[Don't] Let the Bodies HIIT the Floor: Fostering Body Awareness in Fast-Paced Physical Activity Using Body-Worn Sensors

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[Don't] Let The Bodies HIIT The Floor: Fostering Body Awareness in Fast-Paced Physical Activity Using Body-Worn Sensors

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Fig. 1. A typical high-intensity interval training (HIIT) session with *REPLAY* (**R**eflectiv**E** **P**hysica**L** **A**ctivit**Y**). In between performing high-intensity exercises, users study recorded physiological signals from their body-worn sensors (heart rate and movement). Our work showcases how this form of in-session reflective feedback provides users with the means to better understand the effects of fast-paced physical activity on their bodies.

Technologies have become an integral part of physical activity. Yet, the majority of popular programs do not focus on promoting a genuine understanding of how sport affects our bodies. As apps and trackers persuade users to exercise more, lack of body awareness can be detrimental to health. In this work, we propose and evaluate the concept of in-session reflective feedback as a means to support informed exercise routines by design. We designed and implemented *REPLAY*, a system which presents users with a visualization of physiological signals (heart rate, movement) from body-worn sensors during high-intensity interval training (HIIT). Our evaluation showed that participants gained a better understanding of how their body reacted to physical activity, allowing them to understand its effect and recognize own weaknesses. Further, our work demonstrates how the type of feedback can significantly moderate a user's perceived exhaustion. We highlight

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how in-session reflective feedback using bodily signals can promote healthy and effective workouts through creating a deeper understanding of one's own body physiology and limits.

CCS Concepts: • **Human-centered computing → Ubiquitous and mobile computing**; *Human computer interaction (HCI).*

Additional Key Words and Phrases: reflective feedback; HCI for sports; physical activity; body awareness; sensors

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1 INTRODUCTION

Regular physical activity is universally adopted as a means of leading a healthy lifestyle [10, 16]. Advances in technologies for wearable fitness trackers have further strengthened this trend [12], allowing users to closely monitor their workouts [19, 55, 68] and obtain an increasing amount of information about their physical activity. Yet, instead of promoting an understanding for physical activity and its effect on one's body physiology, most popular applications and fitness programs primarily focus on providing performance-oriented feedback. "Harder, better, faster, stronger" is the dominant narrative behind fitness technologies, promising us a vision of better lives through data [64]. Consequently, these systems prioritize success through rapid fitness improvement rather than providing users with the means to gain a deeper understanding of their own body physiology [49].

This focus on performance is most apparent in fast-paced physical activity, e.g., high-intensity interval training (HIIT) programs, commonly part of popular fitness routines [44, 71]. While there are health benefits to HIIT [79], there are also certain health-related risks. The rapid nature of the exercise, combined with a lack of awareness of one's own bodily capabilities, might potentially be harmful to users [60]. Thus, there is a need for understanding the design that let users understand performance through body awareness. To that end, in this work, we study how informed exercise routines can contribute to an effective and healthy fitness program, including awareness of one's own bodily capabilities and limits [78].

Recent research in HCI has already shown that reflection is key to users understanding their activity [35, 75]. While the majority of commercial and research prototypes focus on providing feedback and fostering awareness after completing or continuously during an exercise session [5], in this paper, we explore an alternative approach: designing for *in-session reflective feedback*. Our approach explores the possibilities for reflection during short exercise breaks. Such breaks are effective in helping pace the activity, increasing engagement [46], and providing cardiovascular benefits [22]. We investigate the design of interactive systems that leverage breaks to offer users the means to reflect on their physical activity and potentially enable them to gain an understanding of their own body physiology, facilitating a conscious approach towards healthy exercising [3]. Thus, we aim to further the knowledge in HCI for sports by studying the design of interactive systems that support bodily awareness during intensive exercise in order to facilitate informed decision-making during physical activity.

We designed and implemented *REPLAY* (**R**eflectiv**E** **P**hysica**L** **A**ctivit**Y**), a feedback system that visualizes heart rate and movement data during resting phases in the workout, allowing for *in-session reflection*. We created visualizations for the data in cooperation with experienced sportspeople to ensure their adequacy for lay sportspeople. Next, we conducted a study where participants were asked to perform exercise sets from HIIT while we recorded their data with body-worn sensors. During the workout, *REPLAY* provided them with the means to reflect on their bodily signals in the short breaks between individual exercise sets. We compared our feedback approach with state-of-the-art time-based feedback (cf. [21]) used in most commercial applications.

Our findings show that participants were able to better understand the effects of the individual exercises on their bodies and their effectiveness when provided with in-session reflective feedback. They gained further insights into the limits of their bodies and could identify weaknesses during their exercise session. Additionally, our work shows that the type of in-session feedback is a key design aspect for high-paced activities as its choice significantly changed the users' perceived exhaustion for high heart rate periods. Further, our system demonstrates the benefits of designing for a subjective perception of body awareness rather than comparing to a priori metrics.

Our work contributes insights on how to design for *in-session reflective feedback* using body-worn sensors, in particularly for fast-paced physical activities. Allowing users to make sense of their bodily sensor data and encouraging them to reflect on it led to a deeper understanding of their own body physiology. We envision that this type of reflective feedback has the potential to create a genuine understanding in users of the effects of physical activity on their bodies, thus promoting healthy and informed fitness workouts.

2 RELATED WORK

We see a constant increase in the number of systems designed to support fitness, which was further fueled by the pandemic [12]. HCI has an established interest in designing motivating and engaging but also instructive experiences for users. In this section, we take a closer look at relevant research works that informed our research methodology (Section 2.4).

2.1 Fitness, Feedback and Body Awareness

Designing technology that supports physical activity often results in new forms of feedback, such as feedback to develop increased body awareness [72] and skill development [37]. While some feedback technologies have been successfully deployed, the design space of feedback technologies for sport is yet to be fully explored, particularly across activities with different intensity levels. Past work showed that feedback can lead to increased body awareness (also conceptualized as private body consciousness [50]) in the context of a diverse set of physical activities. In BodyLights, Turmo Vidal et al. [75] presented wearable lights that allow users to enhance their own perception of relative body position during low-intensity exercise, thus improving their exercise techniques and facilitating instruction [74]. The work showed that these additional insights during the exercises fostered skill development. Similarly, in Fitback, Karolus et al. [35] highlighted the importance of biofeedback for users to gain bodily insights into strength exercises which allowed the users to understand the effects of their continued training. Subletee [81] showed that feedback on one's body posture is beneficial in activities that require high-precision movements. Another strain of HCI work explored the notion of gaining a holistic awareness of one's body—soma(esthetic) design [29]. These approaches focus on fostering body consciousness and re-discovering one's body as a medium for interaction [33]. The soma movement inspired radical explorations, e.g., works using ingestible devices [45]. Our work is inspired by soma work to explore the notions of body awareness during fast-paced activities.

These past works highlight that increased awareness of one's own body physiology and proprioception is beneficial for training. Yet, most works in the area focused on relative body position or movement. Our work is interestingly different as it explores body awareness for intense physical exercises. While feedback on body posture is particularly suited for static activities, such as gym exercises, HIIT is mainly about short-term cardio activity. It remains an open question how we can design reflective feedback to enhance body awareness in high-intensity physical activity.

2.2 State-of-the-art technologies for physical activity

The consumer market is full of applications designed to aid in exercise. Commercial solutions to tracking exercises are primarily performance-focused and promote single-number, quantitative goals based on a priori metrics [52]. Smartphone applications such as Freeletics [20, 21], the Nike Training Club [53], or Seven [63] are based around performance-oriented feedback and often fail to generate a deeper understanding of the user's own physiology. Freeletics [21], for example, combines exercises from high-intensity interval training (HIIT) and high-intensity training (HIT) for building muscles, burning fat, and increasing endurance without additional training equipment. The app generates a workout plan tailored to the user's fitness level based on body height and weight [61]. Apart from commercial products, research investigated how to design sensor-based feedback systems. Sensor modalities are plentiful [1] but mainly focus on inertial measurements [42, 51, 77], pressure sensors, e.g., for gym exercises [69], or camera-based approaches [36]. More specialized work also looked into recognizing activities from sensing muscular activity [41].

