# Investigating How Recreational Cyclists Engage with Sport Tracking Technologies to Prepare for Endurance Events

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## ABSTRACT

Sports tracking technologies are increasingly available, offering cyclists rich data to monitor and support training. Yet little is known about how recreational competitive cyclists engage with these tools during event preparation. We explored this through surveys, interviews, and ride data with 11 recreational cyclists. Despite the many metrics available, participants primarily relied on sensor-based metrics such as heart rate and speed. In their preparation, they actively triangulated how they felt, what the data showed, and what was possible given their motivations and constraints of daily life. Many participants completed events that exceeded their recent training, framing these efforts as opportunities to explore their physical limits. By linking activity workload data with participants' reflections, our findings suggest a disconnect between how preparation unfolds in practice and how training tools are designed, encouraging SportsHCI researchers to reimagine ways of incorporating training principles into technologies that reflect the lived experiences of recreational cyclists.

## CCS CONCEPTS

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

## KEYWORDS

SportsHCI, cycling, human-data interaction, sports, recreational athletes, personal informatics, sports tracking, training load management

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## 1 INTRODUCTION

Endurance sports, which demand sustained physical effort over extended periods, have traditionally been available to a narrow segment of the population. Barriers such as limited access to training resources, equipment, and coaching support have historically determined who could meaningfully participate [3]. Today, these barriers are gradually diminishing due to the broader availability of training resources and more available training equipment [15]. This shift is reflected in the increasing participation of recreational athletes in endurance events, from marathons [32] to triathlons [47] to local cycling competitions [28]. Thousands of athletes now train seriously while juggling work, family, and daily life [29]. This democratization of high-performance sports has created a unique class of athletes, *recreational competitors*, who are not professionals but are highly invested in their performance and personal improvement [20]. These athletes navigate a growing ecosystem of sport tracking devices, applications, and training platforms that make performance data, once available only to elite athletes with coaches, widely accessible [40].

For cyclists, performance metrics such as speed, distance, power, and heart rate can be displayed on devices mounted directly to handlebars within easy view [5, 33, 49]. Among these metrics, *power* is considered the gold standard for how much physical work a rider is doing [22]. Power meters are built into the bike and capture power output in watts by sensing how hard and how fast a cyclist is pedaling [6]. While other endurance sports, such as running and rowing [16, 17], have begun experimenting with power-based devices, cycling remains the only mainstream sport where this kind of precise workload monitoring is widely used, particularly by recreational athletes [8]. Cycling training preparation, therefore, can be designed around quantifiable metrics to represent training load, effort, and physiological stress [38], with power serving as a key input.

As a result of all this available data, there is a growing market of commercially available tools and platforms to help cyclists guide their training and prepare for events: the market size is expected to grow from $15.5 billion in 2023 to $82 billion in 2032 [18]. Many cyclists upload ride data to third-party platforms for long-term tracking and review. TrainingPeaks (TP) [1] is widely used for structured training and coach-athlete collaboration, while Strava[2] blends performance insights with community engagement. Garmin Connect[3] and Intervals.icu[4] provide additional dashboards and tools for endurance athletes. Many of these platforms calculate *derived metrics*, which are values generated from a combination of inputs such as power, elapsed time, and athlete-specific thresholds to support day-to-day and long-term training load monitoring [39]. Recovery-focused tools like WHOOP[5], FitBit[6], and Garmin's Body Battery extend this tracking into sleep and 24-hour readiness. Many of these metrics build on foundational training principles such as progressive overload, recovery, and fatigue monitoring as studied in sports science [12].

In sports science, the process of preparing for an endurance event is framed through the concept of *training load*, which refers to the cumulative stress imposed on the body through training sessions [7]. This is rooted in the *general adaptation model*, which states that training relies on a balance of stress and recovery [9]. In principle, training must be challenging enough to drive physiological adaptions, but increases in load must be carefully managed with moments of recovery to avoid overtraining, illness, or injury [14]. Guidelines often encourage gradual weekly increments (e.g., 10%) while cautioning against big deviations or "spikes" from established training patterns. Sharp increases in load may be particularly risky for less experienced athletes [13, 31].

The combination of technologies such as power meters that capture effort, training platforms that transform that data into visualizations to aid in planning and reflection, and *derived metrics* framed around training load and recovery principles has created an unprecedented environment for recreational cyclists. In theory, it should be easier for recreational cyclists to monitor and manage their training loads. In practice, little is known about how recreational cyclists engage with these technologies, or whether their interactions support effective preparation. Understanding this gap requires bridging two domains of research: sports science research which has traditionally focused on structured training methodologies and physiological data [30], and human-computer interaction (HCI) studies which examine how athletes engage with and make sense of the feedback sport tracking technology provides [19, 20, 35]. However, few studies have examined how the two perspectives of training preparation and lived technological experiences interact. This gap motivates our investigation into how recreational competitive cyclists engage with sports tracking tools, metrics, and platforms during their preparation for endurance events.

[1]https://www.trainingpeaks.com/
[2]https://www.strava.com/about
[3]https://connect.garmin.com/
[4]https://intervals.icu/
[5]https://www.whoop.com/
[6]https://store.google.com/category/trackers?hl=en-US

To address this gap, we conducted a three-part study with 11 recreational cyclists preparing for a target event. Our study was guided by three research questions:

- RQ1: *How do recreational cyclists use sport tracking technologies and metrics in preparing for endurance events?*
- RQ2: *How does the effort required by an event compare to participants' recent training history?*
- RQ3: *How do experiences, motivations, and life constraints shape training practices and the use of data in recreational cyclists' preparation for events?*

To answer these questions, we collected multiple forms of information across the preparation and event timeline. We used pre-event surveys to capture participants' cycling background, training practices, and technology use (RQ1); sensor-based training and event activity data (including power, heart rate, and kilojoules) to compare recent workload with actual event demands (RQ2); and post-event interviews to explore how participants made sense of their preparation and performance, as well as how motivations, life constraints, and technological interactions shaped their experiences (RQ1, RQ2, RQ3).

By investigating these questions, we explore how the affordances of sport tracking technologies, the ways recreational cyclists interact with them, and the principles of effective training management come together (or come into tension) during preparation for endurance events. Our findings make the following contributions to SportsHCI:

- We contribute to the ongoing efforts in SportsHCI to understand real-life practices with sports tracking technologies, focusing on how recreational cyclists engage with tools and metrics in their training.
- We extend the recent work on training load management in running to cycling, a sport that offers a rich case for studying data-driven preparation due to its many tools and metrics.
- We integrate activity workload data with qualitative accounts to capture the physical demands of training and event effort alongside recreational cyclists' lived experiences of preparation, offering insights that neither data nor reflection alone could provide.

We position this exploratory study as a bridge between two often disconnected domains: the training preparation methodologies developed within sports science, and the lived, personal experiences of recreational cyclists' use of sports tracking technologies. We advocate for systems that not only support data-driven decision-making but also honor athletes' embodied knowledge, real-world constraints, and diverse motivations. In doing so, we invite the SportsHCI and sports science communities to rethink how sports tracking technologies can better serve recreational cyclists.

