Mapping the Flow of Information from Continuous Wearables: Insights from Elite Collegiate Athletes in the United States

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ABSTRACT

Continuous wearables collect physiological data throughout the day and are increasingly being used to help athletes and training communities achieve performance goals. While valuable, these devices collect extensive personal data with minimally studied sharing patterns. We investigate this issue in the context of elite United States collegiate sports by analyzing 15 semi-structured interviews with student-athletes. This paper reports on a qualitative analysis using the *contextual integrity* framework—an established privacy framework that identifies usage norms—to map the flow of information collected by continuous wearables. We highlight seven key descriptions of how data is being shared, identify privacy considerations, and provide recommendations for the research community to consider how data from continuous wearables is managed. Ultimately, this work presents a first step in aligning privacy protections with the rapid advancement of sport technology. [1]

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1 INTRODUCTION

Continuous wearables are wearable technologies that enable real-time physiological monitoring of metrics such as heart rate, sleep quality, and physical activity. In 2024, over 190 million continuous wearables were shipped worldwide [1]. These increasingly ubiquitous technologies allow for around-the-clock, real-time data collection. Unlike monitoring systems designed for exclusive use in training and competition, continuous wearables track physiological states throughout an athlete's daily life, providing insights into sleep, recovery, stress, and overall readiness [46, 48].

Continuous wearables such as WHOOP bands and Garmin, Coros and Apple smartwatches, integrate biometric sensors to capture many physiological parameters [12, 17, 54]. For example, they estimate heart rate and heart rate variability with photoplethysmography [23] and quantify movement using accelerometers, gyroscopes, and magnetometers to [56]. Users typically interact with the data through a combination of real-time displays, app interfaces, and by uploading data with external applications, such as the social fitness tracking application Strava[2].

With wide-ranging functionality, continuous wearables are being increasingly used in elite sports, including collegiate athletics [28, 45]. In the United States (US), collegiate athletics are a cultural staple, creating deep-rooted rivalries and fan loyalty that often exceed those seen in professional sports. In 2022–2023, the top level

[2]http://strava.com/

of collegiate sports in the US generated a combined revenue of around $17.5 billion [33], comparable to the nearly €20 billion in combined revenue of European Big Five football (soccer) leagues over the same period [9].

At the center of this high-stakes, high-pressure environment is the student-athlete. Student-athletes are eligible to compete in their sport for four to five years while they are enrolled at a university as a student. During this time, student-athletes must balance the dual demands of academic responsibilities and athletic development, often relying on athletic scholarships that fund their academic education. Regulations and protections are put in place for student-athletes to maintain their amateur athlete status and balance academic and athletic obligations [34]. However, the recent and rapid adoption of new technologies, including continuous wearables, hold potentially negative implications for athlete privacy that have not been investigated in research nor addressed in policies. This situation points to important open research questions that we explore in this paper:

RQ1 When student-athletes at a United States collegiate athletic program use continuous wearables, how does the information flow?

RQ2 What are ways that student-athletes do not want information to flow?

To address this research question, we draw upon *contextual integrity* [36, 37], a privacy framework that defines how information is transmitted and constrained. Researchers use this framework to evaluate the appropriateness of the way information is shared, and to understand how privacy is shaped by contextual elements. Using this approach, researchers can produce a detailed and well-defined map of how information flows through a system, making contextual integrity well-suited to examining the emerging and complex dynamics in athletics. We apply a contextual integrity framework in thematic analyses of transcribed interviews with 15 elite collegiate student-athletes. We present information flows and emergent themes that offer a view of how information from continuous wearables circulates within the collegiate athletic environment. Resulting from this process, this paper presents the following key contributions:

- **Identify information flows within the collegiate athletic context:** We are the first to apply contextual integrity to understand how data collected from athletes flows to other individuals within a large sports organization. Specifically, we identify that information collected from student-athletes' continuous wearables flows to a range of recipients, including coaching staff, the student-athletes themselves, and members of their broader social networks. We organize these findings across seven information flows that represent two information types and a total of 12 unique transmission principles that constrain the transfer of data.
- **Privacy with respect to information flows:** We compare descriptions of information flows to discuss relevant privacy considerations, showing how design choices and application capabilities can conflict with the established norms within the context of elite collegiate athletics.
- **Design Recommendations for Continuous Wearables:** We provide this contextual insight to support the SportsHCI community in developing continuous wearables in ways that are not only innovative, but also aligned with the needs of student-athletes operating within institutional constraints. We offer 5 key design recommendations centered around data controls to guide the development of future technologies in sport.

The rest of this paper is structured as follows: Section 2 presents the background and related work. Section 3 describes the methodology, including how we apply contextual integrity in this research. Section 4 presents the results, describing information flows, privacy implications, and context. We continue with a discussion of the results and accompanying recommendations in Section 5. We discuss limitations in Section 6 and conclude with Section 7.

2 BACKGROUND AND RELATED WORK

Our research examines the use of continuous wearables in collegiate athletics through the lens of contextual integrity. In the following section, we describe important areas of background: (1) continuous wearable devices; and (2) contextual integrity. This section concludes with related work.

2.1 Continuous Physiological Monitoring in Sports Through Wearable Sensors

Continuous monitoring provides new opportunities for coaching by supplementing established workload metrics for athletic practices or competitions [5] with non-workout metrics such as sleep, recovery, and heart rate variability. For example, studies suggest that sleep and recovery levels are strongly linked to performance outcomes, with poor sleep being associated with decreased reaction time [51], impaired cognitive function [7], and increased injury risk [30]. Higher heart rate variability is associated with better recovery and training adaptations, while lower values may indicate fatigue, overtraining, stress, or illness [10]. As such, continuous wearables offer rich data to guide training and recovery strategies [47].

Human-computer interaction (HCI) researchers have taken interest in these technologies, focusing not only on the metrics themselves, but also on how athletes engage with, interpret, and apply wearable-derived data [21, 29, 41]. Rapp and Tirabeni [41] find that elite athletes are more adept at integrating insights into their training routines with the guidance of coaches, while amateurs often struggle with misinterpretation or over-trusting data. This aligns with concerns from Cardinale et al. [6] that continuous wearable devices provide abundant physiological data without the necessary context to allow informed decision-making. While HCI research has explored the role of these wearables within workout-based contexts, relatively little work examines the implications of sharing these metrics with a larger community.

2.2 Contextual Integrity

Contextual integrity, developed by Nissenbaum et al. [36, 37], is a framework used to describe how information flows throughout a system to determine whether privacy is maintained or violated. It posits that determining access to information is not a binary decision made once; instead, contextual integrity frames it as a dynamic process shaped by contextual elements and the roles of involved stakeholders. Nissenbaum and Malkin recently proposed

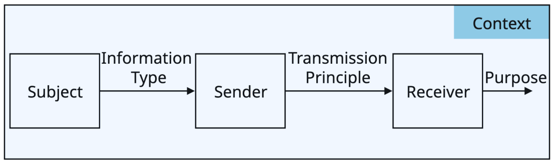

Figure 1: Visual representation of contextual integrity, where, within a given context, a sender shares a subject's information type with a receiver for a specific purpose, under the constraint of a transmission principle. This visualization serves as a foundation for later figures that apply contextual integrity.

the addition of *purpose* to the contextual integrity framework to characterize how data are used and whether that use constitutes a privacy violation [27, 38].

