Coach, Data Analyst, and Protector: Exploring Data Practices of Collegiate Coaching Staff

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Figure 1: Example data sources utilized by the coaching staff in our focus groups. (A) Force plate that captures jumping forces of athletes [60]; (B) Markerless motion capture system used to measure the range of motion in joints [13]; (C) Continuous physiological monitoring device to measure recovery and sleep [63]; (D) Combined GPS and inertial measurement unit worn during practices to estimate workload [6].

Abstract

A rapidly emerging research community at the intersection of sport and human-computer interaction (SportsHCI) explores how technology can support physically active humans, such as athletes. At highly competitive levels, coaching staff play a central role in the athlete experience by using data to enhance performance, reduce injuries, and foster team success. However, little is known about the practices and needs of these coaching staff. We conducted five focus groups with 17 collegiate coaching staff across three women's teams and two men's teams at an elite U.S. university. Our findings show that coaching staff selectively use data with the goal of balancing performance goals, athlete emotional well-being, and privacy. This paper contributes design recommendations to support coaching staff in operating across the data life cycle through gathering, sharing, deciding, acting, and assessing data as they aim to support team success and foster the well-being of student-athletes.

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CCS Concepts

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

Keywords

SportsHCI, sports technology, coaching technology, collegiate sports, human-data interaction, sports performance

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1 Introduction

SportsHCI is an emerging field that studies how to support physically active humans, and much of SportsHCI focuses on how *data* can inform sports practices [39]. Most recent SportsHCI research has focused on athletes or athlete-facing interfaces, shedding light on, for example, runners' trust in their data [26], hikers' preferences among tracking devices [3], motivations for tracking workouts [27], and how athletes pursue their goals among adverse conditions [21]. SportsHCI research has also begun to recognize that for many athletes, one of their most influential relationships is with their coach [24, 29].

Compared to athletes, coaches have been understudied in SportsHCI research. In fact, coaches are so central to many athletes' experiences that research on the coach-athlete relationship has been identified as one of the "Grand Challenges" of SportsHCI [15] because effective coaching can enhance athletes' motivation, confidence, and performance [25, 35]; in contrast, poor coaching can lead athletes to doubt their own abilities, undermining both performance and trust, and even increase the risk of injury [20]. Responding to the coach-athlete grand challenge, this paper examines how coaches use data to guide their decisions and their interactions with athletes in a distinct and important population of coaches: those found in elite *collegiate sports*.

Our work is situated in the United States (U.S.) where collegiate sports refer to the athletic programs that are part of universities. In the high-stakes environment of U.S. collegiate sports, coaching staff operate under immense pressure to achieve success. Collegiate sports programs serve as a major social and cultural gathering [55]. Universities invest millions of dollars in athletic facilities [54], athlete recruitment [53], and performance technologies [7]. This, in turn, drives universities to channel substantial resources into the latest advancements in training, performance analytics, and sports technologies [7, 28].

In light of those emphases, the use of data and technology in collegiate sports has surged in recent years, offering new tools for tracking athletic performance, improving training regimens, and optimizing in-game strategies [52]. Technologies such as GPS trackers, wearable sensors, and advanced movement analysis systems have become standard in many collegiate sports programs, providing coaching staff and student-athletes unprecedented access to detailed performance metrics (Figure 1). For example, in collegiate American football, GPS devices are routinely used to monitor player activity and workload during practice [14, 19], whereas in collegiate basketball, video analysis systems break down player movements and strategies to enhance game preparation [68].

In this context of an elite collegiate sports program, we investigate the following research question: *What are the experiences and data practices of collegiate sports coaching staff?* We conducted five semi-structured focus groups, each focusing on one of the following sports: women's basketball, women's soccer, women's volleyball, men's American football, and men's basketball. In elite collegiate sports, interdisciplinary teams of coaching staff work together to support teams of student-athletes. As such, in each focus group, we engaged with a variety of coaching staff including head coaches, dietitians, athletic trainers, strength and conditioning coaches, sports scientists, and/or administrative staff. In total, 17 coaching staff members participated across the focus groups.

We first present the qualitative findings organized by stages of the data life cycle: gathering, sharing, deciding, acting, and assessing [64]. These findings directly inform design recommendations for systems that aim to support coaches' work. After examining the qualitative results of our focus groups through the lens of the data life cycle, our discussion turns to two roles that emerged within the empirical analysis. We observed that coaching staff take on the roles of **data analysts**, who, despite not usually having formal training, must examine the quality and usefulness of data, find ways to distill and share findings, and navigate an ever-changing landscape sometimes including black-box metrics provided by the various vendors whose tools capture the raw data; and as **protectors** of student-athletes' privacy and emotional well-being.

This work contributes to SportsHCI research in the following ways:

- To our knowledge we present the first SportsHCI research study focusing solely on collegiate coaching staff, highlighting the needs of these essential technology users in the collegiate sports ecosystem.
- The results of rigorous qualitative analysis show how coaching staff use data through the process of gathering, sharing, deciding, acting, and assessing data sources. The findings illustrate the complexities facing elite coaching staff in the highly dynamic environment of collegiate sports.
- Our findings reveal that coaching staff take on roles as data analysts and protectors of student privacy and emotional well-being.
- We suggest a set of design recommendations to guide the SportsHCI community toward designing novel technologies for collegiate coaching staff.

2 Related Work

2.1 Performance Analytics in Collegiate Sports

The growing use of technology in collegiate sports is part of a larger trend in sports performance analytics, where nearly every major professional sports team now uses data to guide important sport management and training decisions [17, 18, 43, 44]. What started with basic tools such as tape measures and stopwatches has evolved to video cameras for film review and sophisticated systems that incorporate biometric data and advanced algorithms to supplement traditional coaching tools [11]. As Martin et al. [36] noted, the value of performance analysis lies in transforming raw data into meaningful insights that support the coaching process. HCI researchers have developed tools and methods such as motion capture techniques [4, 56], advanced sensors [23, 61], and interactive visualizations [34, 47, 48] to help coaching staff understand the large volumes of data generated during training and competition. The insights go beyond basic metrics, offering coaching staff a deeper understanding that can enhance tactical decisions, optimize training load, and prevent injury by identifying early warning signs [23]. As a result, these nuanced insights have become essential for coaching staff in high-stakes environments, requiring them to engage deeply with data interpretation. This role has been traditionally associated with data analysts, and is one we explore in this study. Despite these advances, research has focused primarily on the tools and systems themselves, with less attention paid to the coaching staff who interpret and apply the insights in practice. A scoping review on coaches' perspectives of athlete monitoring systems—tools used to track and optimize athlete performance—found that despite being central to interpreting and applying data in practice, coaches are underrepresented in sports science literature, accounting for less than five percent of study participants [58]. The small number of studies available highlight the value of performance analysis for coaches while pointing to barriers such as data complexity and the need for specialized skills to gain insight [45, 66]. Our study builds on this by being one of the first to bring the voices of collegiate coaching staff to the HCI community, specifically in the unique space of collegiate athletics, offering important insights to inform the design of tools and systems that better support coaches as users of performance analytic tools.