## 2 RELATED WORK

Self-tracking technologies have become increasingly common over the past decade, enabling individuals to collect and reflect on data about their bodies, behaviors, and daily lives. In HCI, research has highlighted that self-tracking practices are shaped not only by data collection or behavioral goals, but also by emotion and social context [23]. From its inception, SportsHCI as a research field has examined the multidimensional roles that tracking technologies play in athletic contexts, where tools can simultaneously support performance measurements and shape subjective experiences. Tholander and Nylander [42] introduced the concepts of a *measured sense of performance*, grounded in objective metrics such as heart rate and pace, and *lived sense of performance*, based on bodily sensation, emotion, and feeling. As illustrated in their study with runners, participants described using heart rate data not only to improve physical conditioning but also to deepen their awareness of effort and sensation.

Rapp and Tirabeni [34] further showed that elite and amateur athletes use sports tracking tools in different ways. Elite athletes often embed data into structured training programs guided by coaches, using sport tracking technologies to support well-defined goals and routines. Amateur athletes, on the other hand, tend to have less defined goals and rely on sports tracking technologies for guidance. However, they may not have the appropriate support, background knowledge, or understanding of how and when to use the data effectively. The authors suggest that athletes at this level need more than visualization and numbers: they need tools that help them make sense of data and use it in meaningful ways.

Building on this, Karahanoğlu et. al [20] examined how runners use sports tracking technologies as their goals shift over time. In their study, runners moved between performance goals and simply keeping up the habit of running. These shifts depended on their life circumstances and they adapted how they used their tracking tools to fit their changing needs. While many used sports tracking technology to log their runs, they typically reflected on the data after the run, not during. Their findings suggest that for those participants, checking data in the moment could feel distracting especially if it misaligned with how their bodies felt while running.

More recently, Karahanoğlu et. al [19] explored how athletes engage with training load advice provided by sports tracking devices. They found that over time, runners often shift from relying on trackers and apps to structure and direct their training to using them as supportive devices that help confirm their own decisions as they gain more bodily awareness and training experience. The study also examined how runners understand and trust different types of metrics. It alludes to a shift in sport tracking technologies that now offer more than just data measured directly collected from sensors. *Measured* metrics, such as heart rate, are directly recorded physiological outputs [38]. Sports tracker technologies have advanced and now provide a range of *derived* metrics such as training load, readiness, and recovery scores, that are generated by combining multiple data sources through calculations. The findings from this study show that while derived metrics offer the promise of simplified, scientific-based insights, they are often poorly understood and viewed with skepticism, especially if they do not align with an athlete's subjective experience.

While these insights largely emerge from running contexts, cycling presents a uniquely data-rich sport where these questions remain underexplored. Most HCI and cycling work has centered on safety [5, 26], navigation [37], alert systems [45], and bike-vehicle interaction [2]. Some work has explored how cyclists engage with sport tracking technology. A study of commuting cyclists found that participants made sense of their recorded data both during and after the rides, using it to become more aware of their bodies and their riding experiences [24]. For instance, participants described using a drop in speed to decide when to change their gears or to reflect on how steep a section of the route might have been. If they felt slower than usual, they described checking the data for confirmation. Demonstrating even for commuting cyclists, sports tracking technology plays a role beyond just logging distance. Others studies have started exploring how physiological data might be used within and between cyclists [1, 46]. Agharazidermani et al. [1], for example, examined collaborative heart rate data displays between cycling partners, showing how shared physiological awareness can influence pacing and group coordination. However, few studies have examined how recreational cyclists engage with sport tracking technologies, especially in the context of training preparation.

This body of related work provides important foundations for our investigation of recreational cyclists who are competitively motivated. Like many amateurs athletes, they often lack formal support but still pursue competitive goals, navigating both data-driven training tools and the realities of fluctuating motivations and life constraints. Prior studies show that sport tracking technologies offer increasingly robust metrics that support training management, goal pursuit, and reflection, while also shaping athletes' subjective experience. However, to our knowledge, no study has combined activity workload data with athletes' reflections to explore how their experiences with sport tracking technologies align with (or diverge from) the physiological principles those technologies are designed to support.

Our study takes a first step toward understanding how recreational cyclists engage with sport tracking tools and exploring whether their interpretations and experiences with training technologies align with the performance-oriented goals those tools are designed to support. In doing so, we respond to the calls for deeper integration between HCI and sports science, particularly in understanding how to design systems that reflect foundational principles such as progressive overload, recovery, and training load management [11, 19, 25].

## 3 METHODS

To explore how recreational cyclists use tools and metrics to guide their training preparation for endurance events, we used a three-part study consisting of (1) an online pre-event survey, (2) training and event workload data collection, and (3) a post-event interview. An overview of the study timeline is shown in Figure 1. This design allowed us to capture participants' goals, preparation practices, technology use, and event experiences from multiple angles. The survey collected background information, motivations, event details, and the specific sport tracking technologies participants used to plan and monitor their training. Training and event data from wearable and/or on-bike sensors provided quantitative insights into each participant's workload leading up to the event and their actual event load. We chose not to conduct repeated interviews or diary studies to avoid influencing participants' behaviors or introducing bias in how they believed they should prepare, simply because they knew a researcher would be checking in. Instead, the post-event interview allowed participants to share how they made sense of their training, reflect on their motivations and experiences, and the role

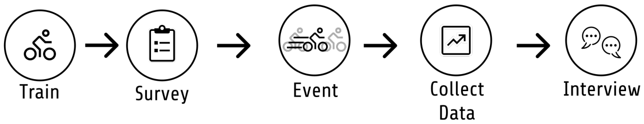


**Figure 1: Overview of study timeline: recreational cyclists who were already training for an upcoming endurance event completed a pre-event survey, participated in the event, shared sensor-based data from training and the event, and took part in a post-event survey.**

technology played in shaping their decisions. Using these sources of data together, we examine measurable patterns of training in the context of athletes' lived experiences using sport tracking technologies to prepare for and reflect on endurance events. We received approval from our university's human subjects Institutional Review Board (IRB) prior to recruiting participants.

## 3.1 Pre-Event Online Survey

We designed a 10-15 minute survey to collect information about participants' training practices, event preparation, and use of training-related cycling technologies. We modeled the structure after a recent survey by Karahanoglu et al. [19] designed to explore how runners use sport tracking technologies to support training load management (TLM), and we adapted it to the context of recreational competitive cycling. We piloted the survey with researchers in computer science, human-centered computing, and sports science who were also recreational cyclists but not involved in the study. Their feedback helped us refine the survey to improve clarity and align the questions with our research goals. The final survey included questions about (1) demographics and cycling history, (2) participants' general approach to training preparation (e.g., self-guided vs. coach-led), (3) metrics and technologies used, (4) self-reported confidence in training preparation, (5) event details, and (6) self-reported pre-event expectations of how the effort required would compare to their recent training.

## 3.2 Activity Workload Data Collection

Participants were already utilizing their sport tracking devices during both training preparation and their event, and they were logging data through their preferred platform. As part of the IRB-approved protocol, participants either (1) shared their activity data directly with the research team or (2) gave us permission to access publicly viewable data from their platform accounts. We collected cycling activity data from the 30 days leading up to each participant's target event, as well as the event itself. We utilize this data primarily to investigate RQ2.

We chose a 30-day time frame because this time window aligns with those used by many commercial fitness platforms when generating training summaries, load scores, and readiness feedback. These systems typically base their analysis on training patterns over two to four weeks [39, 41]. By aligning with these common time frames, we were able to generate a snapshot of training and event effort that reflects how many cyclists already engage with and interpret their data.