This focus on performance-oriented metrics in commercial solutions and research prototypes alike is in stark contrast to research on HCI and sports, which showed that understanding one's physical activity requires a variety of metrics and multiple temporal perspectives to understand the exercise [3]. Our work addresses this issue by exploring design possibilities for fostering body awareness with in-session reflective feedback.

Personal Informatics (PI) for physical exercise is another widespread phenomenon that often accompanies physical activity. With their built-in sensors, fitness trackers like Fitbit [19], Polar [55], and Garmin [24] provide insight into training performance, daily activity, sleep, and more. Recent developments in the design of fitness tracker metrics show an interest in understanding exhaustion, manifested in new metrics such as Fitbit's readiness score [18] or Garmin's body battery [23]. Notably, personal informatics experiences are built to facilitate long-term retrospective reflection with the goal of understanding one's wellbeing patterns over a certain period of time [14]. As such, fitness trackers often do not offer support for reflection during an exercise, often limiting feedback to instantaneous intensity metrics such as heart rate zones. While such measurements often provide an experience of meaning and engagement [70], they offer limited potential for reflection and making decisions about the course of an exercise session. This paper aims to extend the design space of in-session interactions by investigating how we can foster reflection *during an exercise* based on increased body awareness.

2.3 Reflection in Physical Activity

Users pursue physical activity fueled by motivation. Reflection is a means for users to understand the effectiveness of their physical activity [2, 5], which, in turn, can foster motivation for continuing physical activity [76]. Consequently, designing for reflection for physical activity is a recognized design goal in HCI for sports. Most works which addressed reflection in sports focused on post-hoc feedback. Woźniak et al. [82] designed a system which allowed runners to view how their foot strike patterns developed over the course of a run using a tangible display. Kocielnik et al. [40] investigated how conversational agents could prompt users to analyze and reflect upon weekly exercise patterns. Alternative designs included feedback that did not require reflection, instructing the user instead. For example, Hassan et al. [27] built a system that automatically corrected a runner's gait to achieve the desired running form. Overall, we observed that most approaches in past research investigated reflection after the exercise or reflecting on long-term exercise progress. While these types of exercise support are bound to benefit the user, we note that the notion of reflection during an exercise (cf. *reflection-in-action* [62]) was less explored. This work explores if and how *in-session reflection* on physical activity is possible during a high-intensity exercise and investigates its possible user benefits.

2.4 Research Questions and Methodology

We opted for a mixed-method approach, starting with an initial design process (Section 3) for *in-session reflective feedback* in cooperation with expert sportspeople for high-intensity interval training (HIIT), eliciting two usage scenarios and respective sensor types and configurations. We concluded this part with the implementation of *REPLAY*, a feedback system for HIIT, allowing for in-session reflective feedback. In a final evaluation (Section 4), we assessed *REPLAY*'s effectiveness with regard to fostering awareness of users about their own body physiology as compared to state-of-the-art time-based feedback methods.

To guide the individual parts of our work, we formulated the following research questions:

RQ1: *What are technical requirements and design factors to allow for sensor-based feedback during fast-paced physical activity?* HIIT is a fast-paced training routine that leaves little room to process complex visual feedback. Hence, in this first step, we identified opportunities for displaying feedback and suitable sensor types and configurations based on related works and the sensors' suitability to capture physical activities (see Section 3.1). We refined this selection with expert sportspeople (see Section 3.2). This design process ensured that the visualizations for the recorded bodily signals are (1) suitable for fast-paced physical activity and (2) understandable for laypeople.

RQ2: *How can we create feedback systems for HIIT that foster body awareness through in-session reflective feedback?* We distilled two usage scenarios (Section 3.4): *Understanding perceived exhaustion* and *Understanding movement consistency*, which emerged from our expert interviews and captured these through the implementation of *REPLAY*, which delivers in-session reflective feedback based on one's bodily signals during HIIT. To determine the effectiveness of this approach in fostering body awareness, we compared it against a state-of-the-art time-based visualization. We chose this visualization as it represented a strong baseline [30]—a widely used and widely studied [28, 61] commercial solution. We evaluated both conditions through questionnaires and post-hoc interviews, investigating whether participants actively reflected on their body physiology during the training. Further, analysis of the recorded sensor data gave insight into how the type of feedback actually influenced users.

3 DESIGNING FOR IN-SESSION REFLECTIVE FEEDBACK

Our design process as shown in Figure 2 included an initial investigation into the structure of HIIT routines, applicable sensors and opportunities for in-session reflection (Section 3.1). We subsequently created a final feedback design (visualizations of the sensor data) in cooperation with expert sportspeople through interviews (Section 3.2), ensuring that the visualizations can be understood by laypeople. From these findings, we derived implications when designing for HIIT (Section 3.3) and two usage scenarios (see Section 3.4) that inform *REPLAY*'s implementation and demonstrate how sportspeople with different training objectives may use it.

3.1 Requirements for In-Session Reflective Feedback for HIIT

High-intensity interval training (HIIT) is a training protocol based on fast-paced physical activity at cardio level. Intense periods of anaerobic exercise alternate with short break periods [43]. The cycle of activity and recovery (a set) is repeated several times until exhaustion, as depicted in Figure 3. This dynamic and fast-paced nature makes it difficult to integrate feedback during the exercises. Most commonly, reflection — if any — on the training performance and perceived exhaustion happens at the end of a completed workout session based on performance-oriented measures,

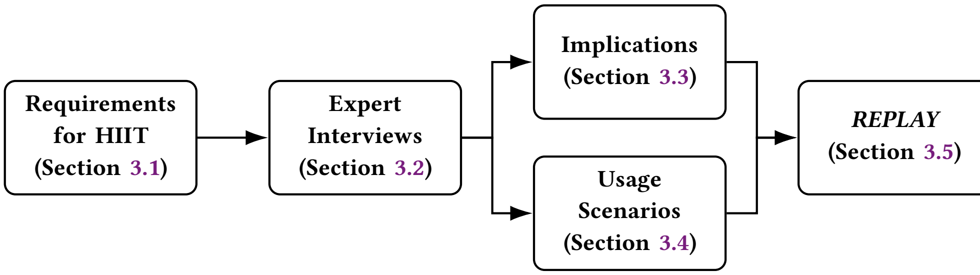


Fig. 2. Our design process considering the characteristics of HIIT and specific requirements when designing for this context (Section 3.1). We further refined the initial design through expert interviews (Section 3.2). This resulted in implications (Section 3.3) and usage scenarios (Section 3.4). These steps then informed the implementation of *REPLAY* (Section 3.5).

such as exercise duration, which limits potential insights into the effectiveness of the training. For example, sportspeople might miss fitness improvements at the cardio level (see *Understanding perceived exhaustion*, Section 3.4), such as lower base heart rate and faster heart rate recovery, as well as muscular-based changes, such as increased control over exercise movements during phases of high exhaustion (see *Understanding movement consistency*, Section 3.4).

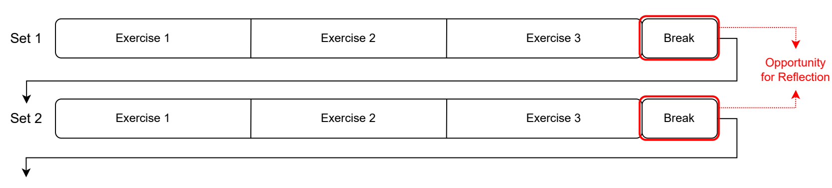


Fig. 3. Typical structure of a HIIT workout, comprising a number of exercises and a break for each set offering the opportunity for reflection.

We considered the nature of HIIT sessions in our design, explicitly targeting the short recovery periods to allow users to reflect on their previous sets (see Figure 3). Compared to actual live feedback during the exercises, e.g., vibrotactile [73] or audio [81] feedback, this option allowed us to deliver more feature-rich visual feedback of the recorded bodily signal. This *in-session* feedback still allows for *reflection-in-action* while not suffering from the limited bandwidth of other feedback types, such as vibrotactile or audio feedback. Further, past research on reflection systems showed that visual stimulus was most widely used both in research and consumer products [5]. To assess the general feasibility of this feedback concept, we opted for a larger screen size — allowing for more detailed visualizations — in this initial evaluation.