2.2 Personal Informatics in Sports

While performance analytics focus on organizational and team-wide insights, personal informatics emphasize individual engagement with data [40, 50, 57]. These systems enable athletes to plan, track, and reflect on performance metrics [26, 46, 67], improve social connectedness [2, 31], and use gamification to create engaging experiences [57]. There has been a notable evolution in the way sports data is viewed in the SportsHCI research space: it is no longer just a functional tool for translating objective metrics to athletes, but a key component in shaping their overall experience [65]. This expanding body of research explores the deeply personal and emotional nature of activity tracking, which often ties into users' self-esteem, achievements, and even challenges, such as body image or mental health [51]. Studies such as "From Metrics to Experiences" have looked at how data influences athletes emotionally, mentally, and behaviorally, showing how it shapes their engagement with their sport through frameworks such as self-determination theory (SDT) [49]. For example, data can provide certainty and guidance for athletes when deciding on workouts or making adjustments, supporting the autonomy dimension of SDT through self-driven decisions. Similarly, sharing metrics on platforms with peers or teammates can foster relatedness, which is another dimension of SDT, by fostering connections and support through shared goals.

Not only can data influence athletes' behaviors and emotions, but research also demonstrates that its meaning depends on how it is interpreted, the situation it is used in, and the purpose it supports [51]. In sports, as in other domains, raw data requires interpretation to align with user goals and activities. For example, studies in workplace and consumer settings highlight users' need to collaborate to interpret IoT and sensor data [16], integrate insights into systems to derive meaning [12], and fit these insights into structured, hierarchical systems [32]. These processes are particularly relevant to sports, where athletes and coaches collaborate to interpret performance metrics [50], apply contextual knowledge to derive meaning [62], and navigate organizational systems [10]. In collegiate athletics, the use of personal informatics often shifts from an individual process to a collaborative effort orchestrated by coaching staff. This is particularly evident with technologies where athletes have limited access to the collected data, relying on coaches and staff to interpret and share the insights.

2.3 SportsHCI Research to Date Focused on Coaches

The coach-athlete relationship has only been examined in a few SportsHCI studies to date [15]. Approximately ten years ago, Wakefield and Neustaedter [62] interviewed eight endurance coaches of amateur athletes and found that these coaches used contextual information such as injuries, sleep, and stress to interpret data and customize training to athletes. While their study offered some of the first insights into how coaches interact with sports data, it focused only on coaches of amateur athletes, amateur athletes themselves, and endurance sports. A recent study by Jones et al. [24] explored the perspective of coaches on wearable sensor data. In that study, the authors found that the coaches carefully decided when and how they shared data with both athletes and parents in sub-elite figure skating, adjusting their approach based on the developmental needs of the athletes and the complexity of the information. In a very recent study, Kolovson et al. interviewed student-athletes and collegiate coaching staff to understand their preferences for using and sharing tracking data [30], the importance of which is emphasized in our findings that the coaching staff we interviewed are so concerned about athlete privacy in the context of tracking data that they sometimes avoid these otherwise useful data sources.

Perhaps most closely related to our work are Clegg et al.'s [10] and Kolovson et al.'s [29] papers on data practices in collegiate sports. Clegg's study offers foundational insight into data literacy practices with a focus on interviewing student-athletes, although they interviewed one strength and conditioning coach. Their study found that student-athletes were motivated to analyze their data, but wanted their coaches' support for data interpretation. Similarly, Kolovson [29] examined the use of personal data in collegiate sports and emphasized the power asymmetries between student-athletes and coaching staff, highlighting that coaching staff often collect data from athletes without involving them. For instance, with a chest-worn wearable sensor, coaching staff can view the athlete's activity data in real-time, but the athletes only have access to this data when staff choose to share it. Our study shifts the focus from student-athletes as subjects of surveillance to coaches as active users and interpreters of data, mediating its impact on student-athletes.

By focusing on deeply understanding the experiences of interdisciplinary coaching staff, our work expands on previous research to explore how these key professionals manage and use data. In doing so, we aim to provide insights and design recommendations for coaching-staff-facing technologies, because coaching staff make decisions that have tremendous impact on many people's lives.

3 Methods

Our study explores how collegiate coaching staff engage with data and technology. We conducted five semi-structured focus group interviews with a total of 17 coaching staff members, resulting in a

Focus Group	Job Distribution	Gender Distribution
FG1	AT, S&C, DT*	0 female, 3 male
FG2	AT, S&C, Coach†, SS, Admin	0 female, 6 male
FG3	S&C, DT, Coach	2 female, 1 male
FG4	AT, S&C, Coach	2 female, 1 male
FG5	AT, S&C, DT*	0 female, 3 male

Table 1: Participant information by focus group (FG). AT: Athletic Trainer; S&C: Strength and Conditioning Coach; DT: Dietitian; SS: Sport Scientist; Admin: Administrative Staff. †Two coaches were present for FG2. *Indicates the same Dietitian participated in both FG1 and FG5. The specific sport (e.g., soccer, volleyball) is not listed in this table because doing so could be identifying to the participants.

sample size that aligns with established practices in qualitative research at CHI [5, 22, 69]. Each focus group represented a sports team (women's basketball, women's soccer, women's volleyball, men's American football, and men's basketball) from an elite collegiate sports program in the U.S.

This study was reviewed by the authors' university ethics review board which approved it as *exempt* due to its minimal risk nature and a study design that collected no identifying research data for individuals. The university's athletic department research sub-committee also reviewed and approved the study protocol. All participants provided informed consent to participate.