We extracted power output, heart rate, and activity duration from rides within the 30-day window and the event itself. We used a custom Python script to process the data. When power data was available, we calculated kilojoules (kJ) for each ride as a measure of total workload, which we use in this study as an indicator of effort. We selected power and heart rate because they are two of the most commonly used physiological measures in endurance sports [30]. When power was unavailable, we estimated kJ using a heart-rate-based equation [21] adjusted for participant sex, as reported in the survey.

We chose kJ as our primary metric because it provides a simple and interpretable measure of work performed. In cycling, kJ can be directly calculated from power output and reflects the total amount of mechanical energy a rider expends during an activity. For example, riding at 200 watts for one hour results in 720 kJ of work, because power (in watts) multiplied by time (in seconds) gives energy in joules (200 x 3600 = 720,000 J), which converts to 720 kJ. Because this is an exploratory study, we prioritized selecting a metric that was interpretable, flexible with the data we had available, and commonly recognized for workload monitoring in sports science and cycling [43].

## 3.3 Post-Event Interviews

To explore participants' reflections on their event effort, training preparation, motivations, experiences, and use of sports tracking technologies, the first author conducted follow-up semi-structured interviews with each participant approximately one week after they completed their target event. All interviews took place in February and March 2025 using Zoom. To maintain confidentiality, only the first author knew the participants' identities, and the rest of the research team remained blinded to this information.

The interview began with general questions about participants' cycling background and goals, followed by a section focused on post-event reflections. This included questions about how the target event went and how it compared to their expectations. The questions then shifted to training preparation, including how participants structured their training and the role of tools and metrics. The interviewer introduced the concept of training load management (TLM) to explore participants' familiarity with the idea, whether they integrate it into their preparation, and whether they use data to monitor or manage training load. The interview concluded with forward-looking questions about how tools or metrics could be improved to support event preparation and personal goals. When applicable, the interviewer referred to participants' survey responses to elicit elaboration or clarification.

## 3.4 Participant Recruitment

We recruited recreational cyclists who were preparing for an endurance cycling event scheduled between January and early March of 2025. We recruited for the study through local cycling clubs and personal networks. For the eligibility criteria, participants needed to be training for a target endurance event during the specified time frame, using either a power meter or heart rate monitor for training and the event, and agree to let us use training and event data. Participants did not receive any form of compensation.

**Table 1: Participant Demographics and Self-Reported Training Characteristics**

| ID | Gender | Age | Cycling Experience (years) | Tracking Experience (years) | Weekly Time (hours/week) | Weekly Mileage (miles/week) | Training Approach Type | Event Type |
|---|---|---|---|---|---|---|---|---|
| P1 | M | 20 | 5 | 5 | 10 | 200 | Unstructured | Road |
| P2 | M | 27 | 2 | 1 | 8 | 150 | Unstructured | Road |
| P3 | F | 51 | 25 | 15 | 10 | 150 | Unstructured | Mountain |
| P4 | F | 24 | 2 | 2 | 8 | 100 | Unstructured | Gravel |
| P5 | F | 18 | 6 | 6 | 8 | 100 | Friends' Advice | Road |
| P6 | M | 26 | 5 | 5 | 10 | 200 | Unstructured | Gravel |
| P7 | M | 20 | 2 | 2 | 8 | 125 | App-Based Plan | Road |
| P8 | M | 20 | 7 | 7 | 11 | 210 | Coach Plan | Road |
| P9 | M | 21 | 4 | 4 | 10 | 200 | Self-Planned | Road |
| P10 | F | 25 | 2 | 1 | 10 | 200 | Coach Plan | Road |
| P11 | F | 19 | 4 | 4 | 5 | 80 | Friends' Advice | Road |
| AVG | | 24.64 | 5.82 | 4.73 | 8.91 | 155.91 | | |

Eleven participants (5 females and 6 males; ages 18-51 years, Mean age = 24.64 years, SD = 9.25 years) completed the study, including the survey, activity data sharing, and follow-up interviews. One additional participant completed the initial survey but was unable to take part in their planned event and did not continue the rest of the study. This sample size is consistent with prior work in HCI research for sports [10, 20, 34] and was within what our research team's resources could support. We used Mckay et al.'s athlete classification framework [27] to identify participants as recreational-level athletes. On average, participants reported 5.82 years of cycling experience (SD= 6.60) and 4.73 years using sports tracking technologies (SD = 3.95). They self-reported an average weekly cycling volume of 155.91 miles (SD= 48.72) and 8.91 hours (SD = 1.70). All completed an organized endurance event during the study, with distances ranging from 36 to 110 miles (M= 65.18, SD = 28.71). Most events were road cycling (n=8), with the remainder in gravel (n=2) and mountain biking (n=1).

Participants used a variety of devices to track their rides while cycling. Some participants used multiple devices across multiple training sessions and events. Devices included Garmin bike computers (n=6), Garmin watches (n=5), Zwift[7] (n=3), Wahoo bike computers[8] (n=2), and others. They also reviewed their training using multiple platforms, most commonly Strava (n=7), Garmin Connect (n=5), TrainingPeaks (n=2), and Intervals.icu (n=2), among others. See Table 1 for participant demographics and training characteristics based on self-reported data from the pre-event survey, and Table 2 for participants' use of sports tracking devices, platforms, and metrics. These values reflect how participants described their training habits and do not represent the ride data we collected during the study.

## 3.5 Data Analysis

Our data analysis used both quantitative and qualitative analysis. We used descriptive statistics for survey responses and to summarize each participant's training load in the 30 days leading up to the event. For each participant, we calculated the kilojoule (kJ) values for each ride during this period, and then computed the average, standard deviation, maximum single-ride kJ value, and total number of training rides. These summary statistics allowed us to compare participants' typical training load to the kJ value recorded for their target event.

The qualitative data consisted of transcripts from participant interviews. Two researchers analyzed these transcripts in two rounds guided by Saldana's *The Coding Manual for Qualitative Researchers* [36]. The first round of coding utilized process, magnitude, and values coding. For the purpose of our research, we define these coding styles as follows: *Process* coding uses gerunds (-ing words) to capture actions in the data, ranging from simple observable activity to broader conceptual actions. *Magnitude* coding uses values to indicate intensity, frequency, or direction of identified themes. *Values* coding reflects participants' attitudes and beliefs, to describe their unique perspectives and experiences.

A lead researcher used a combination of process and magnitude coding to identify the actions that the participants were taking and to what extent they do the actions, for RQ1. For RQ2, they used magnitude coding to indicate the extent to which the participants saw the difference between their event efforts and their training load. For RQ3, they used a combination of values and magnitude coding to indicate the values and beliefs that affected their training preparation and to what extent. A secondary researcher spot-checked the content of the codes at intervals during the first round. During the second round of coding, both researchers worked together to group all themes into broader categories that told a cohesive story and aligned with the dimensions of our research questions.

