Personal informatics for sport: Meaning, body, and social relations in amateur and elite athletes

Personal Informatics for Sport: Meaning, Body, and Social Relations in Amateur and Elite Athletes

AMON RAPP, University of Torino
LIA TIRABENI, University of Torino

Technological advances in wearable computing are changing the sports domain. A variety of Personal Informatics (PI) tools are starting to provide support and improve athletes' performance in many sports. In this paper, we interviewed 20 amateur and elite athletes of different disciplines, using an array of PI devices, to explore how sports, as well as athletes' experience, are affected by such instruments. We discovered that amateur athletes present different patterns of usage compared to elite ones. Moreover, we found that elite athletes make sense of their data by exploiting the knowledge they have about their own body and sport practice. We then proposed four considerations for design that we believe should be explored in the future, to reflect on how self-tracking is changing our perspective on sports, and, by and large, on our everyday life.

• **Human-centered computing→ Human computer interaction (HCI)**

Additional Key Words and Phrases: Personal Informatics, Quantified Self, self-tracking, sport, elite athletes, amateur athletes.

ACM Reference Format:

Author's addresses: A. Rapp (corresponding author), Computer Science Department, University of Torino, Torino, Italy; email: amon.rapp@gmail.com; L. Tirabeni, Department of Cultures, Politics and Society, University of Torino, Torino, Italy.

DOI:http://dx.doi.org/10.1145/0000000.0000000

1. INTRODUCTION

Technological advances in wearables and the increasing offer of self-tracking instruments are opening new possibilities for Personal Informatics (PI) tools, "those that help people collect personally relevant information for the purpose of self-reflection and gaining self-knowledge" [Li et al. 2010]. More and more data can be automatically collected, forecasting a future when PI systems could be applied to a variety of domains, from healthcare to fitness, from entertainment to learning. Among these, the sports context appears to be very promising for PI. Athletes are used to monitoring themselves, by using a variety of means, from objective measures and performance tests [Currell and Jeukendrup, 2008] to conversations with coaches, questionnaires and self-reports [Saw et al. 2015b]. PI technologies might ease this process allowing them to track their performances, tailor their training to their physical condition, and provide new knowledge on their body.

Despite the increasing attention that HCI granted to the sports domain [Ishii et al. 1999; Slovák et al. 2012; Pijnappel and Mueller 2013; Mauriello et al. 2014; Mueller and Muirhead 2015; Kosmalla et al. 2016], the integration of commercial self-tracking technologies into sports practices has received limited attention. With remarkable exceptions [Tholander and Nylander, 2015; Wakefield et al. 2014], the impact of the growing availability of instruments for collecting personal data on sports has not yet been widely explored. Actually, taking into consideration how PI instruments are used within sports practices is important for two reasons. First, it shows how PI tools are transforming specific life domains. Despite an increasing understanding of how self-trackers track, we know far less about how these technologies are used in particular contexts and communities of practice. Previous research mainly focused on the act of tracking per se, rather than connecting it with the users' characteristics, often exclusively stressing purposes of behavior change [Rapp & Tirassa, 2017; Rapp et al., 2017]. On the one hand, focusing on tracking per se has narrowed our perspective on the PI phenomenon. On the other hand, it reduces our capability to design PI tools for novel and specific contexts, where individuals have preexisting habits and goals. Second, focusing on how PI instruments are used within sports practices could show how a specific user group successfully integrates self-trackers into their daily practices, finding them useful for their situated needs. Despite the enthusiastic market predictions [IdTechEx 2014], there is a growing skepticism about the real capabilities of PI tools to provide individuals with concrete benefits [Maddox 2014; Hunter 2014]: a recent research reports that one third of the Americans that purchased a tracker abandoned it after only six months of use [Ledger and McCaffrey 2014]. Athletes, on the other hand, keep track of their performances for prolonged periods. Thus, studying "successful" applications of these technologies provides insights on how we can design better tools, also outside the sports domain.

Therefore, our work aims at providing the following contributions.

- To describe how amateur and elite athletes integrate PI tools into their sports practices, showing how some individuals better exploit PI instruments thereby suggesting "best practices" to be supported in novel designs.

- To outline relevant themes regarding how the current availability of personal data is modifying the sports context and the athletes' self-perceptions. This could also be relevant in order to understand how PI tools are changing important aspects of our everyday life.

- To propose a series of design considerations that will open spaces of reflection for future research in PI, thereby providing insights on how to design PI tools for specific domains.

The article is structured as follows. In Section 2, we outline the previous studies related to PI tools usage. In Section 3, we describe the method employed in our research, while, in Section 4, we expose its findings, highlighting some themes that may be of interest for the domain of our study. Section 5 discusses our results. Finally, Section 6 proposes a series of considerations for design. Section 7 concludes the article.

2. BACKGROUND

2.1 Personal Informatics, physical activity, and sport

Self-monitoring, the act of recording one's own behavior, has been used for a long time in clinical settings [Foster et al. 1999; Korotitisch and Nelson-Gray 1999], both to collect information on behaviors that only the patient can observe continuously (e.g. eating, or smoking), and to modify behavior by exploiting its reactive effects. Reactivity refers to the phenomenon whereby the mere fact of recording behavior causes the behavior to change [Nelson and Hayes 1981]. In the sports domain, self-monitoring has been reported as a means to improve the athletes' performances [Kirschenbaum et al. 1982], to guide training, to detect any progression towards negative health outcomes and associated poor performances [Saw et al. 2015a], and to stimulate greater self-awareness and self-regulation in order to "learn from your mistakes" [Oliver et al. 2010]. Athlete monitoring provides coaches with a greater degree of certainty when prescribing and adjusting training loads [Saw et al. 2015b], reducing the risk of overtraining, injury and illness [Coutts and Cormack 2014; Taylor et al. 2012]. Athletes can monitor performance and physiological and biochemical parameters, as well as use self-reported measures such as questionnaires and diaries [Halson 2014]. However, the implementation of athlete monitoring requires an investment in terms of time and efforts to obtain, analyze and effectively utilize the data [Saw et al. 2015b]. The current diffusion of PI tools may ease this process, by lightening the burden of self-monitoring [Rapp and Cena 2014].

PI research has its roots in life logging projects [Cheng et al. 2004; Gemmell et al. 2006; Mann et al. 2004], even though self-tracking instruments can be dated to the spread of weight scales at the beginning of the 20th century [Crawford et al. 2015], as well as of pedometers in the early fifties [Tudor-Locke and Bassett, 2004]. Only in the last ten years, however, academic research aimed at designing PI systems for therapeutic and behavior change purposes, particularly focusing on the physical activity domain. Chick clique [Toscos et al. 2006] keeps track of the number of steps that are taken each day to motivate teenage girls to exercise; UbiFit Garden [Consolvo et al. 2008a] uses a wearable device and a mobile display to encourage users to do more physical activity; Open Heart Helmet [Walmink et al. 2014] gathers data about the cyclist's heart rate and displays them to others in order to enable social interplay and engagement through the physical exertion activity; Habito [Gouveia et al. 2015] employs goal setting, contextualized cues, and textual feedback to improve a tracker that aims at changing individuals' behavior toward a healthier lifestyle; Into [Ahtinen, Huuskonen, and Häkkilä, 2010] presents physical activity data as a virtual trip on a map-based game world, in order to make such data more understandable. By and large, Ahtinen [2015] provides a wide overview of applications aimed at supporting physical activity, as well as design strategies to improve them.

Moreover, new sensing technologies to detect, recognize and monitor a variety of data, concerning our current domain of investigation have been experimented. Michaelles and Schiele [2005] used wearable sensors to collect data about professional skiers' motions, such as force, rotation, or acceleration. Lapinski et al. [2009] exploited an array of wearable Inertial Measurement Units (IMUs) to measure and track the performance of professional baseball players. Stamm et al. [2013] attempted to measure the swimming velocity using an accelerometer attached to the swimmer's sacrum. Kooyman et al. [2013] used a gyroscope to capture swings in golf. Zhou et al. [2016] developed a soccer shoe, using smart textiles to detect the interaction between the players' foot and the ball. Sundholm et al. [2014] employed a textile pressure sensor matrix that can be integrated into exercise mats to recognize and count gym exercises. Finally, Kosmalla et al. [2015] developed a wearable device that automatically recognizes climbed routes using wrist-worn IMUs.

Besides academic research in activity recognition, the recent availability of commercial wearable devices and applications for self-tracking boosted the popularity of PI among a variety of users and for goals other than promoting a healthier lifestyle. Not only the Quantified Selfers [Marcengo and Rapp 2014], i.e. a class of users extremely engaged in tracking personal data, but also a wider population have now access to this kind of instruments [Rapp and Cena 2016]. Among these, amateur and elite athletes can find devices aimed at collecting data about specific parameters, as well as more generic information, such as location, number of steps, kilometers travelled. Wearables like Garmin Forerunner (running, triathlon), Suunto Ambit3 Vertical (e.g. ski mountaineering), Power Meter (cycling), and OptimEye S5 Catapult (team sports) are starting to provide specific support and improve the athletes' performance in a variety of sports.

This varied landscape prompts some research questions: How do athletes integrate this kind of devices into their sports practices? Are there differences among different athletes and different sports? Do athletes collect and manage data differently with respect to other self-trackers? Does quantifying the sports practice affect training routines and races? Does self-tracking affect body perception, interpersonal relationships and subjective experience? By and large, answering these questions allows us to "learn" from the sports domain, widening our perspective on PI phenomenon, and potentially leading to insights that may inspire the design of novel, more useful and engaging PI tools.

2.2 Understanding PI users

Until now, research on commercial PI instruments focused on how different users use such technologies in their everyday life. Li et al. [2010] first surveyed individuals that collect information about themselves to investigate the issues that they may encounter in this activity, proposing a model of PI use. In a subsequent work, Li et al. [2011] further explored the potential issues raised by the usage of PI devices, and found that people lack adequate support to allow reflection over the long term. Rooksby et al. [2014] pointed out that tracking is often social and collaborative and that there are different styles of tracking: 1) directive, to achieve a goal; 2) documentary, to document activities 3) diagnostic, to connect different parameters together; 4) collecting rewards, to collect incentives; and 5) "fetishized", purely out of an interest in data or technology. Fritz et al. [2014] showed how long-term trackers have a strong attachment to their devices, stressing that they are highly motivated by numerical feedback, goals and rewards provided by the devices they used. Choe et al. [2014] further investigated an "extreme" user group, the Quantified Selfers, describing how even these individuals, very experienced in tracking, encounter barriers in collecting and managing their personal data.

Although not specifically connecting them with the PI discourse, Lazar et al. [2015] investigated how "smart devices" (i.e. wearables) might be abandoned by their users, because they do not fit with the their conceptions of themselves, their maintenance becomes unmanageable, and the collected data are perceived as useless. Rapp and Cena [2016] further studied the tracking practices of people without any previous experience in self-tracking, finding that such individuals consider the act of collecting data burdensome and not sufficiently rewarding, they want to play with their personal information, and are driven by curiosity and serendipity.

Different studies focused on various aspects of PI. However, research has mainly focused on generic categories of self-trackers (expert, long-term, inexperienced) using PI instruments especially for behavior change goals [Rapp & Tirassa, 2017]. Even those studies that explored self-tracking with reference to documentation of behavior, achievement of social benefits, and curiosity [Epstein et al., 2015a], did not strictly tie it to specific user groups' goals, situated needs and communities of practice, integrating their use into particular activities. As a result, we know a lot about the act of tracking per se, but far less on the use of these technologies within specific domains.

2.3 Understanding PI use among athletes

Previous work only incidentally connected PI tools to sports activities, by involving a minor quota of participants who are accustomed to self-track in order to improve their physical performances (e.g. running), or by recruiting users that track for fitness goals. However, they did not focus on how these technologies may present peculiarities when used for sports purposes. Recently, Tholander and Nylander [2015] tried to fill this gap, by asking three elite and seven recreational endurance athletes to describe how they used their GPSs equipped with heart rate monitors in their training practices. They reported that technology plays both an *instrumental role* in measuring performance and feeding data back to athletes, and an *experiential role* in supporting and enhancing the sports experience, allowing them to have a closer connection to their bodily experience. Previously, Wakefield et al. [2014] interviewed eight amateur endurance athletic coaches who tracked some types of athlete-related data, showing that it is important to track athlete-specific contextual factors such as injuries, illnesses, sleep, stress, and mood, as they allow coaches to tailor their training programs.

