from time checking. Participants engaged with their trackers for a median of 5 seconds when checking physical activity feedback. Time checking accounted for approximately 25% (IQR=0-50) of the duration of these sessions (median=1.7sec). Only in 39% of the sessions (n=25) users spend less than a second in time checking.

As one may note in the data, while users engaged more frequently with Fitbit HR, no significant differences were found in the frequency of checking physical activity feedback between the two devices (Mann-Whitney U=16.5, p<.05), despite the the wider range of metrics offered by the *HR* (i.e. numerical step count, heart rate, distance walked, caloric count and floors climbed). Participants however, had longer usage sessions when checking their physical activity feedback on the *HR*, as compared to the *Flex* (Mann-Whitney U=0, p<.01; see Table 2).

Interaction to accomplish goals

Participants were more likely to engage with physical activity feedback when being physically active, as compared to when engaging in sedentary behaviors (see Table 3). In fact, participants checked their trackers 1.1 (IQR=0.8-1.3) times per hour while physically active, and only 0.3 times per hour while sedentary (IQR=0.2-0.4, Mann-Whitney U=10, p<.01).

Table 3. Engagement with physical activity feedback over different levels of physical activity

Level of physical activity (% of sessions, IQR)	Hours spent, of 18h of recording (IQR)	Hourly checking rate (IQR)	Duration, in sec. (IQR)
Sedentary (33%, 18-43%)	9.6 (8.6-10.6)	0.3 (0.2-0.4)	4.3 (2.9-6.0)
Lightly active (37%,14-44%)	4.6 (4.1-5.4)	0.8 (0.2-0.9)	3.4 (2.2-5.9)
Moderately active (20% , 11-40%)	1.4 (1.3-1.6)	1.5 (0.7-2.7)	3.6 (2.8-4.7)
Vigorously active (11% , 0-28%)	0.4 (0.2-0.5)	2.7 (0-6.9)	3.7 (3.1-4.2)

We found engagement during moments of physical activity to be linked to participants' desire to maintain or achieve optimal levels of performance. Participants often set strict goals, and engaging with the tracker served to ensure the goal was achieved before an activity was finished, e.g.:

[P9] "it felt like I had been walking forever, but I wanted to be sure I was already there (3km goal) before heading back home".

Figure 3. Users were nine times more likely to check their tracker during vigorous physical activity than when sedentary. Such engagements increased in frequency near goal completion and fueled users' motivation to meet their goals

Such engagements increased near goal completion and fueled participants' motivation to go beyond their levels of comfort in order to meet their goal, e.g.:

[P9] "the smell of the finish line kept me going… it's all good after I hit those numbers".

Trackers were also used to mediate the impact of an upcoming course of actions, regarding target behaviors. P7, for instance, was found to engage in heart rate checking before adjusting the speed of a treadmill (see Figure 3):

[P7] "it gives a sense of security… seeing that you're doing OK… sticking to your target, before taking that next step".

Learning in a glance

We found that glances serve towards learning gains. All participants, except one, were found to check their activity levels during, as well as right before the start and after the end of a particular activity, such as household chores [P3], commuting to work [P2], or doing groceries [P11] to gain insights on these activities (see Figure 4). These strategic engagements occurred frequently, accounting for approximately one third of participants' usage sessions (median=37%, IQR=22-67%).

[P11] "I am still surprised to learn how many steps I get each day with little things like chores around the house or walking around with my dog. Seeing these little things keeps it simple and interesting"

Figure 4. Trackers were checked strategically towards gaining insights on behaviors – such as right before starting, and after finishing walking a dog, to know how many steps were gained.

This strategic engagement with the tracker hints at a second path to knowledge, next to the deep exploration of past activity data through rich visualizations, one that is more flexible and that can better account for the complexity of daily life. For instance, while a tracker may segment physical activities based on location or time, users' inquiries were often more specific (e.g., how much did I walk while doing household chores). Moreover, participants frequently commented on the variability of even daily routine activities.

