Sex-Specific Head Impact Exposure in Rugby: Measurement Considerations and Relationships to Clinical Outcomes

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Abstract

Concussions are diffuse injuries that affect areas of the brain responsible for a person's physical, cognitive, and emotional health. Although concussions were once thought only to present transient symptoms, mounting evidence suggests potential for long-term neurological impairments. The deleterious effects of concussion can be from a single, high severity impact event or the accumulation of lower severity impacts. Clinical changes that can result from concussion include an elevated symptom presentation and changes in gait, or an individual's walking pattern. It is not well understood if similar deficits result after an accumulation of subconcussive impacts. The majority of research on human tolerance to head injury has been based on American football, using helmet-mounted sensors in male athletes. Limited studies have attempted to quantify biomechanical tolerance in women, despite the sex-specific nature of presentation and outcome of concussion. Biomechanical, physiologic, and psychosocial factors differ between males and females, likely contributing to this difference.

The research presented in this dissertation was aimed at describing sex-specific outcomes of subconcussion in a matched cohort of male and female athletes to gain a better sense of unhelmeted, sex-specific tolerance to head impacts. On-field data were collected from collegiate rugby players using instrumented mouthguards. Rugby involves high energy, frequent head impacts, does not require protective headgear, and is played the same for both men and women. The females in our study sustained fewer impacts per session than the males, but their impacts had similar linear acceleration magnitudes. The kinematics of the concussive male impacts were higher than the kinematics of the concussive female impacts. Both sexes reported concussion-like symptoms in the absence of diagnosed concussion during a season. Females reported more symptoms with a higher severity in-season compared to males after subconcussive and concussive impacts. Female athletes saw deficits in cadence, double support time, gait speed, and stride length post-concussion. The majority of athletes improved in their dual-task gait assessment by the end of the season, suggesting there may not be a negative effect on gait after an accumulation of subconcussive impacts. This work assessed the biomechanics of head impacts and concussions of this population, and evaluated changes in symptom presentation through weekly graded symptom surveys and dual-task gait assessments both after a concussion and as an effect of subconcussive impacts. Understanding the sex-specific clinical effects of head impacts is critical, and can provide insight into concussion diagnostic, management, and prevention tools that are appropriate and effective.

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General Audience Abstract

Concussions are injuries that affect many areas of the brain, including those responsible for a person's physical and emotional health. Although concussions were once thought only to result in short-lived symptoms, new evidence suggests potential for long-term impairments as well. The harmful effects of concussion can be from a single, high intensity impact event or the build-up of lower intensity impacts. Changes that can result from concussion include an elevated symptom presence and changes in gait, or an individual's walking pattern. It is not well understood if similar side effects result after an accumulation of subconcussive impacts, those that are not severe enough to be diagnosed as injuries. The majority of research on human response to head injury has been based on American football, using helmet-mounted sensors in male athletes. Limited studies have attempted to quantify concussion tolerance in women, despite the differences in men and women's symptoms and recovery time after a concussion. Female's neck strength, hormones, and increased honesty in reporting concussion differ from males, likely contributing to this difference.

The research presented in this dissertation was aimed at describing how sex affects the outcome of subconcussion in a group of male and female athletes to gain a better sense of unhelmeted, sex-specific tolerance to head impacts. On-field data were collected from collegiate rugby players using sensor-embedded mouthguards. Rugby involves high energy, frequent head impacts, does not require protective headgear, and is played the same by both men and women. The females in our study sustained fewer impacts per session than the males, but their impacts were similar in magnitude. The males sustained concussions at higher impact energies than the females did. Both sexes reported concussion-like symptoms in the absence of diagnosed concussion during a season. Females reported more symptoms with a higher severity compared to males in general and after a concussion. Female athletes walked more conservatively post-concussion compared to their initial assessment. The majority of athletes improved their gait by the end of the season, suggesting there may not be a negative effect on gait after a season of subconcussive impacts. This work assessed the biomechanics of head impacts and concussions of this population, and evaluated changes in symptom presentation through weekly symptom surveys and gait assessments both after a concussion and as an effect of subconcussive impacts. Understanding the sex-specific effects of head impacts is critical, and can provide insight into concussion diagnostic, management, and prevention tools that are appropriate and effective.

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CHAPTER 1: INTRODUCTION

CONCUSSIONS AND CLINICAL EFFECTS

Concussions are diffuse injuries,[1] affecting areas of the brain responsible for a person's physical, cognitive, and emotional health. They are a type of mild traumatic brain injury that result from biomechanical forces imparted directly to the head or to elsewhere in the body transmitting an inertial load to the head.[2] Although concussions were once thought only to present transient symptoms, mounting evidence has shown the potential for long-term neurological impairments. In fact, a history of repetitive head impact exposure might also result in long-term neurodegenerative complications.[3] This exposure may be only subconcussive impacts, or those below the diagnostic threshold of injury. The clinical effects of concussion have been well studied, but short-and long-term effects of cumulative head impact exposure have been less explored until recently. Later-life neurodegenerative processes including depression,[4,5] cognitive impairment,[5,6] and structural and functional brain alterations[7,8] have been associated with a history of repetitive head impact exposure in former athletes.[9,10] Repetitive head impact exposure, in the absence of a diagnosed concussion, has also been linked to short-term acute cognitive changes.[11-16] This cumulative subconcussive load has also been shown to reduce future concussion tolerance in collegiate football players.[17-20] The deleterious effects of concussion can be from a single, high severity impact event or the accumulation of lower severity impacts.

Concussion diagnostics use a multipronged approach, usually including sideline evaluation, symptom assessment, neurologic evaluation, neuropsychological testing, and a consideration of clinical concussion history.[21] Often, athlete's self-reported symptoms are the basis of diagnosis and return-to-play timeline, but athletes' tendency to hide or underreport symptoms to decrease return-to-play time complicates reliance on symptom scores.[22] Studies have indicated that 30-50% of concussions go unreported.[22,23] This is a concern because athletes who do not immediately report concussion symptoms and continue to participate in activities may be at higher risk for longer recoveries and sustain post-concussion symptoms longer.[24] A more regular monitoring system may help identify unreported concussions in-season and provide management strategies resulting in earlier interventions in a more effective timeline.

In addition to somatic symptoms, decreased postural control and altered gait patterns have been seen in concussed athletes.[25-28] Concussed individuals tend to have a more conservative pattern in gait,[29] and gait assessment tools can be implemented on the sideline and help clinicians differentiate between concussed and non-concussed athletes. Assessing gait is advantageous because it is a non-novel task and can be objectively measured with portable inertial measurement units.[26,27,30-33] It also provides a more holistic perspective on recovery; some studies have seen athletes take months to years for a full recovery in gait performance, especially when the participant's attention is divided.[26,31,32,34] More traditional markers of recovery, like symptom surveys or neurocognitive test performance, typically recover on a shorter timeline.[35,36] Dividing the athlete's attention comes in the form of a concurrent cognitive task during a walking trial is called a dual-task gait evaluation. Because concussions affect both motor and cognitive domains, the divided attention required in dual-tasks may be more sensitive to post-concussion impairments than single-tasks, or walking without a cognitive load.[37] The additional load while walking allows for more subtle motor impairments to become apparent because as the processing demands for the task increase, the available attention decreases, leaving less for the athlete to consciously maintain a normal walking pattern.[38,39]

Concussive injuries are inertially driven from an external force causing brain movement within the skull. During an impact, the brain's motion lags as the skull is rapidly accelerated and decelerated, creating pressures and strains in the brain tissue.[40,41] The linear kinematics of the brain upon impact induce a transient intracranial pressure gradient, while rotational kinematics are associated with the brain's strain response upon loading.[40,42-46] However, measuring the brain's inertial response to impact is not an easy task.

WEARABLE HEAD IMPACT SENSORS

An effective way to study human tolerance to head injury is to instrument contact sport athletes, a population who are regularly exposed to head impacts, with wearable sensors to quantify the magnitude and frequency of kinematics sustained.[47,48] This non-invasive method of measuring skull acceleration and velocity allows researchers to correlate the brain response to impact. The basis of on-field data collection comes from mounted accelerometer arrays in the helmets of male football players.[17,49-52] These helmet-mounted sensors helped researchers understand the head impact tolerance of elite male athletes, and build concussion risk functions to predict injury.[47] The two main limitations with helmet-based sensors are the movement of the helmet relative to the skull-which can result in erroneous recordings or artificially inflate acceleration events, and the specific populations that could be studied. As concern for the accurate assessment of the impact biomechanics of concussion extended beyond football, sensors that could be worn independent of helmets started being developed. These systems include sensors embedded into headbands, skin-mounted patches, earpieces, and mouthguards. The accuracy and usability of these devices varies, and headbands and skin patches are both still susceptible to movement independent of the skull. Instrumented mouthguards provide near-perfect coupling of the sensor to the skull, as they are rigidly mounted to the teeth. Any device implemented on-field should have a high sensitivity, or proportion of head impacts correctly identified, and a high positive predictive value (PPV), or probability that there is an acceleration event when the device records one. These sensors should be validated in-lab, where testing configurations are representative of the specific on-field use, as well as on-field, where they are subjected to sports specific human wear.

SEX-SPECIFIC DIFFERNCES IN CONCUSSION

Concussions can affect males, females, adults, and children alike and there are population-based differences in tolerance to head impact, which can vary by sex and age. Differences in tolerance between youth and adult football players have been previously established.[47,53-55] Data collected from female collegiate hockey players suggested that the magnitude of a concussive head impact is substantially lower for females compared to males.[56] Females sustain more concussions than their male counterparts in every matched sport.[57-62] Despite this prevalence, females have been underrepresented in concussion research. Limited studies have quantified biomechanical tolerance in women.[56,63-66] Currently, female injury tolerance in limited to inertial scaling equations in the automotive industry.[67,68]

The presentation and outcome of concussion is sex-specific,[57,59,69-72] which is attributed to a combination of biomechanical, physiologic, and psychosocial factors that differ between males and females. Biomechanically, females' neck musculature is weaker than males, making it more difficult to decelerate their head under loading, and increasing their risk of concussion.[55,61,73,74] Physiologically, the presence of the hormones estrogen and progesterone in females may contribute to the sex-specific differences by acting as neuro-protectants in brain injury.[71,75,76] Additionally, there are structural differences in axons between sexes that make females' axons more susceptible to injury under dynamic stretch loading, and the pathophysiology of the injury worse when injury occurs.[77] Psychosocially, studies have shown females are more honest in reporting concussions because they are more concerned about their future health, compared to males who are less likely to report because cultural tendencies encourage males to play though injuries.[59,61,78,79] Females generally report more symptoms post-concussion[80] and take a longer time to fully recover[81] than males.

This lack of female biomechanics data is partially due to the overwhelming research on American football, and the ability to instrument helmets with sensors capable of measuring head acceleration. It was not until recently that similar technology translated was into smaller sensors that can be worn independent of helmets, enabling unhelmeted athletes to also be studied, widening the population to finally include women involved in contact and collision sports.

EPIDEMIOLOGY OF HEAD INJURIES IN RUGBY

Rugby is a globally popular full-contact team sport, played similarly to American football. The main differences are that offensive and defensive teams are on the field at the same time, the ball cannot be thrown forward, and it is illegal to block a player who does not have possession of the ball. Players predominately use their arms and shoulders to tackle an opponent, with a tackle higher than the shoulder a penalty. These collisions are forceful, generally with the ball carrier running in the opposite direction as the tackler. The physicality and competitiveness of the sport lends to rapid acceleration-deceleration and rotational forces leading to a high risk of a collision-associated injury[82] and concussion rate.[83] The only protective equipment worn by rugby players are mouthguards, which do not reduce the risk of concussion.[84] Some players choose to wear soft-shelled headgear, but their effectiveness in concussion risk reduction is highly debated.[85-92] Reduced performance with attention and memory tasks in collegiate rugby players have been seen post-season, with only 3% of those subjects reporting a clinically diagnosed concussion in-season.[93] The acute effects of a simulated match load of rugby impacts suggested transient change in cortical function following subconcussive impacts.[94] This suggests a potential neurocognitive vulnerability in contact-sport athletes, who are regularly subjected to impacts below a diagnostic threshold for concussion.

World Rugby and Rugby Football Union have recently come under fire from former rugby players with early onset dementia.[95] It has been estimated that up to 22% of rugby injuries are concussions,[96] corresponding to about 13–17% of rugby players sustaining a concussion during a season. These numbers vary by the play style and player position.[97] Rugby was a game traditionally played by men, but it has grown in popularity among women in recent years.[96] Both men's and women's teams play at various levels of competition, under the same rules.[84] This presents the opportunity to study a matched cohort of unhelmeted male and female athletes and the head kinematics they sustain on-field during practice and competition.

RESEARCH OBJECTIVES

The presented research is multi-faceted, and includes the collection and analysis of biomechanical and clinical data. The overall aim is to describe sex-specific outcomes of subconcussion in a matched cohort of male and female athletes and gain a better sense of unhelmeted, sex-specific tolerance to head impacts. Understanding the sex-specific clinical effects of head impacts in rugby is critical, and can provide insight into concussion diagnostic, management, and prevention tools that are appropriate and effective. On-field data were collected from collegiate rugby players using instrumented mouthguards. This work sought to assess the biomechanics of head impacts and concussions of this population, and evaluate changes in symptom presentation and gait both after a concussion and as an effect of subconcussive impacts.

The overall objectives of this research are:

1. To assess the usability and accuracy of wearable sensors to provide on-field head kinematic data
2. To quantify the head kinematics experienced by collegiate rugby players and compare the kinematics between sexes

3. To quantify the sex-specific clinical effect of cumulative head impact exposure for symptom presentation and dual-task gait
4. To pair concussive biomechanics to clinical outcomes to quantify the clinical effect of concussion

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CHAPTER 2: ON THE USE OF WEARABLE SENSORS TO MEASURE HEAD IMPACTS IN SPORTS

ABSTRACT

Head impact sensors allow researchers to learn more about human tolerance to concussive and repetitive head impacts. These wearable devices have been implemented in helmets, headbands, skin patches, mouthguards, and ear pieces in attempt to couple the device to the head to measure on-field kinematics of athletes to correlate skull biomechanics to brain injury. The objective of this paper is to discuss head impact sensors that are used on-field and explore their practicality and limitations. We present our experience using two instrumented mouthguards, the Wake Forest Instrumented Retainer and the Prevent Biometrics Intelligent Instrumented Mouthguard, to measure head impacts in athletes. We discuss data quality, athlete compliance, general usability, and provide recommendations for future head impact sensor use.

Keywords: Biomechanics, Wearable Devices, Linear Acceleration, Rotational Acceleration

INTRODUCTION

With the prevalence of sports-related concussions and the consequences of long-term sequelae, head-impact sensors are tools that can be used to supplement clinical findings for at risk-athletes, allowing us to understand the effects of high magnitude or repetitive impacts. The concern of concussion biomechanics led researchers to implement sensors in helmets of athletes who were subjected to repetitive head impacts in their sports. The high head exposure rates in hockey and football were capitalized on, as sensors could be mounted in their helmets to study the head kinematics associated with concussion. As concussion awareness increased, more sensor devices have been developed for use independent of a helmet, so that more populations of athletes in different loading conditions can be studied. The devices being implemented for this research need to be accurate, with a high sensitivity, or proportion of head impacts correctly identified as well as a high positive predictive value (PPV), or probability that there is a head impact when the device records one. The objective of this paper is to discuss head impact sensors that are used on-field, their practicality and limitations, and our experience using two mouthguards to measure head impacts in athletes.

Current Head Impact Sensor Landscape

The first widely used sensor system was the Head Impact Telemetry (HIT) System implemented in football helmets.[1-3] With a proof of device usability and data collection, the sensor market expanded in the 2010s with companies developing devices that could be used similarly in the field. Complications with many of these devices exposed challenges associated with them, and as a result, the current sensor market is much smaller than it was at its peak. The systems implemented by researchers include sensors embedded into helmets, headbands, skin-mounted patches, earpieces, and mouthguards. Usability of these devices varies and some sensors are limited in the sports in which they can be implemented with athlete compliance. Challenges accompany on-field data collection, including uncertain accuracy due to imperfect coupling of the device to the skull. Movement of the sensors relative to the skull results in erroneous recordings of or artificially inflated acceleration events that can mischaracterize head impacts. Each sensor type has advantages and disadvantages (Table 2.1).

Table 2.1. Head impact sensor types and their advantages and disadvantages.

Sensor Type	Advantages	Disadvantages
Helmet-Mounted	Easily mounted between padding present in helmets	Subjected to helmet motion relative to the skull
Headband or Skullcap	Can be used in unhelmeted sports	Subjected to headband/skullcap motion relative to the skull
Skin Patch	Can be used in unhelmeted sports	Subjected to dermal motion relative to the skull, perspiration may affect adhesion, athlete anthropometry could affect placement of sensor
Mouthguard	Can be used in unhelmeted sports, offers rigid coupling to skull	May have low athlete compliance in sports where mouthguards are not already required, subjected to athlete handling
Earpiece	Little room to move around	Low athlete compliance

Head Impact Sensor Validation

Validation of head impact sensors is necessary as it provides quantitative data of device performance, measuring kinematic accuracy in a controlled environment such as the lab, as well as measuring count accuracy in less controlled impact scenarios experiences on field. Both components of validation should be taken into consideration when testing these devices. For example, the XPatch by X2 Biosystems was tested in-lab in three different conditions (helmeted, padded bare head and rigid bare head), and reported kinematic values that had low standard error when compared to the reference sensor.[4] However, when this device was implemented in the field, it only positively identified 19% of total real impacts.[5] Not only did the device overpredict the number of head impacts sustained, it also over predicted the magnitude of acceleration, with 9% of the visually confirmed head impacts having over a 90% concussion risk, as estimated by a previously published injury risk curve,[6] despite no concussions identified during the season.[5] This study is evidence that sensor data should not be accepted as reported, without video validation, because exposure numbers would be inaccurate. Other aspects of sensors that need to be validated are frequency response, sampling rate, and filtering. These characteristics are important when measuring different impact durations. The xPatch's sampling rate is likely too low for short duration events, potentially causing the systematic underprediction, which is compounded by aggressive filtering algorithms.[4] It has also been suggested that many wearable devices do not have sufficient sampling rate and bandwidth to capture high frequency, shorter duration events.[7,8] This further reinforces the need for in-lab testing to be representative of on-field use. Additionally, device coupling should be tested in-lab as well as on-field. Players exhibit more dermal artifact, mandibular motion, and handling of the device than test dummies in the lab do.

Laboratory Impacts

Testing head impact sensors in lab is critical to ensure the devices are accurately measuring kinematic events. An impactor in lab imparts a force that induces linear and rotational motion to an anthropomorphic test device (ATD) head that is instrumented with a reference sensor package and is outfitted with the head impact sensor being tested. This lab-fit can affect different sensors in different ways. In order to fit an instrumented mouthguard, a modification must be made to the ATD, like the development of a dentition. In this case, the lack of mandible movement and tight fit should increase coupling in-lab. ATDs have less biofidelic skin without hair, which increases friction that allows for better coupling of headbands and skin patches. However, ATDs couple to a helmet-mounted device more similarly to coupling on-field. Thus, in some cases, lab testing presents an ideal scenario, but not in all cases. On-field, soft-tissue motion around the site of device fixation can substantially influence the frequency response of the head to impact and the sampling frequency necessary to correctly capture those impacts.[8]

The impactor used should have masses and be tested at velocities that are representative of those that will be experienced on-field. The kinematics from the reference sensor can be quantitatively compared to the kinematics recorded by the sensor. An important consideration in lab testing includes the impactor face, for which material stiffness and geometry should be representative of impacts experienced by athletes who will be instrumented with the device. Softer, flatter impactor faces can be representative of helmet-to-helmet impacts and some head-to-body impacts whereas stiffer impactor faces are more similar to head-to-ground and some head-to-body impacts. Unhelmeted events are shorter in duration and require higher bandwidth, which many sensors do not have.[9] Recommendations have been made for minimum sampling rates so that shorter duration events can be accurately captured,[4,7] especially with filtering algorithms unique to devices. Achieving lab impacts that are similar in duration and frequency content to those seen on-field is necessary for functional assessment of the device. The velocity and location at which the ATD is impacted should be informed by the specific conditions of the sport in which the device will be worn. Although it is not possible to test every possible on-field impact scenario in-lab, it is important to test a range of representative impacts.

On-Field Video Analysis

The sensors may perform differently in-lab than on-field with exposure to more acceleration scenarios on-field. Not every acceleration event recorded on-field with be associated with an impact event, as less ideal coupling and the athletes handling the device will amplify noise in the dataset. Because of potential variability when implementing sensors on-field, video validation is crucial to confirm that the events measured are indeed head impacts or events associated with head accelerations. The importance of pairing video data with sensor data in exposure analyses has been emphasized in studies where discrepancies between sensor and video data existed.[5,10-15]

Comparing video to sensor data provides useful information such as confirming true positives (TP)–sensor measured and video confirmed, false positives (FP)–sensor measured but no video confirmation, and false negatives (FN)–sensor did not measure but video confirmation of an impact. Quantifying these gives insight into device sensitivity and precision (also known as positive predictive value (PPV)). Sensitivity is the proportion of impacts actually captured and is calculated by TP / (TP + FN). Precision is the proportion of sensor events recorded that are real and is calculated by TP / (TP + FP). These metrics are used because these classifications of impacts can be reasonable quantified with sensor and video data. It is difficult to quantify false negatives, because of the need to identify an impact that meets the threshold trigger acceleration. True negatives are impossible to identify because there is no impact seen on video nor captured by the sensors. The lack of confidence in this value is a reason we do not calculate specificity of the sensors.

The acceleration threshold trigger varies by sensor, and likely should be optimized for the sport that is instrumented. The trigger should be high enough to remove accelerations associated with dynamic kinematic events,[16] but not too high to eliminate sport-specific kinematic events of interest. Higher triggers likely would reduce the noise in the dataset, and increase a performance metric like sensitivity, because the device is recording fewer low magnitude impacts.

Without video, there should be a lack of confidence in the data reported, which could greatly affect exposure numbers. The sensor could be missing impact data and underpredicting exposure,[12] or it could be recording false positive data and overpredicting.[5] Including false positives in a dataset will likely affect the summary kinematics' magnitudes, and inaccurately characterize the sport being researched. Not only would this affect exposure numbers, but also estimates of concussion risk. On-field testing should be application specific, as different sports have different impact conditions, time domains, and frequency content. Unhelmeted sports usually have impacts that are a higher frequency content and shorter duration, which would differ from a helmeted sport where the padding increases the duration of the impact and decreases the frequency content.[4] It is necessary that the settings of the sensor are appropriate for the conditions relevant to the sport.

