Improve my Performance, Protect my State of Mind: How Collegiate Student-Athletes Engage with their Sports Data

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Abstract

Collegiate student-athletes train and compete in a dense data ecology where information about their bodies and performances circulates among coaches, staff, and fans. To understand how student-athletes themselves engage with this data, we conducted interviews with 20 student-athletes, identifying four modes of engagement: 1) performance-directive, executing training and targeting improvement; 2) reflective-monitoring, assessing the body's reaction to training and daily load; 3) coach-mediated, receiving insights through staff expertise; and 4) selective-disengagement, intentionally stepping back to protect confidence or avoid overload. These findings fill a gap left open by three related areas of research: SportsHCI, collegiate athletics, and personal data engagement. Each mode entails reasons, practices, and trade-offs. Student-athletes draw on different combinations of these modes as they respond to training demands, coaching oversight, and their own well-being. Our findings highlight how an evolving data ecology creates opportunities and pressures, requiring student-athletes to balance performance with protecting their state of mind.

CCS Concepts

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

Keywords

SportsHCI, sports technology, athletics, student-athletes, collegiate sports, human-data interaction, personal data engagement

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1 Introduction

Recent years have seen sports emerge as an important focal area for human-computer interaction (HCI) research [48, 57, 58, 61, 79]. The landscape of increasingly data-driven athletics [27, 54, 55] has in part fueled the growth of the subfield of SportsHCI [22, 47, 52, 59], with ongoing efforts to understand real-life practices with sports data, especially in specific contexts and communities of practice [64]. Much of this work has focused on recreational settings, including running [37, 77], cycling [11], skiing [29], rock climbing [51], and competitive adaptive sports such as TetraSki [56].

An important context and community of practice for SportsHCI research is collegiate sports [18, 40]. In the United States (U.S.), collegiate sports are university-based sports programs in which student-athletes are full-time students and elite athletes at the same time [50, 60]. Top-tier collegiate sports programs operate at the scale and intensity of professional competitions. Their games are nationally televised [70]; events draw tens of thousands of fans [76]; and their universities invest heavily in recruiting [73], building sports facilities [75], and adopting advanced performance technologies [14].

Sports data in this context encompasses everyday measures such as distance, pace, heart rate, and sleep, as well as increasingly common derived metrics such as recovery and load scores [6]. Recent technological advances have reshaped how this data is produced and encountered. Wearables can now collect information continuously and automatically detect activities [15]; recovery and sleep scores are generated through proprietary models [6]; GPS, video, and wellness metrics feed into team systems with little manual input [15]. These data streams are woven into daily routines: readiness scores forecast how student-athletes' bodies may respond before practice [72]; GPS data is tracked during training to guide workload adjustments [8]; and competition statistics are shared with teammates, staff, and fans [13]. These experiences situate collegiate student-athletes in a dense, always-on data ecology at a formative stage in their young adulthood, making them a critical population for understanding how evolving technology shapes both performance and lived experience in ways central to SportsHCI research.

Earlier HCI research on collegiate student-athletes reflects a period before many of the aforementioned technological developments became widespread. These studies, based on interviews collected between 2019 and 2020 [18, 19, 28, 40], document how student-athletes engage with data in settings where coaches and staff control most information. Student-athletes had limited access to their own data and researchers observed power differences that made opting out difficult [18, 19, 40]. Our study reflects a collegiate athletics environment which has undergone changes since it was last examined by SportsHCI researchers. Wearable technologies now provide continuous sensing and give student-athletes new ways to review and understand their own information. At the same time, policy changes such as Name, Image, and Likeness (NIL) rights [33] and expanded transfer rules [65] have altered student-athletes' autonomy and increased their ability to choose environments that best support them. This paper contributes an empirical understanding of how today's student-athletes engage with their data in this fast-changing ecology.

This work also stands distinct from prior accounts which combined student-athlete and staff perspectives [18, 19, 28, 40]. The most recent work that captures the modern ecology of collegiate athletics is Brewer et al.'s 2025 study [10], which focuses solely on the viewpoint of collegiate coaching staff. Brewer et al. describe how staff manage expanding streams of data and act as protectors amid growing concerns about the psychological impacts of new and ongoing wearable tracking on student-athletes. However, the "athlete side" of this modern ecology remains largely undocumented.

Given the changes in recent years within collegiate athletics and the technological landscape, and the need for a student-athlete-centered account, we ask the following research question: *How do collegiate student-athletes engage with their sports data in this contemporary ecology?* We conducted semi-structured interviews with 20 elite collegiate student-athletes across six sports: tennis, track and field, cross country, soccer, basketball, and swimming. Our participants included 14 women and 6 men.

From our analysis of interviews, we identified four modes of how student-athletes engage with their sports data: 1) **performance-directive**, executing training and targeting improvement; 2) **reflective-monitoring**, assessing the body's reaction to training and daily load; 3) **coach-mediated**, receiving simplified insights through staff expertise; and 4) **selective-disengagement**, intentionally stepping back to protect confidence or avoid overload. Importantly, student-athletes do not rely on a single mode, but draw on combinations of modes as they respond to training demands, coaching oversight, and their own well-being. New data streams bring new opportunities and pressures in how student-athletes relate to information, requiring student-athletes to balance two often-competing aims: improving performance while also protecting their state of mind. This balancing act demonstrates that sports data is not just a tool for performance optimization, but a complex presence in student-athletes' daily lives, one that sometimes requires mediation or even disengagement. The modes reported here provide a structured expression for how student-athletes relate to their data. The modes consolidate some familiar patterns dispersed across existing research on athlete data practices, collegiate athletics and personal data engagement research, and add some newly emerging practices of student-athletes. Based upon these findings, we conclude with design considerations and directions for future research.

This work makes the following contributions:

- Empirical findings that provide a dedicated account of how collegiate student-athletes engage with their sports data in the contemporary landscape of collegiate athletics.
- Characterization of four modes of engagement that capture the reasons, practices, and trade-offs of living with sports data in this unique context.
- Findings around the dual role of data as both supportive and mentally straining, showing how this tension shapes student-athletes' experiences.
- Design considerations to guide the HCI community towards designing novel technologies attuned to the needs of collegiate student-athletes.

2 Related Work

This paper fills a gap left open by three related areas of research. First, SportsHCI has given us rich accounts of athlete data practices, but primarily outside the tight institutional structure of organized collegiate sports. Second, research on collegiate athletics has examined that very structure, but has not delved specifically into the student-athlete experience in today's world where student-athlete-facing data streams are more common. Finally, research in personal data engagement has indeed laid a groundwork for how individuals interact with their own data, but our findings show notable differences in how student-athletes navigate these systems compared to everyday users.

2.1 SportsHCI and Athlete Data Practices

The field of SportsHCI has expanded quickly in recent years, with growing attention to how athletes across recreational and competitive contexts integrate technologies into their sporting practices [11, 37, 38, 51, 56, 62]. A consistent finding in SportsHCI is that athletes leverage data to guide effort and develop knowledge about their bodies. For example, Tholander and Nylander [78] showed how athletes use data to execute workouts at prescribed intensities while also using this data as an anchor to develop knowledge about how effort levels correspond to bodily sensations. Building on this, Rapp and Tirabeni [64] demonstrated that athletes' data use varies by expertise: amateur athletes tend to engage in exploratory interactions with their data, whereas elites focus on the metrics that support targeted training goals. While these studies illustrate a range of athlete data practices, most focus on recreational or self-directed athletes. Even research involving elite or sub-elite competitors [64] typically examines athletes operating outside the tight institutional structures of organized sport that might be found in collegiate athletics.

As sports technologies have become more pervasive, SportsHCI researchers have surfaced dualities and grand challenges. Postma et al. [63], drawing on self-determination theory, caution that data can both support and undermine athlete motivation. When data aligns with athletes' goals and provides meaningful feedback, it can enhance competence and autonomy. However, when data becomes controlling or misaligned with experiences, it risks diminishing intrinsic motivation and well-being [63]. This dual nature of data is an emerging area of interest in SportsHCI. More broadly, a grand challenge in SportsHCI calls for research recognizing that athletes are multifaceted individuals whose sport experiences include emotional and social dimensions in addition to physical performance [22]. Yet many sports technologies still prioritize physical performance metrics and give little attention to these other aspects of an athletic life. Our study aims to advance understanding of how collegiate student-athletes experience the dual nature of data as they navigate their multifaceted lives.