With a sufficient definition of expected or normative information flows, as characterized by contextual integrity, a privacy breach can be understood as a deviation from established norms. For example, contextual integrity describes a consenting patient sharing their medical records with a treating physician as an appropriate information flow. Medical records are not inherently private under this framework; instead, a privacy breach occurs only when there is a deviation from the norms. For instance, if the physician shares records with the patient's employer without consent, this constitutes a privacy violation. The seven key parameters described by contextual integrity are illustrated below using medical records as an example and are visually represented in Figure 1.

- **Context**: What is the overarching environment in which the data is shared? (e.g., medical setting)
- **Subject**: Who is the data about? (e.g., patient)
- **Sender**: Who or what shares the information? (e.g., patient)
- **Receiver**: Who receives the information? (e.g., doctor)
- **Information type**: What kind of information is shared? (e.g., medical records)
- **Transmission principle**: What constrains how the information is shared? (e.g., consent and confidentiality)
- **Purpose**: For what purpose is the information expected to be used? (e.g., medical treatment)

Contextual integrity has been widely applied in both security and human-computer interaction research to understand how information should flow within a specific context [3]. Continuous wearables have been examined within medical, research, and advertising contexts using a survey-based contextual integrity approach. Such work has found that individuals are especially concerned about the privacy of their information when it is shared with advertisers, compared to medical or research recipients [4]. Outside of surveys, contextual integrity can be used to review privacy policies, with crowd-sourced participants accurately identifying the components of contextual integrity [49]. Other researchers have combined contextual integrity with network analysis to uncover unapproved information flows within Oculus headsets [52]. In addition to evaluation, contextual integrity facilitates the creation of policies and guidelines for how information ought to flow, for example, to outline the privacy needs of technology users [2], or to develop a permission request mechanism in Android operating systems [55].

Recently, Kumar et al. [25] demonstrate how researchers can apply contextual integrity to qualitative data. They review Fitbit use in a medical context, identifying information flows for further privacy evaluation. Other researchers have since applied contextual integrity to emerging domains, such as evaluating information flows in decentralized social media platforms [19]. Although prior work examines wearable technologies through this lens, our study is the first to apply this framework within the SportHCI community.

2.3 Related Work

Our research is situated at the intersection of continuous monitoring and privacy in sport. In this section, we briefly review prior work in each of these areas to contextualize our contributions and highlight the gaps our study addresses.

Continuous monitoring technologies are used in a variety of contexts, offering both powerful benefits and potential risks. Across data collection in personal informatics and mobile health, technology can help motivate activity and support health benefits [14]. Privacy concerns within this space include security vulnerabilities and unwanted sharing of data with third parties [18, 43]. In healthcare, continuous monitoring through ambient assisted living systems can help families monitor loved ones who seek independence while managing medical concerns [42], although some patients experience these systems as privacy intrusions [32]. Similarly, continuous location-sharing is a popular tool that can support community engagement, enhance safety, or facilitate coordinated meetups [44], yet it also raises concerns. Location-sharing [8] and item-tracking devices [50] can be repurposed for abusive surveillance, similar to overtly malicious tools such as spyware and stalkerware [53]. These systems may diminish personal autonomy by enabling constant monitoring and control [39]. Our work contributes to the space of continuous monitoring by adding the perspectives and dynamics present in college athletics.

In the sports context, privacy has been explored through fitness-sharing applications such as Strava. Prior work repeatedly shows that sharing fitness activities can expose users to location-based privacy risks [16, 31]. Within college athletics, researchers have begun to examine how technology introduces and affects power asymmetries between student-athletes and staff. Kolovson et al. [24] examine the role technology plays in shaping power dynamics in athletics. Our work builds on these foundations by examining how data-sharing practices in collegiate athletics broaden the conversation about technology in sport.

3 METHODS

This section describes the steps we took to conduct and analyze student-athlete interviews. We explain our recruitment methods, interview procedures, and the analytical approach used to examine the experiences of student-athlete participants. Figure 2 provides a visual overview of the data collection and analysis process, including how we applied the contextual integrity framework to map information flows and develop themes.

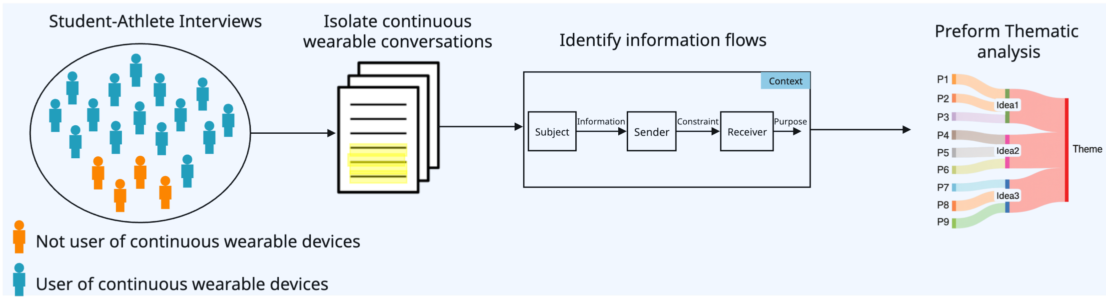

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Figure 2: We began our research with a sample of 15 users of continuous wearables. From the collected transcripts, we extracted all excerpts pertaining to continuous wearables. We then applied the contextual integrity framework to these excerpts to identify information flows and develop themes.

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3.1 Data Collection

Within this research, we used a subset of data from a larger study on how student-athletes use technology. In this broader study, we recruited a diverse range of student-athletes by partnering with a university's athletic department. An athletic department staff member distributed recruitment fliers to select teams and coordinated in-person recruiting sessions. We obtained approval for study procedures, including recruitment materials, from both our institutional review board and the athletic department.

Eligible student-athletes were at least 18 years old and were given the choice of an in-person or virtual interview via Zoom. Coaching staff were blind to athlete participation. After participants confirmed an interview time, we conducted a 30-minute semi-structured interview. We compensated participants with a $25 Amazon e-gift card.

Recruitment yielded a total of 19 student-athletes, including 14 participants from women's teams and five from men's teams, representing both individual and team sports. The first two authors conducted the interviews, dividing them based on availability. We used a semi-structured interview protocol to allow for consistency across participants and flexibility to follow up on individual experiences and perspectives. During the interviews, we asked student-athletes a range of questions about their technology use in sports, without focusing specifically on continuous wearables. Additionally, we specifically asked if there are any types of information that student-athletes believe should be off limits from coaches. The full interview protocol is included in Appendix A.