Some devices have algorithms that filter recorded events and discard events that do not share pulse characteristics similar to those of lab head impacts. Video analysis is used to time-synchronize sensor data in order to confirm measurements on-field. Video should be taken from a midpoint of the field, preferably with a higher elevation, focusing on the instrumented athlete(s), and keeping them in field of the camera at all times. In contact team sports, the opportunity exists for impacts to be obstructed from a single camera's view, which is why multiple camera angles from elevated heights are helpful to identify impacts. However, when impacted players are underneath other players, the situation surrounding their impact could still be unknown. It is also important that video reviewers are trained so that impacts can be identified accurately and consistently. If multiple people are reviewing video, it is important to assess inter-rater reliability.[10]

HEAD IMPACT SENSOR USER EXPERIENCES

We have implemented and evaluated two instrumented mouthguards, Prevent Biometrics and Wake Forest University (Figure 2.1**Error! Reference source not found.**), for on-field use by collecting and validating head kinematic data from non-helmeted rugby players, assessing impact counts, discussing usability, and providing recommendations for future data collection. The athletes in this IRB-approved study were Virginia Tech men's and women's club rugby players and provided written, informed consent. They were custom fit with a mouthguard from either Wake Forest University or Prevent Biometrics, with a similar process of taking 3-diminsional images and reconstructing a dentition for mouthguard molding. It was recommended for both companies that athletes who wear braces not be fit for these mouthguards. We compensated our athletes for participating in the study which may have positively affected compliance.

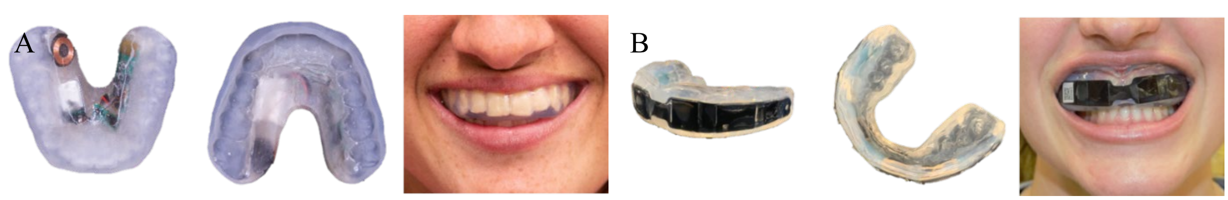

Figure 2.1. (A) Wake Forest University Mouthguard with instrumentation along the upper palate and (B) Prevent Biometrics mouthguard with instrumentation along the teeth.

Many wearable head impact sensors perform inconsistently, depending on impact conditions, and can be inaccurate in peak kinematics, impact count, and impact location.[5,10-15] An instrumented mouthguard has the potential for nearly perfect coupling to the skull by being custom-fit to the upper dentition, addressing some limitation of previous devices. However, when players put their mouthguards in, or take them out of their mouth, or handle them when they are not actively playing, acceleration events may be triggered. This reinforces the need for thorough video validation when using any type of head impact sensor. Without video verification, it is impossible to quantify head impact exposure accurately, even with good coupling. Time-syncing video to impact data allows for the classification and quantification of true positive and false positive events. When calculating PPV, establishing temporal bounds of play can greatly affect the outcome. For our study we included any accelerations that occurred during the time of play in the dataset. Water breaks, half times, and minutes of play that the athlete was not actively participating in a drill or game were included in this time segment. Subjects handling the devices during breaks from play likely resulted in many false-positive events. If these "inactive minutes" were removed from analysis, the PPV values would likely be higher for each device, although this value was not quantified. Overall, Prevent Biometrics' device had a PPV of 6.20% and Wake Forest's device had a PPV of 14.39%.

Despite the video validation, the dataset still includes several suspiciously high accelerations measured for verified impacts. We removed three acceleration events from the original dataset based on the inconsistency in reported magnitude of kinematics and the video-observed impact. We had seven concussions which resulted in no data. In four of these cases (1 Wake Forest, 3 Prevent), the athlete's device seemed to be functioning and recording data leading up to the concussive impact. It is difficult to quantify events seen on film that are false negatives because it is impossible to visually identify if an impact observed yielded an acceleration over 10 g for most impacts. However, missing data from these concussions raises awareness for other potential false negatives that might have been missed. There were at least 17 sessions for which a Prevent mouthguard did not function and 4 sessions of the Wake mouthguard not functioning.

Acceleration and velocity traces were verified for each impact, confirming that the peak of the event was captured, the mouthguard recorded an actual impact, not just triggered on mouthguard motion, and the collection did not include a secondary event or impact that could be more representative of the impact observed on-field. Verifying the shape of the event trace was also important to measuring impact duration, ensuring there was a clear start and end of the peak.

Wake Forest University Instrumented Retainer

Athlete Compliance

Rugby requires the use of a mouthguard, so the athletes were accustomed to playing while wearing one, and even liked the instrumented one due to the custom-fit. However, there was some pushback on the size of the device and its feel. Wake Forest houses their instrumentation along the hard palate of the mouth in a hard, acrylic retainer and they added a polymer guard to protect the athletes' teeth. Lack of comfort was the primary reason for athlete non-compliance, as the device reached too high on their lingual surface, making them gag and trapping their saliva, making it difficult to spit. Wake Forest shaved down the extra material on the lingual surface as much as possible, which helped many athletes. However, we still had athletes who could not wear them due to their lack of comfort. Often the coupling to the athlete's teeth was so good, that they could not remove the mouthguard on their first try. The devices loosened with wear and the subjects could remove them more comfortably. Wake Forest has since attempted to set the instrumentation closer to the teeth, requiring less material on the hard palate.

Data Quality

We had one player sustain a concussion after she was kicked in the head after diving to the ground. The kinematics reported by her mouthguard were 14.2 g and 5.7 rad/s, which deserves scrutiny. Likely the athlete's body impacting the ground and the athlete's head being kicked were two different acceleration events. The kinematic values attributed to this concussion are likely the result of the ground impact. The kick occurred about 167 ms after the ground impact, which is in the 300 ms window that the Wake Forest mouthguard was preparing for the next impact. Awareness of turnover time between impacts is necessary to accurately verify on-field kinematic data. Body-then-head acceleration events within the turnover window are likely common. This complicates video verification, because it is challenging to visually identify if a body impact prior to a head impact is high enough in magnitude to trigger data acquisition and if events occur within device turnover time. Wake does not use any data filtering methods to reduce the number of false positives in their dataset.

General Usability

The device developed by Wake Forest is newer and intended for use as a research tool. Their charging boxes inconsistently functioned, the wireless charging coils were not always well aligned, and there was no indication that the device was fully charged. Many issues involved Bluetooth connectivity, either before or after the game. This limited our ability to set the devices for acquisition and download data. Each device needed to be set up individually in a proprietary application to acquire data before a session. This was generally challenging with 30 devices, all competing with Bluetooth, on the sideline of a rugby field. They recently added a time delay feature, allowing the researcher to set the devices up in the lab, delaying acquisition until the researcher traveled to the field and the session began. The researcher could choose how many impacts should be recorded in the session, which in theory is an advantage, but with exploratory research that number is difficult to know, especially because any time the athletes registers a false positive event, that is counted in the impact number. This generally resulted in the maximum event collection (300 impacts) which sometimes was exceeded. As with the acquisition process, the downloading process is done individually for each mouthguard. You can download data from up to two devices at once on one smart tablet, but downloading 300 impacts took about 34 minutes. We used more than one tablet, but the process still was very time consuming for an entire team of athletes. Wake Forest's devices also had intermittent gyroscope failure, and some of the internal clocks did not sync, both resulting in data that was erroneous and unusable. The battery life on the Wake devices was shorter and there were issues with the charging cases not working, causing several mouthguards to die mid-session. As the seasons progressed, both companies made durability and usability improvements.

Prevent Biometrics

Athlete Compliance

The majority of the athletes did not complain about the comfort of the Prevent device, although the size of the device was larger than they were accustomed to. Prevent houses their instrumentation on the outside of the teeth, which made it difficult for the subject to close their mouth fully around the device. The material was fairly compliant and flexible.

Data Quality

Prevent uses two methods to reduce the collection of false positives: sensors on the device to detect if the athlete has the mouthguard on their teeth and a proprietary algorithm to identify head impacts characteristics. This algorithm is optimized for helmeted athletes and not intended to work for non-helmeted athletes. We turned off the algorithmic filtering so that actual events were not removed from the data (false negatives). In pilot testing with Prevent's device, we missed a head-to-head concussion because their filtering algorithm was based on helmeted impacts, which differ from unhelmeted impacts in frequency content and duration. Their algorithm discarded this concussion and other head-to-head impacts as their high frequency and short duration were unlike typical helmeted impacts. The sensors that determine if the device is on the teeth were still used but were imperfect, and commonly fooled when the athlete put the device in or took it out of their mouth.

General Usability

As Prevent Biometrics intends for their device to be used commercially, their app interface, website, equipment, and data download process were user friendly. Their cases delivered charge and UV light sanitation while the mouthguards were put away. Some issues we encountered were: Bluetooth interference, which usually could be addressed by taking a mouthguard away from competing devices, overwritten data, which was addressed by using a mobile hotspot during games so locally stored data could be uploaded to the cloud, and the material Prevent was using was so flexible that components of the instrumentation would disconnect, rendering the device non-functioning. Sometimes you could manually manipulate the mouthguards so that the instrumentation could reconnect again, but in the following season, Prevent chose a stiffer material for the mouthguards, eliminating this problem. If there were recurring issues with Bluetooth connectivity or inability of the device to charge, Prevent sent a replacement device.

RECOMMENDED BEST PRACTICES

Although head impact devices are important to the development of our understanding to impact tolerance, challenges of using them can be overcome with best practice guidelines, with the goal of maximizing data quality and minimizing data loss. An overview process is shown in Figure 2.2.

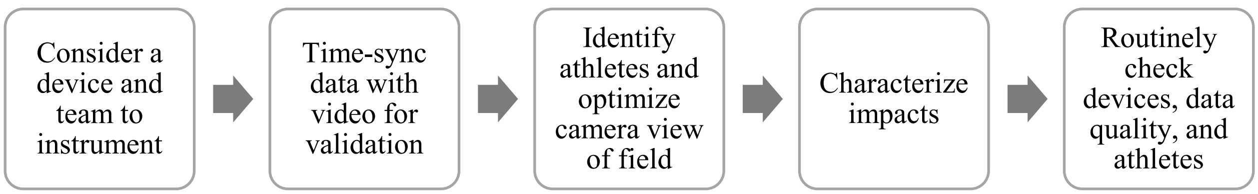

Figure 2.2. Outline of best practices for on-field sensor data collection.

Pre-Collection

- *Validation Information*– The best device to choose is one that has been validated in-lab and on-field in impact conditions similar to those of interest.
- *Participant Compliance*– Keeping player compliance in mind, consider equipment the athletes already wear and if a sensor is already integrated into their equipment. For example, athletes who are already accustomed to wearing mouthguards will likely be more compliant in wearing an instrumented mouthguard than those whose sport does not require a mouthguard. The size of the team should be considered, as some systems are easier to implement on a larger scale than others. Building a relationship with the athletes helps foster trust between the research staff and team and aides in player compliance.

Data Collection

- *Device Quality*– Routinely ensuring all devices are working reduces missed sessions and impacts.
- *Session Log*– Taking attendance at each session increases the accuracy of exposure calculations. Noting times of drills and breaks in play help identify time periods with high false positive rates. This is used as the first filter to identify true positive acceleration events.

- *Video Verification–*
  - *Athlete Identification–* Knowing the athletes and being able to identify them while they are playing is very helpful, especially if they do not wear identifying jerseys in practice, or if the sport involves plays that involve several of the players at once.
  - *Camera View–* The camera should be positioned at midfield, preferably at a higher elevation to maximize field of view. Filming should be sports-specific. For example, a larger field of view is required in sports like football where it is more likely for multiple athletes across the field to experience contact; whereas in soccer, contact, as well as the camera view, is centered around the ball, with only a few athletes who could potentially engage in contact.
  - *Time-Syncing Video with Data–* It can also give context to false positive impacts, if the athletes are handling their devices in between plays or while they are on the sideline during a game. When the data are time-synced, you can identify each impact recorded by the sensor, and find it in the video, and characterize it as a true positive or false positive. In this method, you can also compare the observed impact severity and the recorded magnitude. This is an opportunity to note discrepancies between the two, possibly identifying a secondary peak in the data trace or secondary impact outside of the data collection window. These cases should be handled on an individual basis, potentially excluding them from kinematic analyses but included in impact counts summaries. Regularly checking the quality of data with video helps ensure data is correctly collected.
- *Categorizing Impacts–* Video validation also gives context to the impacts measured. Providing information like what the athlete impacted, where, and what they were doing sheds light on head impact mechanisms in the sport.

Post-Collection

- *Data Quality–* Checking the acceleration traces provides more insight into each impact, and is another layer of data quality assurance. The general shape of the trace, frequency content, and impact duration should be similar to what is expected for the given impact condition. If there are traces that are not similar to what is expected and they will add error or bias in the dataset, exclusion from the final dataset can be considered.
- *Summarizing Data–* When summarizing data, it would be best to summarize data first per-player, and then for the team. This minimizes sampling bias so players with many impacts do not outweigh

the players with only a few impacts. It limits the opportunity for athletes with increased exposure to acceleration events to bias the computed metrics.

CURRENT HEAD IMPACT SENSOR SPACE

Helmet-Mounted Sensors

Helmet mounted sensors present the first significant movement in the head impact space, allowing for a widespread data collection of helmeted athletes. The limitation with these devices is relative helmet motion to the head, although some systems have countermeasures to help accuracy.

Riddell Head Impact Telemetry System

The Head Impact Telemetry System (HITS) integrates a telemetry-based measurement and analysis system with a computational algorithm to provide a wireless sensor system with real-time continuous monitoring of head acceleration data from players on the field.[1-3] The HITS device used 6 single-axis accelerometers that fit into a Riddell Helmet. Researchers have implemented a 6 degree of freedom (6DOF) system with the standard HITS device, which uses 12 single-axis accelerometers that positioned normally to the skull, to monitor football players.[1,17-23] This system has also allowed for continuous head impact monitoring of athletes in hockey,[24-31] boxing,[32,33] soccer[34], and snow sports.[35] It has been used in lab to measure the magnitude of soccer headers.[36] HITS triggers on a 14.4 g acceleration on a single axis, and records 8 ms of pre-impact and 32 ms of post-impact linear acceleration data at a sampling rate of 1000 Hz.

HITS has been validated in lab with pendulum impact testing, resulting in mean errors for linear acceleration of 4% and rotational acceleration of 17%,[37] showing good agreement between measured accelerations of anthropomorphic test device (ATD) headform and HIT System.[38] HITS has also been tested with linear impactors and found to overestimate linear acceleration[39] by 1% and underestimate rotational acceleration by 6%.[40] In one study, HITS identified 19% of impacts as perturbations and removed the data, but otherwise correlated with the ATD headform data.[24] Another study compared the size of helmet on the performance of HITS, and found root-mean-square (RMS) errors of up to 18% and 66% for linear acceleration and rotational acceleration for large helmets, although the high errors were associated with impacts to the facemask.[41] Impacting the shell of the helmet resulted in lower RMSE values.[41] The HIT System is associated with single impact random measurement error of 15.7% for linear acceleration and 31.7% for rotational acceleration.[42,43] However, when data are aggregated, the effect of these random measurement errors are reduced.[42,43]

Authors have noted the sensor's interaction with helmet pads and movement in the helmet, potentially affect the results of validation studies.[39] The helmet is more susceptible to motion than the head, potentially affecting the kinematics measured by an in-helmet system. However, the spring -based system in HITS keeps the accelerometers in contact with the skull during head motion. This system is rather robust, easy to instrument on a large scale, and straightforward to collect and download data. It has been widely used for the collection of football head impact data that has been used to develop a concussion risk function for adult male athletes[6,44,45] and youth athletes,[46] improve helmet design,[47-49] and implement rule changes in Pop Warner[43] and the National Football League to keep the game safer.

InSite Impact Monitoring System

The Riddell InSite Impact Monitoring System is a flexible pressure-based insert that can be fit into a football helmet and used primarily used as a coaches' tool to measure impact count and severity. The system using a proprietary algorithm to classify hits as "high," "medium," or "low" and signals "high impacts" with the intention of medically evaluating the particular athlete. It has been implemented in youth football.[50] The lack of quantitative output data limit's the device's use in research.

GForceTracker

The GForceTracker is comprised of a triaxial accelerometer and gyroscope that allows for the continuous collection of head impact data in real-time.[51] This sensor samples linear acceleration at 3000 Hz and angular velocity at 800 Hz, with the angular velocity signal passing through a low-pass filter with a cut-off frequency of 100 Hz.[51] The GForceTracker has been used to study exposure in men's lacrosse,[52-55] soccer.[56] and football.[57,58] It has been used in-lab to measure head impact kinematics in hockey[59] and football.[60]

Accuracy of the GForceTracker was measured with a linear impactor, initially demonstrating differences up to 150%.[59] However, after applying a regression that took impact direction into account, mean absolute errors were all lower than 15%. The authors recommended helmet-brand specific correction algorithms be developed to transform the raw data to the center of gravity (CG) of the head.[59] With a correction algorithm applied, validation tests showed a strong correlation between sensor data and ATD linear acceleration (R^2=0.97) and rotational velocity (R^2=0.94). Without device specific correction algorithms, the data are quite prone to error, in addition to the error of relative head-helmet motion in helmet-based systems.

Shockbox Helmet Sensor

The i1 Biometrics Shockbox Helmet Sensor uses four binary switches to measure differential voltage instead of a traditional accelerometry system.[61] It has been used to measure head impact exposure in youth football players.[62,63] In-lab validation studies show an aggregate difference of 9% between Shockbox and the reference headform data.[64] Also tested with an impact hammer in lab, peak linear accelerations were shown to have RMS errors of 92-298%.[39] With RMS errors as large as they are in a controlled setting like the lab, it is necessary to be skeptical of data collected on-field, as there are many confounding factors that affect sensor performance *in vivo*.

Headband or Skull Cap Based Sensors

Headband and skull cap-based sensors attempt to fit head impact sensors closer to the head and can be worn independently of helmets. However, these devices still do not provide perfect coupling to the skull, and are limited in consistent measurements.

Checklight

The Checklight is a sensor device that fits into the back of a skull cap and categorizes impact data into “mild,” “intermediate,” and “severe” impacts, and indicates magnitude by a green, yellow, or red light, respectively.[65] This device was implemented in a youth football setting.[66] In validation testing, a football helmet was placed on an ATD, over the instrumented skull cap and triggered the red light at an impact magnitude of 123 g delivered by an impact hammer.[39] Sensor location was tracked by fiducial grids and high-speed video, and showed the skullcap had RMS errors of 16% for peak anterior-posterior linear acceleration and 13% for both peak inferior-superior linear acceleration and peak angular velocity in the sagittal plane.[9]

This sensor is not very useful for head impact studies because there is no way to extract raw data, it does not allow for real-time sideline monitoring, and the threshold limits are unknown. A group that used this also noted management issues including inability to visualize the LED lights in direct sunlight or under the lights at night.[66] Additionally, a skull cap worn under a helmet potentially undergoes some amount of movement relative to the skull.

SIM-G

Triax Technologies developed the SIM-G Head Impact Sensor which houses a triaxial gyroscope and two triaxial accelerometers, high-g, and low-g, mounted on a headband.[67] Exposure has been quantified in soccer,[68,69] football,[70,71] flag football,[71,72] and lacrosse.[73] This sensor has also been implemented into water polo caps to quantify head impact exposure in men’s and women’s collegiate club water polo.[11] However, this group noted the inaccuracies of kinematic measures of the SIM-G during validation testing.[12] The proprietary SIM-G algorithm for classifying true and false positives only classified 55% of impacts correctly, and identified the correct impact location in 68% of those impacts.[12] The developers validated their device with a pendulum impactor, but measured poor correlation of peak linear acceleration (R^2=0.84) and peak angular acceleration (R^2=0.78) to the reference sensor.[67] When tested with an impact hammer, the SIM-G compared to the headform data with RMS errors of 18-75% over the impact locations tested.[39] This device has also demonstrated higher variance in laboratory testing, underpredicting linear acceleration, rotational velocity, and rotational acceleration in helmeted tests.[4]

The ability to house the SIM-G in a headband allows for the collection of data in unhelmeted sports, but external devices on the head can shift around and the presence of hair motion can potentially confound the kinematics measures, especially in the absence of video review.

Skin Patches

Skin patch-based sensors are not limited to head-gear, and can be applied directly on the skin, allowing for more opportunities of on-field data collection. However, this type of skin-adhered patch is susceptible to dermal artifact, as the skin moves relatively to the skull, potentially contributing to sensor inaccuracy.[74]

X2 X-Patch

The X2 X-Patch is a small skin-patch based sensor worn over the mastoid process and comprised of a triaxial accelerometer and gyroscope. The linear acceleration data are sampled at 1000 Hz and rotational velocity data are sampled at 800 HZ, and transformed to the CG with rigid body dynamics.[75] This sensor has been used to collect head impact data for athletes in soccer,[5,13,76] football,[77,78] lacrosse,[79] ice hockey,[74] Australian football,[80-83] taekwondo,[84] and rugby.[85-87] Several of these studies have used video validation to confirm impacts, and noted its importance with sensors such as X-Patch, which lack consistent reliability studies.[13] Another group noted only a 19% true positive rate when comparing impact data to video validated data.[5] Validation included impacting a Hybrid III head and neck with three different sports balls and showed poor agreement between ATD and sensor peak linear acceleration (PLA) and peak rotational acceleration (PRA), especially as stiffness of the ball increased.[8] Other groups have attempted to validate the X-Patch in lab, with little success.[4,9,39] Authors suspected the content of the impact signal was above the sensor's Nyquist frequency.[8]

Research have noted instances of device malfunction, including premature loss of battery and time stamp corruption leading to data loss.[74] X-Patch's proprietary algorithm removes errant data from the dataset, and if these impacts are not identified appropriately, there could be a misleading false positive rate.[74] Additionally, there is no report of the potential influence of between-subject anatomic variability on X-Patch's impact location algorithm.[74]

Mouthguards

Instrumented mouthguards allow for ideal skull-coupling and opportunity for rigid-body dynamics. Athletes not accustomed to intra-oral devices may be less compliant if the mouthguard lacks comfort, but the accuracy of these wearable sensors presents a great opportunity for data collection in many populations of athletes.