[P2] "… It depends on so many things, I might get some cleaning done if I wake up earlier, or be in a hurry and just have time to get dressed and leave, or even leave earlier than usual to run some tasks"

Three participants (P1,P2,P5) were found to track such routine activities to uncover the impact of their variability. P1, for instance, engaged with his tracker when arriving at work – to check for variations in his step count, due to a detour in his daily commute to work (see Figure 5). Another two (P3,10) were found to engage with their tracker when anticipating variations to a routine activity. For instance, P3, a primary teacher, engaged with the tracker before and after her class, to measure the physical activity gained while students performed an exam. These sessions accounted for one fifth of participants' sessions (median=20%, SD=11-20%), indicating that routines are subject to frequent change (as indicated in [17]), with individuals searching for information towards *repairing*, *striving* or *expanding* routines affected by change:

[P3] "I was wondering how many steps I'd get in the class, with the exam going on… checking it before (the start of the class), helped me set a baseline… to come back and see how many steps I gained"

Non-routine activities also led to such strategic engagement with the tracker, geared towards learning. P12 checked his tracker before and after taking a hike, while P6 used the same strategy to track his steps while helping a friend with moving his furniture to his new house.

[P6] "... I was curious to see how much we walked and decided to make some bets (…) surprisingly, we had more than 10,000 steps! My guess wasn't even close"

Figure 5. Trackers were used to uncover variations in routine activities. Examples ranged from checking how many extra steps were gained after taking part in a longer-than-habitual workout (left), and during a detour to work (right).

Glancing at physical activity and time concurrently

We noticed that participants would often glance at the time and their physical activity levels concurrently, or very closely after each other. Approximately half of each participants' engagements with physical activity feedback on Fitbit HR followed time checking (median=44%, SD=25-56%), for at least 2 seconds (median=3.2, SD=2.7-3.7). Participants often commented on the impulsiveness of their engagement with physical activity feedback.

[P5] "… it happens again and again. I check the time, but get dragged to my step count or the distance…it's a click away"

Moreover, we found that 20% of the sessions in which HR users engaged with physical activity feedback (N=65) were either preceded (9 of 13) or followed (4 of 13), within the following 15 seconds, by a usage session in which they checked the time.

We noticed three, interweaving reasons which led users to combine time and physical activity feedback within single or shortly separated sessions: a) assessing the attainability of goals, b) planning future activity, and c) reflecting on activity levels.

Assessing the attainability of goals

Time-checking served to estimate how likely one was to meet a daily goal given the distance walked so far. As one participant noted:

[P1] "… it's not only about how many steps I've gained, but also how much time it took me to get there… and how much (time) I still have to complete my goal"

In this respect, users developed a strategy to counteract the inefficiency of the tracker. While the tracker merely provided descriptive data (i.e., how much they had walked by that point in time), users desired normative data (i.e., "is this good enough?"). During the interviews, we realized that users often had a strong awareness of how much they should have walked by a given point in time in order to meet their goal. For instance, P7 noted:

"On a normal day, I should have 7,000 steps by mid-day… 10,000 around 5 [pm], and 12,000 around 8 [p.m]"

Further, users would also often think about their upcoming plans to estimate the likelihood of meeting their goal.

[P5] "I was going to spend the whole day sitting on my butt, so I knew it was a long shot [reaching step count goal]. There was little space to make up for it, having to pick up the kids from school, cooking, cleaning"

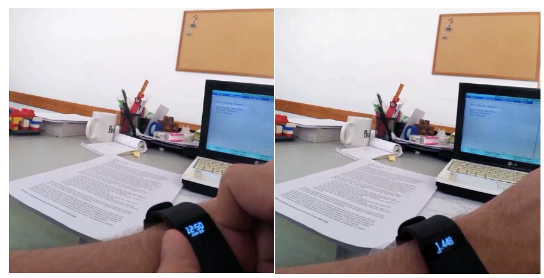

Figure 6. Users often combined PA feedback with time checking to estimate the likelihood of meeting goals. While trackers merely provided descriptive data (i.e., how much was walked by a point in time), users desired normative data (i.e., is this good enough?).

Planning future activity

Besides estimating the likelihood of meeting their goal, users would often use interaction to plan future activity, accounting for half of the sessions in which each participant combined time and physical activity checking (median=50%, IQR=25-67%). Such plans would vary in their temporal proximity and extend, from small detours in the near future such as grabbing some water while waiting for the printer, to ones more significant and distant in time, such as reaching 1000 steps in the next hour, or planning a visit to the gym for the evening, *e.g.*:

[P1] "I try getting out of the office on my afternoon breaks… to make up for heptic mornings. If my steps are low I'll say to myself 'lets try to get 1000 steps done in the next hour'… other days 200 will be enough. It depends on how I'm doing so far"

[P10] “I can’t - and don’t want to stop work or being with my family to walk every time my step is lower than I expect (...) it does, however, get me thinking about how I can get some steps in (...) a longer walk home, taking a dog for a walk after work.”