We audio-recorded each interview and generated automatic transcripts, which were manually corrected by members of the research team. Because our research is specific to continuous wearable devices, the lead author highlighted the portions of each conversation that referenced continuous wearables, following the process described by Kumar et al. [25]. Four student-athletes' transcripts did not discuss continuous wearable devices and were therefore excluded from the analysis.

The resulting dataset used for this paper included 15 student-athletes, with 13 participants from women's teams and two from men's teams. We then applied contextual integrity to this subset for analysis.

3.2 Analysis

To begin analysis, we re-familiarized ourselves with the transcripts by reading the entirety of each conversation while taking notes with any questions or discussion points. Following this discussion, we created a codebook based on the contextual integrity framework [37, 38], including its core parameters: *context, information subject, sender, receiver, information type, transmission principle, and purpose.*

Following Kumar et al.'s approach to applying contextual integrity to qualitative data in HCI research [25], we read through each transcript, identifying codes that corresponded to each parameter of contextual integrity. For example, if a participant stated, *"my wearable device shared my heart rate with my coach automatically after practice"*, we coded for the sender (e.g., the wearable device), the receiver (e.g., coach), the type of information (e.g., heart rate), and the transmission principle (e.g., automatically after practice). Using this structure, we systematically coded each instance that represented the sharing of information from continuous wearables. This process enabled us to describe and organize the structure of data flows based on student-athletes' lived experiences with wearable technology.

Using this coding process, we collaboratively coded one transcript between the first two authors. This allowed us to align on how to identify complete information flows and consistently apply each parameter. We divided the next nine transcripts between the first two authors, with each author independently coding four unique transcripts and using the ninth to compare coding techniques. We met and established a consensus across our codes, and affirmed that our coding processes yielded similar results. For the final five transcripts, each author coded three, again using one overlapping transcript for reliability checking. This structure balanced the workload while providing two interim checkpoints where we discussed the similarity of our coding techniques, and established a consensus. To finalize consistency, the research team conducted a brief review of the coded transcripts, resolving any remaining discrepancies before moving into the theme development phase.

To build from the codes, we conducted three separate meetings to develop themes, organizing our analysis around the receiver in each coded instance (e.g., coach, student-athlete, or other). Each of the first two authors prepared to meet by reviewing and organizing codes that were relevant to the conversation. The resulting artifact of our meetings was a description of how information flows to a receiver including a list of information types, senders, transmission principles, and purposes.

3.3 Positionality

Our research team brings a diverse set of experiences and perspectives to this work, which shape how we approach the topic and interpret the data. Among us are scholars with backgrounds in security and privacy, including work focused on vulnerable populations and edge cases where technologies can be used to cause harm. These perspectives emphasize the importance of anticipating risks and designing for protection and accountability. Others on the team work within professional sports contexts, where wearable technologies and performance metrics are integrated into everyday practice to support and enhance training, recovery, and decision-making. Our team also includes former NCAA athletes who bring first-hand experience navigating compliance and institutional structures, as well as a researcher deeply involved in professional cycling, who was present at a race where a rider lost their life, a tragedy that underscores the real-world stakes of data monitoring and decision-making in sports.

Together, these perspectives enrich the lens through which we investigate how data from continuous wearables flows through collegiate athletics and sports. While we view this diversity as a strength, we also acknowledge that our positionalities shape how we understand and represent the data. We invite readers to remain attentive to these influences as they interpret our findings.

4 RESULTS

In this section, we share the findings of our contextual integrity analysis in response to **RQ1**) *When student-athletes at a United States collegiate athletic program use continuous wearables, how does the information flow?* and **RQ2**) *What are ways that student-athletes do not want information to flow?* Specifically, we outline the SUBJECT, INFORMATION TYPE, SENDER, TRANSMISSION PRINCIPLE, RECEIVER, and PURPOSE across seven identified information flows. All information flows described within the results are presented in Figure 3.[3] We format contextual integrity parameters using the SMALL CAPS FONT, with the corresponding values shown in parentheses (e.g., **TP1**). The acronyms are as follows: Information Type (IT), Sender (SE), Transmission Principle (TP), Receiver (RE), and Purpose (PU). These elements map directly to Figure 3. Frequently used terms and metrics that continuous wearables provide are defined in Appendix B.

Because all continuous wearable data in this study originates with student-athletes, we organize the information flows based on the RECEIVER of the information: Section 4.1 describes flows where the coach (**RE1**) is the receiver; Section 4.2 focuses on cases where the student-athlete (**RE2**) receives their own information; and Section 4.3 covers flows where others in the student-athlete's network, such as teammates and family, receive the information (**RE3–RE7**).

Across our interviews, student-athletes discuss a variety of specific information types. Although these are distinct metrics, multiple types of information are often transmitted together as a result of being from the same device. From the lens of information flows, they can therefore be grouped. For this reason, we present three categories of information types:

- **Physiological data (IT1)**: This category encompasses a variety of metrics including stress, strain, sleep quality, resting heart rate, and readiness. These metrics are provided by WHOOP and provide insights about the body's response to various stimuli, both inside and outside of sport contexts.
- **Workout-specific data (IT2)**: This category includes metrics such as heart rate, workout duration, pace, and splits. These metrics are provided by Garmin and Apple Watch and combine to create a picture of how the body responds within the specific context of sport performance.
- **Shared workout data (IT3)**: Similar to workout-specific data, this category includes heart rate, workout duration, and pacing information, with the key addition of GPS data. These metrics are visualized and shared across the Strava platform.

4.1 Coaches as Receivers

We identify three unique information flows in which the coach (**RE1**) is the receiver of information. The first flow describes student-athletes (**SE1**) as the senders of their own information to coaches. The second flow involves technology providers (**SE2**) acting as the sender. The third flow represents hypothetical information flows, where student-athletes describe how they would or would not feel comfortable having information shared with their coaches.

Student-athletes sharing information with coaches: As described by student-athletes, they share physiological data (**IT1**) with their coaches constrained by two TRANSMISSION PRINCIPLES. The first is a need-to-know basis (**TP1**), where athletes share information if they feel it might be important to their performance. For instance, P7 reports that if the color-coded recovery scores reflect concern, *"Then maybe I'll go talk to [coach] about that."* P3 describes similarly that they will communicate with their coach: *"Yeah, I'm feeling red today."* In the need-to-know method of transmission, the athletes initiate a conversation about the metrics provided, and the metrics become part of the communication.

The second TRANSMISSION PRINCIPLE is coach-requested information sharing (**TP2**). In these cases, coaches prompt the flow of information, with athletes acting as active participants in sharing. P8 describes: *"our fitness coach wanted us to send [them] our resting heart rate."* In this case, the presence of continuous wearables introduces a new information type (i.e., heart rate) to be shared when coaches prompt communication.