While we want the visualizations to be informative enough to draw conclusions about one's current bodily state, they must still be simple enough to integrate seamlessly into the HIIT routine. Visual constraints such as the number of sets, the level of detail for each signal source, and the number of sensors to present to the user need to be considered. In related works, a variety of sensing modalities were used to detect physical activity [1], such as inertial measurements [77], pressure sensors [13], or muscle activity [35]. In addition, physiological data like heart rate, respiration rate, and body temperature provide a feature-rich and objective representation of the user's body state [26, 83].

Given our temporal constraints within a HIIT routine, we eventually opted to include body signals collected from movement and heart rate sensors, as they can provide accurate and feature-rich insights into general exhaustion [8, 59] and movement amplitude [32] as an indicator for exhaustion. Further, both sensor types are readily available in commercial products [19, 24], hence possibly being familiar to users already, easing onboarding.

To summarize, displaying visual feedback of collected sensor data during a HIIT routine is challenging, as the recovery periods are short. In-depth sensor data analysis is not possible for the user, nor is it desirable, as it would break the flow of the workout. Consequently, this form of *in-session reflective feedback* needs to be easily understandable as well as clearly depict distinctive information to facilitate body awareness. Both of our selected sensor types support these characteristics. To ensure that the shown visual feedback adheres to these design factors, we created our final set of feedback visualizations in cooperation with expert sportspeople, as detailed in the following section.

3.2 Refining In-Session Feedback Visualizations Through Expert Interviews

During our design process we experimented with different configurations to display the data. This includes, among others, the amount of data pre-processing, smoothing factors, the visualization of the different accelerometer axis and visualization of the individual sets and exercises in one or several graphs. Figure 4 shows a possible variant. To further refine our set of visualizations, we conducted semi-structured interviews with experienced sportspeople via video conferencing software and used an interactive online whiteboard[1] to show the visualizations, allowing for collaborative sketching. Visualized sensor data included recorded heart rate and movement data from a preliminary evaluation.

3.2.1 Heart Rate Data. For the heart rate data, we plotted the original signal[2] for all three exercises (of a set) in one graph as well as separate graphs for each exercise. We varied smoothing factors and available data history (amount of past sets), e.g., Figure 4a shows the history of the last six sets. Lastly, we probed visualizations of heart rate zones like the one used in the polar beat app [56].

3.2.2 Movement Data. We mainly focused our design around an aggregated version of the measured acceleration[2], combining all dimensions. Analog to heart rate data, we also discussed smoothing options and how to show multiple sets (and sensors) without overloading the visualization, i.d., when and how to separate individual sensor graphs. Figure 4b shows a composite visualization of both acceleration sensors as well as depicts two completed sets of HIIT.

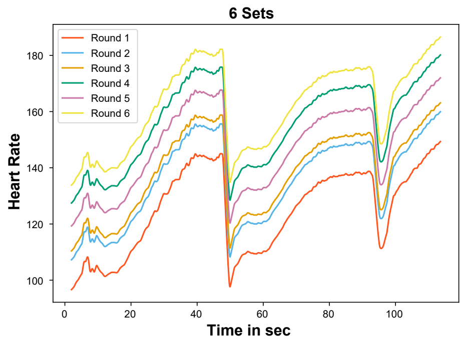
3.2.3 Participants. We recruited three participants with varying sports background and levels of experience with physiological data through personal contacts. They were all experienced with physical activities and high intensity workouts. The interviews were recorded after asking for the participant's consent. Each participant was reimbursed with $10 per hour.

Table 1. Participant profiles of the expert interviews.

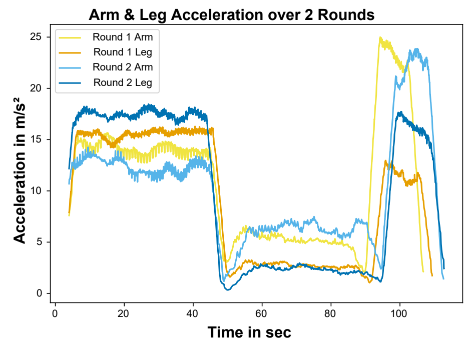
Participant ID	Age	Gender	Area of Expertise related to HIIT	Experience
E1	26	male	Weight lifting, HR zone training, HIIT/Circle Workouts	7.5 y
E2	26	female	HIITs, Triathlon, Hiking/ Trailrun	6 y
E3	27	male	Crossfit, Olympic Weightlifting	5 y

[1] miro: https://miro.com/

[2] See Section 3.5.2 for details on signal acquisition and processing.



(a) Visualization of the heart rate data showing the six most recent sets.



(b) Acceleration data (both arm and leg) for the two most recent sets.

Fig. 4. Example graphs of heart rate data (Figure 4a) and acceleration data (Figure 4b) as used for our expert interviews (see Section 3.2). The full set of visualization is available as supplementary material.

3.2.4 Procedure. After the participants provided informed consent for participation and recording, the interviewer briefly introduced the topic and the project idea to the interviewee. The idea consists of one person doing several high-intensity interval training (HIIT) exercises. These are recorded with wearable sensors (heart rate and movement) and displayed after each set of exercises so that the user can analyze their training.

We started the interview with a questionnaire about the participant's sports background and their experience with fitness trackers, sensors, and apps (see Table 1). We consecutively showed different visualizations[3] of body-worn sensor data, starting with different graphs about the heart rate, followed by visualizations of acceleration data. After introducing each diagram, we asked the participant to interpret the data and to report their impressions if viewed from the perspective of a HIIT user. This allowed us to gauge the complexity and information value of our feedback for HIIT users. For all graphs, we focused on whether the participants could understand the displayed information, which visualizations they preferred for which reason, what appeared most relevant to them and how they suggested to improve the visualizations.

3.2.5 Interview Findings. All interviews (2:12 *h*) were transcribed verbatim. We followed the pragmatic approach to thematic analysis, as described by Blandford et al. [6]. In an initial step, three researchers open-coded one interview and agreed on an initial coding tree. The remaining interviews were evenly split and coded separately. In a final discussion, we refined the coding tree resulting in a code hierarchy with two themes: SENSOR MODALITY and DATA INTERPRETATION. From the interviews emerged implications for the design of in-session reflective feedback during HIIT as well as two usage scenarios that showcase potential approaches to use *REPLAY*.

Sensor Modality. This theme focuses on specific characteristics of the different sensor modalities and how to present the respective data to users. Our experts confirmed that both acceleration and heart rate data are suitable to enable users (1) to identify the individual exercises as well as breaks in a training set and (2) to observe increasing exhaustion over time. For example, E3 was convinced that users are able to distinguish the three exercises from the acceleration signal.

[3] All available as supplementary material.

> *You can see when you are performing, the first [exercise] is like, okay, [they are] starting fast, and then the second one is like, [they are] slowing a little bit down, and the third one [they are] getting higher. (E3)*

Depending on the exercises, E2 considered it helpful to have separate graphs for the arm and leg acceleration because some exercises require more or less arm and leg movement.

Being able to closely monitor both movement data, particularly movement amplitudes, and heart rate data was seen as an opportunity especially for new athletes to learn to assess their exhaustion more accurately and to be able to fully use their potential in training and not stop prematurely due to them not being aware of their own body limits yet.

> *(...) New athletes [gain] a feeling for exhaustion and what exhaustion really means because I know that most people are not training hard enough and are very easily not exhausted but fake exhausted. They stop because they think I'm sweating a little bit. [...] if you don't train hard enough, you don't have the training effect because you need to strain your muscle to a specific degree. I think [...] your system could be very good to give the user the feeling of how exhausted you can really be. (E1)*

Data Interpretation. Our experts commented extensively on different aspects of how users might interpret the shown sensor data. This theme can be further divided into *data volume*, *gaining insights*, and *confirming body perception.*

Our experts suggested displaying not all sets because the graph would become overwhelming and that the granularity of the shown sensor data needs to be moderated, i.d., aggregating the movement data. They all agreed on showing three to four sets only, though they had different preferences on which sets to show.