While in some cases these plans were followed strictly (e.g., meeting one’s 3000-step goal before getting off the treadmill), in most of the cases, the plans were flexible and responsive to the variability of users’ routines.

[P10] “my rule of thumb is to have 1000 steps for every hour spent at work, but you never know, it might be a busier day (…) I’ll tell myself ‘ok, let’s take a 10-minute break’ and go for a walk if I see I’m falling behind”

In those circumstances, users would often adjust their expectations, or form new plans, when the opportunity arose in order to fulfill their plan. For instance, P2 was not near fulfilling her plan as she waited for her friends, she checked the time, and she realized she had 10 minutes for a short walk before her friends were due to arrive.

Figure 7. Users maintained an awareness of their activity levels and formed *micro-plans* such as grabbing water while waiting for the printer, or walking 1000 steps in the next hour.

Reflecting on activity levels

Participants also combined time and physical activity feedback to reflect about points in time, or activities, laying in the past – such as activity levels over a day, or within previously performed activities (e.g. looking back at the steps one has performed while at home [P4], or at the gym [P5]). P5, for instance, engaged with his tracker - while on vacations, to reflect on the amount of physical activity he had managed to include in his morning, and how this compared to his typical morning activity levels.

[P2] “… 5000 steps by 10am! with the vacations going on, I had no clue of how many steps to expect… it got me thinking of where I got them from. Probably from all the walking around the house or the late dancing”

Others engaged with time and physical activity feedback data to assess their performance in recently performed activities. P5, for instance, checked his step count and time before and after a jog, reflecting on the amount of steps gained within that timeframe: “*3km in 20 minutes. pretty slow today*”.

Mitigating waiting time and alleviating boredom

Participants were found to engage with their physical activity feedback during “dead times” [40, pg. 9] - such as commuting via public transport, or waiting for an upcoming activity, accounting for approximately 10% of the sessions in which physical activity feedback was checked (median=11%, IQR=3-24%). “Dead times”, as considered by Perry et al., refer to the time that occurs between tasks and activities, in which participants have little control over the resources they had to hand. P3, for instance, was found to check her step count while waiting for a bus. P1 checked his step count and time while waiting for a printing service.

[P1] “I try to get 12,500 steps before leaving work… there are moments, here and there where I try to get some steps if I see myself really behind… like grabbing some water while the printer is working, but I’ll only bother if I’m more than 2000 or 3000 steps away”

P2 engaged with his tracker while waiting for a client meeting.

[P2] “I played around with it while I was waiting. (...) it helped kill the time, I didn't have much to do (…) I rather spend my time checking and thinking of my health then checking what other people are doing on Facebook.”

Others were found to engage in tracker checking to alleviate boredom. P9 checked his tracker while in class; P3 while taking part in a meeting.

Figure 8. Participants were found to turn to their trackers to help mitigate waiting time . While engaging shortly with trackers, these led to longer-lasting refletions on one’s data.

Contrary to the user-initiated engagement with physical activity data during “dead times”, users often commented upon *engagement anxiety* during cognitively demanding tasks. Engagement with physical activity data was seen as an activity competing for resources – not necessarily due to the time spent within usage sessions, but due to the potential outcome of checking, such as feeling pressured or enforced to keep up to a certain walking goal, disregarding their ongoing availability (e.g., [P9] “*it’s keeps me asking if I’ve done enough, and pushing me to do more. it gets tiring after a while*”). In fact, two participants (P8, P9) noted that they avoid checking their trackers during activities that demanded their focus, such as computer programming and during meetings. All in all, these results highlight the variability of daily life and the need for systems that sense and adapt to users' context. On the one hand, trackers need to be more accommodating, accepting that not all moments are equal and be less demanding in situations that offer little opportunity for physical activity. On the other hand, trackers may leverage "dead times" into opportunities for engaging with one's data, learning from past behaviors, and even motivating short bursts of physical activity.

DISCUSSION

Our findings suggest specific design considerations, such as facilitating learning through glances, providing normative feedback on goal accomplishment, and facilitating micro-plans.