These studies represent a first step in the exploration of the athletes' practices in using self-tracking instruments. However, they only give limited insights on this topic, due to their particular research setting. First, they mainly involved amateur athletes leaving out elite ones, which, instead, could allow deeper analyses on how self-tracking technologies impacts on sports experiences. Tholander and Nylander [2015] did recruit three elite athletes, but the small sample size and its homogeneity (all of them were members of the Swedish national team of orienteerers) prevented the possibility of outlining a nuanced and multifaceted picture of the phenomenon. Moreover, they did not specify and discuss their inclusion criteria in the "elite athletes" category. To differentiate recreational (i.e. amateur) athletes from elite ones, they used the number of weekly training hours (recreational athletes unspecified, elite athletes 15-20 hours), and the number of training sessions per week (recreational athletes 3-7 sessions, elite athletes 9-13 sessions). However, the training load appears insufficient to define an elite athlete, since other factors might be relevant to distinguish the athletes' level of expertise [Swann, Moran, & Piggott, 2015]. Moreover, the authors did not differently present, discuss and compare the results coming from the two user groups. Second, they only considered endurance sports, including a limited number of disciplines: Tholander and Nylander [2015] actually did not specify the main sport of their participants (apart from the three orienteerers), while Wakefield et al. [2014] focused on track & cross country, triathlon and cycling coaches. Finally, the kinds of PI data collected by their participants were limited: the former study was almost exclusively focused on heart rate information, while most of the coaches interviewed in the latter were not using a PI device, but were keeping track of their athletes' performances through Google docs or pen and paper. Moreover, Tholander and Nylander [2015] did not frame the discussion of their findings in the PI discourse.

To summarize, although these studies provide some insights on how self-tracking is carried out in the sports domain, a research that investigates how athletes, and specifically elite ones, integrate PI technologies into their sports practices is in need. This would allow HCI researchers to understand how tracking technologies can respond to situated needs and goals. It would also show a "successful use case" of these technologies, since athletes appear to be highly motivated to use their tracking devices. Accordingly, we interviewed a variety of athletes in different disciplines, at different levels of expertise, and collecting different types of PI data.

3. METHOD

To investigate the impact of PI technologies on athletes' practices we interviewed 20 Italian athletes using semi-structured interviews.

3.1 Sample

We recruited 20 participants (mean age=31,7; SD=6,5; females=8) through recruiting emails and snowball sampling. We split the sample into two groups. The first group (mean age=32,5; SD=6,9; females=5) was composed of 12 elite athletes (E1-E12). To define an athlete as elite and classify her level of "eliteness" we followed Swann et al. [2015], considering the athlete's highest standard of performance, achieved successes, and years of experience at the athlete's highest level, as well as the competitiveness of sport in the athlete's country, and global competitiveness of sport. The inclusion criteria were that athletes 1) had been using one (or more) self-tracking device for at least three months and were still using it, 2) had competed at least nationally during their career, 3) had had successes at least at regional level, and 4) were still involved competitively in sports events. Based on the classification system proposed by Swann et al. [2015], five of the athletes were classified as competitive elite, five were classified as successful elite, and two were classified as world-class elite. The second group (mean age=30,4; SD=6,1; females=3) was composed of eight amateur athletes (A1-A8). The inclusion criteria were that they 1) had been using one self-tracking instrument (or more) for at least three months and were still using it, 2) were exercising at least three times a week, and 3) were spending at least five hours a week practicing; even though competing at amateur level was not required, five participants participated in amateur tournaments.

To increase the heterogeneity of the phenomenon under study, we included different sports in our sample, also recruiting non-endurance athletes. For endurance sports we mean “a sports activity by individual—i.e., non team—athletes in which key muscles are exercised at submaximal intensity for prolonged periods of time” [Segen's Medical Dictionary 2011]. In this category we included swimming, cycling, triathlon, ski mountaineering, cross-country skiing, alpinism and trekking. The non-endurance sports, instead, included soccer, free climbing, and sprint running. Finally, we also took into account the collection of different kinds of data. See Table 1 and Table 2 for the sample composition.

All participants owned a smartphone: they all used regularly the applications and mobile internet access on their phone. All participants were open to technology. However, only two amateur athletes were focused on technology (i.e. they worked in a technology company or studied technological disciplines) and they were also moderately adept at data analysis or statistics. Reasons for participation in the research were mixed. Some participants wanted to talk about the devices they were using, others about their sports experiences, others were interested in both aspects.

Almost all participants were relatively affluent, educated and numerate. The soccer players stopped studying in middle school. Four athletes held a high school diploma, ten a bachelor’s degree, and four a master’s degree. Background information was collected through a preliminary phone interview.

Table I. Sample – Elite Athletes

Elite athletes							
ID	Highest standard of performance	Success at the athlete’s highest level	Experience at the athlete’s highest level	Sport	PI Tool	Experience of use	Main data collected
E1	2nd tier professional league	Success at 2nd and 3rd tier	8 years	Soccer	Polar Heart Rate Monitor	2 years	Heart rate
E2	2nd tier professional league	Success at 2nd and 3rd tier	7 years	Soccer	OptimEye S5 Catapult	2 years	Distance, sprints, position
E3	International level	Success at 2nd and 3rd tier	10 years	Long-distance running	Garmin fēnix 3 HR	10 years	Time, distance, routes, pace, heart rate
E4	National level	Success at 2nd and 3rd tier	5 years	Long-distance running	Timex Ironman Trainer GPS with CARDIO T5K575	4 years	Time, distance, pace, heart rate
E5	International level	Sustained success in intern. competition	6 years	Cycling	Garmin fēnix 3 HR; Power Meter	7 years	Time, distance, speed, heart rate, watts
E6	International level	Sustained success in intern. competition	4 years	Free climbing	Moonboard application	1 years	Boulders
E7	International level	Sustained success in intern. competition	8 years	Ski mountaineering	Suunto Spartan; Suunto Smart Sensor	12 years	Time, altitude, distance

E8	International level	Sustained success in intern. competition	12 years	Cycling	Suunto Spartan; Power Meter	8 years	Time, distance, speed, watts
E9	National level	Success at 2nd and 3rd tier	15 years	Cross-country skiing	Garmin Forerunner 735XT; Suunto Ambit3 Vertical;	15 years	Time, altitude, heart rate, position
E10	International level	Sustained success in intern. competition	5 years	Ski mountaineering	Suunto Ambit3 Vertical; Suunto Smart Sensor	4 years	Time, altitude, heart rate, position
E11	National level	Success at 2nd and 3rd tier	14 years	Sprint	Garmin Forerunner 735XT	11 years	Time, pace, heart rate
E12	International level	Sustained success in intern. competition	3 years	Ski mountaineering	Suunto Ambit3 Vertical; Suunto Smart Sensor	3 years	Time, altitude, heart rate, position

We aligned the sample size to the common practices in qualitative research [Marshall et al. 2013] and to other HCI studies with similar design and purposes [e.g. Li et al. 2011; Rooksby et al. 2014; Lazar et al. 2015]. However, our sample followed the theoretical saturation principle first recommended by Glaser and Strauss [1967]: in other words, the decision of settling for 20 participants came when we realized that additional data would not have produced substantial new results for the aims of our study, following a data saturation criterion [Bowen, 2008].

Table II. Sample – Amateur Athletes

Amateur Athletes							
ID	Profession	Weekly workouts	Competitive amateur events	Sport	PI Tool	Experience of use	Main Data collected
A1	Information Technology Consultant	6 times / week	National	Triathlon	Garmin Forerunner; Garmin Edge; Garmin XT800; Soft strap heart monitor	7 years	Speed, pace, heart rate, calories, steps, sleep, stroke count/rate, routes
A2	Teacher	2-3 times / week	none	Alpinism	Garmin Forerunner 235	3 months	Position, steps, distance
A3	Office worker	2 times / week	none	Trekking	Garmin Vivo Active HR	3 months	Distance, heart rate, sleep, calories, steps
A4	Technical office personnel	3 times / week	none	Middle-distance running	Garmin fēnix 3	2 ½ years	Distance, altitude, routes, steps, sleep

A5	Insurance Broker	7 times / week	Local	Swimming	Garmin Swim	7 years	Lengths, pace, distance, stroke count/rate, calories
A6	Manager	6 times / week	National	Triathlon	Garmin Forerunner 910XT	8 years	Speed, pace, time, distance, routes, strokes
A7	Office worker	3-4 times / week	Local	Free Climbing	Moonboard Application	3 months	Boulders
A8	Freelance professional	6 times / week	National	Sprint	Forerunner 310XT	2 years	Pace, time, distance, calories

3.2 Procedure

The interviews were qualitative and semi-structured. They lasted between 40 and 70 minutes with an average of 58 minutes. Sixteen were conducted face-to-face, while four were completed via Skype.

Interviews aimed to develop an understanding of each athlete's orientation towards (i) their sports experience, (ii) their use of self-tracking devices, and (iii) how such use produced effects, if any, on their sports practices. We began by asking participants to describe the role of sport in their life, the meaning and the value they ascribed to it, and their "career" as athletes. Then, we asked them to outline how self-tracking devices were integrated into their sports practices as well as their habitual modalities of use. By elaborating along these themes, we asked participants to reflect on the impacts the devices had on their workouts, races, and social relationships.

We paid close attention to the terms they used to describe their experiences. We left participants free to explore unforeseen themes in the initial list of questions and, when necessary, we prompted them for clarifications with examples coming from personal histories.

Participants were not compensated for their participation. Each interview was audio recorded and transcribed verbatim for subsequent analysis. The data analysis followed open and axial coding techniques [Strauss and Corbin 1990] to link the collected qualitative data to the research questions. The analysis was inductively oriented. Findings were coded independently by the first and the second author who generated initial codes: data were broken down by taking apart sentences and paragraphs and by labeling them. Then, we reviewed the results segment-by-segment to assess consistency in defining the beginning and end of segments as well as the application of codes within segments [MacQueen et al. 2008]. All inconsistencies were discussed and resolved. The resulting codes were grouped and labeled independently by the two researchers, and then compared to solve inconsistencies.

4. RESULTS

None of the participants reports interruptions, temporary or otherwise, in the use of their instrument, showing continuity and perseverance both in their daily data collection and in the long term. Moreover, both groups report minimal barriers concerning their device. The most common problem is physical discomfort: this is relevant to specific sports (e.g. wearing a bracelet when climbing interferes with movements and the device can be easily damaged). Three amateur athletes also highlight problems in their data display asking for more immediate visualizations to allow for intuitive comparisons among different information. However, despite these rare concerns, they all describe their usage of the devices, during both workouts and races, focusing on their benefits, much more than on their shortcomings. Elite athletes, instead, report almost no issues in using their trackers.

We did not find relevant differences with reference to the use of self-tracking devices between endurance and non-endurance athletes. Instead, some of the individual differences we found were due to the peculiarities of specific sports (e.g., cycling allows athletes to look at their PI instrument even during the race). The most important differences, however, can be observed between amateur and elite athletes.

We will now outline the four main themes that emerged from the analysis. We will focus on how athletes make sense of their data, as well as how such data impact on their experience and on the sports domain. In the last sub-section of each theme (i.e., 4.1.3, 4.2.4, 4.3.3, and 4.4.3) we will elaborate on the results in order to discuss aspects that might be relevant for the design of future PI tools. In doing so, we will refer to the theoretical framework of constructivism, which has its roots in the works of Piaget, Bruner, and Goodman [Perkins, 1991]. Whereas cognitivism embraces an objectivist perspective on reality, and the goal of learning is to map the structure of the world onto the individual [Jonassen, 1991], constructivism sees knowledge as a function of how the individual creates meaning from her own experiences: the mind elaborates what it perceives in the world to produce its own unique reality [Ertmer & Newby, 2013]. In other words, what the mind knows is meaning-laden entities, and meanings can only be subjectively construed by it [Clancey, 1997]. Conversely, mind itself is actively constructed by the individual by acquiring new (self)knowledge. Often paired with the phenomenological approach in psychology [Rapp & Tirassa, 2017], which also stresses the subjective nature of our experience [Husserl, 1969], constructivism might help to understand how athletes make sense of their data.

4.1 Patterns of use

Most of the amateurs (6 out of 8) started to track out of curiosity and then found benefits in constantly monitoring themselves, noticing visible impacts on their performance. Elite athletes, instead, began their use of trackers mainly for convenience, when sport became a "serious matter" in their life: most of them (9 out of 12) emphasize the comfort provided by these tools. Both amateurs and elites access their data in more than one way: They visualize them directly on their devices, especially during workouts, while exploring them more in-depth by using their personal computer or smartphone, usually in the evening, after a training session or a race, or on weekends.

4.1.1 Exploratory use: Amateurs seek novelty and discovery

Several amateur athletes (5 out of 8) monitor a variety of data and seem interested in elaborating on them, looking at their correlations. A1 and A6, for instance, wish for more advanced functionalities that would allow for greater flexibility in combining the tracked variables: "*there are some screens where there are two axes and two variables, I'd like to have the possibility of changing some variables… but it's only out of curiosity, to see something different*", reports A6, highlighting how this need is often moved by a desire for discovery. A1, instead, has his own solution: "*I used ConnectStats on the iPad to have more elaborated graphs than those of the Garmin. I also used Excel to calculate the estimated time in the cycling part of the ironman… I made a sort of combination between my speed on the flat and uphill to understand the equivalence between the two velocities*". The remaining amateurs (3 out of 8) pay attention to a limited set of parameters, but sometimes enjoy exploring different data or functionalities of their device.