The PURPOSE behind information sharing is not always clear to student-athletes. P8 describes this undefined purpose (**PU1**) in a conversation about shared heart rate: *"I don't really know what [they] need it for."* P2 has more clarity, explaining that coaches ask questions about recovery scores *"so that they can kind of help formulate a practice plan."* These perspectives suggest that while some athletes understand the purpose of sharing (e.g., practice planning) (**PU2**), others comply without fully knowing how their information informs coaching decisions.

[3] These findings are also organized in a table format in Appendix C

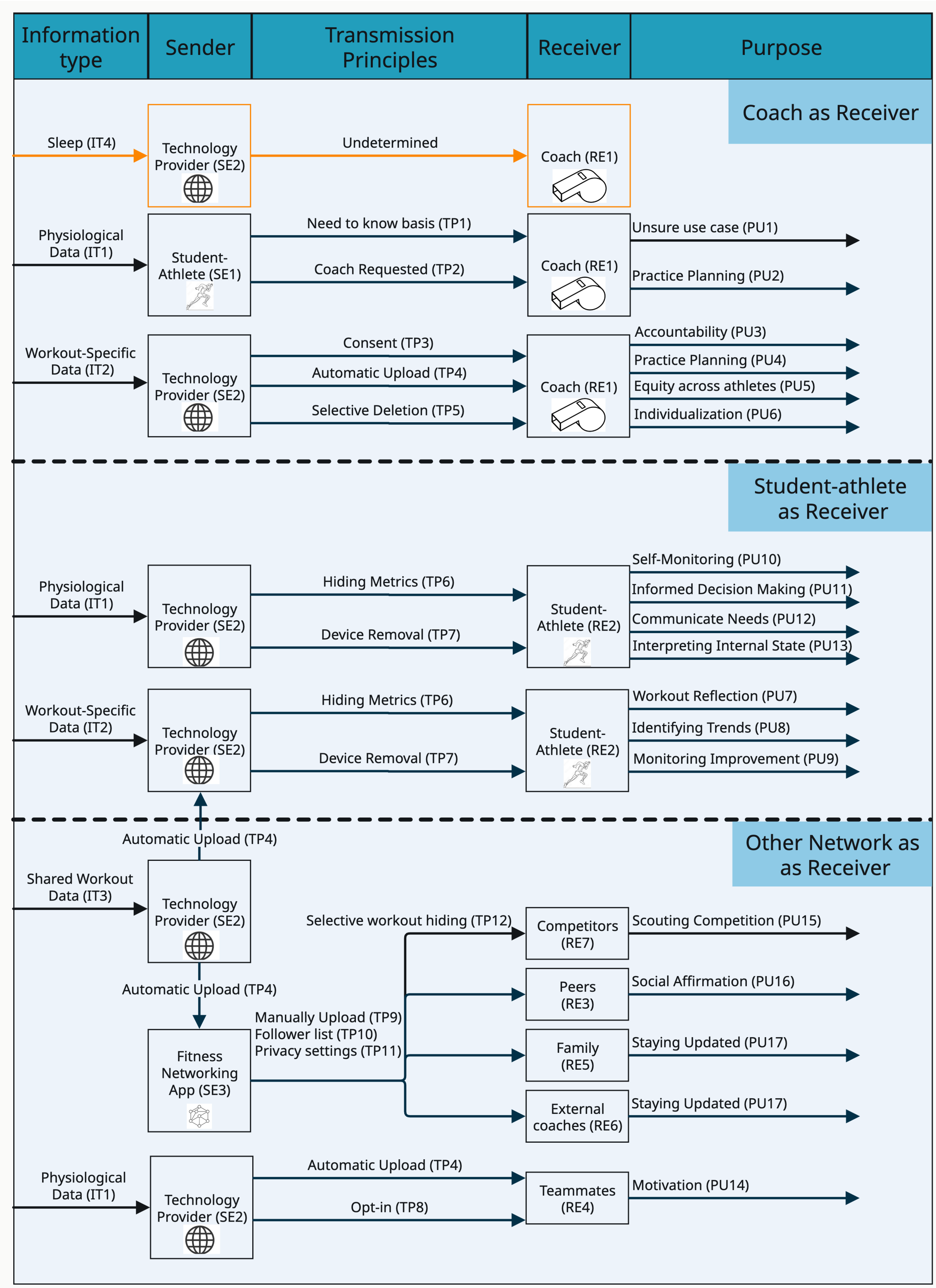

Figure 3: Visualization of how information flows with the subject of each flow being the student-athlete. The information type, sender, transmission principles, receivers, and purpose are outlined from left to right, with values mapping back to the text. From top to bottom, the coach, student-athlete, and broader network are portrayed as the receivers of information. Normative information flows that represent deviations from assumed norms are presented in orange.

Deviations from this information flow that could constitute a privacy breach include: student-athletes not being in control of the sharing; information being shared outside of optional contexts; and the audience expanding beyond the coaching staff.

Automatically shared data: In addition to athlete-mediated flows, student-athletes describe how information is shared with coaches automatically. In these flows, the SENDER is the technology provider (**SE2**), through platforms such as Garmin Clipboard and its Coros equivalent, Training Hub. Unlike the physiological data described in the previous flow, coaches can view workout-specific data (**IT2**) in these applications, serving as a feedback mechanism for accountability (**PU3**) and practice monitoring (**PU4**). As P10 describes: *"they can see pretty much everything that the watch is recording... I think [coaches] can see our sleep scores, but I think you can turn that off."*

Based on our interviews, the TRANSMISSION of workout data is shaped by three constraints. First, athletes must initiate data sharing by providing consent (**TP3**), typically by linking their fitness watch account to the team's coaching platform through the app's settings. Garmin Clipboard, one such platform, is commonly mentioned by participants. When asked whether it was required, P15 responded: *"we do have a couple of people on the team that use a Coros watch, and they have no problems. I'm pretty sure there's some sort of like Coros clipboard equivalent."* This response indicates that sharing workout information is an established behavior within their team environment. Once this connection to the coaching platform is established, data is transmitted automatically upon completion of each workout (**TP4**). Coaches may also receive push notifications when data is uploaded, with P10 noting: *"they get notifications on their phone as soon as we upload."* The third TRANSMISSION PRINCIPLE identified is selective workout hiding (**TP5**), in which a student-athlete actively hides a specific recorded activity to prevent a coach from seeing it. One participant describes: *"So I was doing a couple of [workouts], and we were supposed to not be [working out]. So then I was like, quickly deleting them."* This deletion reflects an effort to override previously consented-to automatic transmission.