Facilitating learning through glances

Personal informatics literature has assumed two primary modes of interaction with respective systems, guided by our *reflective* versus our *impulsive* thinking and decision making systems, respectively [48]. The reflective mode was long assumed to be the dominant mode of interaction: people would collect data, then explore and review them in retrospect (i.e., days, weeks), to identify patterns in their behaviors and plan alternative future courses of action. As such, most of today's personal informatics tools support this process through the high-level aggregation of data over time (e.g. step count over a week or a month) and considerable amount of efforts have focused on the design of personal visualizations to support reflection, interpretation and reminiscing based on data [15].

In contrast, the *impulsive* mode assumes people to process data and take action quickly and unconsciously. From a design perspective, the shifts emphasis from supporting learning to supporting the self-regulation of behavior [1, 22]. Recent research has highlighted the prevalence of the *impulsive* over the *reflective* mode. Gouveia et al. [21] found over 70% of usage sessions with a tracker to related to the so-called *"glances"* – brief, 5-second sessions where users checked their current activity levels with no further exploration. Glances were assumed to support the frequent regulation of behavior; people would estimate how likely they are to meet their activity goal by the end of the day, and introduce new actions when needed.

Our study, however, revealed that such glances may also serve towards learning. Participants were found to check their activity levels right before the start and after the end of a particular activity, such as household chores or commuting to work, with the goal of understanding their actual and potential contribution to their physical activity levels. Such interactions occurred frequently, accounting for approximately one third usage sessions. This points at the need to develop mechanisms to support learning through these frequent glances.

One could imagine intelligent systems – identifying significant correlations among users' data (as in [4]) or feedback that adapts to the particular context of use. But while current technology may help disentangling physical activity in relation to one's location or time of the day, we noticed that participants' inquiries were often simple, yet more precise. More than wanting to know how much they had walked at a certain venue (e.g. work), they wanted to gain specific insights into performed activities (e.g. how much did I walk while doing household chores?). Inferring the start and end time of such activities would be difficult given today's technology. We thus suggest a semi-automated approach, where the tracker enables users to quickly mark moments such as the start and end time of an activity, group these moments into an activity, and support users in labeling, annotating, inquiring into, and comparing different activities.

Providing normative feedback on goal accomplishment

We found that users often check time in conjunction with physical activity to estimate how likely they were to meet their daily goal given the distance walked so far. In this respect, users developed a strategy to counteract the inefficiency of the tracker. While the tracker merely provided descriptive data (i.e., how much they had walked by that point in time), users desired normative data (i.e., "is this good enough?"). This inefficiency of activity trackers had been previously noted by using the example of Fitbit Flex's wristband which features five LEDs that illuminate for each 20% of a daily walking goal achieved. As mentioned, "*even this seemingly simple display requires some quite difficult projections, if one wants to use it for immediate self-regulation*" [22, p.146]. As a solution, they proposed *Normly*, which employs a large database of other people's walking trajectories over the course of a day, and compares the distance one has walked at a given time in a day to that walked by others having the same goal, at the same time in the day. Thus, at each moment a user engages with *Normly*, she receives simple, normative feedback – that she is either doing better or worse than others, at this specific moment.

We contribute an additional concept aimed at providing normative data on goal accomplishment. *Predicto* leverages on users' aggregated accounts of data to forecast the likelihood of goal completion. *Predicto* draws inspiration from prediction markets [5], which leverage on aggregate information to produce predictions about future events (e.g. a political candidate's re-election, the victory of a sports team). The likelihood would be estimated on a number of conditions, such the number of consecutive days in which a user has reached his goals, or the upcoming plans for a day. *Predicto* takes into account the variability of routines [17] by constantly updated predictions (e.g. skipping a habitual trip to the gym lowers the chances of reaching a goal).

Facilitating micro-plans

Our study revealed that users often formed *micro-plans* for the immediate future, such as reaching 1000 steps in the next hour. While the positive effects of proximal goals on motivation and performance have been highlighted by empirical research in goal setting and acknowledged by

Goal Setting Theory [34], the majority of today's trackers, rather without much thought, adopt a daily step goal.