3.1 Participants

We recruited participants using existing relationships with staff in the university's athletic department. The sample consisted of coaching staff working closely with student-athletes in basketball, soccer, volleyball and American football. The sample provided a diverse range of data practices across both women's and men's sports and large versus small teams (see Table 1 for a breakdown by focus group). The participants included the following professionals representing diverse backgrounds:

- **Coach**: Leads the team and makes decisions on practice, game strategy, and player selection. Manages technical and tactical training, media, and recruitment.
- **Dietitian**: Manages nutrition plans to support muscle development and recovery.
- **Strength and Conditioning Coach**: Designs and implements training programs to boost strength, power, endurance, and agility. Prepares student-athletes for the physical demands of the sport.
- **Athletic Trainer**: Prevents, treats, and rehabilitates athletic injuries.
- **Sport Scientist**: Uses evidence-based strategies to enhance physical performance and recovery.
- **Administrative Staff**: Manages logistics and administrative tasks, such as travel, scheduling, and team operations.

3.2 Focus Group Protocol

The first two authors split the role of conducting focus groups between June and August 2024. All focus groups took place in closed conference rooms or offices on the university campus. All focus groups had 3 participants present except Focus Group 2 which had 6 participants. The focus groups ranged from 27 to 58 minutes, with an average duration of 32 minutes. Each focus group consisted of staff grouped by the primary sport they worked with, although some staff members worked with multiple sports. One participant joined two different focus groups to provide insights from their experience in two distinct sport contexts. Participants received a $25 Amazon e-gift card as compensation.

The researchers used 27 questions to guide the semi-structured focus group discussions. The discussions started with roundtable questions to understand each participant's job position and the main objectives within those positions. The questions then shifted to more detailed inquiries about their use of technology, how they interpret data, and their practices for communicating data among staff and student-athletes. We used follow-up questions to explore specific areas in greater depth (see Appendix A for the focus group protocol and questions.) The focus groups were audio-recorded for subsequent transcription by an automated tool. We then manually verified the automatic transcription against the recorded audio and edited it to remove any personally identifying information.

3.3 Analysis

Using the focus group transcripts, we performed a thematic analysis based on Braun and Clarke's guidelines [9]. Given that there is no established codebook in prior literature for this specific context [33], we used an inductive approach with emergent coding to identify themes directly from the transcripts.

To start, each of the first two authors coded a randomly selected interview based on their interpretation of the data. After this independent coding, the authors met to discuss their findings, deliberate on the most notable codes, and merge their individual sets into a unified preliminary codebook. We used parent and child codes as a way to organize and relate the emergent codes [8]. For example, the parent code "Challenges Related to Data" captured difficulties that coaches and staff encountered in their data practices. Under this parent code, we identified several child codes such as "The Black Box," reflecting coaching staff concerns about how certain derived metrics were computed by proprietary software. Another child code, "Data Validity," reflected concerns about the accuracy and relevance of the data used in decision making.

With the preliminary codebook as a foundation, both authors independently coded the remaining four transcripts. During this phase, we integrated new codes as they emerged from each newly reviewed transcript. After coding each transcript, the authors reconvened to review the codes, discuss any discrepancies, and identify new codes that had surfaced. For codes where discrepancies existed, the authors engaged in discussions to reach a consensus on the best fit codes to represent the data. Through this process, the authors continuously refined the codebook, which ultimately became the final codebook.

After identifying codes, we further refined our analysis by exploring relationships between themes. We noticed a pattern that closely mapped to the stages of the data life cycle framework, which includes stages such as gathering, sharing, deciding, acting, and assessing the data. Recognizing this alignment, we mapped our themes onto the data life cycle to provide additional understanding of the data process in college sports.

3.4 Positionality

The researchers on this study have diverse experiences in athletics, including experiences as former student-athletes, university athletic department staff, and professional sports staff. They also have diverse experiences with data-intensive research in computer science, sport science, biomedical engineering, and biomechanics. Our familiarity with athletics and data-intensive research guided our analysis and choice of terminology for codes and themes, with the goal of reflecting the language and concepts in collegiate sports. According to well-established practices in HCI, we have not attempted to conduct the qualitative analyses in the absence of our perspective or backgrounds [41], but rather those backgrounds have informed our understanding of the data, and we provide this positionality statement as context to the reader [37].

4 Results

This section presents the results of the thematic analysis mapped to the data life cycle (Figure 2).

4.1 Gathering: Data Gathering is Constant and Abundant

Our focus groups revealed an abundance of data sources used in elite U.S. collegiate sports. Across the five focus groups, participants discussed 29 different data sources, with each focus group averaging 11 sources that they use. Data source usage amongst different coaching staff and across different athletic teams varied. For example, when FG2's strength and conditioning coach was asked if they use data, they mentioned six data sources. In contrast, FG5's strength and conditioning coach replied to the same question, *"No, I just pay attention to how they [the student-athletes] look"*. The data sources mentioned by coaching staff included inertial measurement units (IMUs), global positioning systems (GPS), film analysis, hydration testing, body composition analysis, force plates, and velocity-based training (VBT) systems, some of which are illustrated in Figure 1.

Coaching staff gather data through different phases of the athletic season including preparation, competition, and recovery. Our focus groups revealed two distinct avenues by which data is collected: *targeted assessment data* involving activities the athletes do for the sole purpose of data collection, and are used as injury screening or to obtain performance baselines; and *monitoring data* generated by activities the athletes would do anyway including practices, games, and daily habit tracking. Many of the groups described their preseason assessments, with a focus on establishing baseline metrics through tests to assess the student-athletes' current fitness levels and identify potential areas of improvement (FG1, FG2, FG3, FG5). As the season progresses, daily monitoring becomes important as some coaching staff extend this data collection to games (FG1, FG3, FG4, FG5), and use this information to decide how the intensity of practices aligns with the demands of competition. Additionally, athletic staff described a specific kind of targeted assessment in which data is collected in response to specific circumstances, such as a student-athlete recovering from an injury (FG2, FG3, FG4). Dietitians mentioned pre-game hydration testing as a way to determine whether student-athletes are physically prepared for competition (FG1, FG3, FG5).