2.2 Earlier HCI Research on Collegiate Athletics

Earlier research on collegiate athletics conducted between 2019-2022 highlighted several factors that shaped student-athletes' data practices. Kolovson et. al [40] and Clegg et. al [18, 19] showed that data collections were often mandated and primarily interpreted by staff, creating clear power asymmetries and limiting athletes' access to summaries or trends. These studies also noted variability in data literacy, with athletes receiving uneven support or opportunities to interpret their own information [18]. Prior work furthered observed differences across teams, as revenue-generating or high profile sports such as American football and basketball tended to have more robust technologies, dedicated staff, and stronger expectations around compliance, while non-revenue teams operated with fewer tools and less formal oversight [19]. Scholarship dependence and socio-economic constraints also shaped whether athletes felt able to push back or opt out of decisions made around their data [28].

2.2.1 Technology Evolution. The technological landscape surrounding collegiate student-athlete data has changed dramatically in the years since earlier HCI studies explored student-athlete data practices. Prior work by Kolovson et al. published in 2020 described environments where athletes manually entered wellness information and had few tools to review or interpret their own data [40]. In the same year, Clegg et al. documented tracking practices dominated by easily measurable metrics such as heart rate, sleep quantities, weight, calorie counts, and number of steps [18]. Student-athletes rarely viewed summaries of interpretations of their submissions, and coaches oversaw most interpretation through GPS-based movement tracking, video review, or subjective assessments. Only one athlete in Kolovson et al.'s [40] sample owned a device that allowed review of personal information at any time. In an expansion of their earlier study, Clegg et al. [19] described an athlete who manually tracked perceived sensations, nutrition, and felt training load to advocate for the training he believed would benefit him best because he did not have access to tools that quantified his workload. In a study published in 2023, Greene et al. [28] described how athletes experienced their bodies as highly visible through tracking while organizational decision-making remained opaque.

Although published between 2020 and 2023, all of the aforementioned studies by Kolovson et al., Clegg et al., and Greene et al. conducted their interviews between 2019 and 2020. A substantial technological shift occurred in the years that followed. Wearables began to provide continuous heart rate variability monitoring, detailed sleep staging, recovery assessments, and indicators of training load [6, 34, 38]. Garmin introduced its Body Battery metric in 2019 [71], Fitbit released its Stress Management Score first on a single device in 2020 and then across its full device line in 2021 [46], and WHOOP contributed recovery and strain metrics [4]. These developments introduced new forms of athlete-facing metrics that draw on integrated biometric signals to generate physiological insights. Collegiate athletics emerged as an early adopter of these systems. The University of Tennessee issued WHOOP straps to all varsity student-athletes in the Fall of 2020 [32], and Penn State adopted WHOOP across several teams [20]. These programs represent small parts of a much larger movement in which collegiate athletic departments integrated commercial biometric platforms after 2020. The COVID-19 pandemic further normalized digital check-ins, daily symptom reporting, and remote performance verification, embedding self-tracking into athletes' daily routines. By 2023, devices such as WHOOP [3], Oura [2], and advanced Garmin models [1] routinely produced automated activity detection, and longitudinal training and recovery summaries that provide athletes with daily information.

Evidence of this technology evolution emerges in Brewer et al.'s study, published in 2025 using coaching staff interviews conducted earlier in 2025 [10]. Although these were coach-facing interviews, the results show that coaching staff are mindful of how continuous data collection (such as from the above-mentioned wearables) may intrude on athletes' privacy or create a sense of being constantly monitored if shared by default. An updated account of the athlete side of this modern ecology remains largely undocumented.

2.2.2 Institutional Policy Changes. In addition to technological change, collegiate athletics in the United States experienced major policy changes that shape the conditions under which student-athletes engage with their sports data. In July 2021, the National Collegiate Athletic Association (NCAA) introduced Name, Image, and Likeness (NIL) rights [33]. NIL, for the first time, allowed student-athletes to earn money from endorsements, social media influence, personal branding, merchandise, and other commercial uses of their identity.

Transfer rules also changed in this time frame. For many years, student-athletes in several sports were required to sit out a full competitive season after transferring, a rule that discouraged many from moving to a new school and reinforced dependence on coaches and program structures [66]. In 2021, the NCAA extended the one-time transfer exception, allowing all student-athletes to transfer once without losing a season of competition [66]. In 2024, the NCAA further loosened restrictions, permitting multiple transfers as long as athletes met academic requirements [81]. Athletes are now free to transfer for any reason but not limited to coaching changes, academic fit, playing opportunities, or concerns about well-being [65]. The result is a landscape in which athletes hold greater agency, and coaches must focus not only on developing talent but also on maintaining environments athletes choose to stay in.

2.3 Foundations of Personal Data Engagement

To understand how student-athletes engage with data, we draw upon foundational research on personal data engagement. Li et al. [43] introduced an early five-stage model of engagement: *1) preparation, 2) collection, 3) integration, 4) reflection*, and *5) action*. They found that users can struggle to select the appropriate tool, face difficulties in collecting reliable data, and encounter challenges in making sense of feedback. These difficulties can compound and sometimes block meaningful data engagement [43]. Later research highlighted the different ways people use data: as a tool to reach a goal (*directive*), as a record of past activity (*documentary*), or as a way to uncover links between one thing and another (*diagnostic*); others are motivated by awards and points (*reward-based*) or by fascination with the device itself (*fetishised*) [68]. Scholars have also examined the purposes behind data engagement, identifying behavior change, habit awareness, and curiosity as primary drivers [23]. Complementary studies have investigated disengagement, pointing to burdensome or repetitive logging, unrewarding feedback, and temporary breaks such as during vacations [30, 45]. A recent mapping review by Epstein et al. observed that most studies remain concentrated in health and well-being and are largely grounded in everyday, individual-oriented tracking [23]. Research on smoking cessation apps shows how tracking practices shift as cravings and psychological motivations change [74]. Work in chronic-illness management further illustrate how individuals use data to cope with emotional uncertainty and maintain a sense of control in unpredictable conditions [5]. Although fitness tracking remains the most visible form of personal data management [23], these examples highlight how personal data practices extend beyond performance to include emotional regulation and self-management. Crucially, Epstein et al. called for more attention to the broader social and organizational contexts in which data practices unfold [23]. Collegiate sports offers one such context: an environment with strong incentives to leverage data, and where personal data frequently shifts from being an individual resource to being part of a collaborative process involving coaches and staff [10, 18]. Understanding these foundational accounts of personal data engagement provides a critical baseline, allowing us to recognize where student-athletes' practices reflect established patterns and where the high-stakes, collaborative context of collegiate sports produces new dynamics.

3 Methods

We conducted semi-structured interviews to explore how collegiate student-athletes engage with sports data. We interviewed 20 elite collegiate student-athletes, a sample size consistent with qualitative research practices at CHI [7, 19, 31, 82].

Many U.S. universities consider student-athletes as a protected research population, requiring additional oversight. Accordingly, we obtained the necessary approval from both the authors' university ethics review board and the athletic department's research subcommittee. All participants gave informed consent before taking part in the study.

3.1 Participant Recruitment

We shared recruitment materials directly with student-athletes as well as through team program coordinators. To be eligible, participants had to be 18 years or older, currently enrolled as students, active members of a National Collegiate Athletic Association (NCAA) sports team, and have completed at least one semester in their athletic program. We included the one-semester requirement to ensure participants had experience within the collegiate athletic environment. Coaching staff knew about the recruitment materials but not who chose to participate. We provided each participant a $25 Amazon e-gift card as compensation.

We recruited a total of 20 student-athletes. Participants represented six sports, including both team and individual disciplines. Sports included tennis, track and field, cross country, soccer, basketball, and swimming. The sample included 14 women and 6 men, ranging in age from 18 to 23 years old ($M = 20.3, SD = 1.53$). Participants in our study comprised five first-year, five second-year, three third-year, four fourth-year, and three fifth-year students.[1] Five participants described having limited competition time, meaning they did not regularly start games or competitions but still participated fully in training and team activities. These athletes included redshirt athletes (those in development roles) or those lower in the team lineup (second string or reserve players). Table 1 provides an overview of demographics of the participants.