In the information flow where workout data is automatically shared with coaches, student-athletes describe a clearer understanding of its PURPOSE. P10 explains the equity (**PU5**) these tools provide: *"there's [a large number] of us, probably at any given time [at the practice facility]. They can understand what was happening, even if they weren't completely focused on us in that moment."* Participants also describe instances where automatic sharing supports more individualized training (**PU6**). One participant shares: *"because I am injury prone, we've had to make a lot of adjustments."* Although training in a different location than teammates, they received an individualized training plan and feedback from their coach based on uploaded activities.

Normative information flows: Across our interviews, student-athletes generally express comfort with current data-sharing practices involving their coaches. However, when asked to consider what types of information, if any, should be considered off-limits to coaching staff, participants offer a range of perspectives. Some raise concerns about automatically sharing recovery and sleep data (**IT4**) through technology providers (**SE2**). P12 explains: *"all the data that was coming out of [WHOOP]. I feel like that would be intrusive... they shouldn't know how much sleep you're getting every single night."* Participants describe how the pressures of balancing academics and athletics complicate their comfort with sharing physiological data. P4 explains: *"If you take a hard major, sometimes you have to stay up 'til 12 or 1 am to do your schoolwork, and you don't really have a choice."* Reflecting on the possibility of this data being visible to coaches, they add: *"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 that I could be doing."*

In contrast, some participants say they would be comfortable sharing this type of data with coaches. P9 remarks: *"it wouldn't be a bad thing for them to be able to see a recovery percentage overnight,"* and P11 shares: *"I can't think of something that'd be off limits."* In this context, comfort with sharing physiological data with coaching staff varies across participants.

4.2 Student-athletes as Receivers

In addition to data being shared with coaching staff, the RECEIVER of information can be student-athletes themselves (**RE2**). Equipment collects information such as heart rate and movement patterns, processes this data through a companion app or cloud service, and returns interpreted insights. While data collection and communication are fundamental to wearing these devices, student-athletes establish TRANSMISSION PRINCIPLES of hiding specific metrics (**TP6**) and selective device removal (**TP7**) to avoid automatic data sharing. For example, P5 shares that they choose to *"not look too much at the calories,"* while P10 notes: *"Sometimes I take off my watch just because I wouldn't want it to like mess with my head."* Across these examples, student-athletes exercise control over the flow of information, with occasional constraints introduced to avoid overthinking.

In this section, we focus on two INFORMATION TYPES that student-athletes receive: workout-specific data (**IT2**), such as pace or distance, and broader physiological data (**IT1**), such as recovery scores or sleep summaries. Each type of data carries different meanings and implications for how athletes understand their bodies and performances, while maintaining similar transmission principles.

Workout specific insights: Participants describe using workout-specific data for the PURPOSE of workout reflection (**PU7**), trend identification (**PU8**), and monitoring improvements (**PU9**). Many insights center around specific workout performances, including breakdowns of pace, heart rate, and other metrics that allow student-athletes to review and compare data across sessions. Several participants describe sharing data with third-party platforms, such as Strava, to view and track their progress over time. For example, P12 shares that they upload their data to Strava to view a mileage *"graph that [they] can see over like the span of 8 weeks."* Similarly, P11 says they use the platform to *"pull up [workouts] from years ago."*

Generally, these insights support the review of information and the identification of anomalies. Access to heart rate alongside pacing offers feedback that extends beyond subjective feel and enables long-term tracking, helping student-athletes recognize what aspects of their training are working and what are not.

Continuous physiological insights: In addition to workout data, student-athletes also engage with physiological insights (**IT1**) provided by their wearables. These include information on sleep, recovery, and strain accumulated throughout the day. Participants describe the PURPOSE of using this data for self-monitoring (**PU10**) and as a way to better understand their bodies and needs over time (**PU11**). P4 explains that the device allows them to *"check in like every single day,"* supporting daily reflection outside of practice. Similarly, P8 shares: *"I really like it for checking my sleep and recovery. That's what really helps."* For some athletes, this feedback informs decisions about rest and readiness. P1 states, *"if I'm in the red after a game, it's like, Oh I should probably like [recover]."* In this case, insights from continuous wearables help the athlete decide and communicate their needs (**PU12**) to the coaching staff, whether that means requesting recovery or continuing with planned training.

Some participants describe how physiological insights serve the PURPOSE of interpreting their internal state (**PU13**). P2 shares that seeing recovery scores can shift their perception, noting that it *"kind of like changes your mentality in a way like maybe I'm not doing as well as I actually feel."* On the other side of the spectrum, one participant describes feeling sick but seeing a recovery score of 98%, which led them to think: *"I kind of feel bad and tired, but like I should be totally fine."* They chose to compete but later learned from a doctor that a concerning illness had been causing the fatigue. In this example, wearable-generated insights shape both perception and action, even when they conflict with an athlete's felt experience.

4.3 Other Information Flows

In addition to coaches and student-athletes themselves, we identify information flows that extend to others within student-athletes' social networks. The RECEIVERS include friends (**RE3**), teammates (**RE4**), family members (**RE5**), former coaches (**RE6**), and, in some discussions, competitors (**RE7**). Two primary platforms (**SE2**) serve as the SENDER of information: WHOOP Teams, which allows for the sharing of continuous physiological data amongst peer groups, and Strava, which enables the distribution of workout data to large communities through mechanisms similar to social networks.

Continuous physiological sharing among social groups: Some participants describe sharing continuous physiological data (**IT1**), including INFORMATION TYPES such as strain, recovery, and sleep metrics. These dashboards allow RECEIVERS such as teammates and roommates (**RE4**) to view each other's interpreted metrics daily or over multiple days, offering a window into their peers' physiological status. To enable this sharing, someone must first create a group within the platform, and others can voluntarily join. As P3 explained: *"we have a team community that we joined voluntarily."* While a cluster of student-athletes describe engaging with this feature, others using the same device make no mention of it, suggesting that while this functionality is available, its use is not ubiquitous.

The TRANSMISSION PRINCIPLE reflects an opt-in model (**TP8**): student-athletes must voluntarily join a group in order for data to be shared. Once opted in, data is automatically and continuously transmitted (**TP4**) to all group members unless access is manually revoked, which means that opting out is the only way to stop transmission. Once shared, engagement with these metrics is driven by the receivers, who have autonomy and agency in how (or whether) they interact with the information.

Within the dashboard-based sharing feature, participants describe the PURPOSE of fostering motivation, camaraderie, and accountability (**PU14**). P2, for example, describes how over the summer: *"we can kind of compete with each other just to hold each other accountable that we're doing workouts."* While the dashboard serves a clear purpose for some, others describe its use as tied to novelty. As P1 shares: *"I feel like I honestly forget to look at it. When it first started, it would be kind of fun."* In these cases, even though the transmission of information continues, conversations suggest that the data is not always actively viewed or engaged with. Within this information flow, a privacy breach could occur if the set of receivers expands beyond the user's expectations.