Despite what may seem like fluency in obtaining data readily, there are challenges at this phase. In some cases the technologies themselves (sensors and software related to data sources) present difficulties. An athletic trainer in FG5, a self-proclaimed *"old school dude"*, admitted, *"I don't understand how to do it...I don't even want to learn"*. There are also athlete-centric challenges: coaching staff believe student-athletes can sometimes feel overwhelmed, particularly during targeted assessments, reaching a point where they think, *"I gotta do another test?"* (FG5). In FG2, a coach highlighted concerns about the accuracy and reliability of testing data, noting that it depends on the *"human element to the effort sometimes with young players,"* meaning that the accuracy of tests can vary based on how much effort the student-athletes put in. He also mentioned that with wearable rings used to track biometric data, *"they [the student-athletes] lose them."* These issues contribute to challenges in gathering consistent and reliable data, which can create downstream problems in data interpretation.

A distinct category of challenges arose around the use of rings and wrist bands for continuous monitoring. Some of these challenges are privacy related: one participant in FG3 explained, *"We don't have access to the actual data...our head coach is very sensitive to the [student-athletes] feeling 'big brothered' because they wear it all the time."*

Finally, we observed a desire for a more streamlined approach to data gathering. In four of the five focus groups a desire for combined data sources was highlighted by coaching staff (FG1,FG3,FG4,FG5). *"We want to put resources into making the [technology] more worth it and better"* (FG4).

4.2 Sharing: Data Sharing is Dynamic

In our focus groups, coaching staff mentioned a variety of communication strategies to share data. Coaching staff frequently engage in verbal discussions (FG1, FG2, FG3, FG5), using face-to-face conversations to exchange information quickly and efficiently. When asked in FG2 how staff share data, two participants laughed and simultaneously said, *"We talk."* FG5's athletic trainer echoed this sentiment, stating that they rely exclusively on verbal communication and texting: *"For me, it's all verbal communication... if it's a in the moment where I just find something out, it's a text"*. Text messages (FG2, FG3, FG5) serve as quick, informal communication methods, especially when immediate updates are needed. They also hold formal meetings (FG1, FG2, FG3) to review comprehensive data reports and strategize in structured settings. For unexpected situations, they rely on ad-hoc meetings (FG1, FG2, FG5) to make quick decisions based on the latest data.

Participants also highlighted the importance of protecting student-athletes' privacy when sharing data among staff. As one participant in FG3 stated, *"when it comes to like the body composition... That's information I can share with our athletic training department and our physician. Those numbers aren't something I can share with the coaching staff."* A participant in FG1 shared, *"So whenever I get all that information, I send that up to the team...within the scope of HIPAA"* (where HIPAA refers to the United States' Health Insurance Portability and Accountability Act, which provides strict protections for the sharing of personal health information [1]).

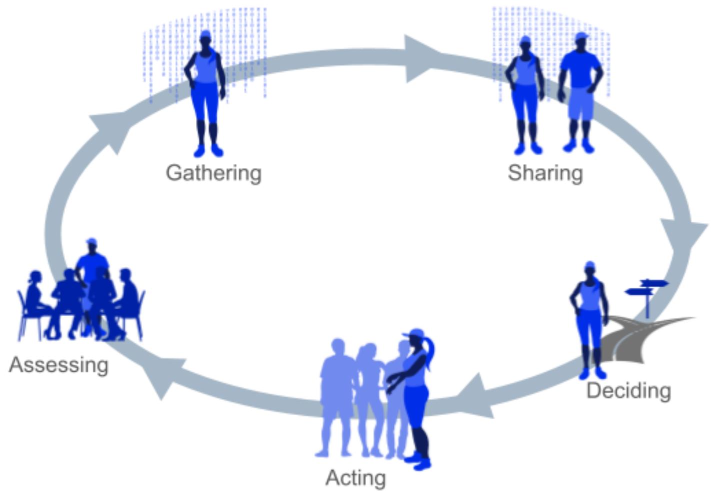

Figure 2: Using data within a college athletic program is cyclical. Coaching staff gather, share, decide on, act on, and assess data.

From the coaching staff's perspective, tools for centralizing and sharing data are either unavailable or insufficient in meeting their needs for sharing data and results. They instead move data from each data source's proprietary platform and export it to other formats, such as organizing data in a spreadsheet and sharing it amongst themselves (FG2). They prepare role-specific reports (FG1, FG3, FG5) which tailor data summaries to different staff members on the interdisciplinary team, and student-athlete specific reports (FG1, FG2, FG5) to provide detailed data on individual student-athletes, supporting personalized training plans and targeted interventions. The athletic trainer from FG5 said, *"We create individualized reports, as well as, you know, a team report, and that's reported directly to the head coach."* FG1's dietitian described a selective approach when sharing between team members: *"I'm gonna put it into a spreadsheet and send that to [athletic trainer] and [strength and conditioning coach] here, so that way everybody's aware. And then that formats a little bit different with [coach], you know, we just show a little bit more of a trend."* Substantial amounts of manual effort go into this process of sharing. Coaching staff expressed a need for a centralized data hub (FG1, FG3) to better coordinate and share information across their interdisciplinary teams. Additionally, efficiency (FG2, FG3) in communication and data usage was emphasized, with a strong preference for technology that provides actionable insights (FG1, FG2, FG3, FG4, FG5) to support rapid decision-making.

4.3 Deciding: Data Interpretation Involves Many Factors

After gathering and sharing data for discussion, coaching staff move into a crucial phase of deciding how to use the collected data. These decisions may be made collaboratively, where the interdisciplinary team members discuss the best course of action, or by individual staff members who are familiar with the data sources and technologies that generated the data. Coaching staff adjust training or recovery strategies in response to meaningful changes in data (FG1, FG2, FG3, FG4, FG5). For instance, an athletic trainer in FG4 mentioned monitoring for *"a sudden increase"* in workload, which could signal a heightened risk for injury. Similarly, another athletic trainer in FG1 uses data to identify certain areas for improvement, noting, *"I can see this is where [the student-athlete] is lacking flexibility."*

Coaching staff also use data as a tool to guide the interpersonal aspect of coaching (FG2, FG3), especially when managing large teams. In FG2, a sports scientist explained how noticing a change such as a drop in force or speed prompts them to check in with the student-athlete: *"Once you see maybe somebody did something well...or maybe somebody did something not so well, you can go to them, and it allows you to ask them how they are feeling."* When coaching staff interact with data to look for relationships between in-game or practice performance metrics and data-derived metrics (FG1, FG3, FG4, FG5), they are identifying patterns or relationships between different metrics (e.g., heart rate, workload, hydration levels) to inform their decision making. Coaching staff independently decide which combination of metrics to use for their own performance objectives.