3.2 Interview Protocol

The interviews took place between November 2024 and February 2025, with the first two authors splitting the role of conducting interviews. Participants chose whether to complete the interview in person or by Zoom via a scheduling link. In-person interviews were conducted in a private room within a university's athletic training facility. In total, 12 participants chose Zoom and 8 participants chose in-person interviews.

We used a semi-structured interview protocol with 12 guiding questions to explore student-athletes' experience with data. After obtaining informed consent, we began each interview by asking about the athlete's role on their team and their year in school. We then asked them open-ended questions about key performance indicators in their sport, how they engage with data, what tools or platforms they use, and what challenges they face when interpreting or accessing information. We also asked about their use of data for well-being, their preferences around data sharing, and how they envision data being used in the future. We used follow-up prompts as needed to explore their responses in more depth (see Appendix A for full interview protocol and questions).

We audio-recorded all interviews and used an automated transcription tool to generate initial transcripts. We then manually

[1] Student-athletes in the U.S. may use up to five calendar years to complete four seasons of competition in their specific sport [60].

Table 1: Demographics of student-athlete participants. We present an aggregate view of demographics to reduce the risk of deductive disclosure, where combinations of attributes could allow participant identities to be inferred.

Sport	Tennis (5), Track & Field (1), Cross Country Running (6), Soccer (4), Basketball (3), Swimming (1)
Gender	Women (14), Men (6)
Year in School	First-year (5), Second-year (5), Third-year (3), Fourth-year (4), Fifth-year (3)

verified and corrected them as needed against the audio file while removing any personally identifying information. The interviews resulted in a total of 7 hours and 2 minutes of audio, with an average interview length of 22 minutes.

3.3 Analysis

We conducted qualitative analysis of the transcripts using thematic analysis. We followed Braun and Clarke's six-phase approach [9], a method widely used in HCI and SportsHCI to examine experiences with technology and data [36, 56, 80]. This approach guided us through the process of 1) familiarization with the data, 2) coding, 3) searching for themes and patterns in the codes, 4) developing and reviewing themes, 5) refining, defining, and naming themes, and 6) producing the report [12]. We describe our process below.

To begin the analysis, the first and second authors each read all 20 transcripts and discussed early impressions *(Phase 1)*. These two authors then led the coding process *(Phase 2)*. They began by independently coding the same two transcripts, then met to review their coding decisions, reconcile differences, and collaboratively create an initial codebook.

To manage the rest of the dataset, they divided the remaining transcripts into five batches. In each batch, both authors independently coded three transcripts: two unique transcripts and a third overlapping transcript. After each batch, they met to discuss impressions and update the codebook as needed. The overlapping transcript allowed them to compare coding decisions, assess alignment, and identify any discrepancies, supporting consistency and rigor throughout the coding process. In the final batch, which included only three transcripts, each author independently coded one transcript, and both coded the final transcript for overlap. After coding all the transcripts and finalizing the codebook, the first author reapplied it across all 20 transcripts for consistency and completeness. Our coding process was primarily inductive [17], but at times we drew directly on participants' own words to capture meaning, for example, "data can get in your head" (often referred to in qualitative research as *in vivo coding* [69]).

The same two authors created a bottom-up affinity diagram to group the codes and explore patterns and potential themes *(Phase 3)*. They organized 111 unique codes from the student-athlete transcripts into 26 code groups. Some examples of these groupings include: *performance-oriented usage*, which included codes related to student-athletes using data to guide training, track progress, and inform competition strategy; *coach-guided usage*, which included codes that described instances where athletes described relying on coaches to interpret and filter data; and *cognitive and mental impact of data*, which included codes related to the mental burden or relief associated with engaging with data.

These code groups served as a foundation for our initial themes. Through a series of discussions, the two authors came to a common understanding of the themes *(Phase 4)* and communicated frequently with the entire research team to refine and finalize the themes *(Phase 5)*. Once the research team agreed on the final set of themes, we integrated them into a coherent narrative that aligned with our research question *(Phase 6)*. The final themes are presented in the following section.

3.4 Positionality

Our research team contributes expertise from academic domains including computer science, cybersecurity, sport science, biomedical engineering, and biomechanics. We also bring direct experience in athletics as former NCAA student-athletes, university athletics staff, and professionals in sport organizations. We view this diverse collaboration as a strength for connecting research with real-life practices in athletics. Consistent with established approaches in HCI, we have not attempted to conduct the qualitative analyses in the absence of our perspective or backgrounds [53]. Instead, we acknowledge our combined experiences shaped how we identified themes, informed our understanding of the data, and guided our presentation of our findings. We offer this positionality statement as context to the reader [49].

4 Results

In this section, we present our findings on how student-athletes engage with their sports data. Through our analysis, we identified four modes of engagement: **performance-directive** (Section 4.1), **reflective-monitoring** (Section 4.2), **coach-mediated** (Section 4.3), and **selective-disengagement** (Section 4.4). For each mode, we examine the reasons that drive student-athletes to use data in this way, how this type of engagement unfolds in practice, and the trade-offs that accompany it. Table 2 provides a consolidated reference of the four modes including their definitions, reasons, practices, trade-offs, and representative quotes.

4.1 Performance-Directive

Student-athletes described engaging with data to support training execution (n = 18), evaluate performance (n = 13), and identify specific areas for improvement (n = 16). We term this mode *performance-directive*. They draw on performance statistics (e.g., publicly available or team-curated), video analysis platforms to review competitions and training sessions, and wearable technologies such as GPS watches or heart rate monitors. They do not simply observe the data, but use it to actively shape training decisions. As P7 put it, *"data is a key for performance."*

Table 2: Comparison of four modes of student-athlete engagement with sports data, including definitions, reasons, practices, trade-offs, and representative quotes.

	Performance-Directive	**Reflective-Monitoring**	**Coach–Mediated**	**Selective–Disengagement**
				
Definition	Executing training and targeting improvement	Assessing the body's reaction to training and daily load	Receiving simplified insights through staff expertise	Intentionally limiting engagement with data
Reasons	Competing at an elite level, maximizing performance, seeking clarity and objectivity	Listening to the body, preventing overtraining, sustaining performance and health	Trust in staff expertise; logistical efficiency	Protecting confidence, avoiding overload, time-value tradeoff
Practices	Tracking sport-specific statistics, reviewing film for errors, scouting opponents, identifying what to target, guiding workout intensity	Reviewing data for signs of fatigue and fitness gains, nudges for recovery and self-care, validating bodily awareness	Being guided by staff interpretations, receiving simplified feedback, experiencing training adjustments	Turning off devices, ignoring certain metrics, analog logs
Trade-offs	Unequal access to data, public visibility creates pressure, loss of context	Overriding perception, anxiety from conflicting signals, need for sport-compatible fit, cost barriers	Fear of judgment, blurred privacy boundaries	Risk of missing warning signs, difficult to fully avoid
Quote	"It shows that this needs to be better and then we can go out and practice that." (P2)	"Sometimes you're like, 'it's in my head,' but the data shows you're also struggling." (P7)	"Me, I just run. Let the coach take care of the data." (P18)	"Confidence-wise, I'd rather not even look at it." (P1)

4.1.1 Reasons for engaging this way. Participants framed their need to guide performance through data as a competitive necessity in collegiate sports. Several emphasized that technology has become increasingly embedded in performance expectations, with P2 noting, *"Everything is becoming a lot more about technology."* Some felt that not engaging with these tools could mean falling behind (n = 3), explaining *"you're putting yourself at a disadvantage not to"* (P6). This perception is related to the belief that winning and staying competitive at this level often comes down to fine margins (n = 5). As P4 explained, *"When you get to a good level, a lot of the time it's like the little 1%...those percentages translate to us either winning the game or losing the game."*

Student-athletes also mentioned deriving a sense of objectivity from the data (n = 7). They valued having performance data presented as *"solid facts"* and information in *"black and white"* to verify execution and guide targeted training sessions. P2 explained *"to be able to actually have a solid fact where it shows this needs to be better and then we can go out and practice that."* Another student-athlete, P5, emphasized the clarity of recorded data, *"It allows you to take that reality and then turn it into specific data that is factual and very much true, because it's recorded and not based off your perception."* Several echoed this "reality check" effect (n = 5), with one tennis player recalling, *"There was a time I thought I didn't make that many double faults and the video showed, no, you did—which is a different perspective on my performance."*

4.1.2 Engagement in practice. When asked in the interviews how they engaged with data, nearly every student-athlete reported interacting with statistics as the primary entry point into data engagement (n = 15). These include sport-specific measures such as serve percentages in tennis, turnovers in basketball, winning the ball in the air in soccer, stroke counts and split times in swimming, and race times in track and cross country.