> *Visualizing three sets is a good amount of sets because you can still clearly see each round, but it's not overcrowded or overwhelming. (E2)*

Apart from commenting on challenges with the volume of sensor data, the experts talked about the insights that a user can gain through data analysis. Especially visualizations of heart rate zones (prevalent in fitness apps, e.g., the polar beat app [56]) might not be familiar to everyone. Novices have not yet developed an understanding of heart rate zones and, therefore, cannot base their training on them.

> *People that are beginning with sports don't know the quick switch and the anaerobic and aerobic area [...] It's visualized by colors, but they don't know what's going on in the zones. (E3)*

Proper reflection is necessary for the user to confirm whether their interpretation of the presented data matches their body perception during the training. Heart rate, in particular, is a straightforward indicator of exhaustion. Experts commented positively on users being able to compare individual sets and use the insights gained about their exhaustion to adapt the training plan.

> *You can compare the last round's heart rate and the current's round heart rate, which also gives you a clear idea of how much more exhausted you are right now to the beginning and to the last round basically, and then make a decision if you should continue or want to continue or not. (E1)*

3.3 Implications for In-Session Reflective Feedback During HIIT

Based on our initial design and the expert interviews, we derived implications for the implementation of *REPLAY*.

3.3.1 Display both acceleration and heart rate data simultaneously. We have seen that the users should be able to distinguish exercises and breaks from the heart rate and acceleration data recorded during HIIT, hence being able to recognize individual exercises. Further, our experts confirmed that both signals depict increased exhaustion over time that is recognizable to the users. *REPLAY* follows this requirement and displays time-synchronized heart rate and acceleration data simultaneously in our feedback visualization. Interestingly, displaying both acceleration and heart data at the same time can allow users to find explanations for either signal, e.g., a higher than normal heart rate increase due to overpacing the exercise (as visible in the acceleration data).

3.3.2 Limit the amount of visualized data. The amount of shown sensor data needs to be carefully moderated. In our final version of *REPLAY*, we opted for only displaying up to three sets at a time. Experts agreed on the importance of the most current and the initial set. Additionally, we always displayed the second to last set as well. We further reduced the complexity of the acceleration signal by aggregating it into the sum of its components.

3.4 Usage Scenarios for In-Session Reflective Feedback During HIIT

Furthermore, two usage scenarios emerged during our interviews that additionally guided *REPLAY*'s implementation and depict possible training strategies when using the system: (1) Understanding perceived exhaustion and (2) understanding movement consistency. We illustrate these in the following and point out how sportspeople can integrate *REPLAY* into their training routine.

Understanding perceived exhaustion. Two months ago, Paul started high-intensity interval training (HIIT) following the suggested training plan provided by an app on his smartphone. On some days, even when he is doing the same exercises and repetitions again, they seem much more strenuous than the other day, and he gets exhausted after only a few sets. When he describes the problem to his friend Marc, who also does HIIT, he advises him to get an HR sensor and to additionally track the training with *REPLAY*. *REPLAY* records the data from the sensor and visualizes it in a graph to look at during the breaks between the exercise sets. With the help of the sensor and *REPLAY*, Paul observes how his heart rate rises during the first set, drops again during the break, and develops throughout the training routine. On another day, when he slept fitfully the night before, he finds the exercises more exhausting. He observes that his heart rate rises to a higher level than normal more quickly and does not return to his usual resting heart rate during the break. As a consequence, Paul deliberately reduces the number of sets on days like this to prevent overexertion and subsequent health risks.

Understanding movement consistency. Alice is a fitness enthusiast, eats consciously, and generally takes care of her physical and mental wellbeing. In her HIIT training, she notices signs of exhaustion in that she has the feeling that the exercises are getting sloppy. She is aware that for an effective and healthy fitness program, the correct execution of the exercises is important. Thus, she wants to investigate where the cause of this feeling lies and how she can counteract it so that she can perform the exercises consistently throughout the entire workout. Her training buddy Laura tells her about *REPLAY* and she decides to give it a try. *REPLAY* shows her heart rate and the acceleration data from her arm and leg from the last, second to last and first set. Thus, she can observe changes during the training. When looking at the visualizations, Alice recognizes that she overpaces at first and then slows down as her legs get tired. Knowing this, she pays extra attention to a consistent movement speed in the next set, deliberately starting off at a slower pace. In her training, the provided feedback on her movement consistency helped Alice improve the quality of her exercise execution.

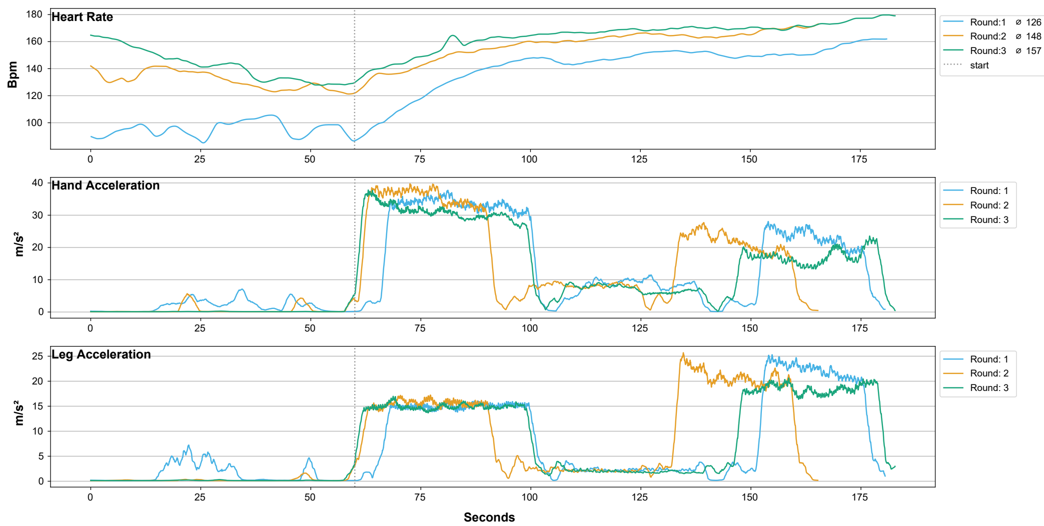


Fig. 5. Visualizations of *REPLAY* shown to the participants in the sensor-based feedback condition during the workout. The top most graph depicts the heart rate, whereas the middle and bottom graphs show the hand and leg acceleration. The dashed vertical line marks the start of each exercise set. One can see the break to the left of this line (decreasing heart rate, low acceleration), while to the right side increasing heart rate and high acceleration indicate the workout part of the set. Note the distinct patterns of each exercise and signs of fatigue in later sets (decreased/inconsistent movements). Note that this visualization is based on the same workout session as the time-based feedback in Figure 6.

3.5 *REPLAY* - An Interactive System Implementing In-Session Reflective Feedback During HIIT

The following section introduces the final design for our feedback visualizations and describes the technical functionality of *REPLAY*.

3.5.1 Feedback Visualizations. *REPLAY* supports two different feedback types, representing the two feedback conditions as introduced with **RQ2**. The sensor-based feedback used the collected sensor data to generate a comprehensible feedback visualization for the user to facilitate in-session reflection. In contrast, the time-based condition was based on performance-oriented feedback, as present in most interactive workout systems (cf. [21, 28, 61]), representing a strong baseline [30].

Sensor-based Feedback. Figure 5 shows an example of the sensor-based feedback. We see that the person is exercising as the heart rate increases (topmost graph), starting right after the break (dashed vertical line). We further observe that the person's heart rate recovers during the break for the following sets (orange and green lines). In the middle and bottom graphs, we can recognize three distinct patterns in the acceleration signal of the hand and the leg, which correspond to the individual exercises (see Section 4.2 for an explanation of the procedure and exercises). For example, jumping jacks and high knees exercises have a higher acceleration than squats in between, where we see very little acceleration of the hand and almost none in the leg. We can also recognize signs of fatigue, e.g., decreasing and inconsistent movements as exercises and sets progress further.