X2 Impact Mouthguard

Similar to the X-Patch, the X2 Impact mouthguard houses a triaxial accelerometer and gyroscope and samples linear acceleration at 1000 Hz and angular velocity at 800 Hz. A collegiate football team was instrumented with this device.[88,89] This mouthguard has been used in an amateur rugby union team, with the authors noting saliva ruining some of the components preventing impact data from being downloaded.[14] Although this device has an impedance-based saliva sensor to determine if the mouthguard is in the mouth,[90] the authors noted that about 65-85% of the impacts recorded per match could be verified in video review.[14] This device was validated in lab, and showed normalized RMS errors around 10% for peak linear acceleration, angular acceleration, and angular velocity.[90] When they fit well, mouthguards offer a potential solution to better coupling to the jaw, hopefully reducing the relative motion between the brain and sensor. When testing mandible interaction in lab, researchers recommend mouthguard design to minimize noise by isolating sensors from mandible loads.[91]

Prevent Biometrics Impact Monitoring Mouthguard

Prevent Biometrics acquired X2, and began to market their own ‘intelligent mouthguard,’ which had been developed at the Cleveland Clinic.[92-94] The impact monitoring mouthguard (IMM) has two sensing packages: the first with 12 channels of linear acceleration and the second with three channels of linear acceleration and three channels of angular velocity.[95] The device samples data at 3200 Hz and off-loads data wirelessly in real time via Bluetooth low energy to the iOS Prevent app and stores 460 impacts locally.[95] A cutoff frequency of 400 Hz is used to filter the data. A transformation formula based on a medium NOCSAE headform is used to transform data to the head CG. The mouthguard requires 25 ms in-between impacts. It has been used to monitor head impacts in football players[95,96] and boxers.[96] In laboratory testing, the device was shown to compare well to the reference sensor in bare head (PLA: $R^2 = 0.95$, PAA: $R^2 = 0.94$, and PRV: $R^2 = 0.92$) and padded (PLA: $R^2 = 0.97$, PAA: $R^2 = 0.90$, and PRV: $R^2 = 0.93$) impact conditions.[95]

Stanford University Instrumented Mouthguard

Stanford University developed an instrumented mouthguard with a triaxial high-range accelerometer, gyroscope, an infrared proximity sensor to determine if the mouthguard is on the teeth, and a support vector machine classifier that was trained on frequency domain features of linear acceleration and rotational velocity.[97] In their lab validation tests with high speed video, their mouthguard had RMS errors of 16%, 18%, and 12% for peak anterior-posterior linear acceleration, peak inferior-superior linear acceleration, and peak angular velocity in the sagittal plane, and showed close skull coupling when the jaw was clenched.[9] Implemented in football players, this group acknowledged the need for video validation, as the device only detected 71.2% of the video identified head impact events.[10]

Wake Forest University Instrumented Retainer

Wake Forest University has also developed a mouthpiece sensor that contains an accelerometer and gyroscope that are embedded in a rigid retainer form, to couple with the upper dentition.[15,98] Wake Forest's device sampled the accelerometers at 4684 Hz and the gyroscope at 1565 Hz. They used CFC 2000 to filter the acceleration data and CFC 270 to filter the angular rate data. Subject-specific transformations were applied to the Wake Forest device data to the head CG. Their device requires 300 ms in-between impacts to prepare for acquisition. This device has been used in youth female soccer players with a sensitivity of 69.2% and a PPV of 80.3%.[15,99] Pendulum validation studies slowed strong correlation between linear acceleration (R^2 = 0.95), angular velocity (R^2 = 1.00), and angular acceleration (R^2 = 0.97) of the instrumented headform.[15]

i1 Biometrics Vector Mouthguard

This mouthguard is equipped with a tri-axial accelerometer and a tri-axial gyroscope to measure linear acceleration, rotational acceleration, impact location, and impact frequency. The instrumentation sits external to the mouth, attached to the front of the mouthguard. No peer-reviewed publications quantify the performance of the Vector mouthguard. Little work has been published with this device, only studying the head impact exposure in American football players from Japanese Universities,[100,101] a pilot studying comparing mitochondrial DNA levels to head impact exposure in football players,[102] and the effect of level of contact in football players.[103]

Other

Endevco Ear Plugs

Small ear plugs contain a ± 500 g's Endevco 7269 tri-axial accelerometer that collect data at 2000 Hz.[104] These ear plugs have been validated[105] and used to measure head accelerations during soccer heading.[104] The participants wore pre-wrap around the head to keep the sensors in place. Authors note that the coupling and reliability of recordings improved in lab tests.[106]

DISCUSSION

There is great potential to use head impact sensors to collect on-field data and learn more about head impact kinematics and concussion biomechanics. However, there are pros and cons to each type, and considerations need to be made to choose the device most suitable for the population of interest. Additionally, steps and precautions are needed to ensure quality data collection. Best practices are presented as recommendations for use with in-mouth sensors based on our experience implementing them on-field.

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CHAPTER 3: A TWO-PHASED APPROACH TO QUANTIFYING HEAD IMPACT SENSOR ACCURACY: IN-LABORATORY AND ON-FIELD ASSESSMENTS

ABSTRACT

Measuring head impacts in sports can further our understanding of brain injury biomechanics and, hopefully, advance concussion diagnostics and prevention. Although there are many head impact sensors available, skepticism on their utility exists over concerns related to measurement error. Previous studies report mixed reliability in head impact sensor measurements, but there is no uniform approach to assessing accuracy, making comparisons between sensors and studies difficult. The objective of this paper is to introduce a two-phased approach to evaluating head impact sensor accuracy. The first phase consists of in-lab impact testing on a dummy headform at varying impact severities under loading conditions representative of each sensor's intended use. We quantify in-lab accuracy by calculating the concordance correlation coefficient (CCC) between a sensor's kinematic measurements and headform reference measurements. For sensors that performed reasonably well in the lab (CCC $\geq$ 0.80), we completed a second phase of evaluation on-field. Through video validation of impacts measured by sensors on athletes, we classified each sensor measurement as either true-positive and false-positive impact events and computed positive predictive value (PPV) to summarize real-world accuracy. Eight sensors were tested in phase one, but only four sensors were assessed in phase two. Sensor accuracy varied greatly. CCC from phase one ranged from 0.13-0.97, with an average value of 0.72. Overall, the four devices that were implemented on-field had PPV that ranged from 16.3-91.2%, with an average value of 60.8%. Performance in-lab was not always indicative of the device's performance on-field. The methods proposed in this paper aim to establish a comprehensive approach to the evaluation of sensors so that users can better interpret data collected from athletes.

Keywords: Concussion, Biomechanics, Accelerometer, Wearable Devices, Helmet, Linear Acceleration, Rotational Acceleration

INTRODUCTION

Measuring head impacts in sports can further our understanding of brain injury biomechanics and, hopefully, advance concussion diagnostics and prevention. To date, researchers have extensively deployed sensor systems in large cohorts of athletes to quantify head impact exposure and concussive biomechanics.[1-7] While we now know more than ever about subconcussive and concussive impacts, we still have much to learn before we can single out concussive impacts from non-concussive impacts, which can seem like needles within a haystack.[2] Several sensor systems have been used in athletes, and all have been criticized for being unable to measure kinematics for individual head impacts accurately.[6,8-11] The ability of head impact sensors to measure kinematics is extremely valuable to the understanding human tolerance to head impacts. The Head Impact Telemetry System (HITS), for example, is the most widely used sensor, and has been implemented for over fifteen years in football players.[12] This research has allowed us to learn about head impact exposure and concussion biomechanics,[13-17] leading to rule changes[18] and improved helmet design that reduce the concussion risk in football.[19,20] However, knowledge gaps remain and extend to sports beyond football. To improve concussion diagnostics and prevention, head impact sensor accuracy needs to be better understood in the context of real-world use, and likely, the accuracy itself needs to be improved.

Previous studies report mixed reliability in head impact sensor measurements. Most studies have been limited to individual sensor models,[21-27] although some have used multiple sensor models.[10,28,29] Often, the developers of the sensor systems test and validate their own technology, each with their own impact method and test matrix.[22,23,30,31] Currently, there is no cohesive methodology for comparing the performance of different head impact sensors. HITS, for example, has had multiple validation studies conducted on it, all under varying impact conditions.[24,30,32,33] Each study reported different levels of accuracy, but computed error differently, further complicating the interpretation of the findings. The entire field would benefit if the impact conditions, data treatment, and error estimates were universal, improving the interpretability of performance results and helping comparisons across types of devices. However, the performance assessment of the devices cannot be limited to in-lab assessments alone, as in-lab accuracy is not always indicative of accuracy on the field. For instance, the X2 Biosystems xPatch was also tested under varying conditions in laboratories,[24,28,32,34,35] with most results suggesting high levels of accuracy. However, when implemented in athletes, the magnitudes and frequencies measured were obviously flawed[9] due to coupling issues related to skin motion[10] that dummy headforms cannot replicate. Although the many validation studies aid in the understanding of sensor functionality, there have not been equal efforts to evaluate head impact sensor accuracy consistently.

Quantifying the accuracy of head impact sensors is challenging for several reasons. Primarily, these devices mount differently and can be implemented into helmets, skin patches, headbands, skull caps, and mouthguards. Some require a helmet while using the device. Sensor performance can be influenced by various factors, such as placement, coupling to the skull, hardware, software, and filtering algorithms. Furthermore, some sensors might work well under idealized lab conditions but perform poorly under real-world conditions. The objective of this work was to propose and demonstrate a standardized approach to evaluating head impact sensor accuracy.

METHODS

A two-phased approach to assessing head impact sensor overall accuracy is proposed and demonstrated. First, in-lab testing under nearly ideal conditions is done to evaluate head kinematic magnitude measures and serve as a system check. Second, on-field evaluation of head impact counts is conducted from video analysis of athletes wearing a sensor. If a sensor does not perform well in the first phase, there is no need to test it in the second phase. However, if a sensor does perform well in the first phase, the second phase is required to ensure that differences between in-lab and real-world conditions do not notably affect performance.

Head Impact Sensors Evaluated

A total of eight wearable sensors were considered for this study. Sensor specifications varied across devices (Table 3.1). A few of the sensors could be mounted directly onto a helmet. The Cue Sport Sensor (Athlete Intelligence, Kirkland, WA) is a sensor that can be attached to a helmet or headband (Figure 3.1A). The CUE sensor is composed of a tri-axial accelerometer and a low power inertial measurement unit (IMU), which houses a separate tri-axial accelerometer and a tri-axial gyroscope. The GForceTracker (GForceTracker Inc, Ontario, Canada) is a helmet-mounted sensor that consists of a tri-axial linear accelerometer and a gyroscope (Figure 3.1B). Accelerometer and gyroscope are both filtered using an anti-aliasing filter. Shockbox Helmet Sensor (Athlete Intelligence, Kirkland, WA) is another helmet-mounted sensor that consists of four binary force switches, which measure linear acceleration based on voltage activation in the range of 80-100 kHz after a head impact occurs (Figure 3.1E).

Another group of sensors was integrated with mouthguards. The Vector MouthGuard (Athlete Intelligence, Kirkland, WA) is a boil-and-bite mouthguard that houses a tri-axial accelerometer and a tri-axial gyroscope (Figure 3.1G). The Prevent Impact Monitor Mouthguard (IMM) (Prevent Biometrics, Edina, MN) is another mouthguard-based sensor that comes in a boil-and-bite (Figure 3.1C) and a custom-fit version (Figure 3.1D), both of which were tested. For the custom-fit version, a technician takes a dental scan, which is used to build a 3D dental mold that the mouthguard fits. Both Prevent IMMs house a tri-axial linear accelerometer and a gyroscope. Prevent uses an algorithm to filter out measurements suspected to be associated with non-impact events. This algorithm remained on during on-field testing.

The remaining sensors were integrated with a headband or mounted directly onto the skin. The SIM-G (Triax Technologies, Norwalk, CT) is a sensor that is fitted inside a headband (Figure 3.1F). The SIM-G consists of a tri-axial linear accelerometer and tri-axial gyroscope. The xPatch (X2 Biosystems, Seattle, WA) is a skin-mounted sensor that consists of three linear accelerometers and three angular rate sensors (Figure 3.1H). The xPatch sensor is built with a filter to determine if an acceleration event is a real or false impact.

These eight sensors were selected because their outputs included linear and/or rotational kinematic measures that could be compared directly with reference sensor measurements. Other commercially available head impact sensors are integrated with indicators that notify the user if a head acceleration event exceeded a built-in threshold. Although that subset of wearable sensors was excluded from this study, details on their technical specifications and performance have been documented elsewhere.[36,37]

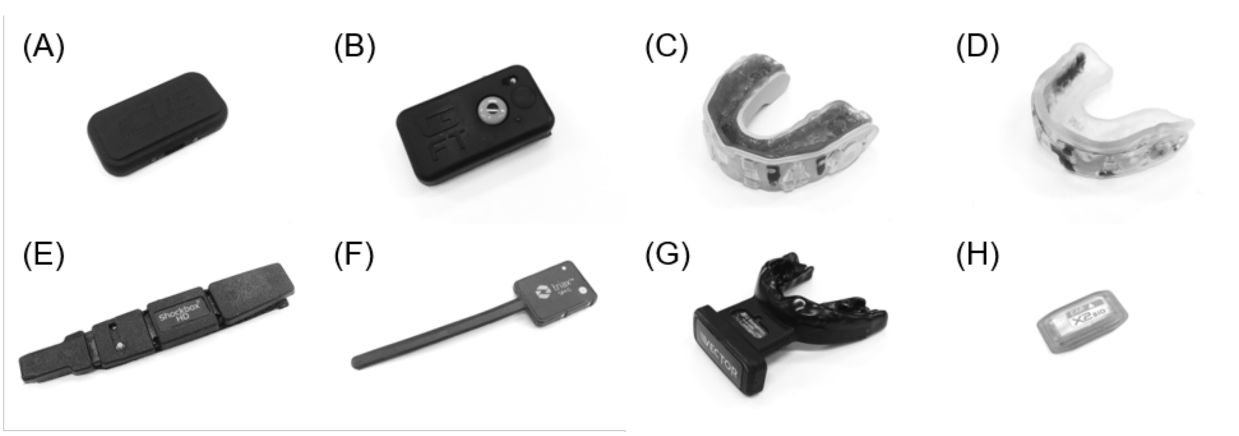

Figure 3.1. The eight sensors evaluated in the current study included the (A) Cue Sport Sensor, (B) GForceTracker, (C) Prevent boil-and-bite mouthguard, (D) Prevent custom mouthguard, (E) Shockbox, (F) SIM-G, (G) Vector MouthGuard, and (H) xPatch.

Table 3.1. Summary of key features for each sensor. CFC: channel frequency class

Sensor	Sampling Rate	Signal Filter	Trigger Mechanism	Pre-trigger, Post-trigger Duration	Export Feature
Cue	1,600 Hz	Unknown	Linear acceleration threshold	Unknown	Peak kinematic measures; full time traces (by request)
GForceTracker	3,000 Hz (gyro: 760 Hz)	300 Hz (gyro: 100 Hz)	Linear acceleration threshold	8 ms, 32 ms	Peak kinematic measures
Prevent Boil-and-Bite	3,200 Hz	CFC 240	Linear acceleration threshold	10 ms, 40 ms	Peak kinematic measures; full time traces
Prevent Custom	3,200 Hz	CFC 240	Linear acceleration threshold	10 ms, 40 ms	Peak kinematic measures; full time traces
Shockbox	N/A	N/A	Voltage differential	N/A	Peak kinematic measures
SIM-G	1,000 Hz	780 Hz (gyro: 250 Hz)	Linear acceleration threshold	10 ms, 52 ms	Peak kinematic measures
Vector	1,024 Hz (gyro: 758 Hz)	CFC 180 (gyro: CFC 40)	Linear acceleration threshold	16 ms, 80 ms	Peak kinematic measures; full time traces (by request)
xPatch	1,000 Hz (gyro: 850 Hz)	Unknown	Linear acceleration threshold	10 ms, 90 ms	Peak kinematic measures; full time traces

In-Laboratory Testing

The objective of in-lab testing is to evaluate the accuracy of wearable head impact sensor kinematic magnitude measures. Before significant time and resources are devoted to on-field evaluation, the kinematic accuracy of wearable sensors should be assessed in a highly-controlled environment. In-lab testing can quantify measurement error through comparison to reference measurements in dummy headforms that are considered truth. On-field testing cannot quantify error in this manner because we do not have similar reference measurements in humans.

In-lab testing was conducted using a pendulum impactor to simulate helmeted and non-helmeted impacts to the head. A medium National Operating Committee on Standards for Athletic Equipment (NOCSAE) headform was attached to a Hybrid III 50th percentile male neck using a custom adapter and then mounted on a linear slide table with 5 degrees of freedom.[38,39] Reference kinematics were measured at the headform center of gravity (CG) with an instrumentation package consisting of three linear accelerometers (Endevco 7264b-2000; Meggitt Orange County, Irvine, CA) and a tri-axial angular rate sensor (DTS ARS3 Pro 18k; Diversified Technical Systems, Seal Beach, CA).

Tests were performed with a rigid impactor to a helmeted head, a padded impactor to a bare head, and a rigid impactor to a bare head to capture the range of impact magnitudes and durations seen in various sports.[40,41] A varsity football helmet was used for helmeted impacts (Riddell, Elyra, OH). For non-helmeted impacts, the padded impactor was vinyl-nitrile foam (127 mm diameter, 40 mm thickness) while the rigid impactor was nylon (127 mm diameter, 25 mm thickness). Impacts occurred at the front, front boss, rear boss, and rear locations of the helmet or headform at target linear head accelerations of 25, 50, 75, and 100 g (Figure 3.2).[28] Two tests were conducted at each configuration.

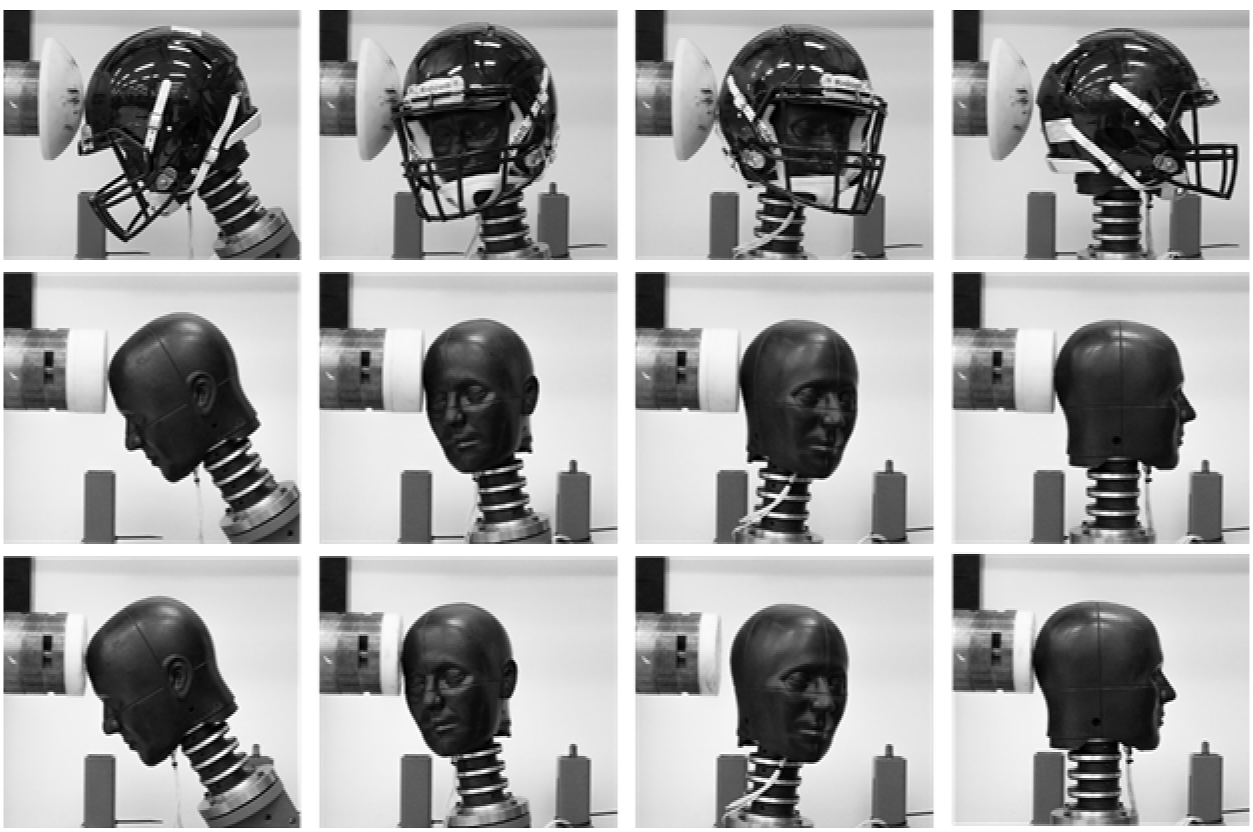

Figure 3.2. Impact locations (left to right) included the front, front boss, rear boss, and rear. Tests included a rigid impactor to a helmeted head (top), a padded impactor to a bare head (middle), and a rigid impactor to a bare head (bottom).

Sensor placement varied by model. The Cue, GForceTracker, and Shockbox sensors were mounted directly inside the helmet. The xPatch was mounted behind the left ear over the mastoid process on the NOCSAE headform using an adhesive patch. The SIM-G was embedded in a headband with the sensor component located at the back of the NOCSAE headform near the intersection of the basic and midsagittal planes. The Vector and Prevent mouthguard sensors were mounted inside a modified NOCSAE headform with a detachable dentition. Boil-and-bite mouthguard sensors were not molded and evaluated using a smooth aluminum dentition, while the custom versions that were reliant on a dentition were evaluated using a 3D-printed detention composed of acrylonitrile butadiene styrene (ABS) plastic (Figure 3.3). In both cases it was important that the dentition was shaped for the mouthguard. An aluminum plate was inserted in the gap between the mouthguard and lower jaw of the NOCSAE head and screwed upward into place until there was no space between it and the mouthguard-clad dentition. The plate functioned as a clamp to prevent independent motion of the mouthguard during testing and to simulate jaw clenching.

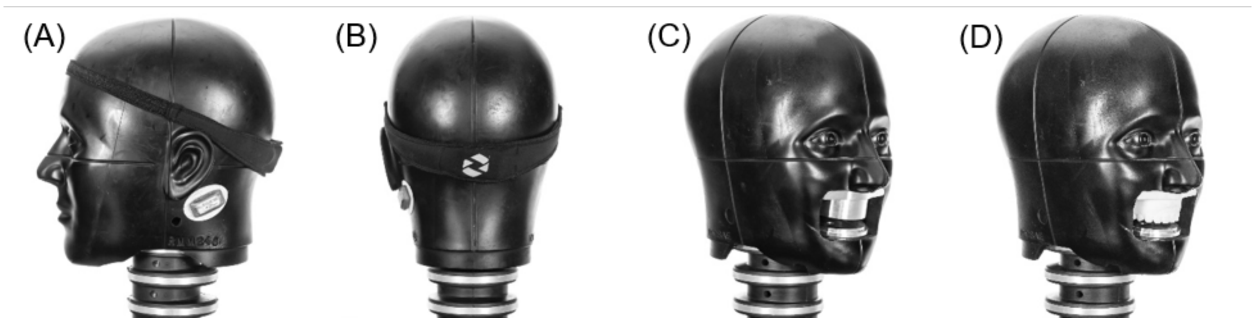

Figure 3.3. Placement of non-helmeted sensors, including the (A-B) xPatch and SIM-G. Comparison between (C) smooth aluminum dentition for boil-and-bite mouthguard sensors and (D) ABS plastic dentition for custom mouthguard sensors.