Film review was also mentioned frequently (n = 10). Student-athletes described using video feedback to evaluate errors, opponents' strengths, and whether outcomes were within their control. P7 explained *"If I play a poor game, [I look to see] did I just make too many errors or was my opponent just having a really good game?"*

Scouting opponents is a frequent use case (n = 8). Student-athletes described reviewing both individual player statistics and team-level data to prepare for match-ups. For example, a soccer player described reviewing penalty kick tendencies, a basketball player reported looking up player stats to see *"who their good players are,"* and a cross-country runner explained using results to decide *"who to line up against"* at the start of a race.

Student-athletes also use wearable devices to guide workout intensity (n = 10). They described relying on heart rate, distance, elapsed time, and pacing metrics to execute a workout, manage exertion, and stay within target intensity levels for the session. P16 explained, *"I track heart rate just to make sure I'm not going too fast."* While, P20 noted, *"it's really important for me to see the pace that I'm going just to make sure I'm actually hitting the criteria [my coaches] want me to hit."*

4.1.3 *Trade-offs.*

Despite the benefits, student-athletes described several trade-offs. Student-athletes shared that access to meaningful performance information often depends on playing time (n = 4). Reserve players or athletes in supporting roles may have limited opportunities for data-informed feedback. As P1 explained *"It'll only show the plays you were involved in...I don't play that much… I'd like to just see everything I'm involved in at practice, not just the clips tied to a stat. I think our video guy would send it to me. But I kind of feel bad asking for it."*

While student-athletes value data for its objectivity, they also pointed out that it is not entirely free from interpretation (n = 3). A soccer player noted that a well-placed pass could be logged as an error if the receiver mishandled the ball: *"It can negatively impact you and your pass percentage...if it's a great pass, but your teammate just can't get there."* Another soccer player echoed this concern, questioning how 'super saves' are defined, *"What do you quantify as a super save? A lot of the times when they're analyzing, 'Oh, this is a super save and this is not a super save,' they're not even a goalkeeper themselves, so they don't even understand what an actual super save is. Sometimes somebody does some crazy acrobatic move to make a save, but at the end of the day they were just out of position to begin with."*

Student-athletes described the public availability of certain data as an accepted and expected part of collegiate sports (n = 4). As P7 put it, *"Yeah, the stats are up after the game—anyone can see them. We're used to it."* Yet public visibility also introduces pressure. A basketball player explained, *"if somebody's three-point percentage isn't what they want it to be, then they might shoot less threes or get nervous when they're shooting threes, and then miss even more."* A cross country runner similarly noted the trade-off of visibility: *"If you have a down day before a race and your competitor sees it, they might think you're not ready. We also don't want people to always know what our thresholds are or how we train."* For others, data highlighting gaps even to themselves could be demoralizing: *"Sometimes I don't want to see how out of shape I am. I already feel it"* (P3).

4.2 Reflective-Monitoring

Student-athletes described using data to reflect on how training, competition, and daily demands affect their bodies over time (n = 14). We term this mode *reflective-monitoring*. Student-athletes reported reviewing recovery scores, strain/load scores, sleep duration/quality, resting heart rate, calories burned, and heart rate-pace relationship. They pair these metrics with how they feel physically and mentally, using the data to recognize relationships between these feelings and their training loads and recovery. This reflective process helps them detect early signs of fatigue or illness and recognize when they are gaining fitness. Wearables such as WHOOP bands[2] and Garmin watches[3] support this process.

4.2.1 *Reasons for engaging this way.*

Student-athletes described reflective-monitoring as a way to cope with the increased physical and mental demands of collegiate athletics (n = 4). Several emphasized the step up from high school or club level to collegiate sports, which brings *"a lot more strain on your body"* (P5). A recurring reason student-athletes mentioned was to better *"listen to my body"* (n = 8) and avoid repeating mistakes such as pushing through fatigue. A first-year student-athlete reflected on a challenging first semester, noting that ignoring recovery scores while feeling *"in a really bad spot"* physically and mentally only made her condition worse. *"I feel the data should help me next time to listen to my body...listen to myself and say 'hey, today, don't practice, don't push yourself that much."*

For some, reflective monitoring also provides reassurance by validating perceptions or offering an explanation for performance dips (n = 7). Student-athletes described situations where they questioned whether fatigue or poor performance was *"in their head,"* only to see the metrics confirm their physical state. As P7 explained, *"Sometimes you're like, 'it's in my head', but the data shows you're also struggling… your body is also struggling, not just our mental health."* Similarly, P20 recalled relief when data confirmed that balancing a heavy course load, an intense internship, and demanding training sessions left them overreached: *"I kind of predicted I was overtraining and it [data] kind of indicated that...it was nice to have the peace of mind, like knowing, okay, that's probably what's going on."*

4.2.2 *Engagement in practice.*

Student-athletes gave several examples of how they reflect on data. Some described checking post-session heart rate and pace trends to detect signs of fatigue. P19 explained, *"Some days your heart rate will be super high [on an easy run]...and you're like, 'Oh, wow, I must just be really tired.'"* Others described looking back over time to identify patterns or relationships: P7 described it as a way *"to learn what works for your body and what doesn't."* P20, for example, uses their device primarily to assess sleep quality, noticing correlations between poor sleep and injury risk: *"I like to see how much sleep I'm getting, not necessarily to gauge how I'm progressing in my sport, but to gauge my recovery...and I like to see what factors play a role in whether I'm getting good sleep or bad sleep because I've noticed like a correlation, if I get less sleep I tend to get injured."*

For some, regular review and reflection on the data serve as nudges to lighten training, increase rest, or improve nutrition (n = 9). A few participants shared that if their resting heart rate is higher than normal, they see it as a warning sign that their body is under stress, either from intense training or as an early indicator of sickness, even before symptoms appeared (n = 4). Others check daily strain scores (a derived measure of how hard a day or practice was) to prioritize fueling and sleep or plan recovery: *"Maybe I need*

[2]https://www.whoop.com/us/en/

[3]https://www.garmin.com/en-US/c/wearables-smartwatches/

to take tomorrow easier...maybe I need to do something a little bit harder at the end of this week" (P19). For others the value was simply staying aware, *"I just like look at it, take it as a suggestion...if I'm tired and it says I'm tired, I'm like, 'oh yeah, that makes sense'"* (P17).

4.2.3 Trade-offs. While reflective monitoring offers many benefits, student-athletes also described several tensions and trade offs associated with using data in this way. Some noted that device feedback could override or distort their own perceptions, affecting how they feel throughout the day. P3 explained, *"if it gives me a good score, even if I don't feel great, I'm like telling myself that my body's okay...sometimes it's contradictory to how I'm actually feeling. Then I tell myself, 'Oh, if my WHOOP says I'm good. I must be okay.'"* They described the reverse also happening, *"I'm feeling okay and then I look at it and it tells me the opposite and I'll be in my head about it and I'll let myself feel sluggish throughout the day."* Another athlete unknowingly competed with a virus in part because, despite feeling fatigued, their device showed excellent recovery scores. They explained, *"I got my score up to a 98, and I was like 'Dang, I should be feeling good,' and I was still not feeling good...it definitely thought I was healthy and ready to go..it couldn't detect that I was sick."* This false sense of readiness influenced their decision to compete, and they experienced poor performances before a diagnosis confirmed they were ill.

Many student-athletes value the passive tracking and simple interfaces of their devices, but have to adapt how they wear them to fit their sport (n = 8). Tennis players described moving wrist-based wearables to their ankles, and a soccer goalkeeper described shifting their device *"higher up on my arm during practice and it's not a problem at all"* so it wouldn't interfere with gloves. A swimmer explained that their heart rate monitor could clip onto their goggles but creates uncomfortable pressure on the temple. To adapt, they sometimes slip it into their swim cap or suit instead, though they worry about losing it.