The *exploratory use* that all amateur athletes often make of their data appears, at first sight, to be aimed at increasing their self-understanding, allowing them to explore the factors that could influence their performance. However, on a closer look, PI tools do not provide a real guidance on how to select, compare, or interpret the collected data: these athletes have a serendipitous attitude, whereby no precise or stable objectives drive the exploration process. For example, half of the amateurs show interest in collecting data about calories, steps and sleep. However, they acknowledge that this has no immediate effects on their sports activities, because of the limited precision of the reporting instrument (calories), or due to difficulties in understanding the correlations between sleeping habits and performances: such information is explored in certain occasions to find novelties, or surprising patterns. For amateurs, comparing, analyzing, and elaborating data appear to be more a "combinatory game" than a means to deepen their knowledge.

4.1.2 Focused use: Elites pay attention to past data, trends, and anomalies

Elite athletes focus, instead, on the parameters and features that they consider important, leaving all the rest aside. E5, for example, thinks that "*if you want, there are features that allow you to plan the workouts, but I don't use them so much… I don't find them useful, I use my feelings, I mean, I have a schedule for the trainings, depending on the period, I follow it, but I manage it*". E9, instead, reports a shared opinion among the elites (10 out of 12): "*honestly I don't elaborate so much on the data, because I don't have time*". Elites have their own consolidated habits, which they do not want to disrupt, and exhibit an extremely *focused use* of their device.

During trainings, they all consider mainly the heartbeat and two or three supplementary parameters depending on the sport they practice (e.g. altitude, velocity and GPS position in ski mountaineering) in order to respect the target goals they have (e.g. remaining below a certain threshold). After the workout, most of the elite athletes (11 out of 12) compare the collected data longitudinally. In doing so, they look at their past data, even going far back in time, a practice that is less common among amateurs. E8, for instance, stresses that "*I go back over my data even three or more years*", while E7 "*I went as far as eight years back looking through the data*". Comparison with past workouts makes the data valuable for two reasons. First, it allows elites to bypass inaccurate information or missing values: they make sense of their data by considering differential variations and recurrences over time, more than by looking at "absolute" and singular values. Second, comparisons allow them to detect trends, which provide projected values in the future. Elites connect the variation of their performances over time with the workload and their perceived physical condition, in order to forecast their future performance: E3, showing her last year stats, explains "*These data give me a snapshot about what happened to myself from season to season. This year I increased my threshold of 4 heartbeats... It goes hand in hand with the reduced sense of fatigue I experienced in the last months. This means that I worked well and that I should keep at it*".

During races the device is almost not used, as we will see below, but after the race, almost all the elites (10 out of 12) look at anomalies, such as peaks and valleys, in their "target" parameters. They, then, try to relate such data to the context in which they occurred, for example using the path registered by the device's GPS. About her last race, E10 recounts how she extracts value from the collected data: "*I only searched for the peaks in my heartbeat. The firsts occurred in the first quarter of the race, I could precisely retrace the altitude and where I was on the map, so I remembered that I was trying to overtake the athlete in front of me, it was normal... I try to figure out an explanation for each anomaly in the data*". When they are not able to find a plausible reason behind a singular anomaly, they discard it as a possible device error. Conversely, if peaks or lows are recurrent, they dig until an explanation is found. Elites, then, turn "numbers" into meanings by retracing the reasons behind them and formulating precise hypotheses for their variation: this is made possible by connecting the data to a context, and by exploiting the knowledge they have about their sports practice and their own body. Such knowledge, which might also take the form of body sensations, as we will see below, is essential to make sense of the data.

To summarize, while elites exhibit a *focused use* of their devices using a very limited set of data and functionalities, such as those that aggregate information over long periods of time in order to detect seasonality, amateurs appear to be engaged in an *exploratory use* of their tools, often showing an interest in the data per se.

4.1.3 Constructing knowledge

The sports context allows us to see how certain technologies diversely impact different categories of users, even in the same domain. The differences in how PI devices are used by amateur and elite athletes can be retraced to the different knowledge they have developed while practicing their sport.

Elite athletes have a deep understanding of themselves, as well as of their discipline, gradually built through their personal experience, i.e. their continuous attempts to reach their physical limits and to exploit their body's potentialities. Moreover, this knowledge has been co-constructed with other professional athletes and coaches within the community of practice to which they belong, enabling a continuous learning. Learning is constructed in the experience, through the interaction with the environment [Maturana & Valera, 1980] and "through membership in a community of practitioners; and mastery is an organizational, relational characteristic of communities of practice" [Lave, 1991, 64]. Trackers contribute to develop athletes' knowledge, e.g. by providing them with fixed measures to which anchor physical sensations. However, as we will see in the following sub-sections, sense-making of data is based on the entire history of previous knowledge that athletes have built [Clancey, 1997]. This knowledge allows elites to select useful data for their situated purposes (e.g. trends), to decide what habits they should maintain despite the many features offered by their trackers (e.g. workouts planning), to develop workarounds to make sense of imperfect data (e.g. discard singular unexplained anomalies), and to understand when it is necessary to rely on objective measures and when to rely on subjective perceptions (e.g. during races). In other words, when they look at their data they see a thick description instead of mere numbers, because the data are actively (re)constructed by their knowledge. Moreover, for them data are only one among many sources of information to be taken into account when training and competing. Data are used instrumentally to achieve their own situated goals, and often play only a marginal role.

Conversely, for amateurs, sport is an important matter but they are not engaged in continuous exchanges with their "peers", they do not have a coach, and they are not immersed in a "cultural milieu" related to their discipline. As a result, their knowledge is developed to a lesser extent: this turns the use of PI tools into an exploratory practice, where no guide is present and data are "read" as intrinsically valuable numbers. This is not a bad thing per se. Amateurs are satisfied with their trackers, which positively affect their performance. However, this approach to the data might jeopardize the achievement of long-term goals, such as the construction of a deeper understanding of the athlete's body, the emergence of an awareness of her physical limits, and the development of knowledge about her discipline. The risk is to excessively "quantify" a given practice, fetishizing the data and missing the true meaning they actually bear.

What is important for PI research, therefore, is that the shared knowledge that is actively constructed by individuals within a community of practice –sport, health, or work communities – seems to be fundamental in yielding a "successful" integration of PI instruments into everyday life. Knowledge allows users not to be overwhelmed by data, as well as to easily interpret them. When we design devices for a specific domain, and not for a "general" tracker, more or less keen on self-monitoring, we should ask ourselves how we can favor the construction of such knowledge.

4.2 Body: Data and sensations

Amateur athletes track themselves to have an objective measure of their physical condition, to which they compare their daily performance in order to improve. A1, for instance, reports that such devices provide him with "*an awareness that you couldn't have before* [...]. *That is, if you're doing the same workout and you're swimming at the same speed, understanding time after time whether your heartbeats are different, this can tell you, in a very deterministic manner, whether you're well-trained or not, whether you're particularly tired or not*". A4 adds that by using the tracker "*you have objective data*". The emphasis on the objective and deterministic nature of the collected information signals trust: almost all amateurs (7 out of 8) see in their device a valuable help to enhance their sports results and are very keen on allowing it to regulate the rhythm of their workouts. Amateurs think that the variables measured by their instruments are reliable indicators of their performance. They believe, for instance, that reducing the "number" of heartbeats recorded by the heart monitor entails an immediate improvement of their performance.

All elite athletes, instead, appear not to accept uncritically the measures given by the instruments they use. They seem to question the objective validity that some physiological data may have for their sports practice. Not relying on the objectivity of data means that elites need other elements, coming from their own subjective experience, when they need to assess their performance, especially during races. E10 explains that "*During the race, I try not to look at it... I try to train my sensibility towards my sensations, to know how I'm doing, whether I'm going too fast, or too slow*".

4.2.1 Athletes might use data to learn how to "read" their sensations

The concept of *sensation* is recurrent among all the elite athletes, while it is occasionally mentioned by only two amateurs. E4 notes that the device may help in understanding *sensations*, especially when the athlete starts practicing a sport: "*the device helps you understand your sensation. When you do a workout and you have* *certain sensations, and you check the heart rate, if you're within the zone and you know how you feel, then you try to memorize it, and then when you are in a race or a workout, and you're without the heartbeat* [tracker]*, you try to understand in which zone you are, if you're in a medium that you can manage for the whole race. Or you're beyond, and then it's better to slow down… The watch helps you understand… You have to make some tests on yourself… before completely relying on sensation it's good to have the watch to give you some baselines*". This opinion is shared by other seven elites. The tracker can help an athlete build a deeper knowledge of her body, providing a fixed benchmark to which the sensations connected with a specific heart rate level can be compared: sensation, here, is sort of a "tool" to better understand one's own physiological processes, and the tracker can help learning how to use this "tool". More precisely, an anchor is needed initially to reduce the extreme variability of the body perceptions to a common ground. Data provided by the tool can then "teach" the athlete that different body sensations can be retraced to the same physiological condition, e.g. a certain heart rate zone: for example, the athlete learns that, when she is pushing too much, the body sends signals that may differ from time to time, depending on the context (e.g. the weather) and her physical preparation. Gradually, the athlete becomes aware that her body can provide more fine-grained information about each performance. In other words, the body becomes meaningful, and the data are turned into a supplementary source of information, e.g. to assess the physical condition over extended periods, as we have seen above.

4.2.2 Sensations embed a knowledge that data cannot represent

Actually, most of the elite athletes (10 out of 12) specify that "sensation" has a wider meaning that goes beyond the feeling of being in a certain heart-rate zone: sensation exceeds what the instrument is able to record. E7 stresses that "*the watch is a machine and measures your activity as if you were a machine, but the human body… there is a mental part and other mechanisms that the watch can't compute*". While E3 goes further into detail: "*To use sensation means that I search some reference points in my body, the rhythm of the hair on the shoulders, how the foot hits the ground, if it's heavy, or more round… I can feel it from the push of the arms, how I'm working, even from the sound of the air on my ears*". This additional information is momentary and contextual to a specific situation, and can also be referred to the athlete's perception of the external conditions (the environment and the opponents). For example, E3, remembering a recent race, highlights that she often regulates her rhythms on the basis of her opponents: "*when I'm near someone, I try to understand what I can do on the basis of my and her breathing… if I feel that I have my breath under control, and I feel that the other person's breathing is more labored, from the sound of her breath, I have some possibilities to try to wear her out with actions that can be more or less strong*". E1 further explains that in sports like soccer, a complete quantification of the performance is impossible, because the outcome of a team is affected by variables that go beyond the physical preparation of the single athlete. Such information, therefore, is presumed as undetectable by the device, and when elites need to assess a specific performance or monitor their physiological parameters in an important occasion (i.e. races) they prefer to rely on this "subjective" knowledge.

This is the reason why several elite athletes (7 out of 12) keep a diary of their sensations: E3 reports that "*I have the habit of writing a diary, so I can also write the sensations tied to the specific performance that I did*". Diaries allow to "translate" into words a form of implicit and intuitive knowledge that would otherwise be lost. Writing is a means for objectifying something that is extremely subjective, so as to make it available for further reflections. Elites athletes that register their sensations use them to enrich their past data: by remembering how they felt in a particular period of the year they understand the reasons behind their performances, and assess their past physical condition better than if they only had their device records. However, such habit is not shared by all the elites, since several of them (5 out of 12) find this task too burdensome to be regularly kept in the long term.

4.2.3 Solely relying on objective data impoverishes the athlete's experience

This gap between the "objective" measure of the device and the "subjective" feeling of the sensation is so evident that elite athletes highlight the risks of exclusively relying on the collected quantitative data, a risk that they observe especially in the amateurs. E11 emphasizes that "*it happens to see athletes, non-professional athletes, athletes of the next generation… you tell them 'run slow for an hour' and they're not capable of running slow because they don't have a reference, they don't have the watch that can tell them that they're running slow, they can't manage themselves*". The narrower vision that the device seems to produce may also undermine the athlete's performance during the race. This is a reason why the majority of elite athletes prefer not to wear, or at least not to look at, the tracker during competitions. E10 well explains how "*there are so many factors in a race that can mess up the heartbeat a bit, that I don't want to be influenced… So many times you feel good and you push forward, and maybe the heartbeat goes beyond the rate that you think you should keep, and maybe by looking at the watch you get frightened thinking that the rhythm that you're keeping is wrong, when maybe your body is actually adapting itself and basically everything is going well*". An exception to this shared attitude can be found in cycling: here the availability of the power meter, an instrument that measures the work the cyclist is doing with her legs, which is directly tied to her performances, may waive the constant focus on sensation. Talking about it, E8 notes that it allows for predictions on the evolution of the race: "*It provides information truly grounded in your performance… Your weight is such, you exert such force on the pedals and you go at that speed* […] *if I know that my threshold is 390 watts, and I begin the rise to 390 watts, I know that for 40 minutes I can keep it, and I'm never wrong*". However, the use of such devices is not exempt from hidden costs: in E8's words, shared also by E5, it clearly appears that "*It becomes a bad thing, because you become truly a machine. And it's a bad thing because sport, in my opinion, must be a little romantic, must value sensations too*".