One might wonder about how technology could further support practices such as the one identified here – that of *micro-plans*, short courses of action planned within daily routines geared towards meeting one's levels of physical activity. Prior work has explored ways to make goal-setting more agile to accommodate the variability of daily life. Munson et al. [38] for instance, proposed the idea of *secondary goals* as fallbacks in days of reduced physical activity, while Konstanti and Karapanos proposed the idea of *micro-updates* – daily step goals that expire at the end of the day, inspired by users' practices (e.g., "*when I know I will be seated a lot e.g. long car trip, I adjust my goal downwards").* However, no work has explored how trackers may further support individuals in planning their days in more detail. Given our findings and Goal Setting Theory, such mechanisms are expected to positively impact users' motivation and performance.

However, a crucial interaction design challenge is how to support this practice while maintaining users' flexibility in adjusting their plans? We found that in most of the cases, users treated those as flexible and responsive to the variability of their routines. They often adjusted their expectations, formed new plans, or enforced nested actions when the opportunity arose in order to fulfill their plan.

Figure 9. ***Mikro*** **compares one's progress to a micro-goal (outer ring) to the time remaining to complete a goal (inner ring) .** ***Mikro*** **also allows users to make short adjustments to goals.**

We detail below two concepts that aim at facilitating the formation and execution of micro-plans. The first one, *Mikro* (see Figure 9), enables users to set a micro-plan manually. The user selects the number of steps and the duration of a micro-plan. *Mikro* then displays the remaining steps and time for the micro-plan along with the total number steps walked in the day. *Mikro* further supports flexible goals. In a similar way alarms allow for 5 extra minutes of snoozing, users are allowed to make small adjustments their goals at any point of their day. The second one, *Mikromoves*, builds upon the commercial application Moves (see [21] for a similar approach), that segments physical activity over the different locations one visits in the course of the day. *Mikromoves* automatically sets a micro-plan for each new location the user visits (e.g., Welcome to *Work*, let's walk 2300 steps over the next 8 hours). The distance and duration are estimated based on past visits at the location, while the user may adapt those values, which also contributes to training *Mikromoves* prediction algorithm.

LESSONS LEARNT AND LIMITATIONS

This paper presented an *in vivo* study of activity tracking. Through the use of video methods, the study took a close look at a number of practices that surround the use of activity trackers in daily life. Most notably, we found the use of these devices to be strongly driven by reflection and *learning-in-action*, contrasting the traditional view that learning is one of deep, retrospective exploration of data.

One should note a number of limitations in this study. First, this is a study of the practices of successful adopters of activity trackers. We chose to do so in order to shed light into the practices that we need to support in order to sustain prolonged use [see also 18]. Yet, one has to take into account that not everyone who tries a wearable activity monitor continues to use it in the long term [21,30]. Understanding failed practices is also a much needed endeavor. Secondly, our study involved only twelve participants and only two days of their engagement with the tracker. We believe these are direct outcomes of some of the challenges of the adopted method. In particular, participation may be hindered due to surveillance and privacy concerns of using a wearable camera [39] and is likely to produce increased discomfort if an extended study duration is required.

In closing, our study took a step forward towards understanding how tracker use is enmeshed within everyday life, and how these devices could be better designed to support long-term use. Activity tracking, as a practice, is diversified, dependent upon and threaded into what goes on around us. Following these developments is difficult. Yet, as these devices become ever more central to the ongoing discourse on behavior change and patient-driven healthcare, a richer understanding of the lived dynamics of activity tracking trackers is crucial.

AKNOWLEDGMENTS

This research was supported by the Portuguese Foundation of Science and Technology grant SFRH/BD/89796/2012.

REFERENCES

1. Alexander T. Adams, Jean Costa, Malte F. Jung, and Tanzeem Choudhury. (2015). Mindless computing: designing technologies to subtly influence behavior. In *Proceedings of the ACM International Joint Conference on Pervasive and Ubiquitous Computing* (UbiComp'15), pp. 719–730 https://doi.org/10.1145/2750858.2805843

2. Jeremy D. Akers, Rachel A. Cornett, Jyoti S. Savla, Kevin P. Davy, and Brenda M. Davy. (2012). Daily self- monitoring of body weight, step count, fruit/vegetable intake, and water consumption: a feasible and effective long-term weight loss maintenance approach. *Journal of the Academy of Nutrition and Dietetics*,*112*(5), pp. 685-692. https://doi.org/10.1016/j.jand.2012.01.022

3. Raymond C. Baker, and Daniel S. Kirschenbaum. (1993). Self-monitoring may be necessary for successful weight control. *Behavior Therapy*, *24*(3), pp. 377-394. https://doi.org/10.1016/S0005-7894(05)80212-6