In our interviews, price was the most frequently mentioned barrier to reflective monitoring (n = 11). This concern arises even among student-athletes with team-supplied devices. They worried about losing access to this level of monitoring once they graduated or left the team. P17 explained, *"I know a lot of [athletes] are graduating...they don't wanna continue the subscription, because it's pretty expensive."* For student-athletes without team-supplied devices, cost was the primary obstacle mentioned. As P11 put it, *"If it wasn't so expensive, I'd try a WHOOP."*

4.3 Coach-Mediated

Student-athletes frequently described engaging with data indirectly through their coaches (n = 14). They wear GPS/Inertial monitoring (IMU) devices, watches, and complete assessment testing, generating data on workload, movement demands, recovery indicators, and strength measures. However, the detailed outputs are uploaded to team platforms that are primarily coach-facing. Student-athletes noted that they can *"request to see it at any time"* (P5), but they rarely do. As P18 shared, *"Me, I just run. Let the coach take care of the data."* In conjunction, they engage through coach feedback, simplified metrics, and by noticing the influence of practice design and workload adjustments on how they feel. For example, P3 explained *"Catapult[4] data is good for our coaches more so, because they get access to all the data. We don't really get to see too much unless we ask for it."* Student-athletes recognize that coaches use the data to evaluate and monitor their performance (n = 13). P1 reflected that data *"made me a better player but that didn't necessarily come from looking at my own data...as my coaches' understanding and use of that kind of data grew, I did become better..."* Many described a combination of approaches where coaches mediate the data but the student athletes guide its application by giving feedback on how they feel, which in turn informs the coaches' training decisions.

4.3.1 Reasons for engaging this way. Student-athletes described two recurring reasons for engaging with data through their coaches. First is a trust in coaches' expertise and intentions (n = 10). Several expressed confidence in their coaches' ability to use data effectively: *"our staff does a really good job of using data"* (P5), *"they put a good amount of thought into it"* (P19) and *"they know how to work those things"* (P10). Some emphasized the value of coaches helping interpret data (n = 8). P2 noted, *"I do need someone to kind of be able to help me interpret it."* This trust extends to data access. When we asked participants what type of data they would not want a coach to see, several participants responded, "none" (n = 8). Many said they are *"completely fine"* with coaches seeing all their data, with one noting *"who cares if they have it...it helps us and it helps them."* Some said coaches *"needed everything"* to do their jobs effectively, while one added that as long as the student-athlete had given consent, there should be no limits, adding *"the more, the better,"*.

Structural and logistical realities of collegiate sports also influence the need for coach-mediated data usage. As one tennis player explained *"It's hard for coaches when there are six of us to watch every single point...so to be able to actually have a solid fact [from the stats] where it's like okay, it shows them this needs to be better."* Data being available for coaches to mediate may be especially important for student-athletes who are outside the spotlight. A cross country student-athlete described how technology makes their efforts visible despite limited attention during practice, *"there's like 45 of us...they're not stopping and watching every single person's workout...but it gives them more insight into what I'm doing even if they're not always tuned into me at practice. And especially for me...someone who's not the top runner, I think it gives them more insight into how I feel."*

4.3.2 Engagement in practice.. Student-athletes described the data being reflected in their coach's adjustments to mileage, workload, or recovery assignments. As a cross country student-athlete explained, *"they go in and look at it and adjust people's mileage because they are able to see how tired people are."* Similarly P12 noted how coaches reduce practice intensity when data shows workloads are too high before a game, *"It's mainly coaches looking at [the data]...if we have a game tomorrow, and this person's workload right now looks a little too high, then they want to lower what they're doing in practice."* When asked about their awareness of their own workload metrics, P12 admitted *"By actual, like statistics and percentage...not really, but like from just oh.. I can just tell I worked harder today, like I'm more tired with my body, stuff like that."*

[4] Catapult is a commercial GPS/IMU device. See https://www.catapult.com/ for details.

The data also creates a shared record between student-athletes and coaches and as a source of accountability for completing training ($n = 7$). P15 said *"it forces me to get out there."* P20 noted *"it's mainly [for them] to see if we're doing everything right...if we are going for our easy runs, doing them at the right pace and stuff."* This shared record also opens lines of communication when something looks off. As P14 described, *"If [coach] sees you had to stop a workout early or something...he'll text us and be like, 'I saw your workout is a little short, is everything okay?'"*

Finally, student-athletes described engaging with data through the selective highlights coaches share, often for motivation or goal setting ($n = 6$). Rather than the full range of data collected by coach-facing technologies, student-athletes described seeing only a few key numbers. As P4 explained, *"[Coach] will maybe share, 'Oh, so-and-so ran 9 miles today in the game.' And we'll cheer for them...that's kind of the extent to the data."* A basketball player noted that while the coaching staff *"look at a ton of stats"*, only three are presented to the team each game. The student-athlete went on to explain that these three stats act as targets they aim to reach.

4.3.3 Trade-offs. For student-athletes, coach-mediated engagement comes with some trade-offs. Some worried that certain information could be misinterpreted ($n = 5$). P2 explained, *"I don't go to bed as early as I should [due to studying] and I personally would not want my coaches looking at that because...I don't want them to almost judge me and think that I'm not doing everything I could be doing, when actually I am."* P17 echoed this concern, *"sometimes there's a fear...if I have a slow run that day or didn't reach the target heart rate I was supposed to hit...I don't want that to factor into a decision for a race in a week."* Similarly, another described apprehension about how recovery scores might be used, with P3 pointing out that if their numbers were low, a coach might *"take that into account for playing time."* One student-athlete admitted, *"I knew my coach was looking at what I was doing...so I went for runs we weren't supposed to and then quickly deleted them."*

When asked directly, some student-athletes identified specific types of data they prefer to keep private. These typically relate to sensitive or personal considerations rather than what may be seen as core sport performance metrics. Examples include mental or physical health ($n = 2$), "WHOOP stuff" which includes sleep times and recovery scores ($n = 5$), sex-related information ($n = 1$), family-related health conditions ($n = 1$), and certain lifestyle data such as location ($n = 1$), weight ($n = 1$), or food intake ($n = 1$).

4.4 Selective-Disengagement

Some student-athletes described intentionally limiting their engagement with data. This approach represents an important way student-athletes relate to data. Selective-disengagement includes abandoning devices, turning them off for periods of time, ignoring certain metrics, or substituting analog approaches such as handwritten logs. The metrics our student-athletes mentioned disengaging from most frequently were recovery and sleep scores, heart rate, and pace.

4.4.1 Reasons for engaging this way. A central motivation for disengaging from their data is to protect their mental state and preserve confidence ($n = 6$). Many student-athletes expressed that data could "mess with your head" ($n = 9$). As P1 explained, *"confidence-wise, I'd rather not even look at it, and just play without thinking."* P11 emphasized the importance of creating space away from it, *"I don't want to be consumed by it 24/7. I need to be able to disconnect."* Concerns also extended to the sheer volume of data in collegiate sports ($n = 2$), with some noting, *"it gets overwhelming and it's just too much."*

For a few, disengagement reflects time and energy trade-offs ($n = 3$). P12 admitted being curious about the data their coaches see but not wanting to take the time to review it, *"it would be less about me wanting to see more and more about me individually looking into it and studying what we are getting...rather than them providing it and I'm like...'alright.'"* When pressed further, P12 admitted, *"Do I want to? Yes. Will I put that time into it? I don't know."* Others echoed this reasoning, pointing to how academic demands shape their willingness to engage. P19 explained, *"I have a teammate who's in engineering...she has to stay up a lot later and do a lot more schoolwork than me, so I'm sure she doesn't look at it as much as I do."* In contrast, they noted, *"I don't have too much of a strenuous major"* which gives them more capacity to engage.