[7] https://www.zwift.com/
[8] https://www.wahoofitness.com/

**Table 2: Summary of Devices, Platforms, and Metrics Used by Participants**

| Devices | Platforms | Metrics | Metrics (Long-Term) |
|---|---|---|---|
| Garmin (n=6) (P1, P3, P4, P7, P9, P10) | Strava (n=8) (P1, P2, P3, P5, P6, P7, P8, P11) | Heart Rate (HR) (n=10) (P1, P2, P3, P4, P5, P6, P7, P8, P9, P10) | Weekly Hours (n=8) (P1, P2, P3, P4, P7, P8, P9, P11) |
| Garmin Watch (n=5) (P1, P5, P6, P10, P11) | Garmin Connect (n=5) (P1, P7, P9, P10, P11) | Elapsed Time (n=8) (P1, P3, P4, P5, P6, P8, P9, P10) | Weekly Distance (n=5) (P4, P6, P7, P9, P11) |
| Wahoo (n=2) (P6, P8) | Intervals.icu (n=2) (P2, P9) | Power (n=7) (P1, P2, P3, P7, P8, P9, P10) | Power Trends (n=4) (P2, P7, P9, P10) |
| Zwift (n=3) (P1, P3, P8) | TrainingPeaks (n=2) (P8, P10) | Distance (n=5) (P4, P5, P6, P8, P11) | HR Trends (n=5) (P4, P5, P7, P9, P11) |
| iGPSPORT (n=1) (P2) | Ride with GPS (n=1) (P4) | Speed (n=4) (P4, P8, P10, P11) | Weekly TSS (n=3) (P7, P8, P9) |
| Apple Watch (n=1) (P5) | Fitbit (n=1) (P4) | Cadence (n=4) (P2, P6, P7, P8) | Cardio Load (n=1) (P4) |
| | | KiloJoules (n=1) (P8) | Recovery Score (n=1) (P9) |
| | | Stress Score (n=1) (P9) | Performance Manager Chart (n=1) (P8) |

**Unless otherwise specified, *Device* refers to brand of bike computer. Zwift refers to the virtual training platform. *Metrics* refers to those relied on during or after a single ride; *Metrics (Long-Term)* refers to metrics used across rides to evaluate training over time. Abbreviations: TP = TrainingPeaks; HR = Heart Rate; TSS = Training Stress Score (from TP); PMC = Performance Manager Chart (from TP)

## 4 FINDINGS

In this section, we organize our findings around our three research questions. For RQ1: *How do recreational cyclists use sport tracking technologies and metrics in preparing for endurance events?*, we group the findings into two themes: (1) during-ride engagement and (2) post-ride reflection and planning. These categories distinguish how participants interacted with tools and metrics while riding versus how they used them afterwards to inform decisions. For RQ2: *How does the effort required by an event compare to participants' recent training history?*, we present quantitative comparisons between each participant's event effort and their prior training load, followed by qualitative reflections on how participants interpreted the relationship between the two. For RQ3: *How do experiences, motivations, and life constraints shape training practices and the use of data in recreational cyclists' preparation for events?*, we report on three themes that shaped participants' training decisions: (1) participants' conceptual understanding of training load principles, (2) motivation and social context, and (3) life constraints.

### 4.1 RQ1: How do recreational cyclists use sport tracking technologies and metrics in preparing for endurance events?

Participants used a range of sport tracking devices and metrics in their everyday cycling routines in preparation for their target events (see Table 2). Most participants used common platforms such as Garmin Connect (n=5), Strava (n=6), and TrainingPeaks (n=2) to log rides. They most frequently tracked accessible metrics that were directly measured by sensors such as heart rate (n=10), elapsed time (n=8), power (n=7), distance (n=5), and speed (n=4). Several participants noted that elapsed time (referred to as "time" by participants) was particularly useful for planning nutrition and hydration strategies (P4, P6, P8).

Across the sample, participants varied in how they engaged with metrics, some interacted with metrics *during* rides, while nearly all engaged with them *afterward* for reflection or planning. The styles were closely linked to the level of structure in their training approaches. When describing their training approach in the pre-event survey, P8 and P10 reported following a coach-provided plan; P9 designed and followed their own plan; P7 followed an app-based plan; P5 and P11 relied on informal peer advice; and P1, P2, P3, P4, and P6 trained without structure, guided by feel (see Table 1).

Participants without formal training plans described an intuitive, day-to-day approach to riding (P1, P2, P3, P4, P6, P7[9], P11). These participants used platforms such as Strava or Garmin Connect to log and reflect, but not to organize or guide upcoming sessions. As P3 described their planning, *"So it was me just picking whatever I felt like doing that day."* P1 said they *"just go by feel and vibes."* In these cases metrics such as weekly hour, weekly distance, and average

[9]P7 reported using an app-based training plan, but also noted that they did not always follow it in practice.

heart were used to monitor general trends or evaluate progress over time, but participants did not use this information to drive daily decisions.

In contrast, participants with more structured routines, whether following an app-created plan (P7) or working with a coach (P8, P10) engaged more intentionally with training platforms. P7 described loosely following structured sessions and using post-ride metrics to evaluate whether they hit the intended prescribed effort, while P8 and P10 completed structured workouts, reviewed feedback with their coaches, and adjusted upcoming sessions based on performance data summaries and perceived exertion. These participants used TrainingPeaks or Garmin workout features, including zone-based prompts, lap targets, and ride summaries to inform their training.

#### 4.1.1 During-Ride Engagement.

All participants recorded their rides using GPS-enabled devices, but their engagement with the metrics during rides varied. Five participants reported placing their devices out of sight in their back pockets, preferring to review data post-ride (P2, P3, P8, P9, P4). Others described "just checking" or glancing occasionally at metrics such as time, power, or heart rate but not using them to adjust effort (P1, P6, P11). For instance, P1 explained, *"Distance, time, heart rate, power, cadence, I have all those, but I kind of just glance at them."* Despite having a full dashboard visible of metrics, P1 clarified: *"I haven't been really paying attention to them or starting any rides with like preset goals for what those are going to be. It's just off of feel and off of like the 'vibe' of the ride."*

The preference to ride by "feel" over feedback was echoed across the full sample. 11 of 11 participants described using bodily sensations, intuitions, or subjective effort to guide their planning and in-the-moment decisions while riding. Several described riding "by feel," making decisions about intensity, duration, or recovery based on how their legs felt, how hard they were breathing, or their mood that day. As P1 explained, *"Right now, I get on the bike and I'm like 'I think I should do a hard day today, the legs feel good. We're going to go do a hard day.' If I'm not really in the mood, I don't do a hard day."* P6 added, *"I usually go by how my legs feel, and if I'm not feeling it, I'll just shift what I do that day."* P4 described gauging effort during a ride by how easy it was to talk or sing, rather than relying on the heart rate metrics they were also recording: *"I've heard a trick where you can kind of judge your zones by your breathing and how well you're able to talk versus sing. I definitely do that."*

Even participants with structured plans, such as P8, described relying on feel. After breaking their bike computer mount, P8 spent the winter riding without viewing any real-time metrics: *"I always have it on the bike. Interestingly, I snapped my mount accidentally and so I rode the whole winter with it in my back pocket. And I didn't look at zones, timing, power-once. Everything was on feel. And by the end of the winter, I could work out exactly what was tempo, what was zone two, and what was zone one just on feel."* They added, *"because you also can't trust all the numbers all the time,"* referencing how factors like heat or illness can affect the accuracy or interpretation of the data.