Time-based Feedback. During the break after an exercise set, we showed the participants in the time-based condition the time they needed for each exercise (see Figure 6). Like the

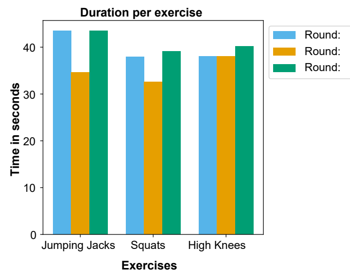


Fig. 6. Visualizations of *REPLAY* shown to the participants in the time-based feedback condition during the workout. Participants were able to see their duration for each exercise of the respective sets. Note that this visualization is based on the same workout session as the sensor-based feedback in Figure 5.

participants in the experimental group, they could compare a maximum of three sets. Here, we can see that the person was fastest for all three exercises in the second set while taking the longest for the jumping jack exercise overall.

3.5.2 Apparatus. *REPLAY* uses off-the-shelf consumer devices for data recording during the exercises. It follows a modular architecture (depicted in Figure 8), allowing to switch sensor devices and types as well as the final stimulus display. We opted for wearable sensors without restricting cables. Participants wore a Polar H10[4] heart rate sensor around the chest, recording at a sampling rate of 130 Hz. The Polar H10 provides consistent and accurate heart rate, especially during high-intensity activities [25]. In contrast, the data from a wrist-worn device can be inaccurate due to the fast-paced movements in these activities. Additionally, the Polar H10 is a popular consumer product already providing interconnectivity with standard fitness watches, allowing easy integration. The sensor was connected via a Bluetooth layer sending the raw ECG signal, as depicted in Figure 7, to a computer.

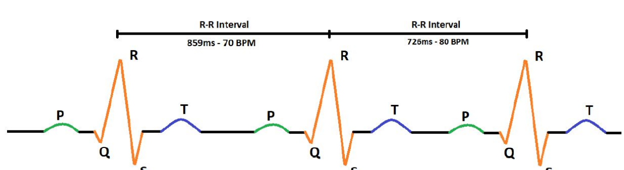


Fig. 7. Simplified depiction of a raw ECG signal (P wave, the QRS complex, and T wave are highlighted, cf. [67]) showing three heartbeats. To estimate the heart rate, it is common to detect the individual QRS complexes [67].

This initial data was cleaned by applying a 0.5 Hz high-pass filter, removing drift and unwanted low-frequency noise, as well as a bandstop filter removing power line noise around 50 Hz. For further signal processing, we used neurokit2 [47], which identifies R-peaks (see Figure 7) in the ECG signal as local maxima, allowing the heart rate to be extracted from the raw signal. Using this method to calculate the heart rate additionally allowed us to identify rejected R-peaks, possibly due to strong body movements, and interpolate between them. We apply a moving average filter of two seconds to smooth the heart rate data. This filter also mitigates any high-frequency noise in the

[4]https://www.polar.com/en/sensors/h10-heart-rate-sensor

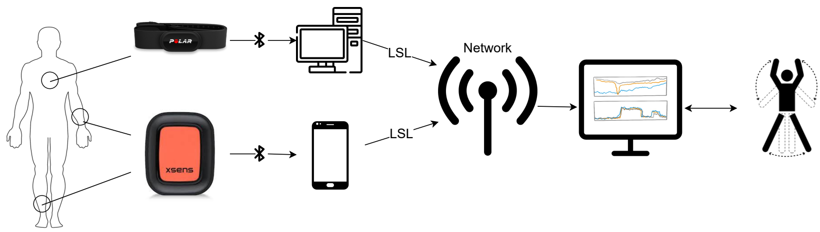


Fig. 8. Communication architecture of *REPLAY*. Sensor data is collected from the respective devices and made available on the network as LSL stream. The stimulus display on the right side interprets the sensor data and provides feedback to the user.

signal. All parameters for these preprocessing steps resulted from the previous expert interviews (see Section 3.2).

We additionally used two IMU sensors (XSens Dot[5]) to record acceleration data (Sampling rate[6]: 60 Hz). One was attached to the wrist of the left arm (mimicking a fitness watch) and another one to the ankle of the right leg to measure the acceleration of the respective body parts during the exercise. A corresponding smartphone application collected signals from both IMU sensors via Bluetooth. Each IMU signal was then aggregated over its three dimensions using the L2 norm and smoothed using a moving average filter of two seconds, guaranteeing that a change in acceleration is still visible, yet the data being clean enough to ensure good readability. Again, all parameters resulted from the previous expert interviews (see Section 3.2).

The processed signal data was streamed into the network via lab streaming layer[7] (LSL) for time-synchronized communication (see Figure 8). The stimulus PC accessed these data streams (heart rate, movement data for arm and leg) via LSL for each set, created the respective sensor visualizations (see Section 3.5.1) at the end of each exercise set, and displayed them on a 27-inch screen for participants to view.

4 METHODS

In our evaluation of *REPLAY*, we focus on our second research question (**RQ2**), investigating design qualities of in-session reflective feedback based on bodily signals. In particular, we evaluate if using sensor-based feedback can elicit a better understanding of the user's own body physiology, i.d., recognizing the positive (and negative) effects of physical activity on one's own body. Further, we report on the employed study design, participants, procedure, and collected measures.

4.1 Study Design

We employed a between-subject study design with the type of feedback visualization (Section 3.5.1) as independent variable. Following common approaches in HCI, we used a state-of-the-art time-based feedback as the baseline condition to compare it to the sensor-based feedback (experimental condition) [58]. We analyzed subjective exhaustion as reported by participants using the Borg RPE scale [7] and collected heart rate and acceleration measures as objective indicators of exhaustion. We further gathered insights about the participants' perceived exercise effectiveness and body awareness through a custom questionnaire (see Table 2) and a post-hoc interview. Lastly, we examined usability aspects of *REPLAY* through validated questionnaires as detailed in Section 4.2.

[5]https://www.xsens.com/xsens-dot
[6]Note that the XSens sensors have a higher internal sampling rate, see [54].
[7]https://github.com/sccn/labstreaminglayer

We chose jumping jacks, squats, and high knees from HIIT as the reference exercises. These exercises are suitable for people with different fitness levels and experiences. The exercises are simple enough that prospective participants can understand and follow them easily, as well as strenuous enough to cause an elevated heart rate during the experiment. Additionally, the movement of the respective body parts differs between these exercises, making them distinguishable. In line with the concept of HIIT [9], one set consisted of 40 jumping jacks, 20 squats, and 50 high knees, followed by a one-minute break. We asked participants to study the provided feedback during the break. In total, we tasked participants to execute at least three full sets, allowing a maximum of six sets[8]. Ethical approval for this study was obtained from the Ethics Committee at LMU Munich.

4.2 Procedure

We split our study into four phases: introduction and preparation, workout, questionnaires, and a post-hoc interview. First, the experimenter welcomed each participant and described the study procedure. After they provided informed consent, we used a questionnaire to collect demographics, information about their fitness level, and their experience with fitness activities, sensors, and apps from the participants. We further asked the participants to complete the IPAQ questionnaire [31] as a validated reference for their fitness level. For the active part of the study, the participants were asked to put on sports attire and attach the sensors, following the experimenter's instructions, in a changing room. The heart rate sensor had to be fastened just below the chest muscles. The two acceleration sensors were attached using velcro tape, one around the wrist and one around the leg. Both a female and a male experimenter were present if participants needed support during this step. Afterward, we confirmed the signal quality of the sensors and started the respective streams. The experimenter demonstrated the three different exercises, and the participants were given time to practice them. Once the exercises were fully understood, the experimenter left the room, and the participant started the workout phase on the stimulus PC.

First, participants were asked about their current base exhaustion by answering the Borg RPE scale [7]. Participants then performed the exercises without the presence of the experimenter as instructed on the screen (see Figure 9). For each exercise, the stimulus PC additionally showed a picture instruction of how to perform it. After each exercise set, participants spent one minute studying the provided feedback during the scheduled break (see Figure 9). At the end of the break, they rated their current perceived exhaustion with the Borg RPE scale [7] again and were asked if they felt comfortable with executing another set. Participants repeated the set between three to six times. We left the decision to the participants on how many sets they wanted to do, though we encouraged them to do a minimum of three sets. To avoid overexertion, we discontinued the workout phase after a maximum of six sets. After the participants finished their last set, the experimenter reentered the room and asked the participants to remove the sensors and take a short break.