All focus groups reported using technology to track individual student-athletes' long-term progress (FG1, FG2, FG3, FG4, FG5) and monitoring team trends (FG1, FG2, FG3, FG4, FG5) as part of their data practices. Additionally, in FG1, the coaching staff discussed using workload metrics to forecast future efforts, allowing them to tailor training and preparation based on historical performance data. For example, they reviewed past games to understand typical workload numbers from the GPS sensors, and then planned accordingly for upcoming competitions.

Sometimes individual coaching staff members use their domain-specific knowledge to interpret a data source. For example, a technology that combines GPS tracking and an inertial measurement unit was consistently used across all five focus groups, but different staff members used the data in different ways. The dietitian in FG5 noted, *"I like to use [the technology] to find some kind of correlation* *between their [the student-athletes] sweat rate and the workload."* Similarly, the assistant coach in FG2 shared, *"all of us as a staff get the [technology] reports, and then [assistant coach] builds the training plans"*. The athletic trainer in FG4 emphasized, *"The [technology] is giving us jump count, which is great for when I'm tracking numbers on jumping for somebody who has an injury."* The strength and conditioning coach in FG2 stated *"we use it more with [head coach] on a day-to-day basis on who needs adjustments."* These adjustments can involve altering how hard the student-athlete pushes, how much they do, or how much recovery they need in practices or conditioning.

Many coaching staff face challenges in making decisions based on data. Some of these challenges are intrinsic to the domain but others are due to limitations in the information that they feel is currently available to them. They consistently expressed frustration with black-box metrics that accompany various companies' proprietary data sources (FG1, FG3, FG4, FG5). For instance in FG1, a staff member shared their frustration: *"I've asked [company] and said, 'Hey what is that formula for that workload number?' And I can't get an answer."*

Benchmarking practices are desirable for teams, but changing technologies and incompatible data storage systems often prevent this valuable practice. Data collected over time may not be consistent or directly comparable. This inconsistency makes longitudinal analyses challenging (FG2, FG3, FG4, FG5). One focus group described using twenty years of historical data from their top players' performance metrics as models or benchmarks for current players. In contrast, another focus group struggled with staff turnover and changing technologies, explaining, *"we missed a really big chunk of our year... we are missing a lot of information there,"* highlighting how such gaps make it difficult to build the knowledge base needed to make informed decisions with the data for current teams and practices.

4.4 Acting: Data is Intentionally Disseminated to Student-Athletes

After gathering, sharing, and making decisions based on data, coaching staff strategically guide how they disseminate the information to student-athletes. Most of the data collected is never intended to be student-athlete facing (that is, the vendors who provide the technologies do not design athlete-facing interfaces), so coaches and staff act as navigators who bridge the gap between coach-facing interfaces and the student-athletes.

Our focus groups revealed that coaching staff manage the flow of data in ways that they believe protects student-athletes' emotional well-being. Many coaching staff expressed concerns that data can be a distraction (FG1, FG3, FG4, FG5), introduce unnecessary complexity (FG2, FG3, FG4, FG5), lead to student-athlete rumination (FG1, FG2, FG3), and overly increase competition (FG1, FG3). As an example of protecting student-athletes' emotional well-being, body composition can be a sensitive topic that pertains to the percentage of body fat a student-athlete has. A dietitian in FG1 says, *"with body composition, that's one I have to be a lot more aware of, of how I deliver that information... some folks, they might be a little more sensitive with it."*

Coaching staff see value in sharing data with student-athletes for motivational purposes (FG1, FG3, FG5) but do so selectively. In FG2, the staff described how they *"only really give them their speeds,"* using these data to encourage performance without overwhelming the student-athletes with large amounts of raw data. For example, in this same focus group, staff used this speed data to spark competition, *"who's holding the average down?"* However, one strength and conditioning coach in FG3 cautioned about the competitive nature of showing data from one student-athlete to another student-athlete, saying, *"I have to be very intentional about when I use it because they [the student-athletes] are very competitive when I do it,"* and similarly, an athletic trainer in FG1 said, *"it's [data] competitive in nature, I just think that needs to stay on the courts."*

In all focus groups, the participants mentioned that they deliberately avoid disseminating specific data to student-athletes, or disseminating only in simplified form (FG1, FG2, FG3, FG4, FG5). In FG2, the staff mentioned that they intentionally do not tell student-athletes, *"hey, your... [data numbers] are high for practice"*, in an effort to prevent overthinking and rumination. One athletic trainer from FG1 explained *"I just think you're giving them something else to mess with their head in a sense. You're giving them something else to worry about that they've never had to worry about before."* As an example of delivering data only in simplified form, in FG1, a dietitian described using a simple color-coded system—green, yellow, and red—to communicate hydration levels with student-athletes rather than a detailed hydration metric, reducing complexity while still motivating action. Similarly, in FG2, staff discussed using a point system to gamify data, incentivizing student-athletes to perform well on ability assessments by rewarding them with points for achieving personal bests.

4.5 Assessing Data for Ongoing Usefulness: Data Usage Evolves Over Time

Our focus groups with collegiate coaching staff reveal that the data process is cyclical, involving assessment within an ever-changing landscape of data sources and individual needs. Newly formed interdisciplinary teams or those with recent staff changes usually begin with a clear assessment phase to understand how technology can supplement existing coaching practices. This was particularly evident in FG1, where the team had been together for less than three years. As one participant explained, *"It's just the relationship that matters the most between us and the coaching staff for their buy-in to change."* This highlights that, while data is helpful, there is a risk of losing the human element of coaching. Another participant from the same group, an athletic trainer, emphasized that the team was still figuring out what would be beneficial and helpful, noting, *"It's just kind of learning what parts we need, what would help us... I think it's a younger staff as we're building a program."*

For more established groups of coaching staff, deciding whether to keep a data source each year is determined by several factors. In some cases, perceived problems with a data source can lead to reconsidering: coaching staff from both FG3 and FG4 reported inaccuracies of a GPS and inertial measurement-based external load monitoring device with staff from FG3 noting, *"It's not very consistently accurate"* and staff from FG4 adding, *"I don't think it's always like 100% accurate."* An athletic trainer in FG4 described the transition from one jump-count technology to another due to technical issues, stating, *"So we went away from the company who was giving us stuff because it was going so poorly with the connections and things."* A staff member in FG2 described how they regularly assess and refine their practices, asking themselves during season transitions, *"What changes, what have we seen, what patterns based off the data?"*

5 Discussion and Takeaways

In this study, we set out to explore how collegiate coaching staff engage with data among their interdisciplinary teams and with their student-athletes. Our findings highlight that coaches and support staff are not passive consumers of performance data but active decision-makers who integrate quantitative insights with their coaching experience and understanding of athletes' needs, performance objectives, and team goals. Coaching staff manage data at every stage of the process while striving to balance data-driven insights with professional judgment and athlete well-being.