4.4.2 (Dis)engagement in practice. Student-athletes described disengagement in several forms. One way was by discontinuing use after sustained engagement with a device ($n = 2$). For example, P11, who *"really enjoys looking at all the numbers,"* explained, *"I understand all the data...it makes sense to me. But the reason [for discontinuing] was because I didn't see the performances I wanted to. It was too much...I was in my head too much."* Similarly, P16 reflected on her long-term use of WHOOP, *"I used it for a long time...but I struggle with sleep sometimes, and I became too obsessive with it, so I stopped using it...mainly because I didn't like overanalyzing all that stuff. But I did and do agree that it was accurate."*

Others disengaged by ignoring feedback that clashed with the realities of being a student-athlete ($n = 5$). P16 described the tension of receiving daily recovery scores they could not act on, *"my days are pretty much the same–class, practice, all of that...and sometimes when I would wake up and WHOOP's like 'you've had no recovery, you're tired,' it's like...I can't change my day."*

Others turned to analog methods. P6 described calculating a daily *"success percentage"* based on whether they achieved small goals such as lifting, hydrating, finishing classwork, and even making time for friendship and social connection. As they explained, *"Today was an 80% percent. . . I'll write on how I'm doing and it's not like big numbers, but a percentage of me saying 'okay, this is how I feel...I did this and that today, and I feel good about it.'"* P16 described their Garmin watch as *"ancient"* and *"pretty crappy"* and emphasized that they did not *"rely on it for general health"* or *"look at my fatigue [score] at all. I just use my body to understand fatigue."* Like P6, they preferred a handwritten training journal that incorporated both athletic and non-athletic dimensions of their life. They explained *"I have a training journal and I write down my progress...whatever I did that day and how that felt...just like general stuff, energy levels, where I might be in my menstrual cycle. If it was a bad day...maybe I didn't fuel correctly...I can go back and understand why."*

Finally, some described context-dependent disengagement, often to protect confidence before competition or during injury recovery ($n = 4$). P13 explained, *"Sometimes I take off my watch just because...I* *wouldn't want it to mess with my head. I don't start my watch usually during a race."* Similarly P20, described avoiding recovery scores before races: *"I like seeing it [recovery scores], but I do not want to view it the day of my race...if I view it, it can kind of skew my perception of how I'm feeling that day."* They went on to describe, *"I actually either take it off or turn off the Bluetooth so I don't see it on the app. Then, as soon as the race ends, I connect it back and I'm totally fine seeing how everything was."* This approach, they explained, was a way to preserve what they called "race day magic." Another student-athlete described intentionally avoiding data such as pace or heart rate that felt discouraging when returning from an injury: *"a lot of time I actually don't like to see a lot of the data because I don't want to see how high my heart rate is so I won't utilize [a device] at all. I'll go based on minutes and I'll rely on a teammate having it"* (P19).

4.4.3 Trade-offs. While disengagement helps some student-athletes preserve confidence and limit the mental load of constant tracking, there are tensions and trade-offs that come with stepping back from data. It is possible for fatigue, injury, or illness to go unnoticed until after they have already impacted the student-athlete, when early warning signs may have been available in the data. P16, who relys on a handwritten journal, described looking back after injuries occurred, *"I'll look back if I got injured, or something, to see what I could have done wrong...if I was going too hard in a period of stress or stuff like that."* Similarly, P11 reflected on a period of poor performances and realized only later that sickness had been the underlying cause, *"I was swimming really bad...then I got sick, and I was like, 'Oh, that's why!'"* Both P11 and P16 speculated that data might have surfaced their risk of injury or illness earlier.

Even student-athletes who prefer not to engage with their data find themselves operating under norms where coaches track workloads, teammates share metrics, and tracking is normalized. Across our sample, student-athletes described data as increasingly difficult to avoid (n = 5), with some explicitly mentioning that tracking has become a norm of sports culture (n = 4). P2 emphasized the importance of adapting to the growing presence of technology noting *"you definitely need to try and get on board rather than feel yourself stuck behind."*

5 Discussion

Our study set out to examine how collegiate student-athletes engage with their sports data. We identified four primary modes of engagement: performance-directive, reflective-monitoring, coach-mediated, and selective-disengagement. These modes capture distinct ways by which student-athletes relate to data, including their motivations and the trade-offs they encounter. Yet, these modes are not mutually exclusive and athletes do not map one-on-one to modes. Rather, student-athletes move between modes, drawing on multiple modes as they navigate a data-intensive collegiate sports environment. This is evident in how P20 described using heart rate data to direct a workout (performance-directive), later reflecting on recovery scores (reflective-monitoring), relying on coaches to interpret workload trends (coach-mediated), and avoiding metrics entirely on race day (selective disengagement).

Prior work in collegiate athletics has suggested that revenue-generating sports such as American football and basketball might push student-athletes toward more coach-directed, institutionally controlled data practices than non-revenue-generating sports [19, 28]. The same research has raised the important concern held by some student-athletes about whether the profits derived from their sport may be placed at a higher priority than their own well-being [19]. While our sample does include student-athletes from both revenue- and non-revenue-generating sports, our analysis does not support a comparison between these. Instead, our results surface additional factors across sports such as year in school (e.g., first-year athletes reporting greater oversight), academic major (e.g., heavier course loads limiting time to engage with data), and playing time (e.g., starters having more visibility and interactions around data). These findings add to the literature on persisting discrepancies that influence student-athlete engagement with, and potential benefit from, data [19, 28].

5.1 The Impact of Athlete-Facing Technologies on Data Engagement

In what follows, we consider how the advent of athlete-facing technologies and expanding data streams have shaped student-athletes' engagement with data, extending previously observed practices, introducing new ones, and even shifting how they experience coach-mediated data engagement. Across this landscape, our findings suggest that student-athletes often perceive a division between technologies "for me" and "for them" (the coaches), which guides the organization of the subsection below.

5.1.1 "For Me": Athlete-Facing Data for Performance and Reflection. Direct, personal access to data now plays a defining role in how student-athletes engage with their sports data. Prior personal engagement research has identified directive (goal-setting), documentary (logging or recording), diagnostic (linking two variables), reward-based (chasing awards or collecting points), and fetishised (curiosity and fascination with the device itself) styles [68], as well as purposes such as goal-setting, checking-in, self-comparison, and curiosity [44]. In our study, directive practice was evident but took on a heightened form, oriented towards performance optimization and competitive demands, rather than behavior-change-focused goal setting described in prior work [23]. This aligns with prior SportsHCI accounts in which athletes leverage data to improve performance and guide the precise path needed to meet their goals [64]. Reflective-monitoring mode mapped closely to diagnostic use and purposes such as checking in or self-comparison. Whereas diagnostic use has been noted as "mundane" or marginal [68], our findings show that reflective monitoring is a central way in which student-athletes engage with data.

A key factor shaping this shift is the prevalence of athlete-facing wearable technologies. Of our 20 participants, 16 reported using personal devices such as WHOOP bands or Garmin watches, giving them continuous, direct access to physiological and derived metrics. The direct data access student-athlete have has transformed reflective practice by integrating embodied experience with continuous streams of physiological data. Prior SportsHCI work demonstrated that athletes routinely link measured signals such as heart rate to felt effort and use this connection to interpret exertion during activity [64, 78]. Contemporary tools now extend this connection beyond momentary effort, providing insight into sleep, heart rate variability, resting heart rate, stress, and recovery that student-athletes can consult across training cycles. Participants described using these metrics for early warning signs of illness or breakdown, extending reflective monitoring beyond validation of present or recent past toward anticipating future problems, which, to our knowledge, has not previously been captured in HCI literature. By contrast, engagement driven by rewards or gamification, curiosity about the data or device, or goal-setting for behavioral change–common in general personal data and health tracking contexts [23, 39, 64]–was largely absent in our study. Instead, student-athletes' sports data engagement was driven more by the demands of competitive performance and the ongoing work of sustaining that performance.

5.1.2 "For Them": Coach-Mediated Data Engagement in a Shifting Landscape. Engaging with data mediated by coaches is not well captured in personal data engagement research, which typically focuses on individual users' relationships with their own tracking technologies. Yet, coach-mediated engagement remains a defining feature of the collegiate sport data environment, where institutional systems shape expectations, structure training, and anchor decision-making authority [18, 19, 28, 40]. Prior collegiate athletics research has documented how these structural asymmetries concentrate power with coaches and staff [19, 40], raising concerns around surveillance and athlete agency [28].