In the next part of the study, the participants answered a couple of questionnaires, starting with rating their self-appraisal of their performance during the workout on a 5-point scale [48], followed by our custom questionnaire, which included questions regarding the participants' perceived effectiveness of the exercises and their body awareness. All items of this questionnaire are listed in Table 2. We further used the flow-short-scale (FSS) [57], the comfort rating scale (CRS) [39], and the usability metric for user experience (UMUX) [17] scale to evaluate flow experience, wearable comfort, and ease of use. We concluded the study with a semi-structured interview inquiring more

[8]We did not limit the amount of sets prior to the experiment, but discontinued when participants wanted to start a seventh set.

Fig. 9. Participant during the study performing jumping jacks (left) and analyzing the sensor-based feedback during the break between the exercises (right).

details about the participants' impressions of the feedback and insights they could derive from it. In total, the study duration did not exceed 90 *min*.

Table 2. Custom questionnaire polling whether the feedback allowed participant to better understand exercise effectiveness and their own body physiology. From strongly disagree to strongly agree; all visual analog scale (0 to 100).

Custom questions regarding the given feedback	
Q1	The feedback helped me to understand how my body reacts to certain exercises.
Q2	The feedback allowed me to understand the effectiveness of the exercises.
Q3	The feedback allowed me to understand my performance more in-depth.
Q4	The feedback allowed me to reflect on my exhaustion level.
Q5	The feedback did affect how I performed the exercises.
Q6	I was able to fully concentrate on the given feedback.
Q7	The feedback was in line with my body perception.
Q8	The feedback was shown to me long enough to process it.

4.3 Participants

We recruited 22 participants through university mailing lists and word of mouth. We communicated that participation in our study did require a decent level of fitness and made sure that prospective participants were aware that they would be asked to wear sensors. The data of 20 ($12\,m$, $8\,f$; age $\bar{x} = 28.0\,y$, $s = 3.6\,y$) were used for the complete analysis. We had to exclude one participant due to technical issues and another due to having difficulties executing one of the exercises. We specifically chose this study population as it represents the target group for HIIT the most [65]. Conditions were evenly split between participants, with ten each for the sensor-based and time-based feedback, respectively. Participants rated high on their self-perceived fitness level[9] ($\bar{x} = 73.1, s = 12.9$), in line with their IPAQ levels ($\bar{x} = 2.6, s = 0.6$), while experience with HIIT[9] was rated at $\bar{x} = 51.5$ ($s = 24.4$). For all of them, we did not find significant differences with regard to the feedback condition. Fifteen participants have used fitness apps before (duration: $\bar{x} = 3.3\,y, s = 2.0\,y$) and 14 participants have used sensors before (duration: $\bar{x} = 2.3\,y, s = 1.6\,y$). Each participant was reimbursed with \$10 per hour.

5 RESULTS

We report on the statistical analysis of our collected measures, including questionnaire responses as well as the collected sensor data. If not stated otherwise, the data was analyzed using one-way ANOVAs after applying aligned rank transformation [80]. Effect sizes are given using η^2 (Partial Eta Squared): small (> .01), medium (> .06), large (> .14). Additionally, we present findings from our post-hoc interviews.

5.1 Workout Duration, Usability, and User Experience

During the experiment, participants completed on average $\bar{x} = 4.9$ ($s = 1.2$) sets, requiring $\bar{x} = 16.2\,min$ ($s = 4.5\,min$) to complete these. Participants reported high levels of self appraisal [48] ($\bar{x} = 32.4, s = 4.4$, 1 to 40) and flow [57] (Flow: $\bar{x} = 5.1, s = 0.8$; Worry (low is better): $\bar{x} = 3.0, s = 1.0$, both 7 point Likert) for their workout. Further, we could not find any usability issues as indicated by a high UMUX [17] score ($\bar{x} = 79.0, s = 14.8$, 0 to 100) and good CRS [39] scores (all subscale means $\bar{x} < 5$; lower is better). None of the above measures showed significant differences between the two conditions.

5.2 Custom Questions on Exercise Effectiveness and Body Awareness

The analysis of our custom questions (Table 2) revealed significant differences (large effects) for Q1: "The feedback helped me to understand how my body reacts to certain exercises." ($F(1, 18) = 19.6, p < .001, \eta^2 = .52$), Q2: "The feedback allowed me to understand the effectiveness of the exercises." ($F(1, 18) = 8.4, p < .01, \eta^2 = .32$), and Q3: "The feedback allowed me to understand my performance more in-depth." ($F(1, 18) = 19.6, p < .01, \eta^2 = .34$). All other questions (Q4-Q8) showed no significant differences. An overview is depicted in Figure 10, highlighting the higher ratings for sensor-based feedback when it comes to recognizing the effects of the exercises on the user's body and understanding one's performance (Q1-Q3). Additionally, both feedback conditions were equally good at allowing participants to judge their exhaustion level (Q4), albeit time-based feedback showed a higher variance. Opinions were a bit more mixed regarding how the displayed feedback affected exercise form (Q5). While some participants made use of it to incorporate changes, others did not. Similarly, participants were able to mostly (more so for sensor-based feedback) concentrate on the given feedback (Q6), though there was always enough time to process it (Q8). The sensor-based feedback was always in line with the participants' own body perception (Q7), achieving a higher rating (not significant) than time-based feedback.

5.3 Correlation of Sensor Data and Perceived Exhaustion

To estimate whether the recorded sensor data correlates to the participants' perceived exhaustion during the exercises, we analyzed their reported Borg RPE values with regard to the measured

[9]Visual analog scale (VAS) from 0 to 100; strongly disagree to strongly agree.

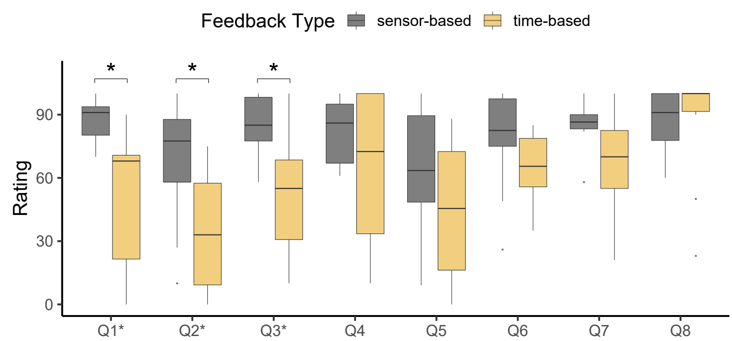


Fig. 10. Ratings for our custom questionnaire (see Table 2). Q1 ("The feedback helped me to understand how my body reacts to certain exercises."), Q2 ("The feedback allowed me to understand the effectiveness of the exercises."), and Q3 ("The feedback allowed me to understand my performance more in-depth.") show significant differences for the type of feedback (sensor-based vs. time-based). Significant questions are marked with *.