In contrast, a smaller group of participants actively used metrics during their rides (P7, P8, P10). Notably, these are the same participants following either a coach-provided or app-based training plan. P10 described using visuals and audible alerts during climbs to manage pacing: *"I'm always watching heart rate on the climbs to make sure I'm not going too hard too early....It beeps when I'm not doing it right."* P8 used LED heart rate zones as a quick-reference visual tool, noting, *"even if I can't look down quickly, I can just scan and see what zone I'm in."* P8 added that while the feature was helpful for them, other riders have used the lights competitively: *"A guy saw the red lights and attacked because he knew I was at threshold."* P7 took a proactive approach by using the course profile of their upcoming event to tailor their training, explaining, *"I knew the climb would be long, so I did efforts around that duration with the power I wanted to hold."*

#### 4.1.2 Post-Ride Reflections and Planning.

Post-ride reflection and planning often involved triangulating between how the ride felt and what the data showed. Some participants reviewed data after their rides to reflect on overall effort (P1, P2, P5, P6). For instance, P5 explained, *"How hard did it feel versus how hard does it look on Strava? [The metrics] are helpful in making sure I don't overdo it."* P6 echoed this, *"To see how I did, I'll look at the stats afterwards. Not really during."*

Others used post-ride reviews to validate their perceived exertion during the ride (P2, P6, P4). For example, P4 said, *"I'm thinking, 'Oh, that felt like a pretty easy ride.' I can then go look and see where my heart rate actually was."* P6 mentioned comparing their physical sensations with data, *"One is feel, like how I'm feeling physically, like in my legs...and I kind of use that with heart rate and the power, and then I can compare."*

Some participants used these comparisons to gain a general sense of fitness (P3, P9 P11). P11 described how mismatches between perceived and actual ride difficulty served as a check on fitness: *"sometimes I'll go on a ride and I'll be like 'that felt like a lot of climbing,' but then I check it and it wasn't. So I feel like that's kind of a good gauge of how fit I am."* Others, like P10, used post-ride data to reflect on how well their body was recovering, *"Riding when you're fatigued or when you've done a really insane effort a few days before...it can show you a lot more of how your body has handled the situation."*

Several noted that harder or structured rides often prompted them to review their data more closely, particularly to evaluate consistency or intensity (P1, P5, P8). As P8 explained, *"If it's like four intervals, I'll look at the consistency...but after a normal ride, I don't look at anything. I only look at it if I've done intervals."*

Participants commonly report using historical data to estimate preparedness for upcoming target events. They referenced comparing the effort, average speed, or duration from previous rides they considered successful (P3, P5, P6, P9, P10, P4). These comparisons helped them evaluate whether their current training aligned with the demands of the event they were targeting. As P4, who was targeting a specific goal time in century event, noted *"I looked at the few times I had done century rides and looked at the speed...trying to figure out if I would be able to do it based on my past rides."*

Participants occasionally mentioned advanced derived metrics such as Training Stress Score (TSS), recovery scores, cardio readiness, or execution scores, but they typically viewed these indicators with skepticism. They described interacting with them out of curiosity rather than relying on them for reflection or decision-making

(P2, P6, P10, P4). P2 said, *"I like to look at the data, but I don't trust it enough to follow it blindly."* P8 noted, *"I couldn't tell you what TSS actually is. It's just a score that the app assigns,"* but also acknowledged that their coach relied on this particular metric to guide and plan their training.

## 4.2 RQ2: How does the effort required by an event compare to participants' recent training history?

Table 3 and Figure 2 provide a summary and visual representation of each participant's event effort compared to their prior 30-day training history. Event-day effort is shown alongside each participant's training average, standard deviation (SD), and highest single-day ride effort, all reported in kJ, along with the number of rides completed in the 30-day window. In the figure, red dots mark each participant's event effort, while horizontal lines indicate each participant's average workload (solid black), as well as one and two standard deviations above that average (dashed line and dotted line, respectively). Blue "x" markers show the participant's highest single-day effort recorded during that period.

Descriptive statistics revealed variations in training behaviors. Average daily workload ranged from 142.4 kJ (P9) to 1,090.8 kJ (P8), and training frequency varied from just 3 rides (P9) to 20 (P10). Standard deviation values ranged from 408.8 to 1267.9 kJ, indicating differences in consistency. Some participants maintained relatively steady workloads (e.g., P3, P5), while others experienced large fluctuations in daily effort (e.g., P2, P6, P8). 10 out of 11 participants completed at least one training ride that matched or exceeded their event-day effort, though these peak efforts were often much higher than their average, indicating that they may not be representative of overall patterns.

Across the sample, event-day effort ranged from 951 kJ (P10) to 3,836 kJ (P6), with most participants expending more effort during the event than they did during their average training load. For five participants (P2, P3, P4, P6, and P9), event day efforts extended beyond the +2 SD mark, indicating workload outside their recent training patterns. Participants P1, P5, P7, and P11 completed events moderately above their usual output. P10 was the only participant whose event-day effort (951 kJ) closely aligned with their 30-day training average (871.1 kJ) and well below their maximum training ride (2,569 kJ).

#### 4.2.1 *Participants' Reflections on Event Effort.*

While some participants exceeded their average training load, with some recording event efforts more than +2 SD, a range that can indicate the event effort was beyond what their body may have fully adapted to, none described this in problematic terms. According to the survey, nine participants expected the event to be either moderately harder (rating 4) or much harder (rating 5) than their average training load. P6 and P10 were the only ones that expected the effort to match their usual training. P10's assessment aligned with their data: their event effort closely matched their training average and was well below their maximal effort. P6, however, recorded an event effort that exceeded their average by more than +2 SD. When asked in the interview how the event compared to training preparation, P6 responded, *"training always feels easier. So I'd say that's true with this event. I don't train like hard."* Several participants described themselves as "still figuring it out" or experimenting with training (P1, P2, P3, P5, P11, P4), which shaped how they interpreted event difficulty. P3 initially anticipated the event would be moderately harder and, in reflection, described the effort similarly, describing the experience as a learning opportunity, saying *"there are definitely things I'll be more prepared for next time."* For these participants, they viewed the event effort as a way to explore their capacity and in some cases, an exciting chance to test their limits.

Among those who exceeded +2 SD, P2 and P9, each described in the interview feeling underprepared heading into their events due to illness or limited training, yet both expressed general satisfaction with their performance. Despite limited time on the bike, P9 shared, *"The lead-up was a little rough… but I surprised myself. That made me feel like maybe I can handle more than I thought."* P2 reflected *"I guess it went better than expected because I was not expecting to hang on for so long."* For these participants, the large difference between training and event-day output became a marker of resilience and possibility.

In contrast, P10, the only participant whose event effort aligned closely with their average training load, followed a training plan created by a coach and reported high confidence in their preparation. They anticipated the event effort would be similar to previous race experiences and the post-event interview reflection confirmed this alignment that the race effort felt similar to training in effort. P10 was also a participant that relied heavily on sports tracking technology throughout their training preparation, reflecting *"I'm learning all these things from technology and having to rely on it...it's really beneficial for me. I've never been more healthy, thank God, like in my life."*

## 4.3 RQ3: How do experiences, motivations, and life constraints shape training practices and the use of data in recreational cyclists' preparation for events?

So far, we have described how participants used sport tracking technologies (Section 4.1) and how their event efforts compared to recent training (Section 4.2.) In this section, we examine the broader context that shaped how they prepared. Participants made training decisions based on what they knew, what motivated them, and what fit into their daily lives. Many understood key principles of training load and recovery but often prioritized feel, fun, social connection, or scheduling needs over data or feedback from training technologies. We highlight three themes: (1) how participants described and applied training load principles (Section 4.3.1), (2) how motivation and social context influenced their training (Section 4.3.2), and (3) how real-life constraints shaped their preparation and engagement with sports tracking tools (Section 4.3.3).