To summarize, if amateurs deeply believe that the objective measures collected by their devices are the most important thing to be considered when assessing their performance, elites know when it is necessary to trust in their subjective sensations more than in the numbers provided by the PI tools.

4.2.4 The mechanical body

Although most PI instruments are primarily addressed to detect and collect body signals, previous empirical studies on PI users paid little attention to how the body and its perception may be affected by self-tracking. Exceptions might be found in Rooksby et al. [2014], who only incidentally noted that PI devices may tie into body image problems, and Lazar et al. [2015], who highlighted how trackers may be uncomfortable for the body. This gap has been apparently filled by Tholander and Nylander [2015]: they stressed the notion of *feeling*, which emphasizes a variety of felt dimensions in the athlete's practice in relation to her body.

Our findings, instead, point to the wider notion of *sensation*. On the one hand, this term embraces a series of physical perceptions that amateur athletes need to learn to regulate their body reactions: trackers may help them develop this knowledge, as E4 well explained. On the other hand, sensation assumes a wider meaning for elite athletes, referring to all those perceptions that cannot be captured by computational means: computation actually risks transforming the body into a mechanical entity, constrained to respond to the incoming data within a continuous and unavoidable feedback loop [Ruckenstein and Pantzar 2015].

What we want to highlight here is that all the benefits, in terms of increased performances, that PI technologies are promising to bring in the next years might meet a counterbalance in the impoverishment of the athlete's self-understanding, as well as in her loss of agency and control over her body. Lupton [2013] highlights that trackers appear to extend the capacities of the body: however, they conceptualize it not as a "sensing organ through which one gains self-knowledge but, instead, a data generating device that must be coupled to sensor technology and analytic algorithms in order to be known" [Schüll 2016, p. 10]. As a result, on the one hand, technology constructs a totally quantified, objective, and "aseptic" body knowledge where data substitute "meaningful" body experience. On the other hand, the repository of body knowledge shifts from the internality of the subject to the externality of the device, entailing the athlete's subservience to technology [Lupton 2012].

The threats described here are also important for all those contexts where PI devices are currently transforming physiological processes into information fluxes. In the health domain, for example, the quantification of the patient's whole body may jeopardize her living experience, moving to the background her visceral sensations (e.g. pain, or her sensations about her illness), in favor of a medical practice based solely on "pure" data. As a consequence, this would make the patient's voice less heard, dehumanizing the doctor-patient relationship.

4.3 Social practices: Sharing with and presenting to others

4.3.1 Amateurs share their data to connect with significant others

Amateur athletes often train with their friends, significant others, or colleagues so that their sports experience becomes a shared one. Trainings are usually fitted in between their working schedule, e.g. at lunch time, or just before returning home. Time, frequency and modality of training appear to be dependent on these athletes' social networks to a certain extent, as amateurs often coordinate with others, or decide to postpone a workout on the basis of their personal needs. In this perspective, self-tracking devices might become a means to strengthen a relationship, whereby data become shared meanings that support communication and enjoyment in spending time together. It must be noted that most of the amateur athletes (6 out of 8) share their data mainly with friends or significant others. This is framed as a playful and recreational activity, where the aim is not to compete but to have fun. A3, for example, exchanges her data only with her partner: "*We look at our data on the website, or we directly compare them on our devices. There's also this feature for sharing data between us.* […]. *Then, I tell him to do the same trail in my same conditions,* [...] *and then we will compare our data. But it's only a game, to make fun of each other*". While A4, who runs mainly with his colleagues, explains that "*yes, we joke. For example, we're in the factory and there are people that have our same device, and we see that they've done this and that. Maybe there's one colleague that's in the* *top five of a segment and then we tell him 'ah you're in the top five!' but we're only joking around*". Data here do not matter for their intrinsic value, i.e. because they represent a performance, but are reinterpreted as material to play with; devices, instead, are used to connect people, especially when they are not physically present in the same place.

4.3.2 Elites share their data to convey a specific image of themselves

A different, more nuanced and somehow strategic attitude toward others can be found in elite athletes. They do not train with their significant others. Actually, most of them (8 out of 12) train mainly alone, while the remaining ones work out with other athletes at more or less the same level. They are well disciplined and strictly comply to their workout program. In other words, their daily routine is built around their training schedule. The device connects them with a social network of other elites, without extending to the sphere of personal relationships, which do not influence their sports activities at all. The social milieu in which trackers are used, therefore, is different from that of the amateurs.

The majority of elites (11 out of 12) use the social features of their devices instrumentally, to obtain information to exploit during the races, to expand their connections, or to convey a specific image of themselves. This is mainly due to the competitive frame in which they move. In such a frame, sharing data becomes a means to acquire more visibility, rather than to affirm friendship. E4 and E9 well exemplify how the application's social features may be used to develop new "instrumental" social relationships: "*Yes, I've enlarged my circle, uploading the results of what I've done to Strava or Garmin Connect* [...]. *And then, maybe they* [other athletes] *start following me, and send me a message, or maybe befriend me on Facebook, just because we share the same sport*", says E4.

The competitive frame entails that data are never exposed without a careful consideration of their public impacts. E7 explains that "*you have people following you, and maybe you're doing a workout and you achieve a strong result, people see it, because there's a leaderboard and all the rest"*; so when the athlete goes to the competition she cannot say *"'Oh I'm so tired, I didn't exercise'. Instead, now if you are on Strava, you cannot tell them that you didn't work out*", E7 adds. The exposition of the "truth" about the athlete's physical condition and performances implies the search for tactics aimed at concealing the "real" data, or misleading the competitors. This attention increases as the level of eliteness of the athletes raises, as confirmed by most of the successful and world-class elite participants (6 out of 7). E8, for instance, says that "*you can share your workouts and hide your physical parameters. I mean, I publish the kilometers, the distance, but who sees that cannot know my heart rate… you know, one cannot lay all the cards on the table*". Therefore, some kinds of data are considered more revealing of the athlete's physical condition than others, and professional athletes carefully select what is advantageous to share and what is better to hide. In fact, trackers support such strategic perspective on data, allowing to share only the information that the athlete wants to publicly display. Such functionalities are considered fundamental by the world-class elites, since the active construction of the athlete's public data sets may also help in creating a public image of the sportsman, in order to tell a story in which others may project themselves. E7 explains that some athletes publish an "enhanced" version of their performances through posts on social network sites: "*'I made 300000 kilometers this week'… That's just some bullshits, they say it to create the myth, to create the legend [...] But for someone who doesn't know the discipline in deep… it might appear an amazing* *result*". Therefore, the possibility of deceiving others through the selective sharing of data sets, or the posting of exaggerated narratives, is part of the active construction of the athlete's public identity, as well as a "game strategy".

4.3.3 Social identities

Although many commercial and research PI applications include social features [Epstein et al. 2015b], empirical studies highlighted that PI users show different attitudes towards sharing. Fritz et al. [2014] emphasized that trackers are inclined to compare their data with peers in order to motivate themselves. Rooksby et al. [2014] stressed that personal tracking is often social, and PI users often track with families, friends and coworkers. Rapp and Cena [2016], instead, highlighted that inexperienced self-trackers prefer not to share their personal information, fearing the possibility of losing control upon it. Tholander and Nylander [2015] showed that athletes had difficulties seeing any personal value or purpose in sharing features, as physiological differences between individuals make it difficult to compare and interpret someone else's heart rate.

Our results highlight a different aspect: amateurs and elites ascribe different meanings to sharing, as they exchange their data within different social contexts. This leads to the construction of different identities, as different social relations yield different ways of defining both the individual's self and that of the other [Andersen, Chen, & Miranda 2002; Kelly, 2005]. Amateur athletes build the use of their devices' social features on their existing intimate relationships, using data sharing to increase opportunities for intimacy while doing sport. Sharing, here, contributes to present their "true self" to significant others. Elite athletes, instead, see sharing through a utilitarian lens: data exposure becomes a means for concealing their "true self" and conveying a carefully and intentionally designed identity to achieve goals that pertain to the sports practice. They use the data to move competition from a physical level (that of performance) to an intellectual/strategic one (that of deception), where the "other" is constructed not as a "friend", but as a "rival" or an "audience", within a competitive relation.

These practices, which resemble the Quantified Selfers' sharing practices intended to create and express their identity [Sharon and Zandbergen 2016], point to how individuals might "reappropriate" their data, overcoming the designers' intentions. While PI design often focuses on providing a greater accuracy of the collected information [Mackinlay, 2013], elite athletes show that it might not be a primary concern. Actually, accuracy may represent a counterproductive feature exposing the athlete's weaknesses; whereas in other domains, such as work, a constant flux of accurate data could turn into a regime of surveillance. On the one hand, this attitude towards data accuracy might lead to reframe the design of PI tools in a variety of contexts, allowing users to manipulate their data to convey the self-image they want to expose. On the other hand, supporting the malleability of data could help "amateurs" understand that data are not fixed entities and valid per se, but could be used and modified to achieve their situated goals.

4.4 Being coached

4.4.1 Amateurs are self-coached and do not find concrete training support in their device

Most of the interviewed amateur athletes are self-coached (6 out of 8), since they do not consider themselves "*good enough to have a real coach*", in A3's words. For them, the device seems to be the only external help they have. A6, for instance, says that "*It gives you the possibility of recording your previous workout and then you can compare yourself with that, you have that ghost that shows you whether you're behind or ahead of it*". Apart from the occasions in which they share data for fun or connectedness, thus, their data collection, exploration, and interpretation are mainly solitary practices. Amateurs use their data as a support for better tuning the training, but this activity is carried out on their own. Actually, some of them (5 out of 8) wish for a greater active support from the tool that should somehow fulfill the role of a real coach. A4, for instance, stresses the importance of having "*something that tells you 'ok, keep this rhythm', or 'you're below the rhythm that you need to achieve your goal'… maybe the current devices are lacking on this aspect*".

The ones who do have a coach (2 out of 8) do not hold a professionalrelationship with her. A1 says that "*he isn't an official coach, he does me a favor*", and A5 further explains that "*he's a sports doctor, now he's following me for the medical examinations and sometimes he gives me some suggestions. I see him once a year and sometimes I call him*". This kind of relationship only allows the athletes to consult their "coaches" sporadically: data exchange with them, then, is limited to exceptional occasions. A5 says that "*I send him my data only when there are unexpected drops, but it rarely happens*". For these amateur athletes, the tracker fulfills the function of a messenger that can register and report some important information, e.g. anomalies or significant progressions, which may justify a considerable change in their training programs.

This lack of "training support" from their device is associated with the exploratory use we have described in Sub-section 4.1.1. To tune their trainings, most of the amateurs only have the "objective data" to trust. When they correlate information or formulate hypotheses about their performance, they have to proceed through trial and error. This process, nonetheless, leads to wandering, rather than to develop new training strategies and a deeper self-knowledge experience.

4.4.2 Elites review their data together with their coaches

For professional athletes, instead, trackers can mediate the relation they have with the coach. All elite participants, except one, have a coach. In most cases (9 out of 12), the athlete sends the data to the coach, they look at the data together, and finally the coach defines a new training. Coaches consistently follow elites, developing all their workouts.

Commonly, at the end of the week, the athlete reports whether she exactly followed the coach's instructions, or diverted from them, e.g. due to her physical condition ("*not because this week my heartbeats don't rise*", E12), to allow the coach to understand whether the assignments worked or not, and avoid overtraining. Then, the athlete and the coach start reviewing the data together: E10 says that "*she has my account's password and she checks everything… if she sees that I've done this and that, she asks me the reason for it, if there was anything particular… what kind of sensations I had… and then we review the data together*". This review process consists in connecting all the data that might be relevant (for example because they present anomalies) with the sensations experienced by the athlete. This information is crucial to ascribe meanings to data: on the one hand, athletes help coaches contextualize the numbers; on the other hand, coaches help athletes explain why certain sensations are connected with certain variations in the data, contributing to develop their body knowledge. E11 explains that the first time he reached and maintained 175 heartbeats, his coach told him that "*it means that we trained better,* *that your body is more rested and in a better shape, we must keep it*". Whereas E3 stresses how her coach made her understand her limit by "*feeling my body... he told me 'push until you have an iron taste in your mouth, this is your limit'*". This advice also impacted on how she later interpreted her data, since she started considering a high heart rate a significant "alarm" only when paired with that physical sensation.