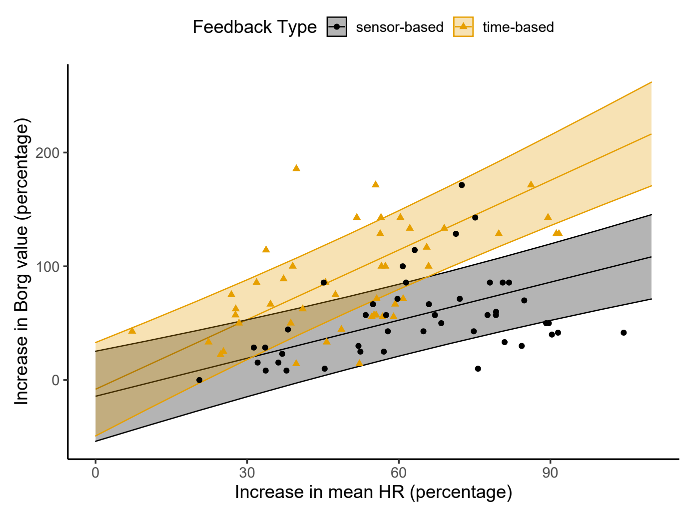


Fig. 11. Visualization of the linear mixed-effect model as described in Section 5.3. Shaded areas depict the .95 confidence interval. Individual data points are plotted and marked based on their respective feedback condition (sensor-based vs. time-based). Note the two-way interaction effect of feedback condition and increase in mean heart rate, as predictions are farther apart for high increases in heart rate.

heart rate[10]. The Borg RPE value is linearly related to the heart rate [7], though research has also revealed inconsistencies in this relationship [11]. To account for variation in bodily physic of our participants, we further normalized both values with their initial values at the start of the experiment and fitted a linear mixed-effect model for the collected Borg RPE values after each executed set. As fixed effects, we used the normalized mean heart rate (over the respective set) and

[10]For this analysis, we excluded one participant from the time-based condition, due to technical issues with the heart rate sensor, resulting in $N = 19$.

the feedback condition as a moderator and a by-subject random effect. Thus, our model describes how a (normalized) increase in the mean heart rate — among other effects — is connected to its Borg RPE value as reported by the participant. The resulting model shows a significant effect for the increase in mean heart rate ($F(1, 81.7) = 98.2, p < .001, \eta^2 = .58$) as well as an interaction effect for the increase in mean heart rate and feedback condition ($F(1, 81.8) = 8.5, p < .01, \eta^2 = .11$). The visualized model is shown in Figure 11. The plot highlights the relation between the increase in self-perceived exhaustion (Borg RPE value) and the measured increase in heart rate, indicating a linear relationship between both metrics. Further, it can be seen that the feedback condition acts as a moderator. It changes the perceived effort as the heart rate increases. We analogously executed the same analysis using mean acceleration (normalized) as a fixed effect instead of mean heart rate. No significant effects were found.

5.4 Interviews

All interviews (1:54 *h*) were transcribed verbatim. Through affinity diagramming [6], we identified positive and negative aspects of the interpretation of the feedback, insights the participants could gain from it, their motivation and *REPLAY*'s usability.

Interpretation of Feedback. All participants in the sensor-based feedback condition rated the feedback positively. They could notice how the signal changed over several sets and had no difficulties with the interpretation of the sensor data. Even if they had issues with the interpretation in the beginning, due to unfamiliarity with the sensor data, the participants were quickly able to grasp its meaning and understand it within the first sets.

> *During the first break, it took me a bit to look at everything that was displayed there, but then I actually found it super exciting. (P11, f, 24 y, sensor-based)*

Even more so, six participants from the sensor-based feedback group remarked explicitly that they already had considered the feedback for their next exercise set and turned their attention to this aspect in the next iteration, indicating reflection and, ultimately, the willingness to adjust their training.

> *Sometimes, I forgot to move my arms, and I remembered when I saw the acceleration, and I'm like, "Okay, yes, this makes sense." Because in the squats, I did not move my arms [...] and also in the jumping jacks." That was very good as an input. (P12, f, 32 y, sensor-based)*

In the expert interviews, we have already seen that people could detect the individual exercises in the signal. Our main study confirmed this observation. Half of the sensor-based feedback group commented that they could identify from the acceleration data when another exercise started and which part in the signal corresponded to the jumping jacks, squats, and high knees.

> *Further, certain exercises have different impacts. For example, jumping jacks had a lot more acceleration of the limbs as was, for example, the exercise which had to do with high knees, but then squats had much lesser usage of the limbs in some sense, acceleration of the limbs. (P19, m, 28 y, sensor-based)*

Yet, we also noticed that people from the sensor-based feedback group with little prior knowledge about acceleration sensor data or experience with it had more difficulties with the interpretation.

> *I briefly looked at that the first time, the movements, but I can't really do anything with it. (P4, m, 31 y, sensor-based)*

Eight participants in the time-based condition stated that the interpretation of the time-based feedback was straightforward and that it was helpful to compare the exercise sets.

> *I could just check how was the time that I was doing and see if I could match the same time in the next round or if I was losing time because I was more exhausted doing it. (P20, f, 27 y, time-based)*

Yet, participants also stated that the information content for time-based feedback was limited. They would have liked to get more information apart from the exercise duration. They stated that, for example, feedback about their pulse would have helped them to estimate their exhaustion objectively.

> *Maybe that I can objectively compare my exhaustion with what my body says about how exhausted I am. What I always like to do with my smartwatches when I use them is that I always check how high my pulse is. (P7, m, 27 y, time-based)*

Insights from the Feedback. Reports from participants indicated that the sensor-based feedback encouraged reflection about their exercise performance and exhaustion. In addition, the participants reported that they gained insights into their body physiology. Especially seeing and comparing the data from different sets provided surprising insights for the participants, for example, how their exercise pace changed over time.

> *You could clearly see that in the first round, especially the high knees were much faster and with a higher intensity, and also the time I needed for that was faster. Per round, the acceleration of the arm and leg somehow always decreased a little bit. (P5, m, 29 y, sensor-based)*

The reflection phase at the end of each set lets them evaluate the correct execution of the exercises and notice signs of exhaustion. For example, with increasing exhaustion, they observed that the quality of the movement got lower and other body parts tried to compensate for the lack of energy in others.

> *The last exercise with these high knees was the one where I noticed that I was tired. Towards the end, you could see that my acceleration values went down. However, with the arms, for example, I could see that I was somehow trying to compensate for this. (P8, m, 27 y, sensor-based)*

Furthermore, the detailed sensor-based feedback matched the perceived exhaustion, and the participants gained new insights from the data they were shown during the exercise breaks.

> *(...) so I would start at 140, 150, and after a couple of intervals, I would have expected it to reach 170, but maybe I think it was just because I didn't do enough repetition of this that it was still at 150. I was not completely exhausted in that sense. (P19, m, 28 y, sensor-based)*

But also, six of the participants in the time-based group perceived the feedback as confirmation of their own perceived exhaustion.

> *I already knew that after a certain time, I was also getting worse [...] and the screen confirmed that [...] I was also getting worse from the fourth or third round on. And it didn't bother me. It helped me to know whether I was getting better or worse now. (P3, m, 27 y, time-based)*

Although participants in the time-based group criticized the limited amount of information in the feedback, some of them were still able to connect the time-based feedback to their exercise form after reflecting on it and were able to analyze the shortcomings of their technique during the exercises.

> *The fact that I was faster again after the third and fourth set surprised me because I actually thought that I was consistently getting slower, but then somehow I got faster there, and it wasn't until the fifth set that I noticed that my technique got sloppy and that's why I was faster then. (P7, m, 27 y, time-based)*

Motivation. Participants from both feedback conditions felt motivated by the feedback. The comments from five participants in the time-based feedback group showed a strong performance-oriented motivation to do the exercises better, more precisely, to be faster in the next set and to observe the progress.

> *Although, of course because I'm kind of competitive, I tried to make it faster the next time while still trying to also do good form, which was fun. (P6, m, 30 y, time-based)*

Yet, participants also mentioned that their primary goal was to execute the exercises correctly and to gain improved fitness, showcasing that simple time-based feedback might not necessarily be sufficient for long-term motivation.

> *For my situation, it was perhaps not necessarily appropriate to know how long I needed for a round because I would not train against the clock. I would rather make sure that I also perform the exercises correctly, and besides, my goal is actually not speed, but an improved fitness, which is not measured by time. (P16, f, 23 y, time-based)*

In the other group, four participants stated that they considered the feedback as motivating to do enough exercises to achieve the training effect and to observe their progress.

> *I would actually say it rather pushed me a little bit and I was more focused because I was reviewing it. Otherwise, when I've done something like that, during the breaks, I've been more like, "Oh dear, another round. How am I going to do this?" (P11, f, 24 y, sensor-based)*

Usability and User Experience. Fourteen participants commented positively on using the break during HIIT for feedback on recent sets. For them, it did not feel like an interruption of their training routine.

> *(...) but the fact that it was in the break did mean that it didn't feel like an interruption. It was like a time when I was going to be not moving anyway. (P6, m, 30 y, time-based)*

Independent of the study condition, participants considered a broad spectrum of user groups that can benefit from such a system, ranging from beginners and amateurs to professional sportspeople. Though, the majority of the participants considered the system more useful for the first two groups.