Community-Based Activity Sharing: Many student-athletes who use watch-based wearables describe sharing their workout data with third-party platforms, such as Strava, that further distribute activity data to a larger social network. This shared workout data (**IT3**) has TRANSMISSION PRINCIPLES that vary depending on platform settings and athlete preferences. Data may be shared automatically (**TP4**) or manually upon activity completion (**TP9**). Once uploaded, visibility is further shaped by in-platform transmission principles, such as who follows the athlete (**TP10**) or how privacy settings are configured (**TP11**). Some transmission constraints are also externally imposed by coaching staff, who may instruct athletes to selectively limit data visibility for strategic reasons (**TP12**). As P10 explained: *"we are not supposed to upload our workouts always to Strava. That's like just their rule."* P11 describes how this data can serve the PURPOSE of scouting competition (**PU15**): *"[viewing competitors' workouts] kind of just gives me an idea of like who I should kind of be next to during a [competition] and kind of put myself in that position."*

Outside of hesitations tied to sharing information with competitors, student-athletes describe sharing data on these platforms for personal reasons. These include PURPOSES such as receiving social affirmation from friends (**PU16**), staying connected with former teammates, and keeping family or previous coaches updated on their training and well-being (**PU17**). One participant shares that posting workouts is *"just like [a] fun to share kind of thing and my old training mates at home, they can see as well."* They added: *"I started using Strava so that my mom and my coach at home could see what I was up to just because I battle injuries over the past year being here."* These examples illustrate how the purpose of sharing can vary even across the same platform depending on the receiver ranging from health monitoring to social connection to competitive strategy. Notably, the same data may serve different functions depending on who accesses it and why.

5 DISCUSSION AND RECOMMENDATIONS

In this paper, we use contextual integrity to map how information collected about student-athletes by continuous wearables flows within the collegiate athletic system. We start by providing a context in which these results are interpreted in section 5.1. We continue with a discussion on how these information flows contribute to an understanding of privacy within this context in Section 5.2. We then discuss the broader dynamics presented by automatic data sharing in Section 5.3 and explore the individual impacts of continuous monitoring in Section 5.4.

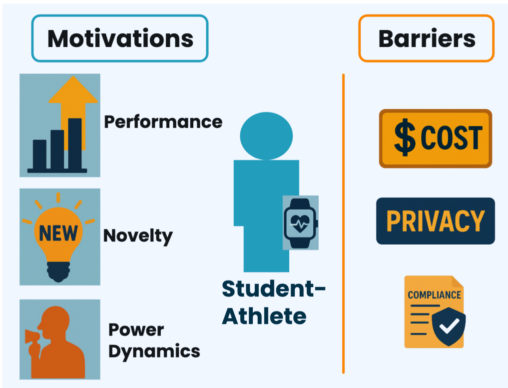

Figure 4: Student-athletes undergo different motivations that underscore the use of continuous wearables. Power dynamics, the novelty of technology, and performance gains motivate usage while cost, privacy, and compliance rules can act as barriers to usage. These factors contribute to shape how information flows within our studied population.

5.1 Context

In the results, we describe different information types, senders, transmission principles, receivers, and purposes that have emerged from our interviews about how information from student-athletes' continuous wearables is shared. Proceeding with the contextual integrity-based analysis, we now examine the context, providing a lens to fully understand how and why these information flows occur. We draw on contextual information directly from the student-athlete interviews, literature on power dynamics in athletics, related work on coaches operating in similar competitive environments, and identify entrenched norms by reviewing compliance rules [34]. These contextual elements are visualized in Figure 4.

From the student-athlete interviews, we find that 9 out of 15 participants received wearable technology directly from the athletic department at no personal cost. Participants who were not provided with wearable technology cited cost as a barrier to access. As P12 explained: *"sometimes, coaches say, 'Oh, you should get this thing that will help you track your performance,' but it's like some of us just can't afford that."* Similarly, P9 shared: *"If it wasn't so expensive, I'd try a WHOOP."*

Student-athletes also discussed the challenge of balancing academic responsibilities with athletic demands. P3 described how their recovery is often affected when they *"have to stay up late to do an assignment."* In these cases, academic work can clash with athletic goals. As P4 explained, they are constantly looking for the *"1% here and there"* that technology can provide. This interplay between athletics and academics can motivate sharing in cases like the need-to-know TRANSMISSION PRINCIPLE, while also driving participants to keep certain metrics, such as sleep, private.

In addition to intrinsic motivation sources, student-athletes often rely on good standing with their team to maintain academic eligibility, athletic participation, and social status. In this position, coaches make decisions on playing time and access to team resources. This authority grants coaches power rooted in their role and in the rewards tied to athletic status [13]. Ideally, this power supports a collaborative coach-athlete relationship built on shared goals, mutual motivation, and open communication [20, 26]. However, this dynamic is not without risks. It has been exploited in cases of sexual, physical, and emotional abuse [15]. More recently, Kolovson et al. show how the growing presence of technology in sports introduces new data types that increase power asymmetries between athletes and coaching staff [24].

In previous research conducted by our research team, we studied the coaching staff of student-athletes [5], finding that coaches are aware of the potential dynamics created by technology. Notably, one coach mentioned with wearables specifically, *"our head coach is very sensitive to the [student-athletes] feeling 'big brothered' because they wear it all the time."* Instead of opting to see data, this staff provides technology solely as self-education tools that help student-athletes recognize how behaviors such as sleep, training, and nutrition influence performance and recovery. This finding illustrates how coaching staff may be attuned to the privacy concerns of student-athletes.

Beyond the interpersonal dynamics between coaching staff and student-athletes, there are codified compliance rules established by the governing body for collegiate athletics [34]. We observe that some codified rules govern aspects of how information flows. A key mechanism is the limitation of practice time through *countable athletically related activity* (CARA) rules. These regulations restrict the duration, among other variables, under which coaches may hold practices, film review sessions, and other team activities. For example, during the athletic season, teams are limited to a maximum of 20 hours per week of countable activity. The governing body has clarified that logging activities, even if voluntary and recorded through a platform like Garmin Clipboard, is considered countable athletically related activity [35]. However, there are currently no clear rules regarding physiological data, such as that collected and potentially shared by WHOOP.

Taken together, our interviews and related literature illustrate that intrinsic motivation, alongside expectations to perform can motivate the use of continuous wearables and the sharing of information. The financial burden can act as a barrier to access, although some teams do provide wearable technology directly. And a combination of decisions from coaching staff, and established rules serve to constrain how information flows.

5.2 Privacy Considerations with Continuous Wearables

By using contextual integrity, we build a map of how information flows and is constrained across a population of elite collegiate athletes. We continue this conversation highlighting tension points where deviations from the established information flows can constitute a privacy breach. We apply this understanding to review design choices and how application capabilities can conflict with established information norms within the context of elite collegiate athletics.