Our findings affirm that these structural realities still exist. Li et al.'s stage-based model [43] assumes that individuals move through preparation, collection, integration, reflection, and action with relative autonomy, selecting tools, gathering data, making sense of it, and deciding how to act. Student-athletes rarely have full autonomy over such steps that are often expected in accounts of personal data engagement [23, 25, 43]. In practice, the preparation stage, which includes choosing what tools to use and what metrics to track, is typically determined by coaches and the athletic department, and much of student-athletes' "personal" data is collected *for* them through coach-facing systems, analyst-compiled statistics, or video platforms they do not control. Integration and reflection are also often mediated: coaches review the data and distill it into feedback or training decisions. Thus while student-athletes live the outcomes of reflection on their data, they may not be conducting this reflection themselves. Acting on data is similarly constrained: decisions are often made by the coach, and even when student-athletes do collect and reflect independently through their own wearable devices, the options for acting on those reflections may be limited by fixed schedules and academic demands. Even when data suggests the need for recovery, rest is not always possible.

Despite these constraints, a notable difference in our findings from prior work is student-athletes' more positive view towards collaborating with coaches on data than described in earlier collegiate studies [18, 19, 28, 40]. Several student-athletes in our study emphasized trust in their coaches' expertise and intentions, often describing staff as people who *"know how to work those things"* and who *"put a good amount of thought into it."* We hypothesize that this shift stems from both changes in institutional policies and changing technological access. The introduction of NIL rights and updated transfer policies may have shifted some power dynamics, giving athletes more leverage and contributing to increased attention to athlete experiences within programs. Simultaneously, the widespread adoption of athlete-facing wearables has given student-athletes direct access to their own physiological data, trends, and visualizations, something limited or nascent in previous literature.

Student-athletes in our study generally trust staff to interpret and make decisions on data from coach-facing systems and are content to let the "coaches' tools" run in the background, rarely demanding transparency. This separation seems to make life more manageable in a data-intensive environment. Yet the boundary is not always clear when data from a Garmin watch, for example, is "for me," but once the data feeds into the coach-facing Garmin Clipboard, it becomes "for them." Direct data access for student-athletes does not remove institutional control, but it may soften its felt intensity by giving student-athletes something of their own data to consult. Even when fixed schedules leave little room to adjust, metrics such as recovery or sleep scores validate feelings of fatigue and offer reassurance that what they sense in their bodies is real.

Student-athletes in our study rarely question the accuracy or security of their personal or institutional data systems. Their concerns mainly center on two issues: data being taken out of context or used to judge their commitment, and loss of access to their personal devices due to cost. Several student-athletes expressed worry about affording WHOOP subscriptions after graduation or if team financial support ended. The fact that athletes worry more about losing reflective-monitoring capabilities than about surveillance underscores how essential these data streams have become to them in this environment.

5.1.3 "Not for Me Today": Selective-Disengagement in a Pervasive Tracking Environment. Selective-disengagement is an important strategy student-athletes use to manage their relationship with data. Examples include muting recovery scores before competition or turning to analog notes when digital systems failed to capture the full scope of their lives. Importantly for this setting, opting out entirely is rarely a real option because tracking is woven into practice planning, roster selection, and rehabilitation, and full disengagement from the systems can ultimately mean stepping away from the sport.

Personal data engagement literature often frames disengagement as lapses or abandonment caused by burdensome upkeep, useless data, or shifting goals [24, 42]. In contrast, collegiate athletics research has at times described disengagement as a form of resistance to institutional structures, such as declining to adopt platforms that would give coaches access to data [28]. Other earlier studies across collegiate and SportsHCI have documented disengagement as withholding activation. Athletes stepped away from data by choosing not to start a GPS watch, not to complete a wellness questionnaire, not to check film or statistics, or not to record weight during stressful periods [18, 40, 78]. In these settings, disengagement meant deciding *not to initiate* engagement.

In our study, disengagement takes a different form shaped by pervasive, automatic tracking. Today technologies track continuously and automatically. As a result, in this contemporary era, disengagement now requires actively disabling default behavior, such as turning off Bluetooth, hiding certain data streams, or temporarily removing a device.

Our participants described selectively stepping away in ways that were intentional and protective. In fact, their experiences align more closely with Smith et al.'s [74] concept of *productive disengagement.* In that work, participants in a smoking cessation program stepped back from an app when reminders became counterproductive, and this disengagement itself contributed to their success. While Smith and colleagues suggested the implications of productive disengagement were most relevant to technologies supporting addiction management [74], our findings extend it to high-performance sports, showing that selective disengagement can be a resilience strategy that allows student-athletes to co-exist with data in a data-intensive environment. In SportsHCI, work such as Tholander and Nylander's [78] has also highlighted that athletes sometimes place experiential feeling of an activity ahead of metrics, offering an example of how athletes may selectively modulate their relationship to data. Importantly, selectively disengaging does not seem to diminish the value student-athletes place on the data itself. Many student-athletes still relied on the record at another time, such as when they revisited trends or reflected after competitive pressures had passed.

5.2 "Helpful" versus "Unhelpful" data: two sides of the same coin

In the contemporary collegiate landscape, direct access to data has expanded rapidly. Student-athletes now review public statistics, scroll through video analysis platforms, and examine detailed metrics and visualizations produced by their own wearable devices. These capabilities give them more immediate insight and interpretive power, yet they also introduce new pressures that accompany continuous feedback and constant visibility. Prior research with collegiate coaching staff indicated that coaches themselves voiced concerns about how expanding data streams could affect athletes' confidence, focus, and sense of being monitored [10]; our findings show how student-athletes themselves now navigate these emerging dynamics firsthand. Data that is genuinely helpful for performance for student-athletes can simultaneously create new pressures and vulnerabilities, and visibility that empowers them can also expose. In the subsections that follow, we unpack these two intertwined dynamics and the implications they carry for designing and deploying data systems in collegiate sports.

5.2.1 Mental Strain Alongside Benefits of Data. Student-athletes consistently described data as valuable for improving performance with its ability to provide direction and accountability. They often said data could take you "out of your head," offering peace of mind by confirming training or recovery needs. Yet many also described how the same data could get "in your head," creating doubt and anxiety. These two phrases surfaced across more than half of the transcripts, making them among the most salient recurring expressions student-athletes used to describe the mental impact of data. Importantly, these dynamics are not confined to one style of engagement but appear across all four modes. In the performance-directive mode, we noted that data offers clarity and direction, but also introduces pressure when numbers are made public or taken out of context. In the reflective-monitoring mode, we observed that data validates athletes' feelings of fatigue and recovery, yet could override their bodily knowledge and generate anxiety when metrics conflict with how they feel. In the coach-mediated mode, athletes appreciate how the data supports their coaches' expertise, but expressed heightened concerns about judgment. Even selectively disengaging to protect their own mental state comes with the unhelpful downsides of competitive disadvantage or missing crucial signals that could prevent injury or illness.

Research grounded in self-determination theory cautions that data can both support and undermine athletes' motivation [63]. Our work shows how this duality is amplified in collegiate sport, where performance expectations, public visibility, and institutional structures heighten the stakes of each data point and student-athletes now have more direct access to their own data. This access expands their sense of agency but also adds a new layer of cognitive and emotional management. In addition to the sport-specific technical and tactical expertise student-athletes need to develop, they now must decide which data are most relevant, which metrics can be ignored, and how to interpret day-to-day fluctuations of metrics. As more sensors and systems enter this space, the challenge is not a matter of avoiding difficult feedback or showing only "inspiring data." Information about weaknesses and risks remains essential for training and health, as it guides performance and signals concerns such as overtraining, injury, or health risks [8]. Instead, our findings highlight a need to understand how helpful feedback becomes mentally taxing, and how athletes develop strategies to navigate this tension as part of their everyday engagement with technology.

5.2.2 Visibility as both empowering and exposing. In our study, visibility emerges as a central dimension of data engagement that must be considered when designing technologies in this context. A thread we noticed across modes is that data brings visibility that otherwise may not be possible. In performance-directive use, student-athletes value the way data reveals small nuances that might otherwise go unnoticed. When used for reflective monitoring, wearables render physiological data visible, enabling student-athletes to "see inside their bodies" to interpret fatigue and readiness. In coach-mediated practices, data makes unseen efforts visible to coaches who cannot observe every repetition. However, the same visibility that can highlight training efforts can also be taken out of context, misrepresent readiness, or signal weakness at moments student-athletes would prefer to keep private. As previously observed by Rapp and Tirabeni, [64], for elite athletes "data becomes a means to acquire more visibility" and elite athletes "never expose data without careful consideration of its public impact." However, collegiate athletes have far less control over how their data circulates. Statistics are public and team systems can automatically upload movement and physiological data streams that can limit student-athletes' ability to curate or contextualize what others see. In this way, the dynamics echo the "panopticon effect," a theory in which the possibility of being observed rather than the continuous monitoring itself shapes behaviors [26, 67]. Student-athletes currently operate under the assumption that much of their data will be shared, including with the public. The broader implication is that visibility is something that student-athletes must actively manage, even as the systems that produce some of this visibility leave them with limited control over how they are seen.