Wearable sensor performance was assessed by calculating the concordance correlation coefficient (CCC) (Equation 3.1). CCC quantifies the agreement between the sensor measurements and reference measurements based on the deviation of paired measurements relative to the concordance line. CCC addresses misleading characteristics of agreement like location shift, scale shift, and precision errors.[42] In Equation 1, ρ represents the Pearson correlation coefficient, x and y represent the reference and sensor measurements, $\hat{x}$ and $\hat{y}$ represent the measurement means, and S_x and S_y represent the measurement standard deviations. Sensors output the peak resultant values for linear kinematic measures (e.g., peak linear acceleration (PLA)) and rotational kinematic measures (e.g., peak rotational velocity (PRV) and/or peak rotational acceleration (PRA)). After the sensor and reference measurements are recorded, both are normalized relative to the maximum reference measurement. CCC values are then computed for the linear kinematic measure, the rotational kinematic measure(s), and then the combination of linear and rotational measures. The combined CCC values are used to evaluate overall in-lab sensor performance and determine if a sensor should proceed to on-field evaluation. The combined CCC accounts for PLA and a single rotational measurement. If a sensor's output includes both PRV and PRA, one combined CCC value is calculated for PLA and PRV while another combined CCC value is calculated PLA and PRA. In this scenario, the higher of the two combined CCC values is chosen to represent the sensor's in-lab performance. It should be noted that the CCC values are only computed for the test conditions that correspond to the sports for which a sensor is designed. For example, a sensor designed exclusively for helmeted sports would be assessed only in tests involving a rigid impactor to a helmeted head, not impacts involving a bare head.

$$CCC = \frac{2\rho}{v+\frac{1}{v}+u^2} \text{ where } v = \frac{S_x}{S_y} \text{ and } u = \frac{\hat{x}-\hat{y}}{\sqrt{S_x S_y}} \qquad \text{(Equation 3.1)}$$

On-Field Testing

We used a combined CCC value of 0.80 or greater as a threshold to qualify for on-field testing. This threshold was chosen because the sensor does not need perfect accuracy to be useful, and its on-field accuracy would be dependent on the application. A sensor could be tested on-field for just a helmeted condition, just an unhelmeted condition, or both depending on its intended use and lab performance. If measurements are not accurate in the controlled environment of the lab, the sensor cannot be accurate on the field. In most cases, on-field use will be associated with larger errors due to less-than-ideal coupling of the sensor to the skull. Poor real-world coupling will decrease accuracy and introduce false event measurements.[9] The goal of evaluating sensors on-field is to check the extent that real-world use conditions deviate from nearly-ideal lab conditions by classifying each event recorded as either an impact event or a spurious measurement.

To test sensors on-field, we equipped athletes with sensors that produced CCC values of at least 0.80 for matched scenarios (e.g., football players for helmeted lab tests or soccer players for unhelmeted lab tests). We recorded video of players wearing sensors for several practices and/or games. Camera placement was situational, depending on which sport was being studied and how many athletes were instrumented. We specify the camera setup by sensor type in the results. All activities related to the collection and analysis of video and sensor data from athletes was approved by Virginia Tech's Institutional Review Board.

Acceleration events recorded by the sensors were time-synchronized with video for verification that each event was associated with an impact experienced by the athlete. A world clock was time-stamped at the beginning of each video, so that the events in the film could be matched to time-stamped sensor measured events. An impact could be either to an athlete's head or body, as both impart acceleration to the head.[6] Only events with peak resultant linear accelerations greater than 10 g were verified, to distinguish kinematic events like running and jumping from impact events.[43] Each event was classified as either a true positive (TP) impact event or a false positive (FP) impact event. TP impact events were defined as event recordings where there was a time-matched impact to the body or head. FP impact events were defined as event recordings where there was no impact with the athlete observed on video. FP events could be generated from actions such as running, jumping, talking, handling or touching a sensor, or taking off and putting on a sensor. We calculated positive predictive values (PPV), or precision, (Equation 3.2) from the TP and FP counts for each sensor that was tested on-field. 95% confidence intervals (CI) were computed for PPV through bootstrapping.

$$\text{Positive Predictive Value} = \frac{\text{True Positives}}{\text{True Positives+False Positives}} \qquad \text{(Equation 3.2)}$$

We were concerned about the role that inactive participation during games and practices could have on the proportion of FP events. Many FP events are recorded during non-playing time where athletes take the sensors off, handle them, and put them back on.[6,44] We aimed to account for this by generating activity logs for each session that differentiated periods of active play from inactivity (e.g., water breaks, substitutions, half-time). We computed PPV two ways: over entire session lengths and then again for only periods of active play within sessions.

RESULTS

Cue Sport Sensor

The Cue Sport Sensor was only evaluated under the helmeted condition since it is a helmet-mounted sensor. Cue outputs included PLA and PRA. Analysis of in-lab tests resulted in a PLA-based CCC of 0.43 and PRA-based CCC of -0.04, which corresponded to a combined CCC value of 0.13 for both kinematic measures. On-field testing was not performed using the Cue sensor because its combined CCC value was below the 0.80 threshold.

GForceTracker

The GForceTracker was evaluated under the helmeted condition only since it is a helmet-mounted sensor. GForceTracker outputs included PLA and PRV. Analysis of in-lab tests resulted in a PLA-based CCC of 0.37 and PRV-based CCC of 0.32, which corresponded to a combined CCC value of 0.33 for both kinematic measures. On-field testing was not performed using the GForceTracker because its combined CCC value was below the 0.80 threshold.

Prevent Biometrics IMM (Boil-and-Bite)

The boil-and-bite version of the Prevent Biometrics IMM was evaluated under helmeted and non-helmeted impact conditions. The Prevent IMM outputs included PLA and PRA. Analysis of helmeted tests resulted in a PLA-based CCC of 0.97 and PRA-based CCC of 0.98, which corresponded to a combined CCC value of 0.97. Analysis of non-helmeted tests resulted in a PLA-based CCC of 0.95 and PRA-based CCC of 0.95, which corresponded to a combined CCC value of 0.95. On-field testing was performed using the boil-and-bite version of the Prevent IMM because its combined CCC value exceeded 0.80.

Two collegiate football players were instrumented with a Prevent boil-and-bite IMM for three practices. Prevent uses an algorithm to identify suspected impacts and filter out suspected non-impact events. Prevent's algorithm identified 218 suspected impacts, and we verified 120 of those on video. This resulted in a PPV of 55.0% (95% CI: 48.2, 61.5). When only considering active minutes within the sessions, Prevent recorded 147 suspected impacts, resulting in an active-minute PPV of 81.6% (95% CI: 75.5, 87.8).

Prevent Biometrics IMM (Custom-Fit)

The custom-fit version of the Prevent Biometrics IMM was evaluated under helmeted and non-helmeted impact conditions. The Prevent IMM outputs included PLA and PRA. Analysis of helmeted tests resulted in a PLA-based CCC of 0.96 and PRA-based CCC of 0.97, which corresponded to a combined CCC value of 0.97. Analysis of non-helmeted tests resulted in a PLA-based CCC of 0.97 and PRA-based CCC of 0.91, which corresponded to a combined CCC value of 0.95. On-field testing was performed using the custom-fit version of the Prevent mouthguard sensor because its combined CCC value exceeded 0.80.

Fifteen collegiate men's club rugby players were instrumented with Prevent custom-fit mouthguards throughout 4 sessions that consisted of a total of 41 athlete-sessions. Prevent's algorithm identified 204 events that were suspected impacts, 186 of which were verified on video. This resulted in a PPV of 91.2% (95% CI: 86.8, 95.1). When only considering active minutes within the sessions, Prevent recorded 193 suspected impacts, resulting in an active-minute PPV of 96.4% (95% CI: 93.3, 99.0).

Shockbox Helmet Sensor

The Shockbox helmet sensor was evaluated under the helmeted condition only since it is a helmet-mounted sensor. Shockbox only outputs PLA. Analysis of in-lab tests resulted in a PLA-based CCC of 0.21. On-field testing was not performed using the Shockbox sensor because its CCC value was below 0.80.

SIM-G

The SIM-G was evaluated under helmeted and non-helmeted conditions due to its integration with a headband. SIM-G sensor outputs included PLA, PRV, and PRA. Analysis of helmeted tests resulted in a PLA-based CCC of 0.47, PRV-based CCC of 0.88, and PRA-based CCC of 0.31. The combination of PLA and PRV produced a CCC of 0.68. The combination of PLA and PRA produced a CCC of 0.40. Analysis of non-helmeted tests resulted in a PLA-based CCC of 0.48, PRV-based CCC of 0.95, and PRA-based CCC of 0.39. The combination of PLA and PRV produced a CCC of 0.74. The combination of PLA and PRA produced a CCC of 0.51. On-field testing was not performed using the SIM-G sensor because its combined CCC values for the helmeted and non-helmeted conditions were both below 0.80.

Vector MouthGuard

The Vector MouthGuard was evaluated under the helmeted condition only because the version tested was advertised exclusively for helmeted sports, including football, hockey, and lacrosse. Vector outputs included PLA and PRA. Analysis of in-lab tests resulted in a PLA-based CCC of 0.94 and PRA-based CCC of 0.61, which corresponded to an overall CCC value of 0.80. On-field testing was performed using the Vector MouthGuard sensor because its overall CCC value was at the 0.80 threshold.

One collegiate football player was instrumented with a Vector MouthGuard throughout 3 sessions. Vector collected 52 events, with 42 of those verified as impacts on video. This resulted in a PPV of 80.8% (95% CI: 69.2, 90.4). When only considering active minutes within sessions, Vector recorded 49 events, resulting in an active-minute PPV of 85.7% (95% CI: 75.5, 93.9).

xPatch

The xPatch sensor was evaluated under helmeted and non-helmeted conditions due to its integration with a skin-mounted patch. The xPatch sensor outputs included PLA, PRV, and PRA. Analysis of helmeted tests resulted in a PLA-based CCC of 0.89, PRV-based CCC of 1.00, and PRA-based CCC of 0.79. The combination of PLA and PRV produced a CCC of 0.94. The combination of PLA and PRA produced a CCC of 0.83. Analysis of non-helmeted tests resulted in a PLA-based CCC of 0.84, PRV-based CCC of 1.00, and PRA-based CCC of 0.46. The combination of PLA and PRV produced a CCC of 0.93. The combination of PLA and PRA produced a CCC of 0.70. On-field testing was performed using the xPatch sensor because its combined CCC values for the helmeted and non-helmeted conditions were above 0.80.

We used data we previously published to assess the PPV of the xPatch.[9] Over 56 sessions consisting of 916 athlete-sessions, 26 collegiate women's soccer players had xPatches adhered to their mastoid processes. The sensors identified 8,999 acceleration events as suspected head impacts. Video validation was used to verify 1,436 of these events as impacts, yielding a PPV of

16.3% (95% CI: 15.5, 17.0). Only head impacts were quantified in this study, and we, unfortunately, do not have a log of active minutes from this earlier study.

Testing Summary

In-lab and on-field performance are compared across sensors in the helmeted and unhelmeted conditions (if applicable) in Table 3.2. CCC, the metric for in-lab performance, summarizes the accuracy of linear and rotational measurements (Figure 3.4). Combined CCC values varied between sensors with a range of 0.13 to 0.97. A total of 4 sensors had combined CCC values greater than 0.80 and were tested on-field. PPV was used to summarize on-field performance by quantifying the percentage of data recorded by a sensor that was associated with an impact event. Considering all data collected by the sensors during sessions, PPV ranged from 6.3% to 91.2% (Figure 3.5). Only considering active minutes of play time, something that must be manually tracked for by the operator, increased PPV universally.

Table 3.2. Summary of CCC values from in-lab testing and PPV values from on-field testing of wearable head impact sensors. The CCC values were determined from reference and sensor outputs, including PLA, PRV, PRA, and combinations of linear and rotational measures. PPV was determined by the quantification of TP and FP events overall-for the whole session duration and during active minutes only-excluding time when there was a break in play for any reason.

		CCC				PPV (%)	
Sensor	**Condition**	**PLA**	**PRV**	**PRA**	**Combined**	**Overall**	**Active Minutes**
Cue	Helmeted	0.43	N/A	-0.04	0.13	N/A	N/A
GForceTracker	Helmeted	0.37	0.32	N/A	0.33	N/A	N/A
Prevent Boil-and-Bite	Helmeted	0.97	N/A	0.98	0.97	55.0	81.6
	Non-helmeted	0.95	N/A	0.95	0.95	N/A	N/A
Prevent Custom	Helmeted	0.96	N/A	0.97	0.97	N/A	N/A
	Non-helmeted	0.97	N/A	0.91	0.95	91.2	96.4
Shockbox	Helmeted	0.21	N/A	N/A	0.21	N/A	N/A
SIM-G	Helmeted	0.47	0.88	0.31	0.68	N/A	N/A
	Non-helmeted	0.48	0.95	0.39	0.74	N/A	N/A
Vector	Helmeted	0.94	N/A	0.61	0.80	80.8	85.7
xPatch	Helmeted	0.89	1.00	0.79	0.94	N/A	N/A
	Non-helmeted	0.84	1.00	0.46	0.93	16.3	N/A

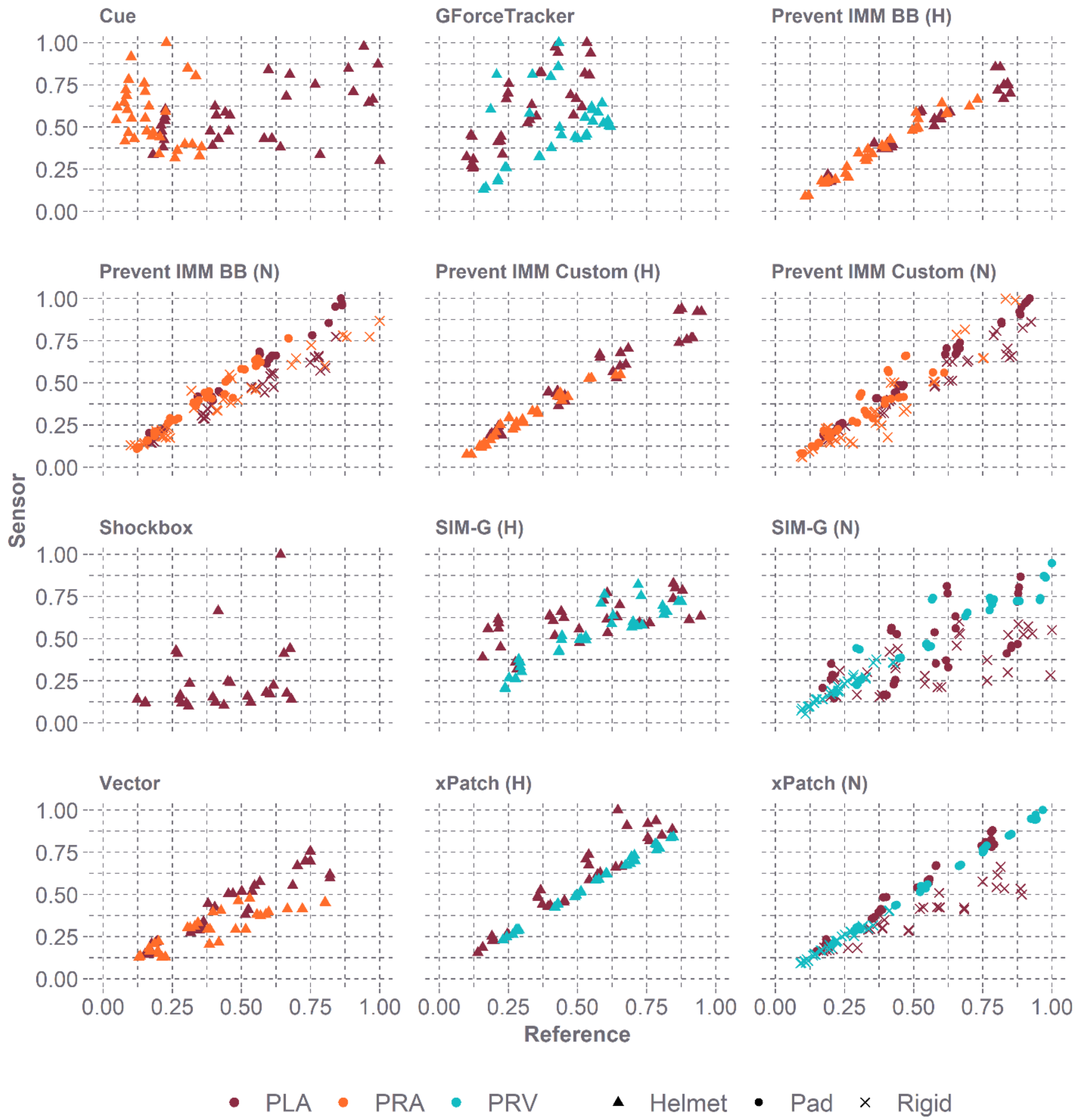

Figure 3.4. Comparison of reference versus sensor measurements by sensor model, impact condition, and kinematic measure. Linear and rotational kinematic measures were normalized and then combined for each scatterplot. If multiple rotational kinematic measures were available, the combination that produced the higher CCC value was selected. Scatterplots for the Prevent IMM boil-and-bite (BB), Prevent IMM Custom, SIM-G, and xPatch sensors were divided further by helmeted (H) and non-helmeted (N) impact conditions.

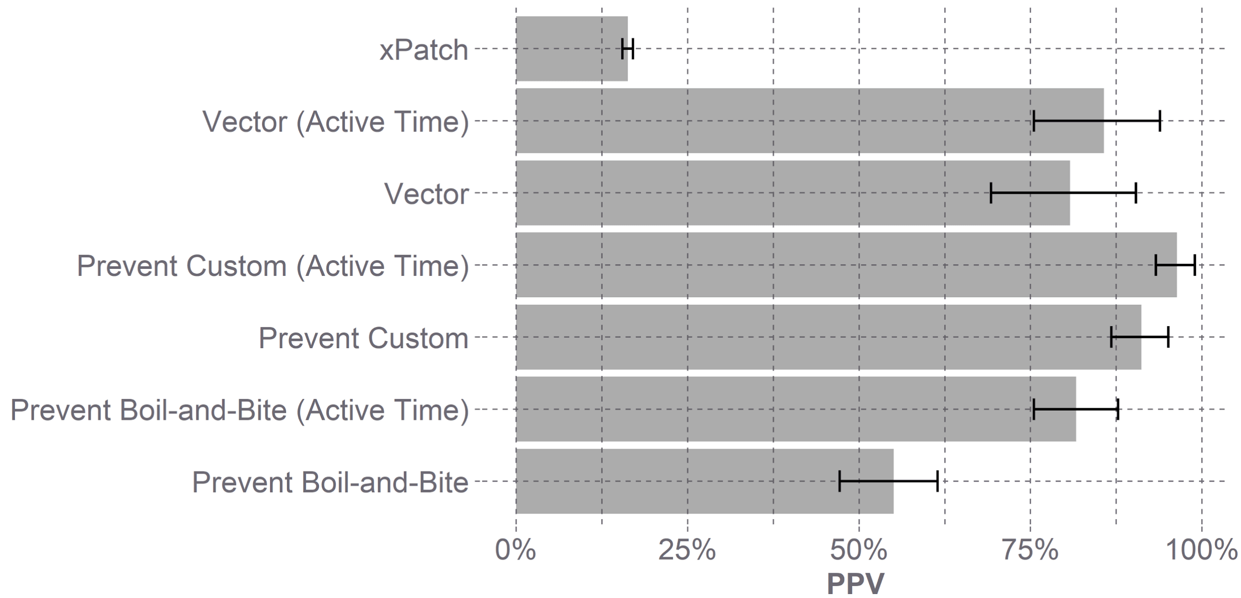

Figure 3.5. PPV was calculated for each sensor that was tested on-field. Bootstrapping was used to calculate 95% confidence intervals for each PPV. Session logs allowed inactive minutes to be parsed out for the Vector MouthGuard and Prevent IMMs, allowing for the calculation of PPV for active minutes, in addition to PPV overall. PPVs calculated during active time were higher in each case than overall. The custom-fit Prevent IMM had a higher PPV than the boil-and-bite version, potentially due to better coupling on-field. The xPatch was the only sensor used in the field that was coupled to the skin, which likely explains its low PPV compared to the mouthguard-based sensors.

DISCUSSION

We propose a two-phase methodology for evaluating the error of wearable head impact sensors. Phase one involves in-lab testing of sensors under conditions representative of their intended use to assess kinematic measurements. Phase two involves on-field testing to assess impact counts. Phase two is conditional on accuracy demonstrated in phase one because a sensor cannot perform well on-field if it cannot measure kinematics reasonably well during ideal lab conditions. Sensor accuracy varied widely, and only some sensors qualified for on-field testing -- a decision based on CCC values being at least 0.80. On-field, PPV values varied widely between sensors that demonstrated good accuracy in the lab due to the uncontrolled nature of use and deviations between real-world and lab coupling to the skull.

The purpose of testing a sensor in the lab is to determine if the sensor measures head kinematics reasonably well. In this paper, we defined "reasonably well" as having a CCC value of 0.80 or greater. All CCC values are reported in the text and summarized in Table 3.2 so that the reader can make their own interpretations of accuracy. Lab testing is needed because there is no way to measure true head kinematics in human subjects. We use gold-standard instrumentation rigidly fixed to a dummy headform to quantify wearable sensor measurement error. Sensor accuracy is dependent on its frequency response, sampling rate, signal filtering, and coupling to the headform.[10,21,28] Sensor limitations related to frequency response and sampling rate were most evident for the rigid impactor striking the bare headform.[28] Most notable was the error related to poor coupling between the wearable sensor and headform. Helmet-based sensors did not perform as well as sensors that were mounted directly onto the headform. This discrepancy can be attributed to the decoupling that occurs between the helmet and headform during an impact. For non-helmeted sensors, the headband experienced more independent motion relative to the headform compared to the motion of the mouthguards and skin patch that were fixed to the headform. The stronger coupling, aided by a clamp, between mouthguards and the headform dentitions resulted in better in-lab performance. The skin patch sensor also performed well due its adhesive mounting to the skinless headform.