4. Frank Bentley, Konrad Tollmar, Peter Stephenson, Laura Levy, Brian Jones, Scott Robertson, Ed Price, Richard Catrambone, and Jeff Wilson. (2013). Health Mashups: Presenting Statistical Patterns between Wellbeing Data and Context in Natural Language to Promote Behavior Change. *Transactions on Computer-Human Interactions* (ToCHI'13), pp. 1–13. http://dx.doi.org/10.1145/2503823

5. Joyce E. Berg, and Thomas A. Rietz. (2003). Prediction markets as decision support systems. *Information systems frontiers*, *5*(1), pp. 79-93. https://doi.org/10.1023/A:1022002107255

6. Virginia Braun, and Victoria Clarke. (2006). Using thematic analysis in psychology. *Qualitative research in psychology*, *3*(2), pp. 77-101. http://dx.doi.org/10.1191/1478088706qp063oa

7. Barry Brown, Moira McGregor, and Eric Laurier. (2013). iPhone in vivo: video analysis of mobile device use. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (CHI'13), pp. 1031-1040. https://doi.org/10.1145/2470654.2466132

8. Lora E. Burke, Jing Wang, and Mary Ann Sevick. (2011). Self-monitoring in weight loss: a systematic review of the literature. *Journal of the American Dietetic Association*, *111*(1), pp. 92-102. https://doi.org/10.1016/j.jada.2010.10.008

9. Robert A. Carels, Lynn A. Darby, Sofia Rydin, Olivia M. Douglass, Holly M. Cacciapaglia, and William H. O'Brien. (2005). The relationship between self-monitoring, outcome expectancies, difficulties with eating and exercise, and physical activity and weight loss treatment outcomes. *Annals of Behavioral Medicine*, *30*(3), pp. 182-190. https://doi.org/10.1207/s15324796abm3003_2

10. 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. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (CHI'14), pp. 1143-1152. http://doi.acm.org/10.1145/2556288.2557372

11. Chia-Fang Chung, Nanna Gorm, Irina A. Shklovski, and Sean Munson. (2017). Finding the Right Fit: Understanding Health Tracking in Workplace Wellness Programs. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (CHI'17), pp. 4875-4886. https://doi.org/10.1145/3025453.3025510

12. 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 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (UbiComp'15)*,* pp. 647-658. https://doi.org/10.1145/2750858.2807554

13. Sunny Consolvo, Katherine Everitt, Ian Smith, and James A. Landay. (2006). Design requirements for technologies that encourage physical activity. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (CHI'06), pp. 457-466. https://doi.org/10.1145/1124772.1124840

14. 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. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (CHI'18), 1797–1806. http://doi.org/fj37wd

15. Daniel Epstein, Felicia Cordeiro, Elizabeth Bales, James Fogarty, and Sean Munson. (2014). Taming data complexity in lifelogs: exploring visual cuts of personal informatics data. In *Proceedings of the ACM Conference on Designing Interactive Systems* (DIS'14), pp. 667-676. https://doi.org/10.1145/2598510.2598558

16. Daniel A. Epstein, An Ping, James Fogarty, and Sean A. Munson. (2015). A lived informatics model of personal informatics. In *Proceedings of the ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp'15),* pp. 731-742. https://doi.org/10.1145/2750858.2804250

17. Martha S. Feldman. (2000). Organizational Routines as a Source of Continuous Change. *Organization Science*, 11(6), pp. 611 - 629. https://doi.org/10.1287/orsc.11.6.611.12529

18. Thomas Fritz, Elaine M. Huang, Gail C. Murphy, and Thomas Zimmermann. (2014). Persuasive technology in the real world: a study of long-term use of activity sensing devices for fitness. In *Proceedings of the SIGCHI Conference on Human Factors in Computing*