5.3 Design Considerations for SportsHCI

Based on our findings, we suggest a set of design considerations. These recommendations highlight opportunities for developing technologies that better support student-athletes in collegiate sports. While our analysis foregrounds athlete-facing engagement, many of these considerations also extend to coach-facing systems and the broader infrastructure in which sports data circulates.

- **Fair and context-sensitive statistics.** Public-facing statistical data is used to promote sports and support recruiting, and athletes draw on it for reflection. However, this information can be subjective (e.g., how many super-saves a goalkeeper has). Because sports data has a direct impact on athletes' future opportunities and current/future livelihoods, the values of fairness and context-sensitivity should underpin all designs in this space. Designers should work closely with experienced athletes to create sport-specific guidelines for subjective statistics, both for how they are calculated and for how they are displayed within user interfaces.
- **Sport-specific design fit.** Data collection devices are designed for different parts of the body (e.g., typically WHOOP is worn on the wrist, Oura[5] ring on the finger, and Catapult between the shoulder blades). These existing devices provide some alternate placements (e.g., WHOOP and Catapult can be placed on different parts of the body or woven into garments). Our student-athletes describe adjusting how they wear devices, or even avoiding data collection, based on sport-specific characteristics (e.g. avoiding wrist worn devices in tennis). As SportsHCI designers work to create the next generation of wearable technologies, they should conduct extensive sport-specific testing to innovate and improve on designs that are cognizant of the demands of target sports.
- **Control over data for coach-mediated engagement.** Selective sharing of performance data with coaches is an important mechanism for student-athletes to better interpret their data. However, continuous sharing, combined with the power dynamics present in athletics, can limit student-athletes' ability to control what data is shared [16]. To the greatest extent possible, athlete-facing technologies should explicitly support sharing with coaches and enabling athlete-coach communication and collaboration while providing convenient ability to permanently or temporarily stop sending particular data streams.
- **Evolve policy frameworks as a necessary complement to design.** More direct athlete access to data cannot, on its own, address the structural power dynamics inherent in collegiate sports when decisions about technology adoption and data usage are still typically made by coaching staff and athletic departments. Prior work shows that challenges arise when athlete data flows beyond what is expected or used in ways not intended [15, 41]. Although NIL opportunities and transfer ability have increased athlete agency in some areas, governance surrounding performance and biometric data have not kept pace with the rapid growth of technology we observe in this contemporary landscape [35]. Alongside design features, accompanying institutional or NCAA-level policies are needed that define appropriate data flows and limit unintended uses. As the data ecology of collegiate sports continues to expand, design, and policy must evolve together.
- **Mechanisms for disengagement.** Student-athletes sometimes disengage from data during specific periods, such as competitions or the off-season. This need may be much less prominent in the general public, and may warrant rethinking the default view in many sports tracking apps. Configurable pause or race-day mute functions should be implemented for individuals who want to disengage without losing the ability to monitor reflectively in the future.
- **Weighing benefits and risks.** Student-athletes engage with technology that in some cases is beneficial and in others could be detrimental, similar to how weight-loss apps can be supportive tools but also hold the risk of contributing to eating disorders [21, 80]. When developing new athlete-facing technologies, designers should deeply consider the potential benefits and risks. Collaborating with experts and with the athletes themselves can help to mitigate these risks in ways that are sensitive to the high-pressure environment in which student-athletes operate. Designers should never lose sight of the question, "Should we build this?"

5.4 Limitations and Future Work

This study offers an in-depth look at student-athletes' engagement with their sports data, but like any research that aims to deeply understand a population of users, it also has limitations. We sought a range of perspectives by including student-athletes from six different sports, spanning both team and individual disciplines, and across all years of eligibility. However, all participants were from high-level, well-funded sports programs operating within a large university. While the themes we identified apply across sports, they may not capture the full diversity of student-athlete experiences. However, the way these collegiate student-athletes engage with data may foreshadow how practices and norms will trickle down to other levels of sport as technologies become more widely implemented.

Second, we recruited participants with the assistance of university athletic staff. Although coaches were not informed of who participated or what was shared, and the interviewers were not part of the coaching staff, it remains possible that some student-athletes felt implicit pressure to present themselves as more comfortable with data use and sharing than they truly are. We attempted to mitigate this risk by emphasizing confidentiality, but the possibility that participants did not feel fully at ease in voicing criticism remains a limitation of this study.

In addition, the interviews capture a moment-in-time perspective. Collegiate student-athlete eligibility spans up to five years, creating a rare opportunity to examine the longitudinal arc of engagement with data. Few studies in SportsHCI have taken such a temporal approach [22], and future work could trace how reasons, practices, and tensions evolve as student-athletes mature, gain experience, or transition out of the sport.

[5] https://ouraring.com/

Finally, a rich body of work has highlighted the power dynamics, inequities, and risks associated with collegiate athletics [19, 28, 40]. While these systemic issues were not the primary lens of our analysis, a study focusing on those issues–building upon prior work and examining the issues in light of the evolving technological landscape–is much needed future work.

6 Conclusion

This paper has provided an in-depth account of how student-athletes engage with their own sports data, providing an essential updated account of student-athlete data practices in the contemporary landscape of collegiate athletics. We identified four modes of engagement: performance-directive, reflective-monitoring, coach-mediated, and selective-disengagement, demonstrating how student-athletes employ multiple modes to navigate the opportunities and trade-offs of a data-intensive sporting environment. By foregrounding the student-athletes' experience, we position these four modes as a shared language for the growing field of SportsHCI to better understand how athletes live with data in competitive environments. As technologies continue to diffuse through collegiate sports and beyond, the practices surfaced here provide a foundation for future design that not only serve users in the unique context of collegiate sports but also inspire new ways of supporting active people in data-driven environments.

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APPENDIX

A Semi-Structured Interview Protocol

At the start of each interview, whether on Zoom or in-person, the researcher and participant introduced themselves. The researcher provided the participant with the informed consent document, asked the participant to review it, and obtained consent. For Zoom interviews, the research reminded the participants that video was optional. The researcher asked for consent to record and then proceeded with the following series of questions:

(**Q1**): To get things started, what is your role on your team?
(**Q2**): How many years have you been on the team?
(**Q3**): What are the most important performance metrics or sources of information that you use to gauge progress?
  (a) Which of those indicators do you track using some kind of data?
  (b) Where does that data come from?
  (c) Do you have any challenges in getting this information?
  (d) How do you view or interact with that data (apps, websites, etc.)?
  (e) How frequently do you interact with that data? (after practice, after games, weekly, daily?)
  (f) Does your interaction with the data vary between the competitive season, training camps, and the offseason?
  (g) How do you use the data to guide your decisions? [For example, how might data influence adjustments to training or recovery plans?]
(**Q4**): What other data is collected by your coaches and staff?
  (a) How does your training staff use this data to help your performance goals?
  (b) Regarding team-collected data: How is this data shared?
(**Q5**): Do you use any information to measure your overall well-being?
  (a) What sources do you use?
  (b) How is this data collected and shared?
  (c) What challenges do you face with engaging or interpreting this data?
  (d) How frequently do you use this data?
  (e) What aspects of data usage do you find most beneficial for your well-being?
  (f) Do you think knowledge of this information influences your performance?
(**Q6**): Do you think there's a need for athletes to be more involved with data?
(**Q7**): What barriers might prevent effective engagement with the data?
(**Q8**): How would you like to see data being used in college athletics in the future?
(**Q9**): For your coaches:
  (a) Are there additional data sources you would like them to collect?
  (b) Are there sources of data you would prefer coaches not to have?
  (c) Does your view change depending on whether only a physical trainer or sports psychologist has access?
(**Q10**): Is there anything you would like to track, or know more about, that you currently aren't?
(**Q11**): Do you feel you have the capacity to incorporate new data sources or technologies into your routine?
(**Q12**): Before we wrap up, what are the main thoughts about data engagement you'd like me to take back to my team?