The purpose of on-field testing was to determine how well the sensor performs during real-world conditions. The reason this type of testing is needed beyond laboratory testing is that the sensor coupling to the head may deviate from the in-lab coupling conditions. As a result, a sensor could perform well under laboratory conditions but not when equipped on an athlete. A user could unknowingly collect and interpret erroneous data without on-field assessments. The Prevent IMM is an example of a sensor that performed well in the lab (high CCC) and the real-world (high PPV), leading us to think that it is an overall accurate system. On the other hand, the xPatch is a sensor that looks good in the lab (high CCC) but has very poor performance on-field (low PPV). This discrepancy in performance is the result of the dummy headform not having skin that can move relative to the skull like that of a human. Relative skin motion on a human results in erroneous measurements of skull kinematics. Unreliable kinematic measurement in the real-world results in the sensor more frequently recording events that are not impacts, as unrelated actions like jumping will register accelerations greater than the sensor’s data acquisition trigger threshold.

We quantified PPV in two ways: 1) considering all events recorded between the start and end of a session and 2) considering only events that were recorded during active play. We think this is an important distinction because events recorded during inactive time during a session are extremely dependent on the individuals and team instrumented. PPV quantified during active minutes, when the athletes are less likely to fiddle with the sensors, is a more objective measure of on-field performance. Obviously, for a user to collect data with the assumption that PPV is equally good as reported here, inactive minutes during sessions would need to be tracked and events manually removed. We view this as a bare minimum effort, and we recommend video verification of all impacts when possible in research efforts.[6] For football and rugby data collection, we kept detailed logs of inactive minutes that allowed us to exclude FPs that occurred during those time windows. Breaks in play included substitutions, half-times, time-outs, and dead time during or in-between drills during practices. FPs were more likely to be generated during those windows because players were more likely to remove mouthguards from their mouths. PPV was higher for all sensors when only the impacts from active time were included. The dataset from the soccer team was previously published and did not include sessions logs that indicated when athletes were actively participating, or if there was a break in play. Therefore, FP events during inactive minutes were not parsed out, and only overall PPV was calculated for the xPatch. We assume that PPV would be improved for the xPatch if we only analyzed active minutes but still suspect on-field performance would be considered poor due to weak coupling that resulted in video-verified head impacts producing unrealistic head accelerations.[9]

PPV is not a perfect metric for on-field accuracy. It does not directly consider kinematic magnitudes and does not capture false-negative event errors. Suspected false negatives are impacts that are observed on camera but do not have any sensor data associated with the time stamp for which the impact occurred. They are only suspected because it is near impossible to visually identify if an impact is greater than the trigger threshold. Video reviewers can observe obvious high magnitude impacts and note a lack of data for particular events. This scenario is most commonly noticed when players sustain concussions and the specific impact is being identified in video review. For example, several concussions were missed with the Prevent custom IMM during the rugby season.[6] However, we suspect that most false-negative impact events are likely low in magnitude, potentially near the data acquisition trigger threshold. These impact magnitudes cannot be confirmed, leading to most suspected false-negative impact events being impossible to verify. We never know true head kinematics and whether they meet any triggering thresholds, but this highlights the potential for other error types that can influence the collection and interpretation of on-field data.

Sensor companies are working on developing methods of cleaning and filtering the data that are measured on-field to reduce the noise and optimize the quality of the dataset. Strategies vary but can include hardware to identify if the sensor is being worn, as well as algorithms that pass individual kinematic signals, characterizing shape and comparing them to known head impacts. For example, the Prevent IMM uses two sensors, a proximity sensor and a light sensor, to determine if the mouthguard is on the teeth during a recorded event. They also look at frequency content and signal-to-noise ratios of events in attempts to reduce recordings that are not associated with impact events. Although sometimes successful, it is important to be aware of the filtering in place with the device being used, as it may not be optimized for the particular sport being studied and could incorrectly filter out true impacts that have atypical kinematic signatures. Such practices are useful because they can be effective at removing non-impact events from recorded datasets; however, there is the potential for increasing false-negative events and misleadingly inflating PPV by overzealously removing events.

We aimed to illustrate how PPV is quantified from different datasets. We included confidence intervals because the number of impacts collected by each sensor was different. PPV uncertainty is influenced by the PPV magnitude and number of impacts recorded. For the same number of impacts, a PPV of 99% will have a narrower confidence interval than a PPV of 50%. For example, at a PPV of 80%, the 95% confidence interval is (68.0, 90.0) for 50 impacts, (72.0, 87.0) for 100 impacts, and (74.5, 85.5) for 200 impacts. Increasing PPV to 96%, the 95% confidence interval narrows to (90.0, 100) for 50 impacts, (92.0, 99.0) for 100 impacts, and (93.0, 98.5) for 200 impacts.

These examples are intended to illustrate how you would choose a minimum number of impacts for on-field assessments. While we did not have a minimum number of impacts because our data are from multiple studies, we present the framework for doing so. Depending on the sport being studied, it may take more time to achieve the desired number of impacts, in addition to resources and effort to collect these data. For +/-10% at PPV of 80%, a minimum of 65 impacts should be collected. There are obvious practical limitations to collecting large datasets with large numbers of athletes over a long time just to see if the sensor performs well. This framework based on calculating uncertainty provides important context on PPV computed from small sample sizes on-field.

Although we offer an inclusive methodology to assess the performance of head impact sensors, there were limitations to this study. Both the Prevent IMM versions tested in the helmeted and unhelmeted conditions resulted in a CCC greater than 0.80, but we did not test both devices in both conditions on-field. The boil-and-bite IMM was only tested in helmeted athletes, and the custom-fit IMM was only tested in unhelmeted athletes. While we do not have reason to think they would produce substantially different results in the missing conditions, we cannot be sure without on-field testing. Using PPV as an on-field performance metric is not perfect, as it does not account for false-negative impacts. The impacts that are missed by sensors are not practical to quantify due to a lack of kinematic reference measurement on-field but are a concern when analyzing and interpreting on-field kinematic data. Additionally, the NOCSAE headform used in lab testing does not have biofidelic skin or hair, which could affect the coupling of the skin patch and headband to the head. We used an aluminum plate to fix the mouthguards into place in the headform to mimic jaw clenching, but this is not exactly representative of how an athlete would wear the device. However, clamping the mouthguard into place allows us to measure the instrumentation in the most ideal coupling scenario, enabling us to better quantify the sensors' accuracy. The ability of each device to couple would be reflected in the on-field assessment of PPV. The skin patch and mouthguards are examples of devices whose coupling ability would differ from in-lab to on-field.

Not every head impact sensor available was evaluated in the process, as some did not output peak metrics necessary to calculate CCC and others were not commercially available and only intended for research purposes. HITS was not included in the evaluation because its use is specific to football, and there is interest to assess devices that can be implemented in other populations. However, the intent of this paper was to present a uniform method to determine sensor accuracy, so sensors beyond those that we included can be evaluated using this approach in the future. We also only used a football helmet to evaluate performance for helmeted impacts. There are other helmeted sports in which the sensors could be deployed. Finally, our in-lab impact configurations are not all-encompassing; we tested each sensor at four locations and four severities, but this seemed to be enough to demonstrate a wide range of performance between sensors.

There is a clear need to evaluate wearable head impact sensors both in the lab as well as on the field, as in-lab performance is not necessarily indicative of on-field accuracy. The uniqueness of wearable sensors, limitations of different devices, and nuances of use warrant a thorough validation process. The methods proposed in this paper aim to establish a comprehensive approach to the evaluation of sensors so that users can better interpret data collected from athletes.

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CHAPTER 4: USING IN-MOUTH SENSORS TO MEASURE HEAD KINEMATICS IN RUGBY

ABSTRACT

Sports-related concussions were once thought to present only transient symptoms, but recent research has shown the potential for long -term neurological impairments. Previous research has instrumented helmeted athletes with sensors to measure head kinematics and concussive biomechanics on-field. However, expanding studies beyond helmeted players will help us to understand sex-specific differences and unhelmeted loading conditions and their relationship to impact exposure and tolerance. Athletes on the men's and women's club collegiate rugby teams at Virginia Tech were custom fit with instrumented mouthguards and monitored over a year to quantify subconcussive and concussive biomechanics in unhelmeted athletes. The objective of this study was to quantify head kinematics sustained from inertially driven (body impacts) and direct head impacts in collegiate rugby players. The majority of the impacts collected were low in magnitude, and head impacts were associated with higher PLAs than body impacts (Δ = 2.5 g, $p < 0.005$). Head impacts had a median PLA of 15.2 g and a median ΔRV of 6.7 rad/s; body impacts had a median PLA of 13.6 g and a median ΔRV of 6.6 rad/s. For each impact type, men and women sustained similar peak linear accelerations (head impact: Δ = 1.9 g, $p = 0.219$; body impact: Δ = 0.5 g, $p = 0.280$), men sustained higher changes in rotational velocities for head impacts (Δ = 1.4 rad/s, $p = 0.003$) and longer impact durations for both head (Δ = 2.6 ms, $p < 0.001$) and body (Δ = 2.8 ms, $p = 0.023$) impacts. These findings can be used to advise best practices for in-mouth sensors and better understand the mechanisms of concussion in unhelmeted sports.

Keywords: Acceleration, Biomechanics, Concussion, Female, Impact

INTRODUCTION

Not only do concussions present acute cognitive impairment at the time of injury and long-term complications, but a history of repetitive head impact exposure may be similarly detrimental.[1] Instrumenting American football players with sensors to measure head impact kinematics has improved our understanding of head impact exposure and biomechanics.[2-6] However, we still do not understand sex-related differences in exposure and head impact tolerance. There is also much unknown about exposure in other sports, especially in those with unhelmeted athletes, who likely undergo different loading conditions than helmeted athletes. Concussive biomechanics in unhelmeted sports have not been quantified because instrumenting these athletes is challenging. Different types of sensors have been used on-field, including those worn in headbands,[7-9] on skin-mounted patches,[10-13] in the ear,[14] and embedded into mouthguards.[15,16]

Of these, mouthguards offer the best solution as they allow for a nearly rigid coupling to the skull, which improves head kinematics measurement accuracy.[17]

Similar to American football, rugby players have a high exposure to head impacts.[18] Worldwide, rugby is a popular full-contact team sport, and its physicality and competitiveness lead to a high concussion rate.[19] The only protective equipment worn by rugby players is a mouthguard, which does not reduce the risk of concussion.[20] About 13–17% of rugby players will sustain a concussion during a season, though this varies by the play style. Both men's and women's teams play at various levels of competition, under the same rules.[20]

Athletes can play Rugby-7s (7s), or Rugby-15s (15s). Rugby-7s is played with seven players on the field (per team) and is played for seven-minute halves. Rugby-15s is played with 15 players on the field (per team) and is played for 40-minute halves. A previous study from Ireland found the incidence and severity of concussion to be higher in Rugby-7s.[21] The same study found that the leading causes of concussion were tackling (7s) and collisions (15s).[21] According to video review, concussion risk for a tackler is elevated in a collision tackle, when the initial contact is made by the tackler's head/neck, when the tackler does not use their arms, or when the tackle is broken by the ball carrier.[22] King *et al.* quantified head impacts in junior league rugby and amateur rugby union (Rugby-15s), measuring resultant head accelerations similar to youth football and some college football, but lower than those in female youth soccer and professional American football.[18,23] The junior league players were instrumented with skin-mounted sensors worn behind the ear, and the union players wore molded instrumented mouthguards.[23]

Most of these studies did not include female athletes (the junior league had five girls who were under 11), nor did they characterize head kinematics by impact type. Additionally, King noted limitations with his devices, including a lack of consistent reliability studies with the skin-mounted sensor systems and saliva ruining components in the instrumented mouthguards.[23] Instrumentation approaches have improved since, with new technologies coming to market. The objective of this study was to quantify head kinematics and impact durations sustained from both inertially driven and direct impact head acceleration events experienced by men and women collegiate rugby players. For this study, collegiate rugby players wore custom-fit instrumented mouthguards. We hypothesized that head impacts would have higher peak kinematics and shorter impact durations compared to body impacts, and that kinematics would not differ between sexes.

METHODS

During the spring and fall of 2019, athletes were recruited from the Virginia Tech men's and women's club rugby teams to participate in this study, which was approved by the Virginia Tech Institutional Review Board. A total of 26 males (age: 20.6 ± 1.1 years, height: 1.79 ± 0.06 m, weight: 88.8 ± 16.3 kg) and 21 females (age: 20.7 ± 1.1 years, height: 1.66 ± 0.08 m, weight: 74.6 ± 18.5 kg) provided written consent and participated in the study. Each athlete was instrumented with a custom-fit mouthguard that contained accelerometers and angular rate sensors to measure head kinematics with six degrees of freedom. The athletes wore their mouthguards for each game and contact practice. Two different mouthguards were used, Prevent Biometrics Impact Monitoring Mouthguard (IMM) and Wake Forest retainer (Figure 4.1), both of which have been validated in laboratory testing.[15,16] The Prevent Biometrics mouthguard had an $R^2 = 0.99$ for linear acceleration and $R^2 = 0.99$ for angular acceleration in lab.[15] The Wake Forest retainer had an $R^2 = 0.95$ for linear acceleration and $R^2 > 0.99$ for angular velocity in lab, and overall sensitivity of 69.2% and a positive predictive value of 80.3% in the field.[16] A compliant material was added to the Wake Forest retainer to fit around the athletes' teeth to modify the device into a mouthguard.

Prevent's device used a sampling rate of 3,200 Hz. When a buffering accelerometer measurement exceeded 5 g on a single axis, 10 ms of pre-trigger and 40 ms of post-trigger data were collected and stored on local memory. The Prevent iOS app was able to download the data in real-time. A low-pass filter of channel frequency class (CFC) 240 was used to filter the data. To avoid possible data loss, Prevent's algorithm to remove suspected false-positive impact events was deactivated. A generalized transformation formula was used to transform accelerations to the head's centre of gravity (CG). Wake Forest's device sampled the accelerometers at 4,684 Hz and the gyroscope at 1,565 Hz. When a buffering accelerometer measurement exceeded 5 g on a single axis, 15 ms of pre-trigger and 45 ms of post-trigger data were collected and stored on local memory. Wake Forest's device used a low-pass filter of CFC 2000 to filter the acceleration data and CFC 270 to filter angular rate data. Subject-specific transformations were calculated from the device to the head CG.[24] The head CG was estimated based on the origin of the Frankfort plane, using the infraorbital margin (IOM) and external auditory meatus (EAM) as facial landmarks, as previously described by Rich *et al.*[24] These anatomical landmarks were identified on images taken of each athlete's face.[24]

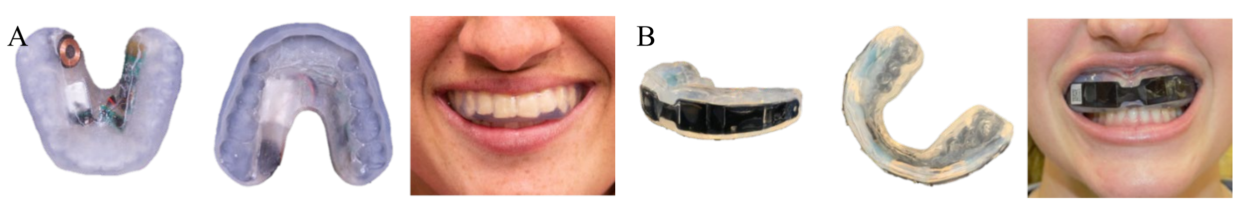

Figure 4.1. (A) Wake Forest University Mouthguard with instrumentation along the upper palate and (B) Prevent Biometrics IMM with instrumentation along the teeth.

Any recorded event with a resultant acceleration below 10 g was excluded from the analysis. A 10 g threshold was used to discriminate impacts events from dynamic movement events associated with activities, such as running or jumping.[25] Time-synced video from one high definition camera was used to verify that recorded acceleration events were associated with impacts. Each verified acceleration event was categorized as either a “head impact”, defined as a head acceleration resulting from a direct impact to the head, or a “body impact”, defined as a head acceleration resulting from an impact to the body (Figure 4.2).

Figure 4.2. (Left) A direct head impact during a men’s practice and (Right) An inertially-induced head acceleration from a body impact during a men’s game.

Although peak rotational velocity was reported for each device, we reported the change in rotational velocity (ΔRV), which is the difference in maximum rotational velocity from the rotational velocity at the onset of impact. This is because we are interested in the change in rotational velocity of the head due to impact. This required Prevent Biometrics’ rotational velocity to be zeroed prior to calculation. Wake Forest already zeroes their rotational velocity data. Therefore, ΔRV was computed for each impact and reported as such. We defined the peak linear acceleration (PLA) as the maximum value for the resultant linear acceleration pulse. It is important to note this because Prevent defines their PLA as the maximum linear acceleration in the 7.5 ms to 20 ms time window of data collection, with the first 2.5 ms of those as pre-trigger data. Therefore, we recalculated PLA for the Prevent data.

Impact duration was computed manually for each impact using the following approach. The start of the impact was identified by a clear increase in resultant linear acceleration for the acceleration pulse, producing the maximum PLA (Figure 4.3). The end of the impact was determined to be a local minimum following the maximum acceleration that seemed to indicate that an external force was no longer acting on the head. The resultant acceleration trace was used primarily for these measurements, although the axis-specific data gave context on the timing of loading (i.e. when each axis crossed zero). If there was a clear separation between multiple peaks, only the width of the pulse with the maximum resultant acceleration was considered. After reviewing all of the traces, 47 (9.4%) of the events were identified as non-typical head acceleration events (e.g. there was no clear acceleration peak, or the full width of the pulse was not captured). These impacts were not considered during the impact duration analysis. These duration-excluded impacts were still included in the impact magnitude analysis because peak values could be quantified.

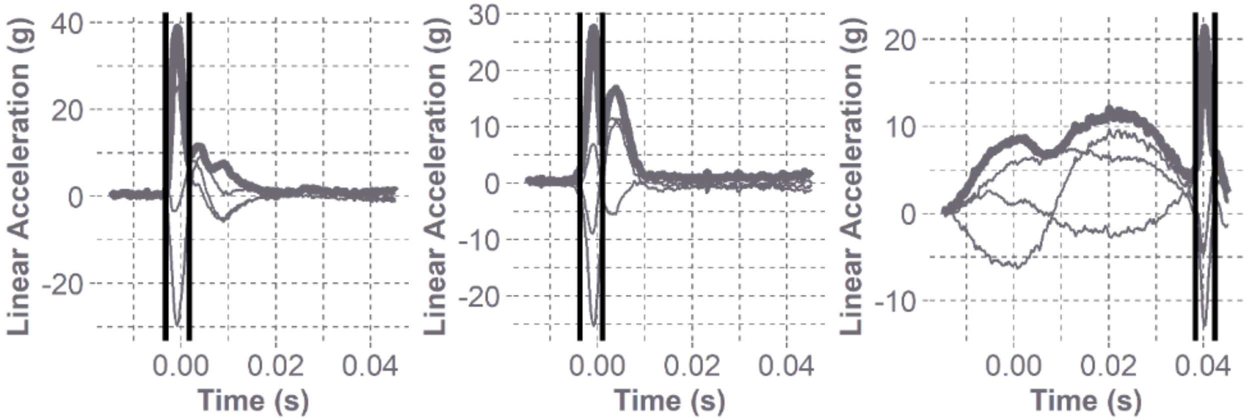

Figure 4.3. Three examples of calculated impact duration. The darkest trace is the resultant acceleration and the lighter traces are the x, y, and z axis-specific traces. The two lines mark the beginning and end of the measured duration for each impact.

Impact exposure for body and head impacts was calculated per player, per session and averaged by sex. The distributions of impact exposure, PLA, ΔRV and impact duration were compared between sexes for head and body impacts. PLA and ΔRV values were log-transformed before performing a two-way analysis of variance (ANOVA) to test the effects of sex and impact type. Wilcoxon signed-rank tests were used to compare impact exposure, PLA, ΔRV and impact duration between and within impact type and sex. The mean difference and 95% confidence interval (CI) were computed to provide an estimate of effect size

RESULTS

The women were instrumented for 12 games and three contact practices. The men were instrumented for eight games and 11 contact practices. In total, there were 736 video-validated acceleration events. Since data were collected from both sexes' 7s and 15s teams, a day of 7s tournament play was considered one game for this analysis. Overall, men and women sustained 0.9 [95% CI: 0.2 to 1.5] more head impacts than body impacts per session ($p = 0.012$). Men sustained 1.1 [CI: 0.5 to 1.7] more impacts per session than the women ($p = 0.002$) (Table 4.1). Women sustained 0.5 [CI: -0.1 to 1.2] more head impacts than body impacts ($p = 0.097$). Men sustained 1.1 [CI: 0.2 to 2.1] more head impacts per session than body impacts ($p = 0.008$). Median values are presented to best capture the central tendency as the data are right-skewed.

Table 4.1. Impact counts, median, and 95th percentile head kinematics for peak linear acceleration and change in rotational velocity experienced by men and women for both impact types.

				PLA (g)		ΔRV (rad/s)	
Sex	**Impact**	**Count**	**Impacts/Session**	**Median**	**95%ile**	**Median**	**95%ile**
Female	Body Impact	75	1.5 ± 0.8	13.9	41.3	6.5	20.8
	Head Impact	122	2.1 ± 1.2	15.2	50.4	5.5	16.5
Male	Body Impact	175	2.4 ± 1.7	13.4	44.3	6.7	19.8
	Head Impact	364	3.5 ± 1.6	15.2	48.4	7.2	17.9

The distributions of peak head kinematic values for both sexes were right-skewed for both body and head impacts. Non-parametric probability density functions were estimated from kernel density estimates (Figure 4.4). For PLA values, 79% of events were less than 25 g, 96% were less than 50 g, and 98% were less than 75 g. For ΔRV values, 74% of events were less than 10 rad/s, 91% were less than 15 rad/s, and 96% were less than 20 rad/s. Head impacts accounted for 66% of the dataset, had a median PLA of 15.2 g [IQR: 11.7 to 24.2 g] and a median ΔRV of 6.7 rad/s [IQR: 4.4 to 10.0 rad/s]. Body impacts had a median PLA of 13.6 g [IQR: 11.0 to 19.7 g] and a median ΔRV of 6.6 rad/s [IQR: 4.0 to 10.3 rad/s]. Overall, head impacts were associated with 2.5 g [CI: 0.5 to 4.8 g] higher PLAs than body impacts ($p < 0.005$). The ΔRV of body impacts were 0.3 rad/s [CI: -0.6 to 1.2 rad/s] greater than that of head impacts ($p = 0.790$). Exemplar traces for head and body impacts can be seen in Figures 4.5 and 4.6.