Systems (CHI'14), pp. 487- 496. https://doi.org/10.1145/2556288.2557383

19. Get Activity Intraday Time Series. (n.d.). Retrieved 19 September, from https://dev.fitbit.com/reference/web-api/activity/ - get-activity-intraday-time-series
20. Rúben Gouveia and Evangelos Karapanos. (2013). Footprint tracker: supporting diary studies with lifelogging. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (CHI'13), pp. 2921-2930. https://doi.org/10.1145/2470654.2481405
21. Rúben Gouveia, Evangelos Karapanos, and Marc Hassenzahl. (2015). How do we engage with activity trackers?: a longitudinal study of Habito. In *Proceedings of the ACM International Joint Conference on Pervasive and Ubiquitous Computing* (UbiComp'15), pp. 1305-1316. https://doi.org/10.1145/2750858.2804290
22. Rúben Gouveia, Fábio Pereira, Evangelos Karapanos, Sean A. Munson, and Marc Hassenzahl. (2016). Exploring the design space of glanceable feedback for physical activity trackers. In *Proceedings of the ACM International Joint Conference on Pervasive and Ubiquitous Computing* (UbiComp'16), pp. 144-155. https://doi.org/10.1145/2971648.2971754
23. Nanna Gorm and Irina Shklovski. (2016). Steps, Choices and Moral Accounting: Observations from a Step-Counting Campaign in the Workplace. In *Proceedings of the ACM Conference on Computer-Supported Cooperative Work & Social Computing* (CSCW'16), pp. 148-159. https://doi.org/10.1145/2818048.2819944
24. Nanna Gorm and Irina Shklovski. (2017). Participant Driven Photo Elicitation for Understanding Activity Tracking: Benefits and Limitations. In *Proceedings of the ACM Conference on Computer-Supported Cooperative Work & Social Computing* (CSCW'17), pp. 1350-1361. https://doi.org/10.1145/2998181.2998214
25. Daniel Harrison, Paul Marshall, Nadia Bianchi-Berthouze, and Jon Bird. (2015). Activity tracking: barriers, workarounds and customisation. In *Proceedings of the ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp'15),* pp. 617-621. https://doi.org/10.1145/2750858.2805832
26. Christian Heath, Paul Luff, P and Marcus S. Svensson. (2007). Video and qualitative research: analysing medical practice and interaction. *Medical education*, *41*(1), 109-116. http://dx.doi.org/10.1111/j.1365-2929.2006.02641.x
27. Daniel Kahneman, Alan B. Krueger, David A. Schkade, Norbert Schwarz and Arthur A. Stone. (2004). A survey method for characterizing daily life experience: The day reconstruction method. *Science*, 306(5702), pp. 1776-1780. https://dx.doi.org/10.1126/science.1103572
28. Evangelos Karapanos, Rúben Gouveia, Marc Hassenzahl, and Jodi Forlizzi. (2016). Wellbeing in the making: peoples' experiences with wearable activity trackers. *Psychology of well-being*, *6*(1), pp. 1-17. https://dx.doi.org/10.1186%2Fs13612-016-0042-6
29. 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* (CHI'11), pp. 3063-3072. https://doi.org/10.1145/1978942.1979396
30. Amanda Lazar, Christian Koehler, Joshua Tanenbaum, and David H. Nguyen. (2015). Why we use and abandon smart devices. In *Proceedings of the ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp'15),* pp. 635-646. https://doi.org/10.1145/2750858.2804288
31. Matthew L. Lee and Anind K. Dey. (2007). Providing good memory cues for people with episodic memory impairment. *In Proceedings of the ACM SIGACCESS conference on Computers and accessibility* (Assets'07), pp.131-138. http://dx.doi.org/10.1145/1296843.1296867
32. Ian Li, Anind Dey, and Jodi Forlizzi. (2010). A stage-based model of personal informatics systems. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (CHI'10), pp. 557-566). https://doi.org/10.1145/1753326.1753409
33. James J. Lin, Lena Mamykina, Silvia Lindtner, Gregory Delajoux, and Henry B. Strub. (2006). Fish'n'Steps: Encouraging physical activity with an interactive computer game. In *Proceedings of the ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp'15), pp.* 261-278. http://dx.doi.org/10.1007/11853565_16
34. Edwin A. Locke and Gary P. Latham. (2002). Building a practically useful theory of goal setting and task motivation: A 35-year odyssey. American psychologist, 57(9), pp. 705-715. http://dx.doi.org/10.1037/0003-066X.57.9.705
35. Donald McMillan, Moira McGregor, and Barry Brown. (2015). From in the wild to in vivo: Video Analysis of Mobile Device Use. In *Proceedings of the ACM International Conference on Human-Computer Interaction with Mobile Devices and Services* (MobileHCI'15), pp. 494-503. ACM. https://doi.org/10.1145/2785830.2785883
36. Jochen Meyer, Merlin Wasmann, Wilko Heuten, Abdallah El Ali, and Susanne C.J. Boll. (2017). Identification and Classification of Usage Patterns in Long-Term Activity Tracking. In *Proceedings of the*