From our analysis, two key roles emerged as central to how coaching staff navigate the challenges and opportunities of working with technology and data. These roles are grounded in topics expressed across at least four of the five focus groups. The first role, *data analyst*, captures the coaching staff's efforts to extract meaningful insights from complex metrics and distill findings in an ever-changing technological and competitive landscape. The second role, *protector*, reflects an imperative that the coaching staff took upon themselves to uphold student-athlete privacy and foster emotional well-being.

The following discussion examines the implications of our findings through the lens of these roles, connecting them to existing literature and highlighting their significance for SportsHCI. We also offer design recommendations for future SportsHCI systems to better support coaching staff in the collegiate sports environment, helping HCI researchers identify key stages within the data process where technologies can be designed to address specific coaching practices.

5.1 Coaching Staff are Forced to be Data Analysts

Our focus groups highlight how data plays a central role in the decision-making process of coaching staff, and the systems and technologies they use shape the evolving role of coaches as *data analysts*. Across all focus groups, coaching staff expressed the need for actionable insights and rapid decision-making support for the high-pressure and competitive environment of collegiate sports. However, their interaction with data often revealed a mismatch between the systems designed for them and their practical needs.

One key wish was the integration of multiple data sources, mentioned in all five focus groups (Section 4.1). Current systems seem to silo information, making it difficult to connect insights across metrics such as workload, calorie expenditure, and the athlete's rate of perceived exertion. One participant in FG3 said, *"I have an embarrassment of resources...but [some way for us to] pull all that together instead of sifting through it and trying to connect it. That's at the top of my wish list."* Coaches recognize that a single stream of data rarely provides the full picture needed to guide training or recovery plans. Instead, they rely on their domain expertise to manually "connect the dots" from multiple sources, such as linking force production to injury rates or balancing workload against recovery scores. These practices align with findings from the earliest studies in SportsHCI, which highlighted the contextual approach coaches take to make decisions [62]. However, the growing volume and complexity of available data has made the task increasingly difficult to manage manually.

Another significant aspect was the reliance on tracking individual athletes and team-level trends, which emerged as central to coaching practices (Section 4.3). Inconsistent data collection, evolving technologies, and inaccessible historical records make it difficult to establish reliable benchmarks or assess trends over time. On top of this, the reality of collegiate sports is the constant turnover of student-athletes, with new players coming in and others leaving every few years adding a layer of complexity for maintaining continuity in data. This gap points to the need for systems that not only support short-term insights but also provide the stability required for long-term planning.

Further complicating these responsibilities is the reliance on derived metrics from sports technologies. Every focus group discussed using these metrics but questioned how the metrics were generated and whether they accurately reflected the realities of their sport (Section 4.3). Karahanoglu's study [26] found that athletes' trust in technology decreases when dealing with derived metrics, primarily due to the lack of transparency in how these metrics are calculated. Coaching staff in our study faced a similar issue. They questioned the accuracy and relevance of the metric when they could not clearly understand how it was derived, and some even reported reaching out to the vendor to request the formula behind a particular derived metric but could not get a clear answer. Building on Karahanoglu's finding that athletes trusted data more when it aligned with their perceived effort, there is an opportunity in the SportsHCI community to explore how coaches build trust in derived metrics. Investigating how alignment—or misalignment—between data and coaches' expertise or observations influences their trust in these metrics and how they use them in practice presents an intriguing research opportunity. Future coach-facing technologies could incorporate designs that allow them to act as calibration tools, allowing coaches to track how well data aligns with their observations and expertise, ultimately helping adjust models to better reflect real-world practices.

5.2 Coaching Staff serve as Protectors of Student-Athletes

Our findings reveal how coaching staff take on the role of *protectors*, navigating privacy concerns and attempting to mediate the impact of data on student-athletes' emotional well-being. We discuss each of these in this subsection.

5.2.1 Protecting athlete privacy. Our focus group results indicate that coaching staff are mindful of practicing within the scope of HIPAA (the Health Insurance Portability and Accountability Act in the U.S.), which provides strict protections for the sharing of personal health information. This legal framework shapes some aspects of privacy, particularly in determining which personal health information, such as body composition, can be shared with other professionals. However, an unexpected finding was the heightened awareness and caution some coaching staff demonstrated towards non-HIPPA-protected performance-related technologies that provide automatic, continuous physiological monitoring (Section 4.1).

This consideration became apparent when discussing the tremendous value of physiological monitoring to estimate internal load, which provides valuable insights into how athletes' bodies respond to training (external load). The staff recognized that tracking heart rate, sleep patterns, and recovery metrics from wearable technologies could offer valuable insights into how their student-athletes are coping with not only the demands of training and competition but also life and academic stress, allowing for adjustments to training. However, the most readily available internal load metrics depend on continuous physiological monitoring through wrist or finger-worn sensors, and because they collect data around the clock, some of the coaching staff we interviewed expressed that they choose not to use that data despite its potential to help student-athletes. A head coach in our interview expressed concerns that continuous data collection could invade athletes' privacy and make them feel constantly watched. The solution mentioned in one of our focus groups was opting to offer these wearable devices as self-educational tools for athletes to track their metrics privately, rather than sharing the data with the coaching staff. This avoids coaching staff being able to ascertain private information such as drinking habits and sexual activity [38].