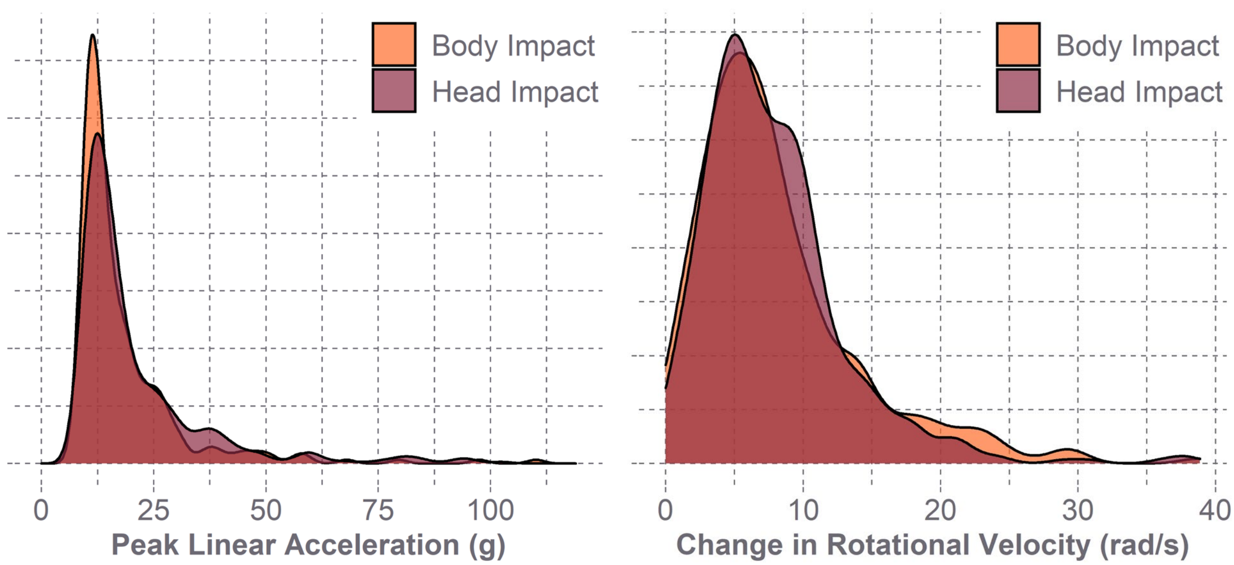

Figure 4.4. (Left) Probability density function (PDF) for PLA, with HI in maroon and BI in orange. (Right) PDF for ΔRV, with HI in maroon and BI in orange. HIs tended to result in greater PLA (p <

0.005). There was little evidence suggesting that ΔRV values differed between the impact types (p = 0.790).

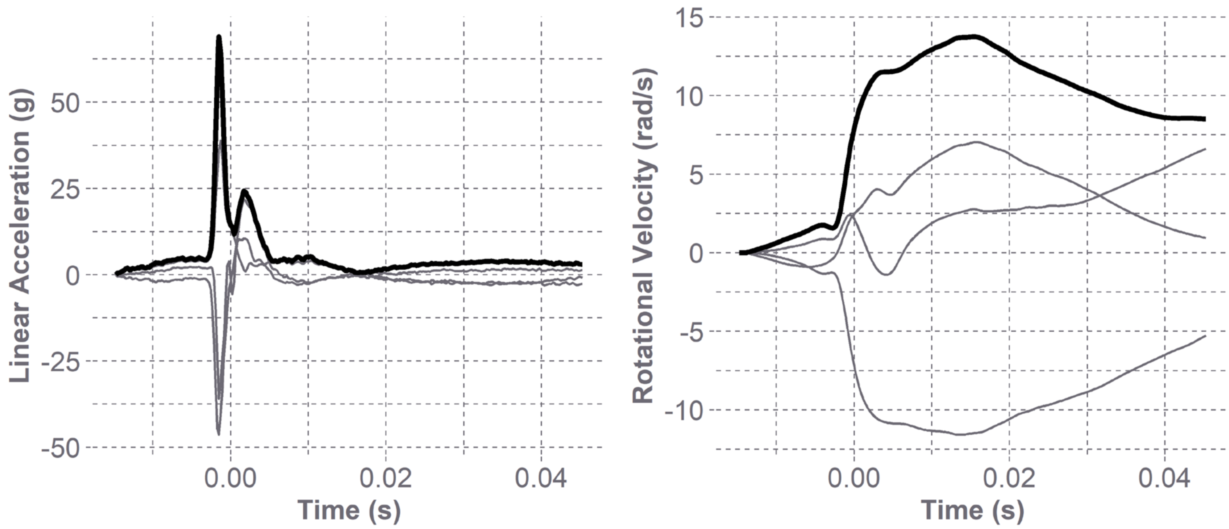

Figure 4.5. Exemplar linear acceleration and rotational velocity traces for a head impact. Resultant trace is black and axis specific traces are gray.

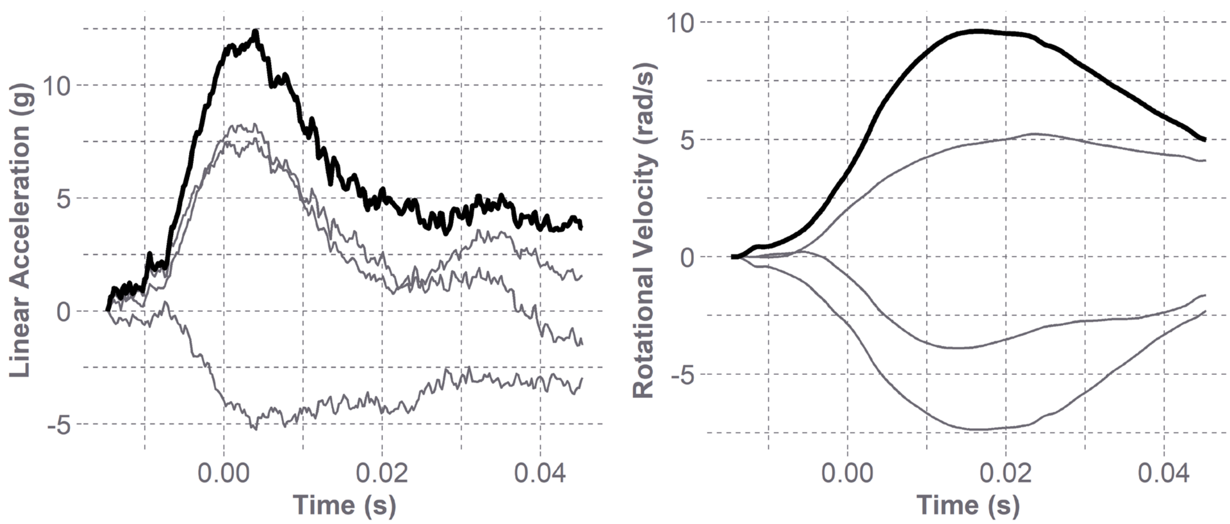

Figure 4.6. Exemplar linear acceleration and rotational velocity traces for a body impact. Resultant trace is black and axis specific traces are gray.

The head impacts that the women sustained had a median PLA of 15.3 g [IQR: 12.1 to 27.8 g], which was 3.8 g [CI: -0.04 to 7.6 g] higher PLA than their body impacts (p = 0.052) (Figure 4.7). For all box plots, outliers were excluded from the plot to better visualize differences in the central tendencies. The men's median head impact had a PLA of 15.2 g [IQR: 11.6 to 23.2 g], which was 2.4 g [CI: -0.3 to 5.0 g] greater than their body impacts (p = 0.004) (Figure 4.7). There was no evidence to suggest that women's body impacts resulted in a meaningful difference in ΔRV compared to their head impacts, with an estimated effect size of 0.9 rad/s [CI: -0.7 to 2.5 rad/s] (p = 0.277). There was also no evidence to suggest that men's body impacts resulted in a meaningful difference in ΔRV compared to their head impacts, with an estimated effect size of 0.11 rad/s [CI: -1.0 to 1.2 rad/s] (p = 0.340) (Figure 4.7).

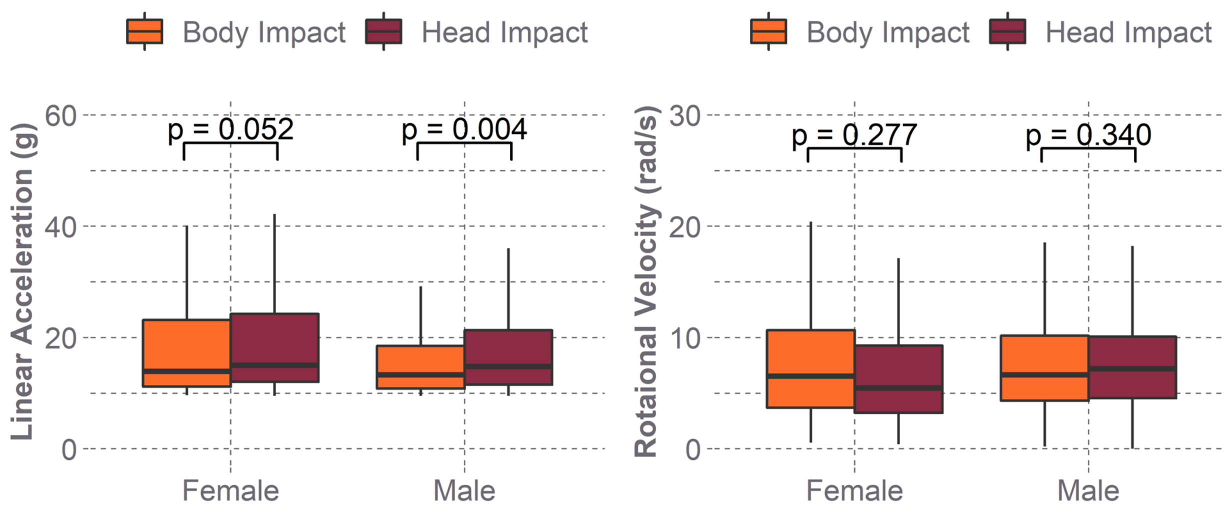

Figure 4.7. (Left) Linear acceleration for impact type compared within sex. (Right) Rotational velocity for impact type compared within sex. Head impacts had a higher PLA than body impacts for both men and women. There was no difference in PRV between impact type within sex.

Men and women sustained similar PLA values for head impacts, with an estimated effect size of 1.9 g [CI: -1.4 to 5.3 g] (p = 0.219) (Figure 4.8). The sustained PLA values for body impacts were also similar between sexes, with an effect size of 0.5 g [CI: -2.7 to 3.7 g] (p = 0.280) (Figure 4.8). Men's head impacts resulted in ΔRV values 1.4 rad/s [CI: 0.3 to 2.4 rad/s] higher than women's head impacts (p = 0.003) (Figure 4.8). The difference in ΔRV between men's body impacts and to women's body impacts was 0.6 rad/s [CI: -1.0 to 2.2 rad/s] (p = 0.636) (Figure 4.8).

Figure 4.8. (Left) Linear acceleration for impact type compared between sex. (Right) Rotational velocity for impact type compared between sex. Men and women sustained similar PLA magnitudes for each impact type. Men sustained higher ΔRV magnitudes for each impact type. Outliers are excluded from the plots.

Of the 47 events removed for the duration analysis (Figure 4.9), 12 were head impacts and 35 were body impacts. This left 215 body impacts and 476 head impacts to characterise impact duration. Body impacts had a median duration of 10.9 ms [IQR: 6.5 to 18.8 ms], which was 1.1 ms [CI: -0.4 to 2.5 ms] higher than head impacts' durations ($p = 0.56$). Head impacts had a median duration of 10.4 ms [IQR: 6.7 to 16.6 ms].

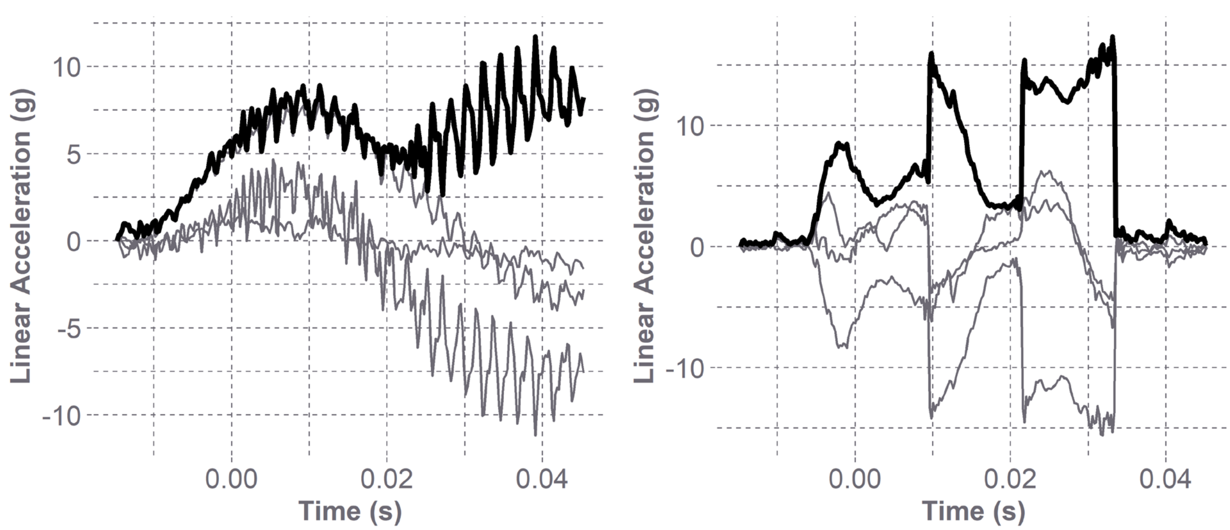

Figure 4.9. Two exemplar linear acceleration traces for impacts removed from the duration analysis due to their lack of consistency to acceleration traces for an impact. Resultant trace is black and axis specific traces are gray.

Men's body impacts were similar in duration to their head impacts, only 1.3 ms [CI: -0.6 to 3.1 ms] longer ($p = 0.432$) (Figure 4.10). Women's body impacts were also similar in duration, only 1.0 ms [CI: -1.3 to 3.3 ms] longer than their head impacts ($p = 0.976$) (Figure 4.10). Men experienced body impacts 2.8 ms [CI: 0.3 to 5.4 ms] longer than women did ($p = 0.023$), and they experienced head impacts 2.6 ms [CI: 1.2 to 4.0 ms] longer than women did ($p < 0.001$) (Figure 4.10).

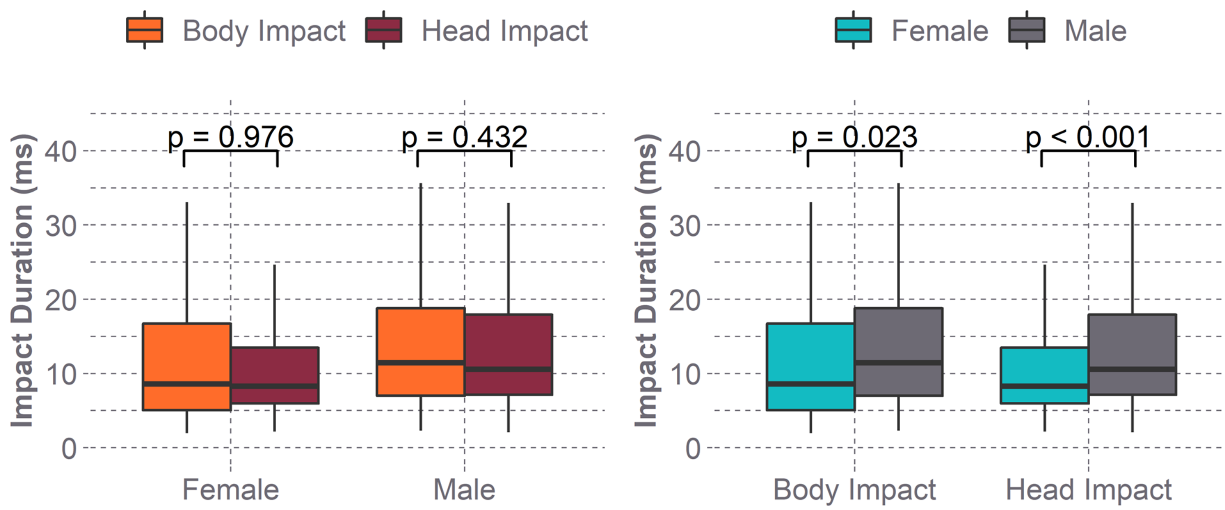

Figure 4.10. (Left) Impact duration for impact type compared within sex. (Right) Impact duration for impact type compared between sex. The men's body impacts were longer than their head impacts. Men sustained longer impacts in each impact type. Outliers are excluded from plots.

Throughout the study, three men and eight women sustained concussions. Of these, biomechanical data were collected for three impacts (2 men's and 1 women's). All occurred during games. One of the men was swung around by his opponent and thrown down, hitting the back of his head on the ground. His impact had a linear acceleration of 81.6 g and rotational velocity of 23 rad/s. The second male player was making a tackle and ran his head into his opponent's chest, knocking himself to the ground. When he finally stood, his balance was compromised and he took several unsteady steps. His impact had a PLA of 74.8 g and ΔRV of 30 rad/s. The female player was holding onto her opponent's legs, trying to make a tackle when she was kneed in the head by her teammate. Her impact had a PLA of 54.6 g and ΔRV of 18 rad/s. Data were not collected on the other concussions because they either resulted in false-negative events or there were device issues on the day of injury.

Table 4.2. Concussive events sustained over the course of the study for both teams. PLA and ΔRV are reported for the three impacts that resulted in measured data. The first concussion's ΔRV value is, noted by *, is likely due to the initial body impact leading to the head impact, not the head impact itself. The fourth concussion, noted by +, was two impact events for which only the initial body to ground kinematics were captured. These values are not considered to be associated with the concussive kick to the head, but are highlighted as a limitation of the event turnover time in this device. The other missed concussions are due to device failure, or a suspected false negative (the device collected data for the rest of the session without issue).

Sex	PLA (g)	ΔRV (rad/s)	Mouthguard	Notes
Male	81.6	18.5*	Wake Forest	NA
Male	74.8	36.2	Prevent Biometrics	NA
Female	54.6	9.7	Wake Forest	NA
Female	14.2^{+}	3.1^{+}	Wake Forest	Body to ground then kicked in head
Female	NA	NA	Prevent Biometrics	Device failure
Female	NA	NA	Prevent Biometrics	Device failure
Female	NA	NA	Prevent Biometrics	Suspected false negative
Female	NA	NA	Prevent Biometrics	Suspected false negative
Male	NA	NA	Prevent Biometrics	Suspected false negative
Female	NA	NA	Wake Forest	Suspected false negative
Female	NA	NA	Wake Forest	Device failure

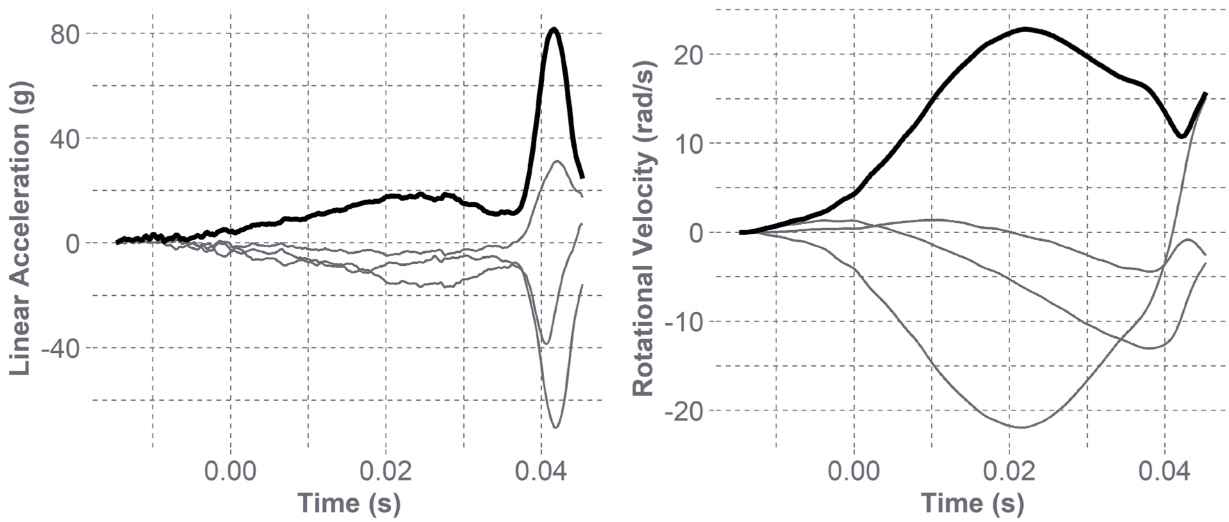

Figure 4.11. Linear acceleration and rotational velocity traces for a concussion on the men's team. It is likely that the rotational velocity measured is associated with the body impact that happened before the head to ground impact, and the change in rotational velocity associated with the head impact was not captured. Resultant trace is black and axis specific traces are gray.

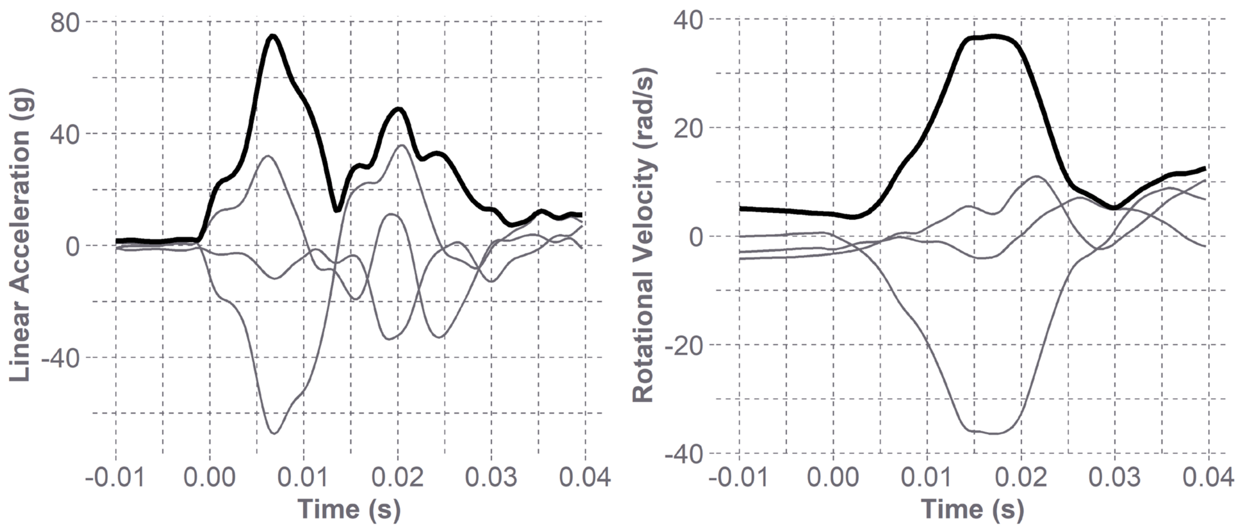

Figure 4.12. Linear acceleration and rotational velocity traces for a concussion on the men's team. The two peaks in linear acceleration likely correspond to two, nearly instantaneous, impact events, potentially a head then shoulder contacting the opponent. This could explain the atypical shape of the rotational velocity curve, with the second impact stopping the head rotation that was initiated with the first impact. Resultant trace is black and axis specific traces are gray.