SIGCHI Conference on Human Factors in Computing Systems (CHI'17)*,* pp. 667-678. https://doi.org/10.1145/3025453.3025690

37. Lorenza Mondada. (2008). Using video for a sequential and multimodal analysis of social interaction: Videotaping institutional telephone calls. In *Forum Qualitative Sozialforschung/Forum: Qualitative Social Research,* 9(3). http://dx.doi.org/10.17169/fqs-9.3.1161
38. Sean A. Munson and Sunny Consolvo (2012). Exploring goal-setting, rewards, self-monitoring, and sharing to motivate physical activity. In *Pervasive computing technologies for healthcare (PervasiveHealth'12),* pp. 25-32. https://doi.org/10.4108/icst.pervasivehealth.2012.248691
39. David H. Nguyen, Gabriela Marcu, Gillian R. Hayes, Khai N. Truong, James Scott, Marc Langheinrich, and Christof Roduner. (2009). Encountering SenseCam: personal recording technologies in everyday life. In *Proceedings of the International Conference on Ubiquitous Computing* (UbiComp '09), pp. 165-174. http://dx.doi.org/10.1145/1620545.1620571
40. Misha Patel and Aisling Ann O'Kane. (2015). Contextual influences on the use and non-use of digital technology while exercising at the gym. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (CHI'15), pp. 2923-2932. https://doi.org/10.1145/2702123.2702384
41. Mark Perry, Kenton O'hara, Abigail Sellen, Barry Brown, and Richard Harper. (2001). Dealing with mobility: understanding access anytime, anywhere. *ACM Transactions on Computer-Human Interaction (TOCHI)*, *8*(4), pp. 323-347. http://dx.doi.org/10.1145/504704.504707
42. Stefania Pizza, Barry Brown, Donald McMillan, and Airi Lampinen. (2016). Smartwatch in vivo. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (CHI'16), pp. 5456-5469). https://doi.org/10.1145/2858036.2858522
43. James O. Prochaska, Wayne F. Velicer (1997). The transtheoretical model of health behavior change. *American journal of health promotion*, *12*(1), pp. 38-48. https://doi.org/10.4278/0890-1171-12.1.38
44. PWC Consumer Intelligence. (2016). The Wearable Life 2.0: Connected living in a wearable world. 55. https://www.pwc.com/us/en/industry/entertainment-media/assets/pwc-cis-wearables.pdf
45. David Riley. Owner of Activity Trackers, Smartwatches Expected to Jump at Least 4 Percent this Holiday Season. *The NPD Group*. https://www.npd.com/wps/portal/npd/us/news/press-releases/2015/ownership-of-activity-trackers-smartwatches-expected-to-jump-at-least-4-percent-this-holiday-season-according-to-npd/
46. Yvonne Rogers. (2011). Interaction design gone wild: striving for wild theory. *Interactions* 18(4), 58.
47. John Rooksby, Mattias Rost, Alistair Morrison, and Matthew Chalmers Chalmers. (2014). Personal Tracking as Lived Informatics. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI'14), pp.1163–1172. http://doi.acm.org/10.1145/2556288.2557039
48. Fritz Strack and Roland Deutsch. (2004). Reflective and impulsive determinants of social behavior. *Personality and social psychology review*, *8*(3), pp. 220-247. https://doi.org/10.1207%2Fs15327957pspr0803_1
49. Catrine Tudor-Locke, C. and David R. Bassett Jr. (2004). How many steps/day are enough? *Sports medicine*, 34(1), pp.1-8. https://doi.org/10.2165/00007256-200434010-00001
50. Adam G. Tsai and Thomas A. Wadden. (2005). Systematic review: an evaluation of major commercial weight loss programs in the United States. *Annals of internal medicine*, *142*(1), 56-66. http://dx.doi.org/10.7326/0003-4819-142-1-200501040-00012
51. Muhammad U. Warraich. (2016). Wellness Routines with Wearable Activity Trackers: A Systematic Review. In *Proceedings of Mediterranean Conference on Information Systems,* (MCIS'16). http://aisel.aisnet.org/mcis2016/35