The finding that coaching staff may avoid using potentially valuable data sources out of concern for athlete privacy was unexpected in our study. While previous work, such as Kolovson's exploration of power asymmetry in college sports [29], touched on the automatic tracking of sleep data, it highlighted how the automatic collection diminishes an athlete's ability to control what they share and how they present themselves. Student-athletes in that study expressed concerns that metrics such as poor sleep could affect their status on the team, how hard they were asked to train, and even whether they were allowed to compete. Some even intentionally distorted their data to avoid negative consequences. In contrast, our findings shed light from the coaching staff perspective, revealing a delicate balance between leveraging data for performance and respecting athletes' privacy. While avoiding certain data sources protects athlete privacy, it also has potential downsides. For instance, an athletic trainer pointed out that tracking menstrual cycles could significantly optimize training and prevent injuries for female student-athletes. However, that staff member stated this type of data is not being collected, likely due to privacy concerns or the sensitivity surrounding such personal information. Our findings point to a new and more nuanced challenge to consider in SportsHCI: supporting the coach-athlete relationship by balancing the need for actionable data with privacy considerations. Balancing these competing priorities is a key challenge for coaching staff, and is a call to action for SportsHCI researchers to design systems that are ethically and legally built, protect privacy boundaries, and still provide actionable data that supports effective coaching.

5.2.2 Protecting athlete emotions. In our focus group discussions, we found that the coaching staff often took steps intended to protect their athletes' overall experiences, including their emotional well-being, by carefully delivering performance data (Section 4.4). Recent SportsHCI research explored how technology and data shape athletes' experiences, applying frameworks such as self-determination theory (SDT) to understand the impact of data on motivation and behavior [49]. The role of coaching staff as protectors touches on the three key aspects of SDT [42]: competence, relatedness, and autonomy. While much of that prior work examined how athletes directly engaged with data, our findings expand this conversation by showing how coaches can actively mediate these dimensions of SDT, shaping athletes' engagement and experiences with sports data. We discuss each SDT dimension in turn below.

A significant insight from our study is that coaching staff purposefully avoid disseminating specific data streams to student-athletes or simplify their presentations to protect athletes' sense of **competence**. As one athletic trainer highlighted, *"I just think you're giving them something else to mess with their head in a sense. You're giving them something else to worry about that they've never had to worry about before,"* and *"We don't want them to go out and think that they need to do extra work just because their numbers might be lower."* Across four focus groups, participants discussed how data, when presented in a raw or overly complex format, can distract athletes and introduce unnecessary complexity (Section 4.4). By carefully managing the flow of information, coaching staff aim to facilitate a better motivational environment.

We found that coaching staff also use data to facilitate discussion with athletes, which may potentially foster the self-determination theory dimension of **relatedness**. Clegg et al. described how student-athletes in their study often needed support from coaches to engage in data analytic practices, and how coaches used data to guide student-athletes after an injury or to navigate difficult performance metrics [10]. In our study, noticing changes in student-athletes' performance metrics often prompted coaches to check in, using data as a starting point for meaningful conversations about well-being and progress. Additionally, relatedness can also emerge from a curious student-athlete, as one strength and conditioning coach describes, *"I always try to promote... let's talk about what I'm tracking on my end, and the why behind everything you do in the weight room."*

When discussing the third aspect of self-determination theory, **autonomy**, a delicate tension arises in the context of collegiate sports. In general, a widely accepted value of user-centered design is that users should have agency over their data [59]. While at a fundamental level athletes are given the choice to opt out of data collection in collegiate sports contexts, as Kolovson et al. established, power differentials between coaches and student-athletes may make this choice challenging [29]. In either case, the reality in collegiate sports today is that the majority of data sources highlighted in our focus groups have no athlete-facing interfaces, leaving the responsibility of data interpretation and dissemination to the coaching staff. The call to action for the SportsHCI community is twofold: first, we must further investigate the balance between student-athlete autonomy in data and the improved feelings of competence and relatedness that tailored delivery provides. Second, it is important to explore a novel class of coach-facing technology that allows this balance to be achieved.

5.3 Design Recommendations for Coach-Facing SportsHCI Systems in Collegiate Contexts

Based on our findings, we suggest a set of design recommendations organized by stages of the data life cycle for those who wish to develop novel SportsHCI technologies to serve coaching staff. Note that these design recommendations focus on coaching-staff-facing technologies as opposed to athlete-facing technologies which have not been the focus of the present analysis.

5.3.1 Gathering: Ensure Compliance, Cross-Stream Data Integration, and Privacy. In the gathering stage, 1) systems must comply with all applicable laws regarding collection and storage of athlete data, particularly health information. These laws are often nuanced and can be even more stringent than human subjects protections provided by ethics review boards. 2) Data should be gathered in mechanisms that make downstream reasoning across data streams possible. Relying on proprietary or black-box methods, however convenient, may undermine downstream goals of sensemaking across data streams rather than being limited to each one individually. 3) When potentially sensitive data streams are needed (such as data from 24-hour wearables), options should be given to control the granularity of data initially provided from the source (that is, give the athlete agency to determine how the data is transmitted). Once data is transmitted, minimum aggregation over time periods or sampling to reduce time frequency may be needed to enable coaching staff to analyze the data without compromising athlete privacy. Further recommendations for use of student athlete tracking data are detailed in a speculative design paper focused deeply on this point [30].

5.3.2 Sharing: Provide Hierarchical Access, Flexible Export Options, and Streamlined Design. In the sharing stage, 1) interfaces should provide mechanisms for those with full access to data to provide other staff with less detailed data reports to comply with athlete protections, rather than needing to move the data out of the interface entirely to remove detail. 2) Interfaces should support the compilation and export of data into a wide variety of formats, not just display data in a proprietary format that a vendor believes is most useful to coaching staff. 3) Systems should be designed with efficiency and simplicity in mind to facilitate easy data sharing among interdisciplinary coaching staff in collegiate sports, recognizing that the fast paced environment demands that coaching staff, often managing multiple teams, be able to quickly relay key information. 4) Systems should be created with the ability to centralize data streams in one place, simplifying the process of viewing, accessing, combining, and sharing from multiple data sources among coaching staff.