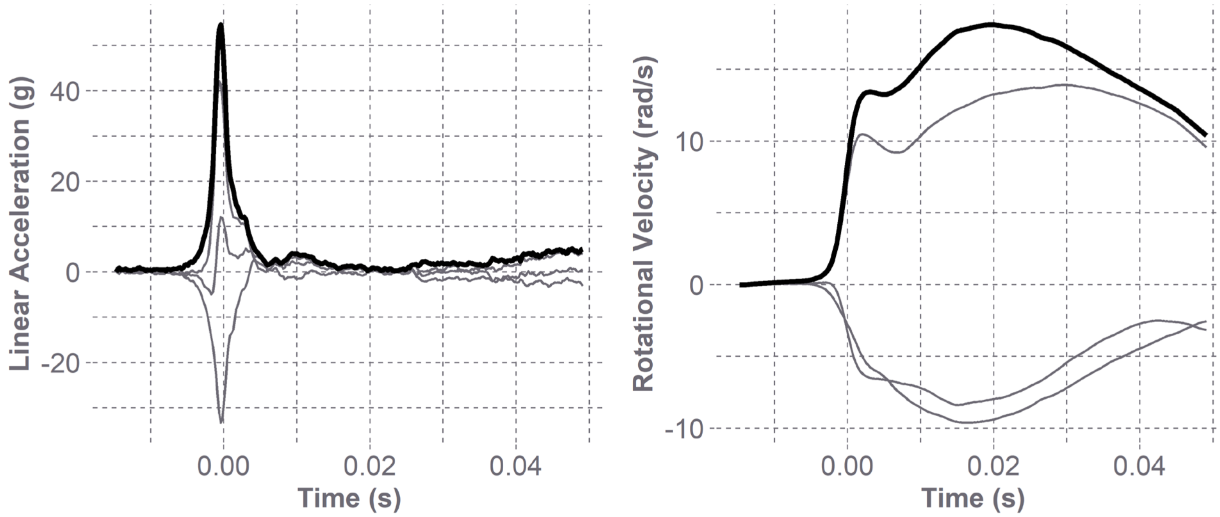

Figure 4.13. Linear acceleration and rotational velocity traces for a concussion on the women's team. These traces similar shapes to those seen in lab impacts. Resultant trace is black and axis specific traces are gray.

DISCUSSION

This study aimed to quantify head kinematics associated with head and body impacts in collegiate rugby players. Most of the kinematic data collected were low in magnitude, which is consistent with other studies.[18,23,26] The head impacts in this study had an average PLA of 20.9 g and a median PLA of 15.2 g. King *et al.* reported PLA values with a mean of 22 g and median of 16 g for a junior league.[18] Similarly, his mean linear acceleration for union players was 22.2 ± 16.2 g.[23] Reconstruction of 13 non-injurious head impacts in unhelmeted Australian football players resulted in a mean PLA of 59.0 g (SD 37.2 g) and ΔRV of 18.4 rad/s (SD 7.6 rad/s).[27] The median PLA for instrumented collegiate football players has been reported to be 17.5 g (average 22.3 g), with the majority of impacts less than 20 g.[26] Impact surface and location were not considered in this analysis and may affect reported kinematics. The data used in this analysis were aggregated for men's and women's 7s and 15s teams. Differentiating them from each other may yield different results.

Although there was evidence suggesting that the men's team sustained more impacts per session than the women did, there was not strong evidence suggesting a difference in PLA between sexes. Although it is often suggested that men play contact sports more aggressively than women, it has been shown that women are as willing to subject themselves to similar physical risks in sports.[28] The men's ΔRV values were slightly higher than the women's PRV values and slightly higher than subconcussive ΔRV values (5.5 rad/s) seen in football players.[29] We do not know if these values are clinically meaningful regarding acute or cumulative effects.

Direct head impacts were associated with slighter higher PLA and significantly higher ΔRVs than body-driven events. However, body impacts still resulted in notable head kinematic magnitudes. Accordingly, limiting exposure analyses to only confirmed head impact, and not considering all video-verified acceleration events, will underestimate the true exposure of athletes. Although contact phenomenon has shown importance in brain injury tolerance,[30-32] the clinical symptoms that accompany an inertially induced acceleration event can be as severe as those associated with a direct impact, and their effect on cumulative exposure should not be overlooked.[33] Impact type is a confounding variable that should be accounted for given differences in loading duration. We saw durations 8% greater for body impacts than for head impacts. It is important to note that the change in angular velocity is occurring over a different time interval than the duration reported, which hampers its interpretation compared to peak linear acceleration.

Five acceleration events were removed from the initial 741-event dataset based on perceived video-observed impact severity and mouthguard-measured magnitude discrepancies. One impact was sustained from a men's player and resulted in a PLA recording of over 290 g. The video showed he was in a ruck, and an opponent's arm struck his head, but 290 g is not consistent with the impact severity observed. The video was of a sufficient quality to identify this discrepancy. A similar scenario occurred for a female player whose mouthguard measured a 135 g acceleration when tackling her opponent without making any head contact. This magnitude is not consistent with any of the body impacts we have seen. The third event removed was a 127 g measurement for a ball-to-face impact from one of the women's players. After the ball bounced off her face, she caught it and continued to play. Previous studies have measured soccer ball headers to be around 20 g,[34] nearly a fifth of the magnitude measured. The fourth is a 187 g impact from the men's team who was lying on the ground in a ruck, and was hit with a forearm. He appeared unaffected by the impact. The fifth and final event removed had a magnitude of 158 g and occurred when a women tackled an opponent to the ground and braced on her head on the ground after the impact. She continued to play without any sign of significant injury, which would be expected with a PLA as high as this.

Good coupling to the skull is an advantage of using instrumented mouthguards to measure head impacts in athletes. However, this approach is reliant on athletes wearing the mouthguards properly. If a mouthguard is not set correctly on the teeth during an impact, the measured kinematics will be erroneous, potentially explaining the inflated kinematics in the three events removed from the dataset. We removed 47 impacts from the duration analysis given their atypical head acceleration traces. Poor coupling to the teeth is one explanation for being suspicious of these events' data quality.

The three concussive kinematic values in this study are similar to the concussion magnitudes found in two union rugby players which were 94.8 g and 5319.8 rad/s^2 and 54.9 g and 9935.2 rad/s^2.[23] The concussion magnitudes measured in the current study are also within the range of observed in football players.[29] There is very little data on concussion in rugby and as we collect more, we expect the kinematics resulting in concussion in unhelmeted rugby players to be less than that of helmeted football players, partly due to different frequency content and contact phenomena.

There was another concussion on the women's team resulting from being kicked in the head after diving to the ground. Her mouthguard measured impact kinematics of 14.2 g and 6 rad/s. For this case, there were likely two acceleration events: the athlete's body impacting the ground; and the athlete's head being kicked. The Wake Forest devices require 300 ms between recording events. The kinematic values attributed to this concussion are likely the result of the ground impact. The kick occurred approximately 167 ms after the initial impact, which is during the time the mouthguard was preparing for the next impact. In comparison, the Prevent mouthguard only has a 25 ms delay between impacts. Understanding this turnover time between impacts is another critical component of properly verifying on-field kinematic data. Rugby players often undergo body-then-head acceleration events during tackles. This can complicate video validation if it is difficult to know if a body impact before a head impact is enough to trigger data acquisition and if events are outside the device turnover time. King *et al.* also noted complications with video validation in rugby, as athlete head position is difficult to distinguish in some tackles, rucks, mauls and scrums.[23] The double-impact scenario was something evident when inspecting the traces in our dataset. There were many events observed that had secondary peaks within the data-collection window, sometimes having higher values than the initial peak.

An obvious concern is the seven concussions for which data were not recorded. Four of these cases were suspected false negative events (three Prevent Biometrics, one Wake Forest) and three were device issues on the day of injury. Missing data from these concussions raises awareness for other potential false negatives that the mouthguards may be missing, thus underestimating impact count estimates in exposure studies. There were 17 instances of the Prevent mouthguard not functioning, and four instances of the Wake Forest mouthguard not functioning. Sometimes the issue was Bluetooth connectivity, either before or after the game, which complicated setting the devices for acquisition and downloading data. Wake Forest's devices also had intermittent gyroscope failures and some of the internal clocks did not sync, resulting in data that were erroneous or unusable. The battery life on the Wake Forest devices was shorter and there were issues with the charging cases not working, causing several mouthguards to die mid-session. As the seasons progressed, both companies made durability and usability improvements to reduce data loss.

Another limitation of this dataset is the inability to summarise the data on a per-player basis. This is because not every player in the study sustained enough impacts for an individualized analysis. In summarizing the overall data, those athletes who experienced more impacts exert more weight in the analysis than their counterparts with fewer impacts. Continued data collection will allow for the characterization of head kinematics on a per-player basis, which would be critically important for defining exposure in rugby.

Potential systematic differences between the mouthguards were explored in the dataset presented. Impacts measured by Wake Forest devices had a median PLA of 13.9 g [IQR: 11.2 to 21.1 g] and a median ΔRV of 5.6 rad/s [IQR: 3.5 to 9.0 rad/s]. Impacts measured by Prevent Biometrics devices had a median PLA of 15.2 g [IQR: 11.6 to 23.9 g] and a median ΔRV of 7.5 rad/s [IQR: 4.9 to 10.5 rad/s]. Attempting to stratify the dataset to reduce confounding factors (like sex, session type, and individual players' aggression) decreases the sample size and resolution for comparison. The slight differences seen between devices are more likely due to variance as a result of confounding factors than as a result of systematic differences between the sensors.

On-field use of the in-mouth sensors proved challenging and interpretation of data nuanced, especially with the missed concussions. Instrumented mouthguards offer great potential to collect on-field kinematic data for women and unhelmeted athletes, but much consideration needs to be taken when collecting and analyzing this data. Carefully monitoring each device and its functionality is imperative before and after each session. Video validation is critical because each device recorded many false-positive events.

On-field head kinematic data were collected for male and female collegiate rugby players using instrumented mouthguards. More head impacts per session than body impacts were sustained, and men sustained more impacts per session than the women did. Head impacts had greater PLA values than body impacts. Women sustained head impacts similar in PLA, lower in ΔRV, and shorter in duration to their male counterparts. Analyzing and characterizing the axis-specific traces of each impact type provides more insight into different kinematic signatures of acceleration events. This study suggests that users of in-mouth sensors should carefully consider the technical specifications of sensors and further highlights that video verification of acceleration events is required for meaningful dissemination of data.

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CHAPTER 5: CONCUSSION RELATED SYMPTOM PRESENTATION IN MEN'S AND WOMEN'S RUGBY

ABSTRACT

Concussive injuries are prevalent in many sports, but risk is higher in full-contact, team sports such as rugby. Between 13% and 17% of rugby players sustain a concussion each season. The style of play and lack of effective protective equipment put athletes at a higher risk for concussive brain injuries that can result in neurological impairments. Diagnosis of concussion includes assessment of athlete reported symptoms, but the rates of underreporting remain high due to players' attempt to shorten their return-to-play time. The objective of this study was to investigate in-season presentation of symptoms characteristic of concussion and their relationship to head impacts sustained on the field. A matched cohort of male and female rugby players were studied over a six-week period in the middle of a season. Head impacts from games and practices were tracked through video identification and a Graded Symptom Checklist was administered weekly to each athlete. The survey included 27 symptoms that were graded on a scale of 0-6, with 6 being the most severe. The aggregate score for each week is the Symptom Severity Score (SSS). On average, the men and women reported 1.8 symptoms per week, with a total SSS of 2.6. Approximately 25% of athletes reported an SSS greater than or equal to 10 (23.1% of men and 26.3% of women). Although SSS were elevated, they are much lower than those typically associated with concussions. Headaches were the most common symptom reported by the women, while fatigue was the most commonly reported by the men. More than 63% of subjects that reported elevated symptom scores experienced at least one head impact in the week leading up to the symptom survey. This study demonstrated that symptoms associated with concussion could be observed after head impact in the absence of diagnosed concussion in-season.

Keywords: Head Impact, Biomechanics, Underreporting, Subconcussive

INTRODUCTION

Concussions are brain injuries that are induced by biomechanical forces resulting from impact to the head.[1] They affect the brain through a complex pathophysiological process and characteristically result in the onset of acute neurological impairments.[1] Sports-related concussions can be diagnosed with an assessment of athlete-reported symptoms, physical signs, cognitive or neurobehavioral impairment, or sleep disturbances.[1] However, detection and diagnosis are complicated by a player's tendency to underreport or hide symptoms in order to shorten return-to-play time.[2] This is a growing concern, as the consequences for subsequent impacts while still sustaining symptoms from a previous concussion can be catastrophic.[3] Underreporting has also been attributed to players' lack of knowledge of potential consequences of head injuries and their inability to recognize signs and symptoms of concussions.[4] Some sports-related concussions present symptoms immediately and can be attributed to a single impact. Others, however, result in a delayed symptom presentation and thus make identifying a single impact more challenging.[5-7] It is not yet known how cumulative head impacts affect the pathophysiology of the brain or the clinical manifestation of injury, but a player's concussion history has been shown to be related to a slower neurological recovery.[8]

Concussion is a concern in many sports, but risk is higher in full-contact, team sports.[9] Rugby is the most popular full-contact, team sport in the world, and has a correspondingly high concussion rate.[9] Although style of play varies, it has been reported that between 13% and 17% of rugby players sustain a concussion each season[10] This is due to the physicality of the sport, usually played without protective equipment.[11] Some athletes choose to wear mouthguards and soft-shell headgear, but neither have been proven to reduce the risk of concussion.[12] Effective protective equipment would reduce the linear and rotational accelerations that the head experiences during impact, thus reducing concussion risk.[13,14] The objective of this study was to monitor in-season presentation of concussion symptoms in the absence of diagnosed concussion and relate it to head impacts experienced on-field in collegiate rugby players.

METHODS

The study was approved by and conducted according to the ethical guidelines of the Virginia Tech Institutional Review Board (IRB). During the fall of 2018, athletes were recruited from the Virginia Tech club women's and men's rugby teams. Written informed consent was obtained from each participant after explaining the purpose, associated benefits, and risks of the study. All participants were identified with a unique study ID to maintain confidentiality of study measures. The athletes were studied over the course of six weeks, in the middle of their fall season. Video was recorded for each game and practice for the purpose of visual identification of head impacts. A head impact was recorded if a player's head impacted another player, the ground, or another object on the field. Two research personnel identified each head impact in the videos, and their reports were compared and finalized to quantify head impact frequency.

Each week, subjects were emailed a survey that included a Graded Symptom Checklist (GSC), which included 27 symptoms that were graded on a scale of 0-6, with 0 being no presentation of that symptom, and 6 being the most severe presentation (Table 5.1).[15] The total symptom frequency score (maximum of 27) and the aggregate score, computed as the Symptom Severity Score (SSS) (maximum of 162), were quantified for each week. Likert-style symptom score checklists have been validated as a simple and effective method of self-reported symptom monitoring, and have been shown to differentiate between concussed and non-concussed athletes with a sensitivity of 64% to 89% and specificity of 91%-100%.[16-20]

Only athletes that completed all six weeks of surveys were included in the analysis. This resulted in a final study cohort of 19 female and 26 male athletes.

Table 5.1. List of 27 concussion symptoms in the Graded Symptom Checklist that subjects grade on a scale of 0 (None) to 6 (Most Severe). Total scores are determined for the total symptom presentation (maximum of 27) and total symptom severity score (maximum of 162).

Blurred Vision	Unusually Emotional	Poor Concentration
Dizziness	Irritability	Ringing in the Ears
Drowsiness	Loss of Consciousness	Sadness
Sleeping More than Usual	Loss of Orientation	Seeing Stars
Easily Distracted	Memory Problems	Sensitivity to Light
Fatigue	Nauseous	Sensitivity to Noise
Feeling "In a Fog"	Nervousness	Sleep Disturbances
Feeling "Slowed Down"	Personality Changes	Vacant Stares/Glassy Eyes
Headache	Poor Balance/ Coordination	Vomiting

An athlete's SSS for each week was compared to the number of head impacts they sustained in the week leading up to the survey. For athletes that reported an elevated SSS, greater than or equal to ten, their distribution of symptoms and severities and head impact histories were characterized.

RESULTS

Over the six-week span, there were 496 video-identified head impacts. The men's team accounted for 356 of those, while the women's team sustained the other 140. The women's team sustained 132 impacts from three games in the six-week period with head impacts occurring at a rate of 3.43 ± 2.5 impacts/player/game. Their games were played in weeks four, eight, and nine. During practices, the impact rate was 1.0 ± 0 impacts/player/practice. The other eight were sustained during the two practices that head impacts were observed. The men's team played in six games in the six weeks, and sustained 339 head impacts at a rate of 3.32 ± 1.59 impacts/player/game. The impact rate for practices was 1.45 ± 0.69 impacts/player/practice.

The symptom checklist data was summarized each week for each athlete. Overall, the average number of symptoms reported per player each week was 1.8, which was associated with an average SSS of 2.6. The women reported 1.9 symptoms on average, with an SSS of 2.9. The men reported 1.8 symptoms on average, with an SSS of 2.3. There was no pattern of SSS over the season, although SSS was slightly higher in the weeks that the women's team had games (4, 8, and 9) (Figure 5.1). The most commonly reported symptom for the women was headache, accounting for 12.0% of the symptoms reported. The most commonly reported symptom for the men was fatigue, accounting for 13.6% of the symptoms reported. There was no reported loss of consciousness, loss of orientation, or vomiting.

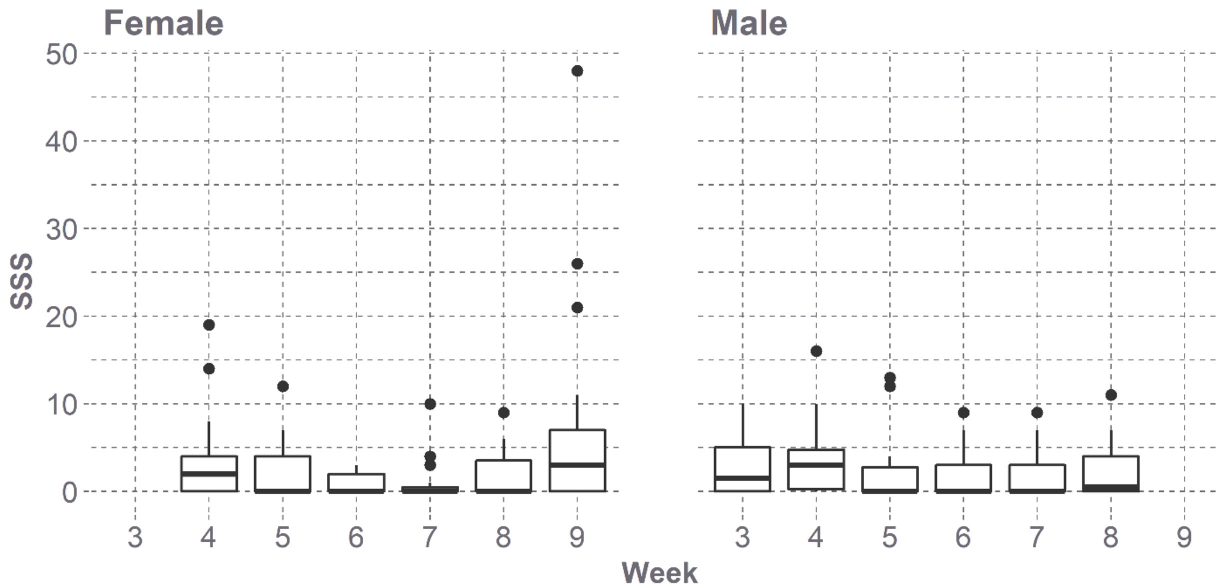

Figure 5.1. Box plots of Symptom Severity Score (SSS) for the female and male athletes each over the course of six weeks in-season. Data collection started 4 weeks into the women's season and 3 weeks in to the men's season. Although some athletes reported a notably high SSS, the average values for each week are under 5, with the exception of week 9 for the women's team.

Fifteen surveys from 11 subjects (6 male and 5 female) resulted in an SSS greater than or equal to 10 over the six-week time period. Their SSS was paired to the total number of head impacts they sustained in the week leading up to the survey (Table 5.2). Of this subset of subjects, 63.6% had at least one head impact associated with an elevated SSS. The symptom profiles varied between players, but a common trend within the athletes with an SSS greater than or equal to 10 was a low severity score for several symptoms. On average, these athletes that did not experience any head impacts the week prior reported 8.9 symptoms with a severity of 1.8. That athletes that did experience a head impact the week prior reported 9.4 symptoms with a severity of 1.7.

Table 5.2. Summary table for athletes that reported elevated symptoms (SSS ≥ 10) and their corresponding head impacts for the week leading up to the symptom survey. An elevated SSS is commonly experienced by subjects during the season, some of which are associated with a history of head impacts, and others that are not.

Sex	Study ID	Week	SSS	Total Impacts
Male	VTM003	5	13	0
	VTM004	3	10	4
	VTM004	4	10	1
	VTM026	4	16	7
	VTM027	3	10	10
	VTM035	5	12	3
	VTM036	8	11	2
Female	VTW003	9	26	0
	VTW004	9	48	7
	VTW005	4	14	8
	VTW015	4	19	0
	VTW015	5	12	0
	VTW015	9	21	0
	VTW023	7	10	0
	VTW023	9	11	0

DISCUSSION

The objective of this study was to monitor the symptoms associated with concussion in rugby players in the absence of diagnosed concussion and then see if there was an association with the presentation of symptoms and exposure to head impact. SSS and number of head impacts varied across the two teams, as some players sustained many head impacts without presentation of symptoms, and some players reported high SSS without sustaining many or any video-identified head impacts. The men's team experienced more head impacts than the women's team, but a lower rate per player per game. This could be due to style of play and the semester schedule; the men's team had twice as many games than the women's team.

There was a large disparity between the number of head impacts sustained during games compared to those sustained during practices. Neither team had many practices that included contact, and those that did, typically involved drills that focused on tackling technique, and thus the subjects were less likely to hit with their heads. This accounts for the small percentage of head impacts occurring at practice, while the other 95.0% of impacts occurred during games.