#### 4.3.1 *Conceptual Talk of Training Load Management.*

In the pre-event survey, all participants rated how confident they felt in managing their preparation for the event (M = 3.55, SD = 1.29, min = 1, max = 5). Although many participants exceeded their typical training load on event day, interviews revealed that they conceptually understood the basic principles related to training load management. All participants (n=11), regardless of their confidence rating,

**Table 3: Participant Training and Event Effort Summary (From Sensor Data)**

| Participant | Training Avg (kilojoules) | SD (kilojoules) | Event Effort (kilojoules) | Max Single-Day Effort (30d) (kilojoules) | # of Rides (30d) (count) |
|---|---|---|---|---|---|
| P1 | 714.7 | 841.5 | 1878.0 | 3073.0 | 16 |
| P2 | 602.2 | 1012.3 | 3041.0 | 3380.0 | 11 |
| P3 | 269.9 | 408.8 | 1379.0 | 1547.0 | 12 |
| P4 | 642.1 | 563.2 | 2874.0 | 1822.0 | 15 |
| P5 | 568.6 | 577.4 | 1261.0 | 1687.0 | 18 |
| P6 | 958.8 | 1267.9 | 3836.0 | 4678.0 | 14 |
| P7 | 542.9 | 716.6 | 1326.0 | 2129.0 | 13 |
| P8 | 1090.8 | 1197.4 | 2862.0 | 4464.0 | 18 |
| P9 | 142.4 | 458.7 | 1438.0 | 2050.0 | 3 |
| P10 | 871.1 | 808.9 | 951.0 | 2569.0 | 20 |
| P11 | 468.3 | 800.6 | 1305.0 | 3434.0 | 11 |

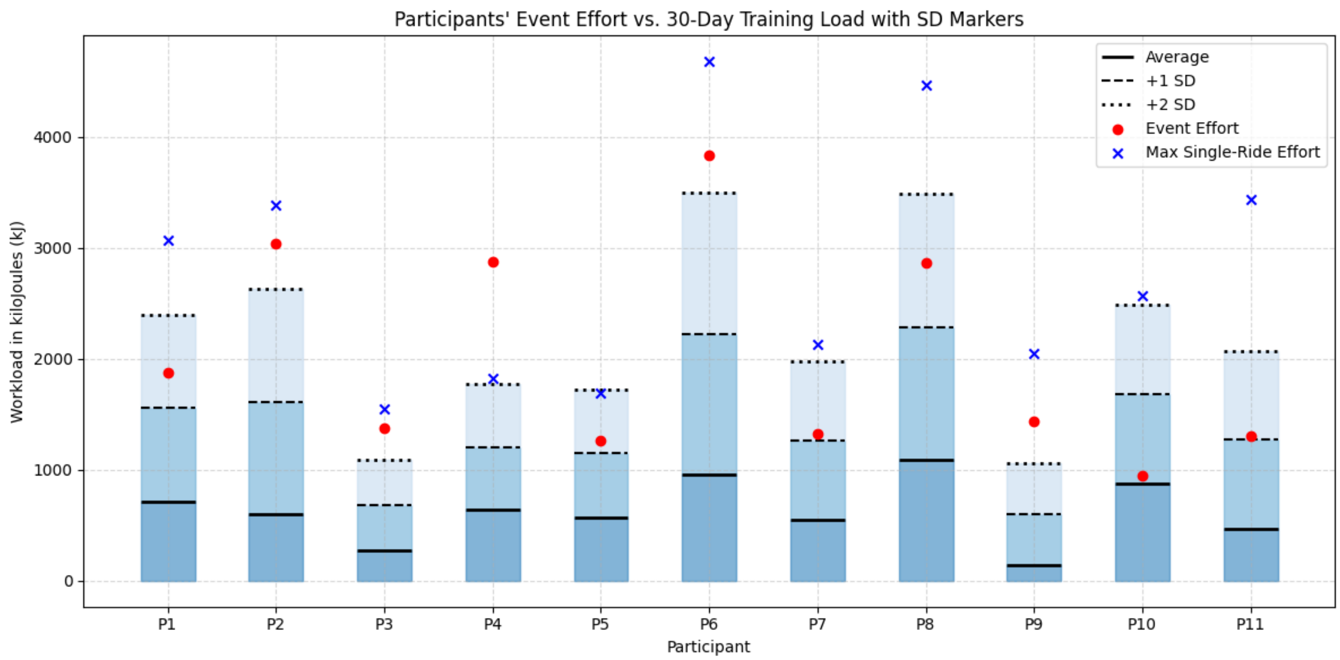


**Figure 2: *Participant Event Effort and Max Single-Ride Effort Compared to 30-Day Training Averages.* This figure compares each participant's event-day workload (red dots) and their highest single-ride effort in the prior 30 days (blue Xs) to their recent 30-day training history in kilojoules (kJ). Horizontal lines indicate the participant's average workload (solid line), +1 standard deviation (dashed line), and +2 standard deviations (dotted line), with shaded bars visually grounding the ranges between these markers.**

described the importance of balancing hard and easy sessions and incorporating rest. Notably, this awareness emerged unprompted, even among those who reported low confidence in managing their preparation (P2, P5, P4), before the interviewer introduced the topic.

Several participants described their personal approaches to this. P1 said *"I've been trying to go about like one day easy, one day hard,"* and explained that a hard day might be *"two or three hours with [redacted]...my legs are going to be stinging the entire time,"* while an easy day was *"just got out and riding chill for an hour or two."* P2 described their pattern as *"two or three weeks of increasing volume and then one week decreasing."* P11 said, *"It's been like a nice balance of kind of shorter, easier rides and kind of longer, harder rides."* Even P4 who described themselves as one "still figuring it out" explained, *"okay, I went on a couple causal rides last week. This week, I should do a longer solo ride, and then one faster ride with some people that I know are up for pushing a faster pace."*

Participants who did not have coaches described how they learned these ideas. Several said they watched YouTube videos

(P6, P7, P9), or used information from training platforms such as Garmin Connect and Interval.icu as sources for understanding fitness, fatigue, and preparation (P7, P9). Others said they learned by riding with friends (P2, P5, P11) or through trial and error (P4). P1 and P3 shared that they had previously worked with personal coaches, which helped shape their current understanding of how to manage training preparation.

*4.3.2 Training Preparation as Social, Flexible, and Fun.* Participants described motivations and riding practices shaped by enjoyment, challenge, and social connection. P3 and P6 said "fun" was their primary motivation for cycling, while others such as P1, P2, and P5 said personal performance goals. Across interviews, participants often reported basing their riding decisions on what felt enjoyable, convenient, or socially engaging.

Participants described planning rides around opportunities to ride with others or join group events. P3 said, *"We had two rides from work...it was totally for fun. This was just like a good opportunity to get people together outside of the office."* P11 explained, *"You'll have the option to do a ride that's less enjoyable...or you could go on a ride with your friends and do whatever they're doing. That could be more fun. I'm always going to pick the one with friends...I'm doing it because I want to have fun."* P7 said, *"If you give me two options and say, 'Go do your training block for the day,' or 'Go on this random long ride,' I'll probably go do my training block. But if my friends are doing the long ride, I'll probably go with my friends."* P4 shared *"If there's something that someone plans that I really want to do, that would definitely interfere with my ability to stick to any kind of structured rest schedule or planning."*

Even when participants used sport tracking technologies that offered guidance or performance feedback, many said they chose to ride based on social plans or personal preferences rather than following a device or recommended ride suggestion. Some reported ignoring or dismissing feedback from sport tracking technologies when it conflicted with what they wanted to do. P3 noted, *"If it was a nice day and I had an opportunity to go do a fun ride with somebody, I'm not going to be like, 'oh no, sorry, my WHOOP said I shouldn't do that today.'"* P1 criticized Garmin's post-ride messaging, saying *"No, I don't like when Garmin's like 'you've been unproductive.' I'm like, 'you're a buzzkill!'"* P3 added, *"You get done with the ride and it tells you that you need like 48 hours of recovery. I'm like 'okay, whatever.'"*

*4.3.3 Riding Around Real-Life Constraints.* While participants expressed motivations to prepare for events and could describe principles on how to do so effectively, many shared that life responsibilities, school, health conditions, finances, and other constraints shaped how and when they trained. As P2 put it, *"I just kind of do it when I can-if I have the time."*

Many participants mentioned scheduling challenges (P1, P2, P3, P6, P7, P4). P3 said, *"I ride when I can ride,"* and noted that weather played a role in their decisions. P7, a full-time student, described riding decisions around their busy schedule: *"This week I'm not going to ride much because I've got work, I've got school, and I've got projects I need to get done."* P6 and P4 shared that they fit training around their work obligations.