When coaches are the receiver of data, our population describes constraints on what data they can see, and how some information is shared. An established norm is for physiological data to be shared on a need-to-know basis while and explicit concern defined by some student-athletes is automatically sharing sleep with their coaches. While privacy is clearly valued, sharing physiological data is a built-in feature of platforms like Garmin Clipboard. Garmin markets this visibility as a way to reduce uncertainty in coaching, stating: *"coaching a team of athletes has required a bit of guesswork. Are they sleeping well? Are they working hard enough? Are they allowing enough time for recovery between intense workouts? These may be educated guesses, but they're guesses nonetheless — until now"*[4]. In our context, this presents a tension between established information norms and the way products are designed and marketed. Within Garmin Clipboard, athletes are given the option to share recovery metrics, with the default set to off. However, coaching staff cannot opt out of viewing these metrics once shared, representing a lack of agency to set boundaries that some coaching staff may want to implement [5]. Controls for managing what data types are visible should be implemented within coaching applications to allow both athletes and coaches to set privacy preferences.

Recommendation 1: Design technology to ensure that all relevant parties including coaches and athletes are able to manage data visibility and privacy needs.

Outside of coaches being the receiver there are constraints that manage what groups are able to see specific information. Within Strava, this can be constrained through followers and privacy settings, where within WHOOP Teams, users opt-in to sharing data with a group. An aspect within WHOOP Teams allows any member of the group to invite another WHOOP user without group-wide approval. For example, a team captain could invite a coach into the shared group, exposing all members' daily recovery data. Based on our framework, this would constitute a privacy breach, as the user did not opt-in to specifically sharing their data with this group.

With this foundational understanding of what constitutes a privacy breach within elite collegiate athletics, future research can explore how these dynamics vary across cultural contexts, levels of competition, and athlete age groups.

Recommendation 2: Include mechanisms for per-member consent when group composition changes, ensuring that no unintended parties can access information without the information source knowing.

5.3 Automatic Data Sharing

In observing information flows, we identify that a common method of data sharing is automatically after a one time consent. This occurs with coaches receiving information through Garmin Clipboard, sharing of physiological data through WHOOP Teams. This method of sharing provides an easy way to share data, however, it can create a dynamic where opting out becomes difficult. This sharing also represents a new way of sharing that is misaligned with established rules in the environment of college athletics.

[4]https://www.garmin.com/en-US/blog/fitness/garmin-clipboard-a-free-easy-way-for-coaches-to-track-athlete-performance/

Across ambient assisted living systems [32, 42], and continuous location-sharing applications [8], automatic and continuous sharing can a valuable tool but may become problematic as interpersonal dynamics shift over time. This dynamic can present in college athletics where student-athletes may opt into data sharing early in their careers without fully anticipating how those dynamics might evolve. Once enabled, automatic and continuous data sharing can effectively lock athletes into a decision that becomes socially difficult to reverse. Adjusting privacy settings may be interpreted as a signal of distrust or non-compliance, particularly within the hierarchical structure of collegiate athletics. Given the power dynamics at play, student-athletes may hesitate to change privacy permissions out of concern for how it could impact their team standing, playing time, or relationship with coaching staff [24].

We observe this dynamic in select cases involving the transmission principle of selective workout deletion. In these scenarios, a student-athlete is aware that their coach can view workout data and may wish to remove specific entries without drawing attention. However, this behavior is complicated by the fact that coaches often receive notifications upon workout completion, creating a potential mismatch: a coach may be alerted to a completed workout while the student-athlete has already deleted the data.

The appropriateness of data sharing may shift over time as athletes progress through different stages of their careers, recover from injury, or face varying demands, such as preparing for a national championship versus managing stress during exam periods. Consent for data sharing should respect these shifting boundaries and, rather than being indefinite, allow for time-constrained sharing that aligns with athletic program schedules and athlete autonomy. Additionally, critical design used within personal informatics [22] can be used to highlight the extent of data sharing in athlete-coach relationships.

Recommendation 3: Design interfaces and systems that encourage athletes and coaches to actively review and reaffirm what information is shared, such as by re-authorizing data sharing at the start of each season or annually.

The automatic data sharing through continuous wearables also represents a change to the norms for compliance rules. Specifically, countable athletically related activities (CARA) within elite United States collegiate athletics, restrict workout information to 20 hours a week. Interestingly, with platforms such as Garmin Clipboard, the athlete, not the coach, is the one initiating the data flow that becomes countable. This can create compliance risks in that a well-meaning or highly motivated student-athlete, or an adversarial student-athlete, could log voluntary activities outside of regulated practice hours, placing their coach in violation of CARA restrictions. While some platforms allow coaches to block activity logging on specific days, more robust features are needed to capture all parameters relevant to CARA limits. This example illustrates how collegiate athletics policies are insufficient for managing training limits in an era of technologies that enable automatic activity uploading. While this may reflect the need for a policy adjustment, as it stands the current system could put coaches at risk of compliance violations due to student-athlete actions enabled by wearable technologies.

Recommendation 4: Allow compliance controls and roles for team administrators that help widespread adoption of technologies without compliance risks.

5.4 Self Reflective Capabilities

Using the lens of contextual integrity we observe a key information flow where student-athlete are the receiver of interpreted insights from technology providers. While beneficial for self-education and evaluation, insights can significantly influence behaviors and mindsets, an impact the SportHCI community should carefully consider. Many student-athletes shared that these tools contribute positively to their sense of awareness and self-efficacy, which aligns with prior research on the motivational potential of sports technology [40]. However, poor scores may lead to rumination or altered training behavior, even when not physically warranted. One participant, who experienced prolonged illness, described how device-generated interpretations misrepresented their condition and ultimately led them to continue competing while sick, highlighting the risks of over-reliance on metrics. These insights support a SportsHCI grand challenge [11], which emphasizes the need to consider non-athletic performance data. Our findings offer further motivation for this challenge by showing that over-reliance on quantitative metrics can lead to significant, even harmful, consequences.

Some athletes described turning off their devices to avoid the risk of receiving discouraging metrics, even when doing so meant missing out on potentially valuable post-competition insights. This mirrors findings from Karahanoglu et al. [21], who observed that runners sometimes disengage from trackers during workouts when data introduced more doubt than clarity, ultimately disrupting rather than supporting the athletic experience. Instead of removing devices, a "competition mode" customized to the athlete's needs could prove useful, temporarily suppressing the transmission of interpreted feedback during key moments while still collecting data in the background for later review. WHOOP, for instance, lacks an onboard display, which some athletes in our study viewed positively, because it prevents athletes from accessing real-time metrics during training or competition.

Recommendation 5: Include modes that allow athletes to more easily restrict the transmission of data during sensitive periods such as competition, illness, or mental fatigue.

6 LIMITATIONS

In our semi-structured interviews with student-athletes, our questions did not focus specifically on continuous wearables. Mentions of wearables emerged organically within broader discussions of technology use. The depth of these references prompted us to perform this focused analysis. While this approach limited the depth of specific wearable-related discussion, it allowed for unprompted insights free from potential bias introduced by more targeted questioning. A similar process is outlined in Kumar et al.'s work describing how to apply contextual integrity to qualitative data [25].