Although this process is initially led by the coach, as the athlete's experience with the device increases the two parts collaborate more, exchanging hypotheses on the data. E7 describes a recent episode that is recurrent in most of the participants' recounts (7 out of 12): "*it happened last month... my coach was pretty sure that I wasn't keeping the heart-rate threshold because I wasn't pushing as I could... I hypothesized that it could have been related to the fatigue coming from the last season... This made him understand how tired I was and read the data differently*". Besides the solitary practice of displaying and interpreting data, then, elites pursue a shared understanding, where meaning is built in the constant confrontation with their coach; in turn, such confrontation contributes to develop the knowledge that elites precisely need to read their data on their own. An exception (2 out of 12) is represented by those cases in which the interpretation is totally driven by the coach. E1 and E2 both highlight that in their team data are held by the coach, and the athletes do not have direct access to them. E2 explains that "*he downloads the data, looks at them, controls them*". Here, the coach is the gatekeeper of the collected data and decides what data are relevant, how they should be read, and how to make them actionable: *"he explains to me whether I run well or not* [...] *if I looked at the GPS, at the downloaded data, I wouldn't understand them as much, and honestly I'd have to ask him what is good and what is bad*", as E1 stresses.

Finally, the coach defines the training for the subsequent week. To set a personalized workload, the coach usually starts from a target parameter, which might vary from sport to sport, but is commonly represented by the heart rate: *"on the basis of our heartbeats, he defines a program to make us work on specific aspects"* E2 says. For example, by working on intensity rather than on resistance through an increase of the number of twitches, E2 further adds. In doing so, the tools' data are not used alone, but connected with the information about the previous workouts and the athlete's sensations, as well as with the overarching athlete's goals. E12, for instance, explains that "*this year I have the objective of reaching the podium in the world championship. My coach distributes the workload over the year keeping this goal in mind*".

Elite athletes never question assignments, they show a total trust in their coaches' advices, following their instructions literally. E10 explains: "*I'm an automaton. If he says 'keep running for two hours at 145 heartbeats' I do it'*". However, what is important here is that trainings are assigned not in the form of mere numbers, but often explained in their rationale, so that the athlete figures out the reason behind the coach's choices: "*he defines a scale, with some averages, for each of us. He doesn't give us just numbers, he has a scale built on our workouts, and he tells us if we were below, above, or within our averages*", E1 explains.

The "typical" elites' training path we outlined above shows how data are turned into meanings and made actionable within a collective interpretative frame, where both the coach and the athlete contribute to build a knowledge base that enables a fruitful use of the tracking devices.

4.4.3 Interpretative power

The relationship between athletes and their coaches represents an important part of the sports activity. Wakefield et al. [2014] found that amateur athletic coaches feel that it is important to know athlete-specific contextual information, in order to evaluate, adapt, and improve the athlete's training. In our study, we pointed to the athletes' interpretative goals rather than to the coaches' information needs. While most of the amateur athletes are not used to lean on the advices of a coach, relying instead on the (little) help provided by the PI tool, elites widely exchange data with their trainers, making a practice of shared understanding visible, which helps them define their workouts. This aspect reflects the way Quantified Selfers discuss their data together, offering knowledge to others, while getting some in return [Sharon 2016]. Coaches formulate hypotheses and guide the elite's interpretative process, until she gains a sufficient understanding to almost act as a "peer".

Here, the interesting aspect is that the mutual exchange between athletes and coaches might be configured as different grades of hierarchical "power". Amateurs who have a coach remain the "owners" of their data, being only in search for a sporadic support in order to translate them in effective workouts. However, they may remain in an "inferior" position with reference to the PI tool, given its presumed authority. Elites and coaches, instead, are almost peers regarding the gathered information: their ownership is shared equally between them and the meaning of the data is constructed through a continuous bidirectional exchange. In some cases, however, the coach may have a privileged or almost exclusive access to the athlete's data, and be completely in charge of the interpretation process. In this perspective, therefore, knowledge means power, and it needs to be shared to establish horizontal relationships. By explaining the reasons behind their assignments, and by teaching athletes how to interpret their own data, coaches bring their position on the athlete's level. This needs to be considered when designing PI tools aimed at substituting real coaches, or at addressing specific domains that might involve individuals at different degrees of interpretative power.

5. DISCUSSION

Studying a specific category of PI users, such as athletes, allows to see how PI tools might penetrate a given domain, with its own social structures and practices. Table 3 presents a snapshot of the differences we discovered between amateur and elite athletes, as well as relevant related research within HCI. It shows that elites represent an idiosyncratic category of PI users, as they have well integrated self-tracking into their practices. This, on the one hand, emphasizes that tracking might be appropriated by individuals who have their own situated goals and needs. On the other hand, it suggests that some "best practices", carried out by certain individuals, can be translated to other categories of users, preparing designers to develop future tools addressing contexts with specific features, such as health, learning, and work.

Table III. Comparison of our main findings with previous research

Key points	Amateur athletes	Elite athletes	Previous research
Main motivations to track	Improving performance, curiosity.	Supporting sports practices, comfort.	Behavior change [Li et al. 2010, 2011; Fritz et al. 2014; Choe et al. 2014]; remembering [Li et al. 2011]; goals, documenting, diagnosis, rewards, pure interest in technology [Rooksby et al. 2014]; behavior change, instrumenting an activity, curiosity [Epstein et al. 2015a];

			playfulness and curiosity [Rapp and Cena, 2016].
Patterns of use	Exploratory use: exploration of different data and correlations motivated by curiosity; elaboration on collected data	Focused use: focus on specific parameters; little to no elaboration on collected data.	Use of written charts or spreadsheets to better analyze the collected data [Li et al. 2010; Rooksby et al. 2014]; deep examination of the collected data and self-experimentation [Choe et al. 2014]; superficial exploration of data and willingness of immediately discovering useful or surprising insights [Rapp and Cena 2016].
Data and sensations	Trust in the objectivity of the monitored parameters	Preference in relying on subjective sensations	Importance of feeling; the device may help in better understanding the feelings, since they are tied to physiological parameters, like heart rate [Tholander and Nylander 2015]
Sharing	Sharing with friends or significant others for fun or to reaffirm existing relationships.	Public sharing to Social Networks to increase connections or convey a specific self-image.	Rooksby et al. [2014] noted that PI users track with families, friends and coworkers; Fritz et al. [2014] emphasized that long-term fitness trackers compare their data to motivate themselves or compete; Tholander and Nylander [2015] stressed that athletes are not interested in sharing.
Coaching	Self-coaching. PI tools do not guide them in the understanding of data.	Trained by a professional coach. Athletes and coaches review the data together	Amateurs' coaches need to know contextual information to define the workouts [Wakefield et al., 2014].

A way to tie the results together is to highlight that elites are engaged in a highly structured sports practice, whereas the amateurs' practise is much more "vague". One of the key differences between elite and amateur athletes is the difference in clarity of goals. Elites have specific objectives to achieve (which might come, for example, from the coach) and know the precise "paths" to accomplish them, while amateurs do not show the same focus, apart from enjoying their training and challenging themselves. For elites, this implies routines, rules and tasks to be followed. Amateurs, instead, are less able to define goals, seeking help in their PI devices without finding any real support. Similarly, the elites' sports experience is driven by more precise values than that of the amateurs. Understanding the body is an essential competence that is worth learning, despite all the efforts that it requires, and the imperceptible gains that it might provide in the short term. Amateurs, instead, do not know what is really worth attending to, and consequently are less capable of exploiting their data to improve themselves. Furthermore, elites are engaged in highly structured communities of practice, where roles (e.g. trainee-coach) and relationships (e.g. rivalry) are well defined. Amateurs, instead, are embedded in a much more blurred social context, where friends might become training companions, and coaches might not be stable reference points. These findings could orient the design of future PI tools for the amateur domain suggesting that trackers should provide more structure and guidance to amateurs' experience. For example, they should recommend precise objectives to be accomplished as well as detailed ways to reach them. Moreover, they should highlight values to be pursued, and priorities to be considered, stimulating the user's commitment to engage in overriding activities for their whole sports experience. Finally, they could provide a social space with technical support, where positions are clearly traced and athletes can know whom to ask for help. By and large, these suggestions could work for every domain where a category of "inexperienced" individuals has to use PI data (e.g. patients that have to track body symptoms or physical activity but do not have a deep knowledge of their chronic condition).

The successful use that elite athletes make of their self-tracking instruments points to further opportunities for PI design. On the one hand, it highlights that "expert" individuals have learnt to assign the "right role" to their PI devices, adapting them to their preexisting habits, as well as building use on their situated knowledge. This role is never predominant, and always serves their ends. On the other hand, it emphasizes that "inexperienced" individuals might give excessive importance to data, holding a misperception of the trackers' limits and potentialities, ignoring especially the benefits they might provide. For PI research, this entails to move the practices in which self-tracking is situated, rather than data collection, management, and visualization issues, to the foreground,. Making data more understandable [e.g. Epstein et al., 2014] might not be sufficient if "amateurs" are not taught when they should use them. This would mean to design PI tools that do not aim to pervade the user's activity in a certain context, but are capable of recognizing when they are not necessary, or even counterproductive to the users' values and goals. This would imply to design also for non-use [Satchell & Dourish, 2009], for example by introducing self-inhibiting options to prevent the use of certain functions at a certain time [Pierce, 2012]; or by exhibiting limits and impossibilities, rendering clear when individuals need to rely on other means to achieve their goals.

In the next Section we will proceed to outline more articulated design suggestions to improve the design of PI instruments addressed to the sports context, and, more generally, to specific situated practices.

6. CONSIDERATIONS FOR DESIGN

The following design considerations do not focus on technical aspects and are kept on purpose at a high level of abstraction so that they can be used even in contexts that do not pertain to sports. We want to outline different perspectives, both theoretical and practical that may open new opportunities for PI designers, more than specific design guidelines.

6.1 Design for learning

Over the years, the PI debate has been largely dominated by an emphasis on the intrinsic value of data, which could be extracted through a thorough examination of correlations among variables, regardless ofthe wider context where they were collected [Rapp et al., 2016, 2017]. Recently, Rooksby et al. [2014] argued for a description of people's real practices when tracking data, whereas Nafus et al. [2016] stressed that designers should carefully consider the fundamental unpredictability of what people see in their data. Despite the increasing attention to the situatedness of data usage, studies exploring how PI tools can help people learn to integrate data into their practices are still rare.

In this regards, we want to emphasize that people can better exploit PI tools for their own purposes when they bear a deep knowledge of the practice in which they are situated. Instead of providing mere numbers, the device should favor the development of such knowledge in less "expert" individuals. In doing so, PI could rely on constructivist approaches for learning, which emphasize the need for e.g. building on real life experience [Jonassen, 1994], creating a safe environment for learners to express themselves freely [Hamilton, 1996], or involving collaboration with more capable peers [Huang, 2002].

The PI instrument should help "amateurs" formulate hypotheses about their data, supporting them in developing an interpretative competence. For example, it could prompt different explanations accounting for a certain data value or trend, each with its own degree of probability, calculated on contextual factors and the athlete's history (e.g. weather, previous workouts, presumed exertion, similar situations). Moreover, it could highlight anomalies in the data that do not fit with the athlete's trends, also proposing not to consider them when a likely explanation is not available. It could also suggest ways to put into test such hypotheses. This may shift people's attention from numbers to the experiences and reasons that generated them. Karkar et al. [2016] noted that patients with Irritable Bowel Syndrome come to learn their potential triggers through trial and error, and proposed an application that automates experiment design and suggests a study plan to test hypotheses. This shows that this approach could be applied even in domains other than sport.

Drawing on Schön's notion of reflective practicum, Slovak, Frauenberger, and Fitzpatrick [2017] stressed that designers should scaffold the learning process to facilitate reflection around experience. In this perspective, the PI instrument may directly act as a "trainer", taking inspiration from how real coaches instruct elites. For instance, the PI tool should avoid to simply present training recommendations (e.g. "You should rest for 24 hours"). On the contrary, it should 1) explain the reasons that rest behind such suggestions (e.g. "Because this week you trained for ten hours, and when you did so you got very tired"); 2) give suggestions triggered by the amateurs' current condition, pointing to how their behavior works or not, and to alternative solutions; 3) provide "simulations" where amateurs can experiment elites' experiences and see how they might achieve short-term and long-term goals; 4) make their progresses more visible, for example with reference to the process of developing their body knowledge, or by fostering their motivation to gain such knowledge, e.g. exploiting gamification techniques designed to elicit intrinsic motivation [Rapp, 2017].

Slovak et al. [2017] further emphasized the role of the mentor and peers in scaffolding the learning processes. PI tools may then support the admission of amateurs into elites' communities of practice, by creating online communities where less expert users can learn from expert ones. This might be achieved by designing small and "safe" groups of discussions, where people would be more inclined to publicly share their doubts or to listen to others, or by leveraging mechanisms of mentorship. PI systems, then, could provide support to the mentors themselves so that their advices may become more effective [Slovak et al., 2017]: for example, elites could be instructed with the amateurs' needs and habits, or prompted with questions to guide their interaction with them. At the same time, PI tools could shape the amateurs' experience around post-training debriefs with elites.