For some, health conditions shaped what was possible. P5, who lives with Type 1 diabetes, explained, *"That glucose is a big determiner of my effort...if I'm running low and I can't get my blood sugar back up...I might have to cut the ride short."*

Participants also described how cost and access influenced their ability to prepare the way they wanted (P7, P9). P7 discussed the expense of cycling equipment and training tools, *"It's incredibly expensive to have access to this...if you're not from a financially well-off background...it's just very hard."* They added that this affects access to structured training and proper event preparation, *"You either have to educate yourself or pay to have someone do it for you."* In addition, many participants described using the free version of Strava or other platforms, which influenced the kinds of metrics they viewed and the data they engaged with (P1, P2, P3, P5, P7, P9, P11). P11 explained, *"Strava, I don't get a lot from because I don't have premium...I really just get speed."*

Others describe how sport tracking technologies sometimes fail to support the variability of their lives. P1 mentioned that switching between mountain biking and road riding made distance-based metrics feel inaccurate, as the shorter, more intense mountain bike rides were not reflected fairly. P7 described struggling with their training app's derived execution score, explaining *"I struggle to get anything above an average"*, attributing the issue to terrain, stops, and other factors on their outdoor rides that made it hard to stay within the technologies' prescribed intensity range. P3 explained that they skied regularly during the winter instead of cycling, saying that skiing contributed to their overall fitness, but it wasn't captured in cycling-specific training metrics or reflected in recommendations.

Several participants expressed a desire to engage more fully with structured tools and derived training metrics (P2, P3, P7, P9, P4), but felt their current life circumstances made it difficult. P2 explained, *"A training load metric doesn't mean a lot. Only if you know, if the rest of my life is pretty consistent, then I think training load and all those other metrics make way more of a difference."* P3 shared that they weren't actively seeking out structured plans or training preparation tools unless they had a specific performance goal and the time to commit.

## 5 DISCUSSION AND IMPLICATIONS

This discussion reflects on how recreational cyclists engaged with sport tracking technologies as they prepare for endurance events. In our study, participants report basing their decisions on what felt enjoyable, socially meaningful, and realistic within the constraints of daily life, all while maintaining some awareness of training load principles such as mixing "hard" and "easy" days. Most participants encapsulate this process as "figuring it out," actively triangulating how they felt with what the data showed and what their life allowed. In what follows, we explore how these participants use data for reflection more than prescription, how participants engage with (or diverge from) science-informed models, and how sports tracking technologies might evolve to better support these lived practices. Throughout this section, we use bold text to highlight opportunities for future research and design implications identified from our findings.

### 5.1 Metrics that Support an Athlete's Narrative-Driven Reflection and Planning

While all participants used sport tracking tools, they most often used them *after* rides to reflect on effort and progress, rather than using them *during* rides to guide training decisions. Reflection is well-documented in many sport tracking studies, where athletes use data not just to assess performance but to make sense of their experiences [34]. In our study, participants primarily engaged with the metrics directly recorded from their sensors such as distance, elapsed time, speed, and heart rate not because they were the most scientifically robust, but because they were intuitive, emotionally resonant, and available free across most technologies. Karahanoğlu et al. [19] were early in highlighting the distinction between these *measured* metrics (values directly recorded by sensors) and *derived* metrics (algorithmically generated and offered through many sport tracking technologies) in SportsHCI research, highlighting the metrics' differing roles in engagement, trust, and training adjustments. While all participants in their study used at least one *measured* metric, their engagement with derived metrics varied depending on how transparent or purposeful the metric felt. We extend this line of research by showing a new perspective on how recreational cyclists engage with these different types of metrics: In our study, participants drew on *measured* metrics to narrate their experience because they connected directly to their sense of effort, accomplishment, and meaning. These metrics helped them answer reflective, narrative-driven questions about their training preparation: *Did I go far? Did it feel hard? Was I faster than last time? Have I done a ride this hard or this long before?*

In contrast, derived metrics rarely invoked storytelling or played a central role in our participants' narratives. Participants did not spontaneously reference Training Stress Score (TSS), cardio loads, or readiness scores to describe their rides or event efforts. However, some did recall derived metrics when the system's narrative clashed with their own. One common example was Garmin's "unproductive" message, a post-ride assessment that reflects training load status[10] through a derived metric. Several participants mentioned this term explicitly, one even describing it as "a buzzkill," especially after rides they had enjoyed or felt proud of. This mirrors findings by Bentvelzen et al. [4] on derived metrics in fitness trackers, who observed that while users often have internalized reference points for certain metrics (e.g. knowing that 7-8 hours of sleep is ideal), they struggle to interpret other stress or health scores, such as whether a derived stress score of 70 is good or bad. **This points to an opportunity in SportsHCI to better understand how system-generated metrics shape sense-making and how tools might better support recreational cyclists' reflective practices as they prepare and make sense of their efforts on their own terms.**

Our participants described reflective practices that often extended into preparation for future events. Participants regularly used the same directly recorded (*measured*) metrics as reference points when evaluating their readiness for their target event. Many described their preparedness in what they had experienced, and whether they had done something similar before. This extends prior research by Rapp et. al.'s [34], which suggested that forecasting based on past data was primarily a practice of elite athletes. In contrast, our participants, recreational cyclists, also forecasted in their own way by reviewing previous rides to assess whether a future target event felt achievable. They treated metrics such as distance or average speed as personal benchmarks. These recreational cyclists' practices suggest that forecasting with data is not exclusive to elite athletes, but also serves as a meaningful part of how recreational cyclists make sense of their preparation alongside data, and construct a narrative of their capability and readiness. **This presents an opportunity to support narrative-driven forecasting by designing tools that help athletes connect past experiences to future goals using intuitive and personally meaningful metrics.**

We as researchers were surprised at how many participants reported placing their bike computers in their back pockets, a few due to broken mounts or needing a light on the handlebar, but often without actively replacing them for extended periods. Based on our personal experiences with cyclists, we had expected that these recreational cyclists would make use of the convenient positioning available on the bike handlebars to see many available pieces of data. However, these participants recorded their data on the bike computer but rode primarily "by feel", checking the data later. When turning to the literature, we found that the behavior of putting a device out of sight while continuing to passively record has been documented, but primarily among elite athletes [35]. That same study reported that amateur athletes tended to view and use their tracking devices actively during workouts and events, monitoring metrics in real-time to regulate effort and pace. A notable exception to that finding was two elite cyclists whose devices were mounted on their handlebars, enabling them to check data as needed. Our findings complicate this distinction. Although our participants were recreational cyclists, not elite, some nonetheless displayed tendencies toward de-prioritizing real-time data engagement in favor of riding by feel. This suggests that device engagement may not be tied to amateur or elite status or sport-specific device accessibility. Instead, some recreational cyclists may adopt more selective or reflective strategies, choosing more experiential aspects of riding over constant attention to technology during a ride. **This opens an opportunity to design technologies that accommodate athletes who intentionally train without actively engaging with data, maybe offering features that allow them to temporarily hide or mute real-time metrics. SportHCI research could also explore the motivations behind this choice.**

### 5.2 Reconciling Training Load Guidance and Lived Experience

Although participants described different approaches to training, all expressed familiarity with the idea of alternating hard and easy days. This foundational concept in training load management was widely recognized, even if applied through embodied self-guidance rather than by data. This pattern was also reflected in the data: the average standard deviation (SD) in the sample was 824 kilojoules (kJ), suggesting day-to-day variability in effort.