Additionally, our work is situated within the specific context of elite NCAA Division I collegiate athletics in the United States. While our sample represents a small subset of the population, predominantly from women's sports, the complex dynamics and rapid evolution of this space make elite collegiate athletics a useful case study for the broader sports community adapting to new technologies. While norms may differ across contexts, an overarching lesson is to provide data controls and protections that allow athletes to have effective and protected data usage across levels of competition.

7 CONCLUSION

In this paper, we examine the landscape of continuous wearables within the competitive environment of NCAA Division I athletics. We identify how information collected from student-athletes by continuous wearables flows through different individuals within the collegiate system, highlighting coaches, peers, and student-athletes themselves as recipients of this information. Furthermore, we show that program-specific norms are emerging, shaped by careful consideration of how these new technologies can be meaningfully introduced. In reviewing existing regulatory policies and the broader context in which these technologies are deployed, we observe potential tensions related to continuous data sharing and provide recommendations to guide how technology should be incorporated across different levels of competition.

This work represents a first step toward a broader understanding of the privacy implications of technology in sport. Dozens of technologies are used by various entities across complex athletic systems, each presenting a unique challenge for understanding how information does flow, and how it ought to flow. As the role of technology continues to evolve at all levels of sport, we aim to ensure that privacy remains central to the conversation.

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APPENDIX

A STUDENT-ATHLETES SEMI-STRUCTURED INTERVIEW PROTOCOL

Before starting the interview, student athletes received a physical informed consent for in-person interviews and a link to an online informed consent for online interviews. After reading the document, if the student-athlete provided an audible "yes" in response to being asked if they agreed to participate, we began a semi-structured interview guided by the following 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? Any apps, websites, or anything else that you use?
- (e) Can you share how frequently you interact with that data? (e.g., after practice, after games, weekly, daily, once per semester?)
- (f) What factors influence how frequently you interact with this data?
- (g) Does your interaction with the data vary between the competitive season, training camps, and the offseason?
- (h) How do you use the data to guide your decisions? [e.g., using data to adjust your training or recovery plans]
- (i) What aspects of data usage do you find most beneficial for your performance?
- (j) What are the primary challenges you face when using this data?

(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 data used by the team, how much of it is shared with you as an athlete?
- (c) How is this data shared?
- (d) Have you ever had some data shared with you and it was not helpful to see it? [Prompt: data can sometimes feel stressful or disappointing]
- (e) Has there been a time that seeing data has been helpful? [Prompt: perhaps a time you felt off, but data gave reassurance]
- (f) Do you have means to access and interpret the data yourself?

(Q5): Do you use any information to measure your overall well-being?
- (a) Regarding information used for well-being, what sources do you use?
- (b) How is this data collected?
- (c) Do you share this data with others?
- (d) Any challenges with engaging with the technology?
- (e) What about interpreting the data?
- (f) How frequently do you use data to measure well-being?
- (g) Does anything influence the frequency of how often you use this data?
- (h) What aspects of data usage do you find most beneficial for your well-being?
- (i) Do you think the knowledge of this information has an influence on your performance?

(Q6): Do you think there's a need for athletes to be more involved with data?
- (a) What barriers might prevent effective engagement with the data?

(Q7): How would you like to see data being used in college athletics in the future?
- (a) Are there any types of data that you feel should be off limits from coaches?
- (b) Are there any changes that you would like your coaches to make with how they use data?
- (c) Are there any sources of data that you would not like your coaches to have?
- (d) Does the way you feel about this information change if the only person who has access is a physical trainer or sports psychologist?

(Q8): Is there anything you would like to track in terms of data or know more about, that you currently aren't or don't know?
- (a) Do you think you have the capacity to incorporate new data sources or technological tools into your routine?
- (b) Whether it's existing data or new sources of data, our group's goal is to make it easier for you to do what you want to do with data. What are the main thoughts you'd like me to take back to my team?

(Q9): Before we wrap up, it will be helpful for us to record a few pieces of demographic info about you.
- (a) Specifically, we'd like to collect your age and your race/ethnicity. The athletics department has this on file, is it ok if we use that information?
- (b) If you prefer to tell us now instead, or prefer that we don't record it, that is ok too.

(Q10): Thank you for your time. Is there anything else you would like to add before ending the recording?

B TERMS AND DEFINITIONS

Term	Definition
Stress	The body's natural response to physical or mental challenge.
Strain	Measures cardiovascular and muscular exertion.
Recovery	Measures how prepared the body is to perform on a given day.
Sleep	Total sleep quantity and quality.
Heart Rate Variability	Indicates the variation in time between heartbeats, often used as a marker of recovery.
Resting Heart Rate	The number of heartbeats per minute, used as a marker of recovery.
Pace	The speed at which a workout is performed, typically measured as time per distance unit.
Distance	Total distance traveled throughout a workout.
Pace (Detailed)	A breakdown of paces across a workout, including splits.
GPS	Captures movement data using satellite positioning to track speed and location.
Physiological Data	A combination of stress, strain, and sleep metrics.
Workout-Specific Data	A combination of distance, pace, and duration.

Table 1: Definitions of Fitness and Recovery Metrics

C INFORMATION FLOWS

Information Flow	Explanation	Key Privacy Considerations
Information Flow 1	Coaches receive interpreted physiological insights from student-athletes. Within this flow, practice planning is a described purpose.	Data being shared automatically instead of from the student-athlete.
Information Flow 2	Coaches receive workout-specific data automatically from technology providers. Within this flow, data is used for accountability, practice planning, individualization, and equity.	Information type being changed to include physiological data.
Information Flow 3	This normative information flow describes student-athletes concerns with sleep as a metric being shared automatically with coaches.	Allowing this information flow unconstrained would constitute a privacy breach.
Information Flow 4	Student-athletes receive interpreted physiological data from technology. In this flow information is used for self-monitoring, informed decision making, communicating needs, and interpreting internal state.	The receiver of this data should stay as the student-athlete and tightly constrained by their needs within this flow.
Information Flow 5	Student-athletes receive workout-specific information from technology providers. In this flow information is used for workout reflection, identifying trends, and monitoring improvement.	The receiver of this data should stay as the student-athlete and tightly constrained by their needs within this flow.
Information Flow 6	Fitness networking applications share workout data with social groups. This information is used by competitors for scouting competition, peers for social affirmation, and family, and former coaches for staying updated.	Ensuring that data permissions are properly configured and maintained. Additional privacy considerations need to be in place for potential derived metrics.
Information Flow 7	Technology providers share physiological data among consenting social groups. This is used for the purpose of motivation and accountability.	Ensuring that consent is maintained as a principle, and that the receivers are properly constrained is key to this information flow.

Table 2: Definitions of Fitness and Recovery Metrics