6.2 Design for the living body

Within the common rhetoric of PI, numbers appear scientifically neutral compared to the less reliable data that one's instincts or physical sensations may generate [Lupton 2014]. Our findings, instead, show that elite athletes learn to distinguish when it is appropriate to rely on PI data, and when they need to trust their own sensations. These opposite perspectives somehow mirror the current contrast between the dominant framework employed in PI, focused on behavior change and effectiveness, and the phenomenological approach that is starting to be considered in PI research [Ayobi et al. 2016]. Building on the work of Rooksby et al. [2014], Epstein et al. [2015a] first proposed to shift the focus of PI from behavior change to how the tracking practices are experienced in everyday life. Elsden et al. [2016], then, reaffirmed the need of analyzing how PI data are made accountable in people's daily routines; whereas Ohlin and Olsson [2015a] and Rapp and Tirassa [2017] explicitly argued in favor of framing PI technologies within a phenomenological framework. Phenomenology has been proposed within HCI as a lens through which to look at the body [Svanæs 2013]. The lived body, as defined by Merleau-Ponty [1962], is the body as experienced by a person as herself, which points to the importance of the feeling dimension in the user experience [Svanæs 2013].

Following these insights, we suggest framing the athlete's body in a phenomenological perspective, as a *living body* (recalling Merleau-Ponty's definition), that is the body experienced from a first-person point of view. By exclusively providing quantitative information, self-tracking devices risk to transform the natural regulative process of the body into a merely intellectual activity, where the body is tuned by the athlete through continuous, data triggered, rational choices (e.g. looking at the current number displayed by the device, and then deciding to increase or reduce the power until the target number is met). This implies a third-person perspective on the athlete's body, valuing its exogenous adjustment.

The living body, instead, calls for the exploration of novel interaction modalities that support its internal regulative mechanisms, which are subjective and visceral. For instance, the device may exploit channels that directly talk to the body, by leveraging sounds, tactile feedback, or heat; or it may recommend that athletes pay more attention to certain sensations that they are experiencing, for example by amplifying their bodies' sensations, or by representing them metaphorically. This would more strictly tie the tool to the athlete's body, allowing for the incorporation of the instrument into one's own body schema, i.e. the way we represent the body to ourselves: in other words, PI tools would become *ready-to-hand* prostheses [Heidegger, 1927/1990; Svanæs 2013], extending the body capabilities instead of substituting them.

A phenomenological perspective also entails that what the body perceives is not abstract objects or dematerialized information, but subjective, embodied meanings. Designers could also experiment new ways to present the collected data, by providing evocative images of the body's performance (e.g. by using avatars), instead of mere analytical information. Such solutions could also restore a "romantic" take on the sports experience, and help amateur athletes learn to listen to their body. Moreover, PI tools could support athletes in easily annotating their digital data with the bodily sensations felt during a race or a workout. On the one hand, this would help those athletes who are now used to keep notes on paper diaries, by saving this important information. On the other hand, it would help amateurs reflect on their body sensations, transforming them into meanings to be remembered, making the data more "qualitative".

6.3 Design for self-presentation

The entire discourse of PI revolves around the concept of self-knowledge, which entails the idea that personal data might render the "true" nature of the individual visible. The Quantified Selfers' practice of self-experimentation [Choe et al. 2014] is precisely aimed at using data to isolate the "real" factors that may affect a certain condition (physical or psychological). In this perspective, quantitative data appear exact [Lupton 2014]: they do not lie, unless the collecting instrument is inaccurate. This explains the many concerns for accuracy within PI research [Kay et al. 2013; Mackinlay 2013; Yang et al. 2015].

The results of this study somehow suggest to reverse this assumption, namely that trackers should always serve the "truth". As a matter of fact, they might be even call for concealment or deception. Deception has been studied within HCI, being traditionally seen under a negative light. Research focused on eradicating malicious interfaces [Conti and Sobiesk 2010] and recommended not to "lie to the user" [e.g. Rubinstein and Hersh 1987]. Recently, HCI community recognized that designers may be allowed to design for a benevolent deception [Adar et al. 2013], and that people commonly modulate what they share online [Hancock et al. 2009]. Van Kleek et al. [2016] explicitly argued for a design capable of assisting users in pro-social forms of online deception. O'Kane, Rogers, & Blandford [2015] noted how people can hide their health tracking devices in uncertain social situations or show them off to achieve a purpose, framing these phenomena in Goffman's theatre metaphor of onstage and offstage behavior [Goffman, 1959]. From this point of view, "deception" may be better framed within the concept of "self-presentation".

PI tools could provide features that allow athletes to use their data to convey different images of themselves, depending on their goals: when they are used "onstage" they should be seen more as building blocks for identity construction, rather than cues for increasing self-knowledge. For example, elites could be supported in the management of their own personal data, omitting certain data types (e.g. their heart rate) or specific data sets, and even "falsifying" certain data values, when addressed to their competitors. A more inflated representation of themselves, supported by a "bettered" version of their data, could be shared on social network sites for a broader audience, when the aim is to gain new followers or to create a positive narrative about the athlete. For amateurs, instead, self-presentation mechanisms could be exploited for fun or to joke with the significant others with whom they share their passion for sports, thus creating an intimate environment. In this perspective, PI data could be used for the creation of multiple identities with different degrees of adherence to the "true self", and athletes could be provided with a greater control on them. PI systems might then facilitate the management of such identities, for example, by allowing users to set default rules about what kind of data are to be shared, in which form, and with whom, and by broadcasting various forms of the same data at once, depending on the audiences they are addressed to.

A modified presentation of the user's self could also be used to help athletes achieve their sports objectives. For example, the system could prompt the athlete with an "enhanced" version of her data just before an important race, in order to depict a more positive view of her physical condition. This could be of help when the athlete risks being demoralized, by seeing, for instance, that in her last workouts she did not achieve her usual results. By contrast, when she becomes overconfident in her performances, the system could provide her with a pejorative version of her data, in order to motivate her to put more effort in training. When designing for self-presentations, however, designers should be aware of its ethical consequences: allowing people to present a modified image of themselves might jeopardize the trustworthiness of PI data.

6.4 Design for shared knowledge

Although data collection and interpretation is often framed within an extremely individualistic point of view in Quantified Self (QS) rhetoric [Ruckenstein and Pantzar 2015], QS communities grow around the members that share their data, creating a circumscribed space where individuals exchange different perspectives on how to achieve their own goals [Barta 2016]. Research has shown that reviewing PI data socially supports reflection and sense making, helping users to contextualize what they collected [Fleck and Harrison 2015]. Our findings showed, in this regard, that elite athletes exchange perspectives on their data with their coaches to gain insights about their performances.

In this consideration, we emphasize the opportunity to design for the social interpretation of data. Many PI applications for fitness and sports try to help users make their data actionable, by providing features that automate the definition of personalized training programs. In order to conceptualize the relationship between PI systems and humans, Ohlin and Olsson [2015b] identify different possible levels of cooperation, ranging from human-driven cooperation, in which users act with PI systems to reach their goals, to computer-driven cooperation, where the system initiates the interaction. While PI tools proactively support amateurs that do not have a coach, elites mainly value other humans, namely their coaches, when interpreting their data.

In this context, a PI instrument may act as a mediator for the social interpretation of the collected data, providing space for social interactions that privilege a dyadic relationship and support the development of shared knowledge. Athletes and coaches, for instance, could be both allowed to manipulate and comment the collected data, working together to find and shape the relevant meanings for the athlete's performance. Moreover, PI tools could enable coaches to display and analyze the athlete's data almost in real-time, providing a communication means to remotely intervene on her ongoing performance. To reduce power asymmetries, PI systems could allow users to set rights and privileges on the collected data. This point could be relevant for all the interactions where different roles are required for the management of personal information, for example between doctors and patients, as well as between workers and employers.

7. CONCLUSION

In this article we made three key contributions. The first contribution is to highlight how amateur and elite athletes differently use and make sense of PI instruments, exploring how personal data can be integrated into a specific domain. The second contribution refers to the four themes emerged from the analysis of our findings: they highlighted that PI tools do not allow amateurs to construct a deep knowledge of their sports practice and also may risk to mechanize the human body, while at the same time they might provide ways to mediate the relationship between the athletes, their public and their coaches. The last contribution lies in the design considerations we outlined, which are addressed to the sports domain, but might be applied, with appropriate adjustments, also to other specific contexts. For example, the idea of providing an "enhanced" version of the data on the user's past performances could be employed in the learning domain, when the goal is to encourage the learner facing an exam, by enhancing her self-confidence.

We are aware that our results could also lead to different implications. For instance, the differences we found between amateur and elite athletes could yield opportunities for designing tools for different levels of eliteness, carefully adapting the devices' interaction modalities to the athlete's expertise. This might elicit new reflections on how we could design more personalized PI tools. However, in this work, we decided to focus on the themes that we believe are more relevant in order to account for how athletes make sense of PI data.

A limitation of this study is that we proposed only the athletes' perspective without involving other relevant actors that may intervene in the practice of a sport. For example, we did not interview coaches. A further development of this work could then be a thorough comparison between the athletes' and the coaches' point of view. Another limitation is that we did not implement our considerations, thus they are not tested "on the field" yet. Following Hekler et al. [2013], we present these considerations as "design hypotheses", which will require further evaluations to prove their validity. We hope that this work will benefit both designers and researchers, raising awareness on the ongoing transformations that the increasing availability of personal data is producing on sports, and, by and large, on everyday life.

REFERENCES

Aino Ahtinen, Pertti Huuskonen, and Jonna Häkkilä. 2010. Let's all get up and walk to the North Pole: design and evaluation of a mobile wellness application. In Proceedings of the 6th Nordic Conference on Human-Computer Interaction: Extending Boundaries (NordiCHI '10). ACM, New York, NY, USA, 3-12.

Aino Ahtinen. 2015. Mobile Applications to Support Physical Exercise - Motivational Factors and Design Strategies. (Tampere University of Technology. Publication; Vol. 1318). Tampere University of Technology.

Susan M. Andersen , Serena Chen & Regina Miranda. 2002. Significant others and the self. Self and Identity, 1, 159–168.

Eytan Adar, Desney S. Tan, and Jaime Teevan. 2013. Benevolent deception in human computer interaction. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '13).* ACM, New York, NY, USA, 1863-1872. DOI: http://dx.doi.org/10.1145/2470654.2466246.

Amid Ayobi, Paul Marshall, and Anna L. Cox. 2016. Reflections on 5 Years of Personal Informatics: Rising Concerns and Emerging Directions. In *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems (CHI EA '16).* ACM, New York, NY, USA, 2774-2781. DOI: http://dx.doi.org/10.1145/2851581.2892406.

Kristen Barta and Gina Neff. 2016. Technologies for Sharing: lessons from Quantified Self about the political economy of platforms. *Information, Communication & Society* 19, 4(2016), 518-531.DOI:. http://dx.doi.org/10.1080/1369118X.2015.1118520.

Glenn A. Bowen.2008. Naturalistic inquiry and the saturation concept: A research note. *Qualitative Research* 8, 1(2008), 137-152. DOI: http://dx.doi.org/10.1177/1468794107085301.

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 32nd annual ACM conference on Human factors in computing systems (CHI '14).* ACM, New York, NY, USA, 1143-1152. DOI: http://doi.acm.org/10.1145/2556288.2557372.

Eun Kyoung Choe, Bongshin Lee, Matthew Kay, Wanda Pratt, and Julie A. Kientz. 2015. SleepTight: low-burden, self-monitoring technology for capturing and reflecting on sleep behaviors. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '15).* ACM, New York, NY, USA, 121-132. DOI: http://dx.doi.org/10.1145/2750858.2804266.

Clancey, W. J. (1997). Situated cognition: On human knowledge and computer representations. New York, NY: Cambridge University Press.

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 (UbiComp '15).* ACM, New York, NY, USA, 647-658. DOI: http://dx.doi.org/10.1145/2750858.2807554.

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 '08).* ACM, New York, NY, USA, 1797-1806.