5.3.3 Deciding: Enabling Data Integration, Anomaly Detection, Longitudinal Analysis, and Clarifying Metrics. When it comes to deciding on data, 1) new systems should enable meaningful compilation of data from multiple sources, navigating the varied time granularities and data types. New systems should also be backwards compatible to support longitudinal benchmarking. 2) Streams of sensor or other data should flag periods of time when their readings are out of the ordinary, to assist coaching staff in identifying noisy or unreliable data. 3) Interfaces should enable longitudinal views of data within and between individual athletes, to support coaching staff reasoning over historical data trends beyond the (short) tenure of a specific collegiate athlete. 4) Tools should be designed for domain experts who are not highly trained data scientists. When metrics are the main deliverable to coaching staff, the rationale behind these metrics should be provided in a way that is clear and accessible to these professionals.

5.3.4 Acting: Supporting Coach-Athlete Data Delivery. In the acting stage, interfaces should allow coaching staff to tailor views of the data to support conversations with athletes, rather than coaching staff having to export and format the data themselves to prepare an athlete-facing view.

5.3.5 Assessing: Support for Self-Guided Data Exploration and Provide Access to Raw Data. Finally, in the assessing stage, 1) systems for coaching staff should provide mechanisms for these staff to explore relationships between data streams and outcomes to facilitate critical decision making on what data streams may need to be collected from year to year. 2) Systems should provide access to raw data to allow for specialized use cases.

5.4 Limitations and Future Work

Like any research that aims to deeply understand a population of users within a context, this work has limitations. We attempted to gain diverse perspectives by including coaching staff from five different sports including both women's and men's teams. However, these coaching staff are all from the same university, and the extent to which the findings may be repeated beyond that context is unclear. Second, this paper has only reported on coaching staff's perspectives. This intentional focus provides a unique perspective on the collegiate sports landscape, distinguishing our work from other SportsHCI studies. However, the issues reported here deeply involve student-athletes, and a crucial direction for future work is to investigate student-athletes' perspectives. One such study is commencing within our group as of the time of this writing. Finally, by conducting our research at a high-level, well-funded sports program operating within a large university, we recognize that the findings here do not represent the experiences of coaching staff at other levels of athletics. However, because the coaching staff in this study are operating on the high-tech frontier of collegiate sports, we contend that the design recommendations uncovered through this work provide a forward-looking view that could serve athletics programs with fewer resources as technologies become increasingly more ubiquitous.

This work points to several important open research questions. First, while derived metrics in SportsHCI are intended to simplify decision-making, our findings raise another potential research question: *Do these tools actually reduce cognitive load for coaching staff, or do they inadvertently add to it by introducing uncertainty?* Understanding how the ambiguity of derived metrics affects cognitive load could provide insights for designing better coaching-staff-facing technologies. A second open question arises from our findings that coaching staff believe that data, if shared indiscriminately, could negatively impact student-athlete emotional well-being or performance. This raises the question, *How can coaching and athlete-facing technologies be designed to mitigate potential harm from data while still empowering athletes to engage meaningfully with their own* *performance data?* Finally, the findings presented here highlight an open question pertaining to potential democratization of high-quality coaching insights to a broader population. Future work should investigate the question, *In what ways could the lessons presented here inform athlete-facing technologies for those who do not have access to elite coaching?*

6 Conclusion

This paper has examined the data practices of collegiate coaching staff, an under-researched group of technology users within SportsHCI. We organized our findings through the stages of the data life cycle: gathering, sharing, deciding, acting, and assessing, revealing that coaching staff act as data analysts and protectors who intentionally use data in an attempt to balance performance goals, athlete emotional well-being, and privacy. We have provided design recommendations for future SportsHCI systems that are built to support coaching staff. We have also pointed the way toward future work that is needed to make advances in the SportsHCI Grand Challenge of supporting the coach-athlete relationship. This study contributes to the growing field of SportsHCI by offering new insights into the data-driven practices of collegiate coaching staff and helping HCI researchers identify areas within the data process to design technologies that support specific areas of coaching practice. The findings and design recommendations may have broader relevance for coaching staff and athletes at other levels, potentially forging a path toward better supporting the goals of active humans through technology.

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APPENDIX

A Semi-Structured Focus Group Protocol

Upon entering the meeting room, each participant in the focus group was given a name tag and informed consent. Once the entire staff was present, the researcher discussed the informed consent, asked each participant to read, and obtained consent. Following this process, the researchers introduced themselves to the staff. The goal was to discuss the protocol, set the tone, and do any norm setting that may aid in the flow in the interview. To begin the interview, the researcher asked for consent to record, and asked the following series of questions:

(Q1): To get things started, what is your role within your athletic program?

(Q2): m How would you each describe the main goal within this job?

(Q3): Amongst yourself, could you brainstorm what sources of information you use to help those goals? [What are the most important sources of information for you to be successful?]

(Q4): Ok, thanks for sharing those, for each data source:
- (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 the data?
- (d) How do you view or interact with that data? Any apps, websites, or anything else that you use?
- (e) When or how often do you interact with that data? (for example, after practice, after games, weekly, daily, once per semester?)
- (f) Does the way you use data change between the competitive season, training camps, and the offseason?
- (g) How do you use the data to make decisions? [If they don't know what you mean, you could say something like, using data to change what you recommend for an athlete on a given day]

(Q5): For all data sources together:
- (a) What data do you share with the other members of your training staff?
- (b) What methods do you use to share this data?
- (c) What do you like most about using all of this data to support your needs?
- (d) What are the primary challenges you face when using these different data sources together?
- (e) Is there a policy for managing athlete data when a student graduates or leaves the team?

(Q6): Do you communicate with the athletes about their data?
- (a) **If yes:** How do you communicate with your athletes about their data?

(Q7): Do your athletes have the ability to interact with the data themselves?
- (a) **If yes:** How do you think the athletes interact with data?
- (b) **If yes:** Do you wish athletes would engage more with data?
  - (i) What are the reasons you see that might keep student-athletes from engaging successfully with data?
- (c) **If yes:** What percentage of student-athletes do you expect to interact with the data?

(Q8): So now back to you as (coaches/staff). Are there any additional ways you would like to utilize existing data?
- (a) Are there any additional sources of data you would be interested in integrating?
- (b) Do you feel that you would have the bandwidth to integrate new data sources or technology tools into your workflow?
- (c) Before we end this interview, I would like to reiterate that our main goal is to further optimize how you use data. What are the main takeaways you'd like me to take back to my team?

(Q9): Thank you for your time, is there anything else you would like to add before ending the recording?