6 DISCUSSION

In this work, we investigated the potential of in-session reflective feedback based on bodily signals in fast-paced physical activity, such as high-intensity interval training (HIIT). In the following, we discuss design implications for future systems that want to employ in-session reflective feedback for physical activity.

6.1 In-Session Reflective Feedback Is Beneficial for Fast-Paced Physical Activities Such as HIIT

Our investigation confirmed that having access to one's bodily signals through sensor-based feedback allowed participants to evaluate the effectiveness of the exercises and the effects on their bodies more accurately (**RQ2**). In this feedback group, users were more aware of how HIIT affected their body physiology (Q1-Q3). Interestingly, participants were able to closely read into their exercise form by analyzing the acceleration signal as well and reflected on their mistakes (see Section 5.4), e.g., recognizing overpacing at the start of individual exercises. Participants in the time-based condition were sporadically able to recognize overpacing as well, albeit only on the set level. Consequently, providing users with the means to analyze their own body signals can foster an increased awareness of their physical capabilities [35, 75]. Our work has confirmed that **even short intermediate breaks during fast-paced physical activity can serve as reflection**

phases (**RQ1, RQ2**) and do not break the exercise flow. This suggests that feedback during short exercise breaks may be equally effective in building body awareness as real-time feedback [37, 81].

6.2 Reflection on Exhaustion Does Not Necessarily Require Feedback But Benefits From It

While we observed the benefits of the sensor-based feedback condition in terms of fostering body awareness for users, this does not necessarily indicate that participants were better at predicting their own exhaustion (Q4). Although sensor-based feedback provided a good way to reflect on exhaustion, it was not significantly better than time-based feedback (**RQ2**). We attribute this to the high variance present within the latter. Combined with the post-hoc interviews, we could identify that simply asking participants to state their current exhaustion (using the Borg RPE scale) was enough for some participants to actively reflect on it (**RQ1, RQ2**). Yet, if the time-based feedback was not in line with the participants' perception, they lacked the means to further investigate the cause. This effect was much less prominent for the sensor-based condition, partly because participants agreed more with the feedback (Q7) but also were able to identify reasons for their misperception (see Section 5.4). These findings are in line with studies of personal informatics that show that **effective reflection requires substance, opportunity** and encouragement [2, 3, 66]. Our system provided active prompts for reflection at dedicated time intervals while also querying the users about their perception of exertion. Thus, *REPLAY* showcases how activity breaks can be used as opportune moments to effectively foster body awareness (**RQ2**).

6.3 The Type of Feedback Changes a User's Perceived Exhaustion as Heart Rate Increases

In our analysis, we also examined how the different feedback conditions influenced the relation between perceived exhaustion and measured heart rate (see Section 5.3). Our findings are particularly relevant to understanding exhaustion measurement and feedback, as research has already reported inconsistencies regarding the linear relationship between the Borg RPE scale [7] and objective measures for physical exhaustion [11], such as heart rate. Similarly, we found that the type of feedback presented to users can significantly change their perceived exhaustion as their heart rate increases (**RQ1**). While this effect is not distinctive for low increases in heart rate, it significantly affects how users evaluate their own exhaustion for high increases in heart rate. As such, feedback on one's physical exhaustion, such as sensor-based feedback, not only has the potential to inform users but can also have adversarial effects if purposefully used to alter a user's perceived exhaustion (**RQ2**). Our work shows effects that could potentially be exploited to persuade [34] users to believe that they are performing less strenuous tasks. Thus, there is a need for future designers of technologies for physical activity, which feature means of interpreting one's exhaustion to strictly adhere to ethical principles and ensure that misinterpretation is prevented.

Our findings also have implications for designing heart rate visualizations for commercial products, e.g. heart rate zones [56]. Incorrectly designed representations of heart rate data may potentially lead to a skewed perception of exhaustion, especially if novice users are not familiar with the visualizations, as mentioned in our expert interviews. Ideally, such feedback methods **need to be personalized for the individual user, ensuring that they are empowered to interpret their heart rate measurements accurately** (**RQ2**). Further, we recognize that the design choice involved in *REPLAY* imply that the system performs (partial) data interpretation for the user, changing their assessment of the exercise session. This is an observation analogous to studies of recent developments in the fitness tracker market [4] where the complexity of processing an abundance of tracking data is addressed through the fitness application providing simplified, derived metrics. Yet, as (part of) the data interpretation is delegated to the system, such design requires rigorous approaches to the responsibility of the system designers and additional measures to prevent interpretations which may have negative consequences. *REPLAY* focuses solely on immediate assessments, limiting not only data interpretation by the system but also its moderation effect to a short time horizon. Consequently, we observe that our system effectively supports in-session reflection, cf. [3].

6.4 Performance Is a Strong but Not Universal Motivator

As evident from related work and commercial products, time-based feedback is a strong, performance-oriented motivator for users to undertake physical activity. However, this feedback concept is particularly suited for short-term motivation, inciting a competitive nature within users [38]. Yet, people with predominately qualitative goals, i.d., wanting to improve one's general fitness and wellbeing, often struggle to associate these goals with quantitative metrics, such as 'completion time' or 'number of repetitions' (see Section 5.4). Our work proposes **reflective feedback as a different angle for a person's motivation**. We argue that this feedback approach can provide those users with the means to gain insight and understanding of the effectiveness of the physical activity with regard to their own personal goals [52] (**RQ2**).

6.5 Limitations and Directions for Future Work

In our evaluation, participants did not report any usability issues with *REPLAY* (see Section 5.1). However, they expressed concerns about the increased cognitive effort required to analyze the signal, making everyday use more cumbersome. Yet, HIIT or related training exercises should not be performed daily, making increased setup and interpretation efforts less problematic. Similarly, our employed study setup used a large screen to allow for a detailed signal analysis by participants. We understand that state-of-the-art commercial products (e.g., Fitbit [19], Polar [55], and Garmin [24]) are more limited in terms of screen sizes (smartwatch, mobile phone, tablet). Hence, in this work, our focus was first and foremost on the general feasibility of in-session reflective feedback using bodily signals (cf. Section 2.4). In this regard, our results have shown that the concept is valid, and we believe downsizing the visual feedback to tablet dimensions is possible. Serving even smaller display sizes warrants further research [15] and potentially provides good starting points on how to simplify data visualization for more easy-to-digest, immediate access by users, while still facilitating a better understanding of one's body physiology.

Further, we have seen that providing participants with the means to analyze the effects of HIIT on their bodies can already foster increased body awareness during one training session, even with a limited selection of sensors as chosen based on our design process (cf. Section 3). It remains an open question for further investigations on how the long-term use of the system will affect their body awareness and how more specialized sensor types suit individual exercise forms. We also recognize that simply taking Borg RPE measurements after exercise sessions draws attention to one's exhaustion. However, in our work, this was a factor present in all conditions of our study, and thus we expect that it does not affect our analysis. This is potentially interesting for future research directions comparing the effectiveness of in-session versus after/before-session reminders.

7 CONCLUSION

In this paper, we presented design qualities of feedback systems that foster body awareness through in-session reflective feedback for fast-paced physical activity using the example of high-intensity interval training (HIIT). We designed and implemented *REPLAY*, a system which allows users to study their bodily signals (heart rate, movement) from body-worn sensors during HIIT. In addition, we evaluated *REPLAY* in a user study comparing its sensor-based feedback with baseline time-based feedback. Our findings confirm that reflective feedback enabled users to gain a better understanding of how their bodies reacted to the exercises and judge their effectiveness. We also found that the type of feedback moderated the users' perceived exhaustion.

Our work highlights implications for designing new types of interactive fitness applications which employ in-session, but not real-time, reflective feedback. Such systems should not focus on performance but instead allow users to actually foster their body awareness. We showed that this reflective feedback changes how users perceive their physical activity. Participants in our study used the feedback to better understand their bodily reactions to different types of exercises, allowing them to gain deeper insights into their own physiology and supporting informed exercise routines. We conclude with cues for the design of exercise systems that make use of sensor-based in-session reflective feedback.

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