DOI=http://dx.doi.org/10.1145/1357054.1357335.
Gregory Conti and Edward Sobiesk. 2010. Malicious interface design: exploiting the user. In *Proceedings of the 19th international conference on World wide web (WWW '10)*. ACM, New York, NY, USA, 271-280. DOI=http://dx.doi.org/10.1145/1772690.1772719.
Aaron J. Coutts and Stuart and Cormack. 2014. Monitoring the Training Response. In: *High-Performance Training for Sports*, David Joyce and Daniel Lewindon (Eds), Human Kinetics Publishers, Champaign USA, 71- 84.
Kate Crawford, Jessa Lingel, and Tero Karppi. 2015. Our Metrics, Ourselves: A Hundred Years of Self-Tracking from the Weight Scale to the Wrist Wearable Device. *European Journal of Cultural Studies*, 18, 4-5 (2015), 479-496. DOI: http://dx.doi.org/10.1177/1367549415584857.
Kevin Currell and Asker E. Jeukendrup. 2008. Validity, reliability and sensitivity of measures of sporting performance. *Sports Med 38*, 4 (2008), 297–316. DOI: http://dx.doi.org/10.2165/00007256-200838040-00003.
Chris Elsden, David S. Kirk, and Abigail C. Durrant. 2016. A quantified past: Toward design for remembering with personal informatics. *Human–Computer Interaction 31*, 6 (2016). DOI: http://dx.doi.org/10.1080/07370024.2015.1093422.
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 2014 conference on Designing interactive systems (DIS '14). ACM, New York, NY, USA, 667-676. DOI: https://doi.org/10.1145/2598510.2598558
Daniel A. Epstein, An Ping, James Fogarty, and Sean A. Munson. 2015a. A lived informatics model of personal informatics. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '15)*. ACM, New York, NY, USA, 731-742. DOI: http://dx.doi.org/10.1145/2750858.2804250.
Daniel A. Epstein, Bradley H. Jacobson, Elizabeth Bales, David W. McDonald, and Sean A. Munson. 2015b. From "nobody cares" to "way to go!": A Design Framework for Social Sharing in Personal Informatics. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing (CSCW '15)*. ACM, New York, NY, USA, 1622-1636. DOI: http://dx.doi.org/10.1145/2675133.2675135.
Rowanne Fleck and Daniel Harrison. 2015. Shared PI: Sharing Personal Data to Support Reflection and Behaviour Change. In *Workshop papers CHI 2015 on 'Beyond Personal Informatics: Designing for Experiences of Data'.(CHI '15)*. Seoul, South Korea.
Sharon L. Foster, Cambra Laverty-Finch, Daniel P. Gizzo, and Janay Osantowski. 1999. Practical issues in self-observation. *Psychological Assessment 11*, 4 (1999), 426-438. DOI: http://dx.doi.org/10.1037/1040-3590.11.4.426.
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)*. ACM, New York, NY, USA, 487-496. DOI: http://dx.doi.org/10.1145/2556288.2557383.
Jim Gemmell, Gordon Bell, and Roger Lueder. 2006. MyLifeBits: a personal database for everything. *Commun. ACM* 49, 1 (January 2006), 88-95. DOI=http://dx.doi.org/10.1145/1107458.1107460.
Barney G. Glaser and Anselm L. Strauss, 1967. *The Discovery of Grounded Theory: Strategies for Qualitative Research*. Chicago, IL, Aldine Publishing Company.
Erving Goffman. 1959. The Presentation of Self in Everyday Life. Penguin Books Ltd., London.
Rúben Gouveia, Evangelos Karapanos, and Marc Hassenzahl. 2015. How do we engage with activity trackers?: a longitudinal study of Habito. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '15)*. ACM, New York, NY, USA, 1305-1316. DOI: http://dx.doi.org/10.1145/2750858.2804290.
Shona L. Halson. 2014. Monitoring Training load to understand fatigue in athletes. *Sports Medicine 44*, Supp. 2 (2014), 139-147 DOI: http://dx.doi.org/10.1007/s40279-014-0253-z.
Hamilton D (1996) Learning about education: an unfinished curriculum. Open University Press, Bristol.
Jeff Hancock, Jeremy Birnholtz, Natalya Bazarova, Jamie Guillory, Josh Perlin, and Barrett Amos. 2009. Butler lies: awareness, deception and design. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '09)*. ACM, New York, NY, USA, 517-526. DOI=http://dx.doi.org/10.1145/1518701.1518782.
Heidegger, M. (1927/1990). *Being and time*. Albany: SUNY Press.
Eric B. Hekler, Predrag Klasnja, Jon E. Froehlich, and Matthew P. Buman. 2013. Mind the theoretical gap: interpreting, using, and developing behavioral theory in HCI research. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '13)*. ACM, New York, NY, USA, 3307-3316. DOI: http://dx.doi.org/10.1145/2470654.2466452
Maiken Hillerup Fogtmann, Kaj Grønbæk, and Martin Kofod Ludvigsen. 2011. Interaction technology for collective and psychomotor training in sports. In Proceedings of the 8th International Conference on Advances in Computer Entertainment Technology (ACE '11), Teresa Romão, Nuno Correia, Masahiko

Inami, Hirokasu Kato, Rui Prada, Tsutomu Terada, Eduardo Dias, and Teresa Chambel (Eds.). ACM, New York, NY, USA, , Article 13 , 8 pages. DOI: http://dx.doi.org/10.1145/2071423.2071440.

Hsiu-Mei Huang. 2002. Toward constructivism for adult learners in online learning environments. British Journal of Educational Technology, 33(1), 27-37.

IDTechEx, 2014. Wearable technology 2014-2024: Technologies, markets, forecasts e-textiles, wearable electronics, medical diagnostics, smart glasses, smart wristbands and more. (July 2014). Retrieved March 1, 2016 from http://www.idtechex.com/research/reports/ wearable-technology-2014-2024-technologies\ -markets-forecasts-000379.asp.

Hiroshi Ishii, Craig Wisneski, Julian Orbanes, Ben Chun, and Joe Paradiso. 1999. PingPongPlus: design of an athletic-tangible interface for computer-supported cooperative play. In *Proceedings of the SIGCHI conference on Human Factors in Computing Systems (CHI '99)*. ACM, New York, 394-401. DOI=http://dx.doi.org/10.1145/302979.303115.

Teena Maddox 2014. Wearables have a dirty little secret: 50% of users lose interest. Tech Republic Inc. (February 2014). Retrieved March 1, 2016 from http://www.techrepublic.com/article/wearables-have-a-dirty-little-secret-most-people-lose-interest/.

Jean Lave. 1991. Situating learning in communities of practice. In L. Resnick, J. Levine, and S. Teasley (Eds.), Perspectives on socially Shared Cognition, Washington, D.C.: American Psychological Association, 63-84.

Leah Hunter. 2014. Are wearables over? Fast Company Inc. (April 2014). Retrieved March 1, 2016 from http://www.fastcompany.com/3028879/most-innovative-companies/are-wearables-over.

David H. Jonassen. 1991. Objectivism versus constructivism: Do we need a new philosophical paradigm. Educational Technology Research and Development, 39(3), 5–14.

David H. Jonassen. 1994. Thinking technology: Toward a Constructivist design model Educational Technology March/April 34-37.

Ravi Karkar, James Fogarty, Julie A. Kientz, Sean A. Munson, Roger Vilardaga, and Jasmine Zia. 2015. Opportunities and challenges for self-experimentation in self-tracking. In Adjunct Proceedings of UbiComp/ISWC'15. ACM, New York, NY, 991-996. DOI: http://dx.doi.org/10.1145/2800835.2800949

Matthew Kay, Dan Morris, mc schraefel, and Julie A. Kientz. 2013. There's no such thing as gaining a pound: reconsidering the bathroom scale user interface. In *Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing (UbiComp '13)*. ACM, New York, NY, USA, 401-410. DOI: http://dx.doi.org/10.1145/2493432.2493456.

Kelly, G. A. (1955). The psychology of personal constructs. New York, NY: Norton.

Daniel S. Kirschenbaum, Arnold M. Ordman, Andrew J. Tomarken, and Robert Holtzbauer. 1982. Effects of differential self-monitoring and level of mastery of sports performance: Brain power bowling. Cognitive Therapy and Research 6, 3 (September 1982), 335-342. DOI: http://dx.doi.org/10.1007/BF01173581.

William J. Korotitisch, and Rosemery O. Nelson-Gray. 1999. An overview of self-monitoring research in assessment and treatment. *Psychological Assessment 11*, 4 (1999), 415-425. DOI: http://dx.doi.org/10.1037/1040-3590.11.4.415.

Felix Kosmalla, Florian Daiber, and Antonio Krüger. 2015. ClimbSense: Automatic Climbing Route Recognition using Wrist-worn Inertia Measurement Units. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (CHI '15)*. ACM, New York, NY, USA, 2033-2042. DOI: http://dx.doi.org/10.1145/2702123.2702311.

Felix Kosmalla, Frederik Wiehr, Florian Daiber, Antonio Krüger, and Markus Löchtefeld. 2016. ClimbAware: Investigating Perception and Acceptance of Wearables in Rock Climbing. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. ACM, New York, NY, USA, 1097-1108. DOI: http://dx.doi.org/10.1145/2858036.2858562.

David J. Kooyman, Daniel A. James, and David D. Rowlands. 2013. A feedback system for the motor learning of skills in golf. *Procedia Engineering 60*, 0 (2013), 226 – 231. DOI: http://dx.doi.org/10.1016/j.proeng.2013.07.014.

Audra Landers. 2001. The value of training logs. *Olympic Coach* 11, (2011), 6-7 Colorado Springs, CO: Coaching USA.

Michael Lapinski, Eric Berkson, Thomas Gill, Mike Reinold, and Joseph A. Paradiso. 2009. A Distributed Wearable, Wireless Sensor System for Evaluating Professional Baseball Pitchers and Batters. In *Proceedings of the 2009 International Symposium on Wearable Computers (ISWC '09)*. IEEE Computer Society, Washington, DC, USA, 131-138. DOI: http://dx.doi.org/10.1109/ISWC.2009.27.

Amanda Lazar, Christian Koehler, Joshua 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 (UbiComp '15)*. ACM, New York, NY, USA, 635-646. DOI: http://dx.doi.org/10.1145/2750858.2804288.

Dan Ledger, and Daniel McCaffrey. 2014. Inside wearables: How the science of human behavior change offers the secret to long-term engagement. *Endeavour Partners LLC 93*, (2014), 36-45.

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). ACM, New York, NY, USA, 557-566. DOI=http://dx.doi.org/10.1145/1753326.1753409.

Ian Li, Anind K. Dey, and Jodi Forlizzi. 2011. Understanding my data, myself: supporting self-reflection with ubicomp technologies. In *Proceedings of the 13th international conference on Ubiquitous computing (UbiComp '11).* ACM, New York, NY, USA, 405-414. DOI=http://dx.doi.org/10.1145/2030112.2030166.

Martin Ludvigsen, Maiken Hillerup Fogtmann, and Kaj Grønbæk. 2010. TacTowers: an interactive training equipment for elite athletes. *In Proceedings of the 8th ACM Conference on Designing Interactive Systems (DIS '10).* ACM, New York, NY, USA, 412-415. DOI: http://dx.doi.org/10.1145/1858171.1858250.

Deborah Lupton. 2012. M-Health and Health Promotion: The Digital Cyborg and Surveillance Society. *Social Theory & Health*, 10 (2012), 229-244.

Deborah Lupton. 2013. Quantifying the body: monitoring and measuring health in the age of mHealth technologies. *Critical Public Health 23*, 4 (2013), 393-403. DOI: http://dx.doi.org/10.1080/09581596.2013.794931.

Deborah Lupton. 2014. Self-tracking cultures: towards a sociology of personal informatics. In *Proceedings of the 26th Australian Computer-Human Interaction Conference on Designing Futures: the Future of Design (OzCHI '14).* ACM, New York, NY, USA, 77-86. DOI=http://dx.doi.org/10.1145/2686612.2686623

Steve Mann. 2004. Continuous lifelong capture of personal experience with EyeTap. In *Proceedings of the the 1st ACM workshop on Continuous archival and retrieval of personal experiences (CARPE'04).* ACM, New York, NY, USA, 1-21. DOI=http://dx.doi.org/10.1145/1026653.1026654.

Alessandro Marcengo and Amon Rapp. 2014. Visualization of Human Behavior Data: The Quantified Self. In *Innovative approaches of data visualization and visual analytics*, Mao L. Huang and Weidong Huang (Eds). IGI Global, Hershey, PA, 236-265. DOI: 10.4018/978-1-4666-4309-3.ch012

Bryan Marshall, Peter Cardon, Amit Poddar, and Renee Fontenot. 2013. Does Sample Size Matter in Qualitative Research? A Review of Qualitative Interviews in Is Research. *Journal of Computer Information Systems 54*, 1 (2013),11-22.DOI: http://dx.doi.org/10.1080/08874417.2013.11645667.

Humberto D Maturana, and Francisco J. Varela. 1980. Autopoiesis and cognition: The realization of the living. Dordrecht: Reidel.

Matthew Mauriello, Michael Gubbels, and Jon E. Froehlich. 2014. Social fabric fitness: the design and evaluation of wearable E-textile displays to support group running. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '14).* ACM, New York, NY, USA, 2833-2842. DOI: http://dx.doi.org/10.1145/2556288.2557299.