In several cases, participants' event efforts exceeded their 30-day training average, sometimes by more than two SD. It is important to

[10] https://www.garmin.com/en-US/garmin-technology/cycling-science/physiological-measurements/training-status/

note that exceeding one's average training load on event day is not inherently problematic, especially in endurance sports. However, it is the sudden "spikes" and large deviations in workload that may pose a risk. From a sports science perspective, such spikes may suggest that the intensity or volume of the activity goes beyond what the body has adapted to [13], potentially increasing the risk of injury, illness, or poor performance [14]. In cycling, moderate evidence links high loads and large differentials between training and event effort to overuse injuries [44]. Wilber et al. [48] similarly found that 85% of recreational cyclists reported an overuse injury in a 12-month period, with over one third seeking medical attention. Many contemporary sports tracking technologies such as TSS, acute-to-chronic workload ratios, or ramp rate guidelines, are designed to help athletes identify and manage these fluctuations. Rooted in high-performance sports, such tools aim to support preparation towards performance optimization while minimizing injury risk [7, 19].

**Our findings highlight a potential disconnect between the support these sport tracking technologies are designed to offer and the way recreational cyclists approach preparation.** Cyclists in our study made training decisions based on mood, weather, social plans, or work schedules. Motivation was fluid, sometimes driven by preparation goals but just as often or more by community, exploration, or the fun of riding. While some participants exceeded the training load guidelines typically emphasized in sports science, many did not see this as a concern. Instead, they framed it as part of an exploration, a personal challenge, an opportunity to learn their body's capabilities, and a marker of resilience.

Most participants completed at least one training ride that matched or surpassed their event effort. These high-effort sessions, though often well above their training average, seemed to serve as meaningful touch points, whether as markers throughout their preparation of what they felt capable of, or simply opportunities afforded by weekend availability. Automated platform feedback (e.g. "unproductive") often failed to align with these motivations, and in some cases, participants dismissed or resented it. This kind of messaging imposes system-defined success or failure onto activities that participants understood very differently.

It is clear that even despite the mismatches between recreational cyclists' approaches and the things many sports tracking tools prioritize displaying, participants are still enthusiastic to use these technologies. For example, participants such as P7, P8, and P9 enthusiastically pulled out their cycling computers during interviews, flipping through their dashboard displays to show the metrics they interacted with the most, while P10 reported relying heavily on metrics and platform feedback throughout their preparation. These athletes' excitement was not in "perfect execution" but in the thrill of tracking, tinkering, and trying.

**Here we see an opportunity for systems and the SportsHCI community, not to abandon sports science principles, but to re-imagine how they can be experienced by recreational cyclists.** We do not advocate for removing training guidelines or downplaying the physiological realities of overload. Instead, we advocate for integrating these models into systems that respect users' lived context and embodied knowledge. Systems should account for the different ways non-elite users frame success and risk. Rather than treating efforts that go beyond recent training as flaws, systems could recognize those efforts as part of how recreational cyclists explore their limits, especially early in their sporting journeys. Instead of presenting users with judgmental language in warning messages, systems could offer adaptive guidance. This means allowing athletes to recognize when they're going big, not to stop them, but to help them adjust, recover well, and reflect on what they learn.

Designing for the reality of recreational cycling means recognizing that metrics are interpreted through lived experiences. A training load score or platform recommendation not to ride is likely to be ignored if the sun is shining and friends are riding. Conversely, a gentle ride might actually be more appropriate than a challenging interval session after a stressful week at work, even if the challenging intervals are designed to cover important physiological goals for event preparation. A new generation of systems that understand context and allow space for it in planning and reflecting will better support recreational competitive cyclists in real-life preparation for events.

## 5.3 Limitations

The study carries several limitations that are important to acknowledge when interpreting the findings. First, the sample size was small (n=11) and skewed towards younger participants (mean age = 24.64 years), which may not reflect the experiences of cyclists at different ages or life stages. Second, cycling is a diverse sport with many disciplines and a wide range of ways to experience competition. Even within the same discipline, such as mountain biking, athletes may prepare for vastly different types of events, including short track, cross-country, and 24-hour relay formats, each with different physical demands and training strategies. Commercial platforms such as Garmin recognize this diversity, offering discipline-specific metrics such as *Flow* and *Grit* designed for mountain biking. Given this variation and our small sample size, we do not aim to generalize our findings across all types of cyclists or cycling events. Instead, this study offers a starting point for understanding how recreational cyclists use sport tracking technologies. Future research should include a broader age range and explore how training practices and technology use vary across cycling disciplines.

Second, all the events in this study occurred during the months of January through March. Seasonal factors such as weather and day-light availability could influence how athletes prepare, which may not be typical for training during other times of the year.

Third, this study relied on user-generated data: data that participants themselves tracked and chose to upload through devices and digital platforms. While this reflects real-world practice, it introduces the possibility of miscalibrated devices, inaccurate readings, or inconsistencies in the data collected from participants that we could not control for.

Additionally, we chose a statistical approach to summarize training and event load in a way that would be interpretable across both sports science and HCI audiences. While more advanced models such as intensity-weighted measures or the Acute:Chronic Workload Ratio (ACWR) may offer more dynamic assessments of load and readiness, our aim was to provide a straightforward baseline for comparison and interpretation.

## 6 CONCLUSION

This study explored how recreational cyclists engage with sports tracking technologies as they prepare for endurance events. Through surveys, ride data, and interviews, we found that cyclists actively triangulated perceived effort, device-reported data, and life constraints to guide their training decisions. While our participants used a wide range of tools and platforms, most treated them as mediums for post-ride reflection. Participants gravitated towards intuitive, emotionally resonant metrics that helped them make sense of effort and progress in personal terms. Many participants completed events with efforts that exceeded their recent training load. Rather than viewing this as problematic, they embraced it as part of the lived experience of recreational endurance sport. For many, social motivations outweighed training effectiveness, and performance goals were often shaped—or interrupted—by the realities of daily life.

Our work contributes a multidimensional account of sport technology use in recreational cycling, combining activity workload data with participants' reflections to advance understanding of how these training technologies are experienced and interpreted in everyday practice. While many sports tracking tools incorporate sports science principles in their designs, our findings suggest a disconnect in these intended uses, how recreational athletes actually prepare for events, and how event preparation might ideally be managed. We encourage the SportsHCI community and designers of sports tracking technologies to reimagine how sports science principles are communicated by honoring users' embodied knowledge, embracing diversity of motivations, and respecting the constraints of users' everyday lives. These lines of research hold the potential to support safer, more sustainable training habits, and more meaningful participation in cycling.

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