Molly Z. Mackinlay. 2013. Phases of Accuracy Diagnosis: (In)visibility of System Status in the Fitbit. *Intersect: The Stanford Journal of Science, Technology and Society 6,* 2 (2013), 1-9.

Kathleen M. MacQueen,, Eleanor McLellan-Lemal, Kelly Bartholow, and Bobby Milstein. 2008. Team-based Codebook Development: Structure, Process, and Agreement. In *Handbook for Team-Based Qualitative Research*, Greg Guest and Kathleen M. MacQueen (Eds.), AltaMira Press, Lanham, UK, 119-136.

Maurice Merleau-Ponty.1962. *Phenomenology of Perception*. Routledge & Kegan Paul, London, UK.

Florian Michahelles and Bernt Schiele. 2005. Sensing and Monitoring Professional Skiers. IEEE Pervasive Computing 4, 3 (July 2005), 40-46. DOI: http://dx.doi.org/10.1109/MPRV.2005.66.

Jere H. Mitchell, William Haskell, Peter Snell, Steven P. Van Camp. (2005). Task Force 8: Classification of sports. *Journal of the American College of Cardiology 45*, 8 (2005), 1364-1367. DOI: http://dx.doi.org/10.1016/j.jacc.2005.02.015.

Florian 'Floyd' Mueller, Darren Edge, Frank Vetere, Martin R. Gibbs, Stefan Agamanolis, Bert Bongers, and Jennifer G. Sheridan. 2011. Designing sports: a framework for exertion games. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '11).* ACM, New York, NY, USA, 2651-2660. DOI: http://dx.doi.org/10.1145/1978942.1979330..

Florian 'Floyd' Mueller and Matthew Muirhead. 2015. Jogging with a Quadcopter. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (CHI '15).* ACM, New York, NY, USA, 2023-2032. DOI: http://dx.doi.org/10.1145/2702123.2702472.

Dawn Nafus, Pete Denman, Lenitra Durham, Omar Florez, Lama Nachman, Saurav Sahay, Evan Savage, Sangita Sharma, Devon Strawn, and Rita H. Wouhaybi. 2016. As Simple as Possible but No Simpler: Creating Flexibility in Personal Informatics. In *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems (CHI EA '16).* ACM, New York, NY, USA, 1445-1452. DOI: http://dx.doi.org/10.1145/2851581.2892541.

Fredrik Ohlin and Carl Magnus Olsson. 2015. Beyond a utility view of personal informatics: a postphenomenological framework. In *UbiComp/ISWC'15 Adjunct.* ACM, New York, NY, USA, 1087-1092. DOI: http://dx.doi.org/10.1145/2800835.2800965.

Fredrik Ohlin and Carl Magnus Olsson. 2015. Intelligent Computing in Personal Informatics: Key Design Considerations. In *Proceedings of the 20th International Conference on Intelligent User Interfaces (IUI '15).* ACM, New York, NY, USA, 263-274. DOI: http://dx.doi.org/10.1145/2678025.2701378.

Aisling Ann O'Kane, Yvonne Rogers, and Ann E. Blandford. 2015. Concealing or Revealing Mobile Medical Devices?: Designing for Onstage and Offstage Presentation. In Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (CHI '15). ACM, New York, 1689-1698. DOI: https://doi.org/10.1145/2702123.2702453

Emily J. Oliver, James Hardy, and David Markland. 2010. Identifying important practice behaviors for the development of high-level youth athletes: Exploring the perspectives of elite coaches. *Psychology of Sport and Exercise 11*, 6 (2010), 433–443. DOI: http://dx.doi.org/10.1016/j.psychsport.2010.05.004.

Perkins, D.N. (1991). Technology meets constructivism: Do they make a marriage? Educational Technology, 31(5), 18–23.

James Pierce. 2012. Undesigning technology: considering the negation of design by design. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (CHI '12). ACM, New York, NY, 957-966. DOI: http://dx.doi.org/10.1145/2207676.2208540

Sebastiaan Pijnappel and Florian Mueller. 2013. 4 design themes for skateboarding. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '13).* ACM, New York, NY, USA, 1271-1274. DOI: http://dx.doi.org/10.1145/2470654.2466165.

Amon Rapp. 2017. Designing interactive systems through a game lens: an ethnographic approach. *Computers in human behavior*, 71, C (June 2017), 455-468. DOI: https://doi.org/10.1016/j.chb.2015.02.048

Amon Rapp and Federica Cena. 2014. Self-monitoring and Technology: Challenges and Open Issues in Personal Informatics. Universal Access in Human-Computer Interaction. Design for All and Accessibility Practice. Lecture Notes in Computer Science, 8516 LNCS (PART 4), 613-622. DOI: http://dx.doi.org/10.1007/978-3-319-07509-9_58

Amon Rapp and Federica Cena. 2016. Personal Informatics for Everyday Life: How Users without Prior Self-Tracking Experience Engage with Personal Data. *International Journal of Human-Computer Studies* 94, (October 2016), 1-17. DOI: http://dx.doi.org/10.1016/j.ijhcs.2016.05.006.

Amon Rapp, Federica Cena, Judy Kay, Bob Kummerfeld, Frank Hopfgartner, Till Plumbaum, Jakob Eg Larsen, Daniel A. Epstein, and Rúben Gouveia. 2016. New frontiers of quantified self 2: going beyond numbers. In Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct (UbiComp '16). ACM, New York, NY, 506-509. DOI: https://doi.org/10.1145/2968219.2968331

Amon Rapp, Federica Cena, Judy Kay, Bob Kummerfeld, Frank Hopfgartner, Till Plumbaum, Jakob Eg Larsen, Daniel A. Epstein, and Rúben Gouveia. 2017. New frontiers of quantified self 3: exploring understudied categories of users. In Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2017 ACM International Symposium on Wearable Computers (UbiComp '17). New York: ACM, 861-864. DOI: https://doi.org/10.1145/3123024.3124456

Amon Rapp and Maurizio Tirassa. 2017. Know thyself: A Theory of the self for Personal Informatics. Human-Computer Interaction. *Human-Computer Interaction*, 32(5-6), 335-380. doi:10.1080/07370024.2017.1285704

John Rooksby, Mattias Rost, Alistair Morrison, and Matthew Chalmers Chalmers. 2014. Personal tracking as lived informatics. In *Proceedings of the 32nd annual ACM conference on Human factors in computing systems (CHI '14).* ACM, New York, NY, 1163-1172. DOI: http://doi.acm.org/10.1145/2556288.2557039.

Richard Rubinstein and Harry Hersh. 1987. The human factor: Designing computer systems for people. In *Human-computer interaction,* R. M. Baecker and W. A. S. Buxton (Eds.). Morgan Kaufmann Publishers Inc., San Francisco, CA, USA ,502-509.

Minna Ruckenstein and Mika Pantzar. 2015. Beyond the Quantified Self: Thematic exploration of a dataistic paradigm. *new media & society*, DOI: http://dx.doi.org/10.1177/1461444815609081.

Christine Satchell and Paul Dourish. 2009. Beyond the user: use and non-use in HCI. In Proceedings of the 21st Annual Conference of the Australian Computer-Human Interaction (OZCHI '09). ACM, New York, NY, 9-16. DOI=http://dx.doi.org/10.1145/1738826.1738829

Anna E. Saw, Luana C. Main, and Paul B. Gastin. 2015a. Monitoring the athlete training response: subjective self-reported measures trump commonly used objective measures: a systematic review. British Journal of Sports Medicine 50, 5 (2015), 1-13, DOI: http://dx.doi.org/10.1136/bjsports-2015-094758.

Anna E. Saw, Luana C. Main, and Paul B. Gastin. 2015b. Monitoring Athletes Through Self-Report: Factors Influencing Implementation. *Journal of Sports Science and Medicine14*, 1 (2015), 137-146.

Natasha D. Schüll. 2016. Data for life: Wearable technology and the design of self-care. BioSocieties 11, 3 (2016), 317-333, DOI: http://dx.doi.org/10.1057/biosoc.2015.47.

Segen's Medical Dictionary. 2011. "Endurance Sport." Retrieved November 25 2016 from http://medical-dictionary.thefreedictionary.com/Endurance+Sport

Tamar Sharon. 2016. Self-tracking for health and the quantified self: Re-articulating autonomy, solidarity, and authenticity in an age of personalized healthcare. *Philosophy & Technology*, 1-29, DOI:

http://dx.doi.org/10.1007/s13347-016-0215-5.

Tamar Sharon and Dorien Zandbergen. 2016. From data fetishism to quantifying selves: Self-tracking practices and the other values of data. *new media & society*; 1-15, DOI: http://dx.doi.org/10.1177/14614448166360900.

Petr Slovák, Joris Janssen, and Geraldine Fitzpatrick. 2012. Understanding heart rate sharing: towards unpacking physiosocial space. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '12).* ACM, New York, NY, 859-868. DOI: http://dx.doi.org/10.1145/2207676.2208526.

Petr Slovák, Christopher Frauenberger, and Geraldine Fitzpatrick. 2017. Reflective Practicum: A Framework of Sensitising Concepts to Design for Transformative Reflection. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '17).* ACM, New York, NY, 2696-2707. DOI: https://doi.org/10.1145/3025453.3025516

Andy Stamm, David V. Thiel, B. Burkett, and Daniel A. James. 2011. Towards determining absolute velocity of freestyle swimming using 3-axis accelerometers. *Procedia Engineering 13*, 0 (2011), 120-125. DOI:http://dx.doi.org/10.1016/j.proeng.2011.05.061.

Anselm L. Strauss and Juliet M. Corbin. 1990. Grounded theory research: Procedures, canons, and evaluative criteria. Qualitative Sociology, 13(1), 3–21.

Mathias Sundholm, Jingyuan Cheng, Bo Zhou, Akash Sethi, and Paul Lukowicz. 2014. Smart-mat: recognizing and counting gym exercises with low-cost resistive pressure sensing matrix. In Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '14). ACM, New York, NY, 373-382. DOI=http://dx.doi.org/10.1145/2632048.2636088

Dag Svanæs. 2013. Interaction design for and with the lived body: Some implications of merleau-ponty's phenomenology. *ACM Trans. Comput.-Hum. Interact*. 20, 1, Article 8 (April 2013), 30 pages. DOI=http://dx.doi.org/10.1145/2442106.2442114.

Kristie-Lee Taylor, Dale W. Chapman, John B. Cronin, Micheal J. Newton, and Nicholas Gill. 2012. Fatigue monitoring in high performance sport: A survey of current trends. *Journal of Australian Strength and Conditioning 20*, 1 (2012),12-23.

Tammy Toscos, Anne Faber, Shunying An, and Mona Praful Gandhi. 2006. Chick clique: persuasive technology to motivate teenage girls to exercise. In *CHI '06 Extended Abstracts on Human Factors in Computing Systems (CHI EA '06).* ACM, New York, NY, USA, 1873-1878. DOI=http://dx.doi.org/10.1145/1125451.1125805.

Catrine Tudor-Locke and David Bassett. 2004. How many steps/day are enough? Preliminary pedometer indices for public health. *Sports Med. 34*, 1(2004), 1-8.

Max Van Kleek, Dave Murray-Rust, Amy Guy, Kieron O'Hara, and Nigel Shadbolt. 2016. Computationally Mediated Pro-Social Deception. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16).* ACM, New York, NY, USA, 552-563. DOI: http://dx.doi.org/10.1145/2858036.2858060.

Brett Wakefield, Carman Neustaedter, and Serena Hillman. 2014. The informatics needs of amateur endurance athletic coaches. In *CHI '14 Extended Abstracts on Human Factors in Computing Systems (CHI EA '14).* ACM, New York, NY, USA, 2287-2292. DOI=http://dx.doi.org/10.1145/2559206.2581174

Wouter Walmink, Danielle Wilde, and Florian 'Floyd' Mueller. 2014. Displaying heart rate data on a bicycle helmet to support social exertion experiences. In *Proceedings of the 8th International Conference on Tangible, Embedded and Embodied Interaction (TEI '14).* ACM, New York, NY, USA, 97-104. DOI: http://dx.doi.org/10.1145/2540930.2540970.

Rayoung Yang, Eunice Shin, Mark W. Newman, and Mark S. Ackerman. 2015. When fitness trackers don't 'fit': end-user difficulties in the assessment of personal tracking device accuracy. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '15).* ACM, New York, NY, USA, 623-634. DOI: http://dx.doi.org/10.1145/2750858.2804269.

Bo Zhou, Harald Koerger, Markus Wirth, Constantin Zwick, Christine Martindale, Heber Cruz, Bjoern Eskofier, and Paul Lukowicz. 2016. Smart soccer shoe: monitoring foot-ball interaction with shoe integrated textile pressure sensor matrix. In Proceedings of the 2016 ACM International Symposium on Wearable Computers (ISWC '16). ACM, New York, NY, 64-71. DOI: https://doi.org/10.1145/2971763.2971784