Overall, the average SSS was 2.6, with 1.8 symptoms reported per week. An SSS around five has been reported as a baseline value for collegiate football players [21]. Many symptoms included on the checklist can be caused for a number of reasons unrelated to concussion, and therefore we would not expect a player to have an SSS value of zero [16]. Approximately 25% of athletes reported an SSS greater than or equal to 10 (23.1% of men and 26.3% of women). Although SSS scores were elevated, they are much lower than those typically associated with concussions. An SSS of 21 has been shown to differentiate a concussed athlete from a non-concussed athlete [18,19]. Of the 11 athletes who reported elevated an SSS, 63.6% had at least one head impact in the week leading up to the symptom survey. They report a similar number and severity of symptoms than those that did not have head impacts associated with an elevated SSS. Elevated SSS with a lack of head impacts could be attributed to the symptoms reported by the athletes; factors like hydration, amount of sleep, and stress could be the cause. In one instance, a subject self-reported a concussion from an impact in a game but did not report elevated symptoms until the following week. Delayed onset of symptoms and neuropsychological deficits have been shown in high school and collegiate athletes [22].

The results of this study could be affected by the symptoms surveys and the tendency of players to underreport their symptoms. Due to the fact that the study did not start before the season for either team, there is not a true baseline symptom score for each individual for comparison of later time points. Although we chose to email a survey link personalized email to each athlete to maintain confidentiality and attempt to decrease underreporting, there is still the chance athletes fail to report an accurate frequency of severity of symptom. Another limitation is the use of researchers to video identify head impacts. In some instances, the video angle, obstructions in the field of view, and resolution of the camera made identifying head impacts challenging. However, the use of the two independent video observers aimed to minimize human error.

The purpose of this study was to monitor in-season presentation of concussion symptoms in the absence of diagnosed concussion and relate it to head impacts experienced on-field in collegiate rugby players. These data demonstrate that the symptoms of concussion are commonly experienced by rugby players during a season, some of which are associated with a history of head impact, and others are not. Including self-reported symptom checklists in-season provides a simple and effective monitoring system will help reduce underreported injuries.

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CHAPTER 6: IN-SEASON CONCUSSION SYMPTOM REPORTING IN MALE AND FEMALE COLLEGIATE RUGBY

ABSTRACT

Repetitive subconcussive head impacts put athletes at risk for neuropsychological changes and cognitive impairment. The clinical symptoms associated with these impacts may allude to potential undiagnosed concussions. Despite differences in symptom presentation and outcome of concussion, no return-to-play protocol takes sex into account. The purpose of this study was to monitor a cohort of contact-sport athletes and compare the frequency and severity of in-season concussion-like symptom reporting between sexes. Graded symptom checklists from 144 female and 107 male athlete-seasons were administered weekly to quantify the effect of subconcussive impacts on frequency and severity of in-season symptom reporting. In-season, mean SSS ($p = 0.026$, mean difference of 1.8), mean number of symptoms ($p = 0.044$, mean difference of 0.9), max SSS ($p < 0.001$, mean difference of 19.2), and max number of symptoms ($p < 0.001$, mean difference of 6.8) were higher in the females. The females' survey results showed differences between elevated and concussed SSS ($p < 0.005$, mean difference of 28.1) and number of symptoms reported ($p = 0.001$, mean difference of 6.6). The males did not have a difference in SSS ($p = 0.97$, mean difference of 1.12) nor in number of symptoms ($p = 0.35$, mean difference of 1.96). Rugby players report concussion-like symptoms in the absence of a diagnosed concussion in-season. Female athletes reported elevated symptom frequencies with greater severities than the males, but both sexes reported considerable levels throughout the season. These findings suggest that the presence of symptoms in-season could indicate subconcussive tissue changes or undiagnosed injuries.

Keywords: Concussion, Subconcussion, Symptoms, Sex-specific

INTRODUCTION

Although most people will fully recover from a concussion, their signs and symptoms may last minutes to months after their injury.[1] Long-term concussion complications can affect memory, cognition, learning, language, and emotions.[1] Research suggests that subconcussive impacts can be similarly harmful. These impacts below the diagnostic threshold for a concussion have been of interest due to their potential deleterious effect on neurological function.[2,3] Results are mixed, with some studies identifying neuropsychological changes,[4-7] while others do not.[7,8] Repetitive impact exposure has resulted in acute cognitive changes in some studies[4-6,9-13] but no cognitive impairment in others.[14-16] Functional neuroimaging has been used to understand brain structure changes when subjected to repetitive subconcussive impacts with more consistent results. Researchers have identified lower fractional anisotropy in a brain region associated with memory,[17,18] neuro-metabolic alterations in brain regions associated with cognition[19] specifically in female athletes,[20] and decreased white matter integrity in the absence of symptom presentation.[21]

Concussion diagnosis has taken a multi-pronged approach to include a consideration of clinical history, acute sideline evaluation, a symptom assessment, detailed neurologic evalulation, and neurpsychological testing.[22] Diagnosis is complicated by athletes' tendency to hide or underreport symptoms to decrease return-to-play time.[23] Some studies have indicated that 30-50% of concussions go unreported.[23,24] Athletes who do not immediately report concussion symptoms and continue to participate in activities may be at higher risk for longer recoveries and sustain post-concussion symptoms longer.[25]

Clinical symptoms associated with concussion begin at some level of repetitive subconcussive head impact exposure, and likely those changes will worsen with increased impact exposure load. Without routine monitoring in-season, the clinical effect of these repetitive head impacts and their similarity to diagnosed concussions are unknown. A symptom inventory is subjective but helps clinicians understand the athlete's self-assessment of the presence and severity of symptoms. They are designed to assess changes over short time periods, making them useful tools for repeated tests.[22] In combination with neuropsychological assessments, symptom resolution is generally the guideline for return-to-play for the athlete. Regular monitoring of in-season symptoms would help researchers understand the presentation of subconcussive impacts that are below typical diagnostic thresholds.

This study's objective was to monitor and compare in-season concussion symptom reporting between sexes. We studied a cohort of collegiate rugby players because the females and males play by the same rules and routinely experience head impacts.

We hypothesize that rugby athletes routinely experience mild concussion-like symptoms throughout a season and that symptom presentation is sex-specific. Variation in presentation and outcome of concussion by sex have been previously established.[26-31] Neuroprotectants, such as estrogen and progesterone in females, may contribute to the changes in tolerance between sexes.[30,32,33] Further, some studies have shown sex-specific differences in axon structure can lead to more severe pathophysiology in dynamic stretch-injury in females.[34] Beyond physiologic explanations, systematic differences in symptom reporting have been suggested, as females report more concussions and greater severities than males.[26,35,36] Previous studies have noted females report higher symptoms at baseline,[22,37] as well as post-injury.[28,37] Females have also exhibited a greater cognitive change post-concussion and more variation in cognitive assessment performance than their male counterparts.[12] Despite these differences, no return-to-play protocol takes sex into account.[28]

METHODS

Subjects

In the spring of 2018 through the spring of 2020, men's and women's club rugby teams were recruited to participate in this study. Written informed consent was obtained from each participant in accordance with the ethical guidelines of the Institutional Review Board (IRB). 58 females and 57 males participated in over the four seasons, with many participating in multiple seasons. A total of 144 female-seasons (age: 20.5 ± 1.3 years, height: 1.66 ± 0.08 m, weight: 73.3 ± 17.1 kg) and 107 male-seasons (age: 20.6 ± 1.3 years, height: 1.80 ± 0.08 m, weight: 89.4 ± 15.6 kg) participated.

Symptom Checklists

Before starting the season and at the beginning of each week in-season, athletes were emailed a survey that included a Graded Symptom Checklist (GSC) and an open-ended question. The GSC consisted of 27 symptoms that athletes graded on a scale of 0-6, with 0 meaning a symptom was not present and 6 meaning the most severe presentation (Table 6.1).[38] Likert-style symptom score checklists have been validated as a simple and effective self-reporting method that exhibit good sensitivity and specificity.[39-43] The total symptom frequency score (maximum of 27) and the aggregate score, computed as the Symptom Severity Score (SSS) (maximum of 162), were quantified by athlete per week. The open-ended question asked athletes to report anything notable from the previous week that could explain their symptoms (such as a hard head impact, sickness, stress). Surveys were validated with Fall 2019 Sports Concussion Assessment Tool 5 (SCAT5) baseline data administered through Club Sports.[44] The SSS and number of symptoms reported were paired for 31 athlete-seasons and correlated with Pearson's coefficient (r).

Table 6.1. List of 27 concussion symptoms in the Graded Symptom Checklist that subjects grade on a scale of 0 (none) to 6 (most severe). Total scores are determined for the numbers of symptoms reported (maximum of 27) and total SSS (maximum of 162).

Blurred Vision	Loss of Consciousness	Sadness
Dizziness	Loss of Orientation	Seeing Stars
Drowsiness	Memory Problems	Sensitivity to Light
Easily Distracted	Nauseous	Sensitivity to Noise
Fatigue	Nervousness	Sleep Disturbances
Feeling "In a Fog"	Personality Changes	Sleeping More than Usual
Feeling "Slowed Down"	Poor Balance/Coordination	Unusually Emotional
Headache	Poor Concentration	Vacant Stares/Glassy Eyes
Irritability	Ringing in the Ears	Vomiting

Statistical Analysis

Any survey that mentioned a reason other than head impact during play for their symptom presentation (ex. illness, car accident, etc.) was excluded from the analysis. Surveys were grouped by athlete-seasons and summarized to identify any symptoms presentations (SSS > 0) during baseline and in-season. A McNemar's Chi-squared test was used to determine if there was a relationship between symptom presentation at the two time points: baseline and in-season. Data were then summarized at the athlete level (combining multiple seasons worth of data for some athletes). The mean and maximum number of symptoms and SSS were quantified for baseline and in-season for each athlete. The median and interquartile range (IQR) were computed for each time point and sex. A paired Wilcoxon signed-rank test was used to determine if athletes reported more symptoms in-season compared to baseline within sex. A paired t-test was used to estimate the effect size and precision. A Wilcoxon rank-sum test was used to determine if there were differences in reporting between sexes at the two time points. A Welch two-sample t-test was used to estimate the effect size and precision.

We chose the maximum baseline SSS for each sex to represent a threshold for "elevated" symptom presentation in-season. The max SSS at baseline for both sexes was 11. Proportions were calculated for the number of athlete-seasons that reported elevated symptoms. We also quantified the proportion of those athlete-seasons that reported recurring elevated symptoms and how many weeks they were reported. We defined recurring elevated symptoms as when an athlete reported more than one week of elevated symptom presentation within a season, not necessarily in consecutive weeks. A Chi-square test was used to compare the proportions of elevated athlete-seasons per sex. A Fisher's exact test was used to compare the proportions of recurrent elevated athlete-seasons per sex due to small sample sizes.

The elevated surveys' SSS median and IQR were analyzed with Wilcox tests and mean differences to estimate the effect size to compare elevated SSS by sex. The same was done for the median and IQR of the number of symptoms reported. The mean and maximum value of each symptom was computed per sex. We computed the proportion of surveys that reported a given symptom with moderate severity and compared the differences in proportions between sexes. We defined an individual symptom severity score greater than two (> 2) as moderate severity.

We wanted to see if the in-season symptoms being reported were consistent, albeit less severe, than the symptom patterns associated with diagnosed concussion. Symptoms were categorized into six subtypes to explore patterns of presentation: Cognitive (easily distracted, feeling in a fog, feeling slowed down, memory problems, poor concentration), Oculomotor (blurred vision, seeing stars, sensitivity to light, vacant stares/glassy eyes), Headache/Migraine (headache, nauseous, sensitivity to noise, sensitivity to light, vomiting), Vestibular (dizziness, feeling in a fog, loss of orientation, nauseous, poor balance/coordination, ringing in the ears, vomiting), Anxiety/Mood (fatigue, unusually emotional, irritability, nervousness, personality changes, sadness), Sleep Disturbances (drowsiness, sleeping more than usual, fatigue, sleep disturbances).[45] Subtype score was computed by counting the number of symptoms in the subtype that had a severity score greater than two then dividing by the number of symptoms within the subtype. This step was done to normalize the scores because each subtype's number of symptoms was not the same. The score represented the proportion of symptom frequency reported with a moderate severity. The elevated surveys were binned into three categories based on subtype score: none (no subtype with symptoms of moderate severity), one (only one subtype with symptoms of moderate severity), and more than one (multiple subtypes with symptoms of moderate severity).

We wanted to identify similarities in symptom presentation between unreported subconcussion levels and diagnosed concussion levels. A Wilcoxon rank-sum test was used to compare reporting between clinically diagnosed athletes and those that reported elelvated symptoms. A Welch two-sample t-test was used to estimate the effect size and precision. The elevated surveys were from athlete-seasons who did not sustain a concussion so that post-concussion surveys were not included.

RESULTS

During the 144 female-seasons, 1440 of 1751 surveys were returned (82%). During the 107 male-seasons, 793 of 938 surveys were returned (85%). 123 female and 66 male surveys indicated confounding causes of symptoms and were excluded from the analysis. There were 1317 surveys from females and 727 surveys from males included in the analysis. There was no baseline data for Spring 2018 or Fall 2018 as the IRB was not approved before the season started, only Spring 2019 – Spring 2020. Fall 2019 baseline SSS and number of symptoms are significantly correlated with SCAT5 results (SSS: $r = 0.70$, $p < 0.001$; number of symptoms: $r = 0.58$, $p < 0.001$). Of study participants, 10 females and 4 males were diagnosed with concussions.

Overall Presence of Symptoms

When comparing athlete-season symptom presentation between the two time points, McNemar's Chi-squared test suggested a relationship between symptom presentation (SSS > 0) at baseline and in-season ($p < 0.001$). If an athlete reported symptoms at baseline, they were more likely to report symptoms in-season. Table 6.2 and Figure 6.1 show the distribution of symptom presentation between time points for each sex.

Table 6.2. Summary of symptom presentation reported from paired baseline and in-season time points for male and female athletes. Males reported a higher mean SSS at baseline, but females reported higher SSS and number of symptoms in-season. The median scores of 0s suggest many surveys had reports of low symptom presentation. The mean and max SSS and number of symptoms were calculated for each athlete and then the median and IQR of the groups were summarized.

Sex	Time Point	Athlete Count	SSS Median of the Mean [IQR]	SSS Median of the Max	# Symptoms Median [IQR]	# Symptoms Median of the Max
Females	Baseline	36	0 [0.0, 3.2]	0	0 [0.0, 2.0]	0
	In-Season	36	3 [0.8, 5.2]	19	1.9 [0.7, 3.7]	12
Males	Baseline	35	2 [0.5, 3.5]	3	1 [0.3, 2.0]	2
	In-Season	35	1.5 [0.5, 3.2]	7	1.1 [0.4, 2.3]	5

The female athletes reported higher mean SSS ($p = 0.001$, mean difference of 2.1 [95% CI: 0.9, 3.3]), number of symptoms ($p = 0.003$, mean difference of 1.1 [95% CI: 0.3, 1.9]), higher max SSS ($p < 0.001$, mean difference of 24.7 [95% CI: 15.4, 33.9]), and higher max number of symptoms ($p < 0.001$, mean difference of 9.7 [95% CI: 7.1, 12.3]) in-season compared to their baseline time point. The male athletes reported similar mean in-season SSS ($p = 0.645$, mean difference of 0.02 [95% CI: -0.7, 0.7]), number of symptoms ($p = 0.6671$, mean difference of 0.041 [95% CI: -0.4, 0.5]), higher max SSS ($p < 0.001$, mean difference of 5.2 [95% CI: 3.2, 7.3]), and higher max number of symptoms ($p < 0.001$, mean difference of 2.7 [95% CI: 1.7, 3.6]) compared to their baseline time point.

At baseline, the mean SSS for females was not higher than for the males ($p = 0.151$, mean difference of 0.3 [95% CI: -1.5, 0.9]), nor was the mean number of symptoms reported per athlete ($p = 0.102$, mean difference of 0.2 [95% CI: -1.1, 0.7]), max SSS ($p = 0.204$, mean difference of 0.2 [95% CI: -1.7, 1.2]), nor max number of symptoms reported ($p = 0.163$, mean difference of 0.3 [95% CI: -1.3, 0.8]). However, in-season, mean SSS ($p = 0.026$, mean difference of 1.8 [95% CI: 0.3, 3.2]), mean number of symptoms reported ($p = 0.044$, mean difference of 0.9 [95% CI: 0.02, 1.86]), max SSS ($p < 0.001$, mean difference of 19.2 [95% CI: 9.7, 28.7]), and max number of symptoms reported ($p < 0.001$, mean difference of 6.8 [95% CI: 4.0, 9.5]) were higher in the females.

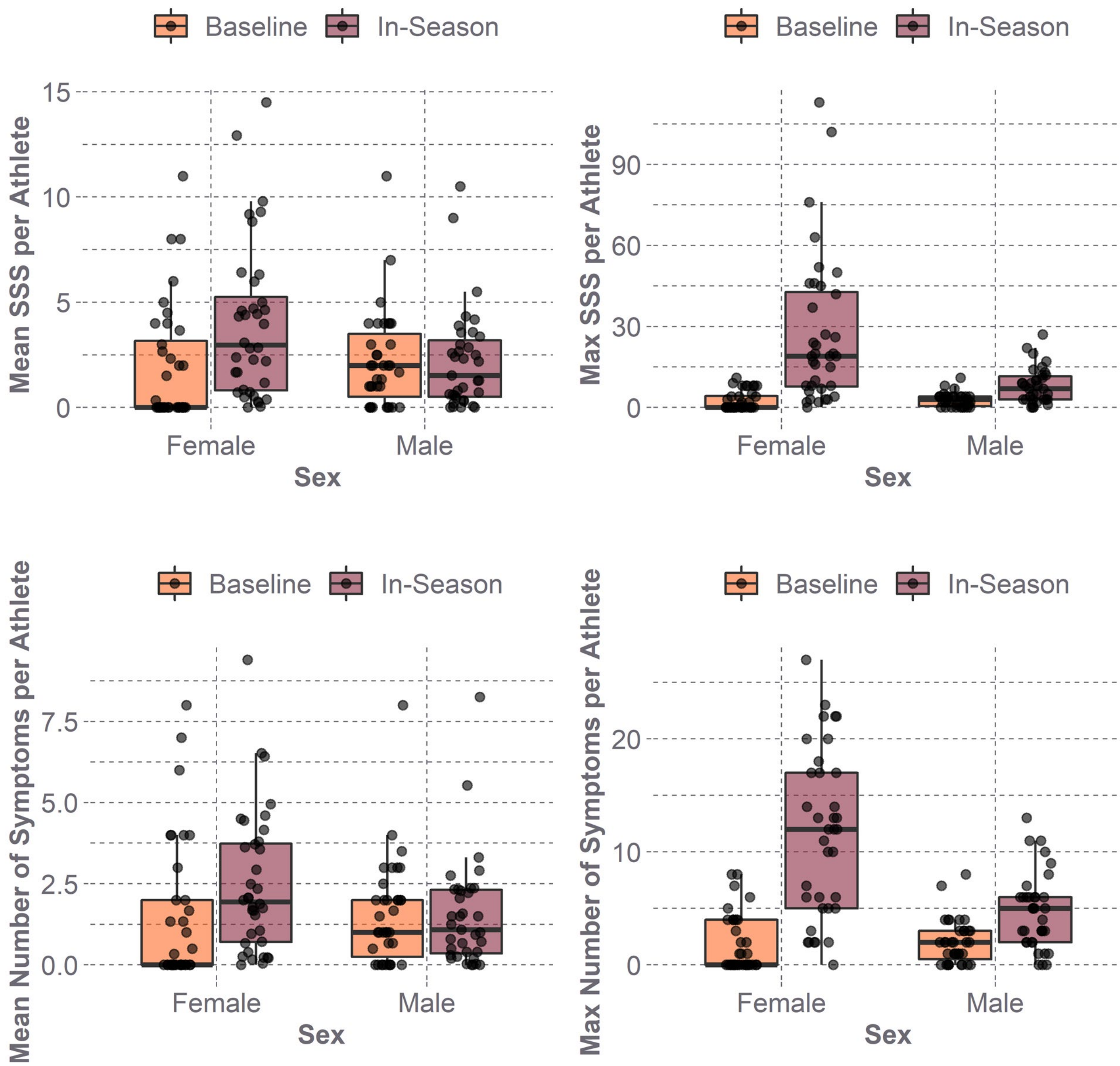

Figure 6.1. Boxplots and points for mean and max SSS and number of symptoms for males and females for paired baseline and in-season surveys. The median of the mean and max SSS and number of symptoms were higher in-season than those at baseline for the females, but were much more similar in magnitude for the males. These data are summarized by athlete per time point.

Elevated Symptom Presence

59 female athletes (41.5%) and 15 male athletes (14.7%) reported elevated symptoms (SSS >= 11) at some point during the season. The proportion of females that reported elevated symptoms was higher than that of males (Chi-square test for proportions, $p < 0.001$, 95% CI: 0.15, 0.38). 30 female athletes (50.8%) and 4 male athletes (26.7%) reported recurrent elevated symptoms. Fisher's exact test was used to determine if

the reporting of recurrent elevated symptoms was related to sex ($p = 0.146$, 95% CI: 0.074, 1.38). For those that reported recurrent symptoms, we compared the number of times an athlete reported elevated symptoms between sexes. On average, 3.1 ± 1.8 surveys completed by females reported elevated symptoms and 3.3 ± 1.9 surveys completed by males reported elevated symptoms. This corresponded to 29.5% ± 14.3 of those females' surveys and 47.8% ± 18.5 of those males' surveys.

The severity of elevated symptoms differed by sex. Table 6.3 summarizes elevated surveys per sex, and Figure 6.2 shows that the central tendencies were similar, but deviate at higher end of the IQR. The difference between the median SSS is 2, compared to the difference at the 75th percentile, where the difference is 9. SSS showed evidence of a difference between sexes, with a mean difference of 8.9 (95% CI: 5.0, 12.8, $p = 0.044$). The number of symptoms reported showed more evidence of difference between sexes, with a mean difference of 3.6 (95% CI: 2.1, 5.1, $p = 0.0012$).

Table 6.3. Number of in-season surveys collected in total and those that reported elevated SSS per sex. A higher proportion of female surveys reported elevated symptoms. The females' surveys also had a higher median SSS and number of symptoms reported.

Sex	In-Season	Elevated (SSS ≥ 11)	SSS Median [IQR]	# Symptoms Median [IQR]
Females	1251	121 (9.67%)	17 [13, 26]	11 [9, 15]
Males	674	24 (3.56%)	15 [12.8, 17.3]	9 [6.8, 11]

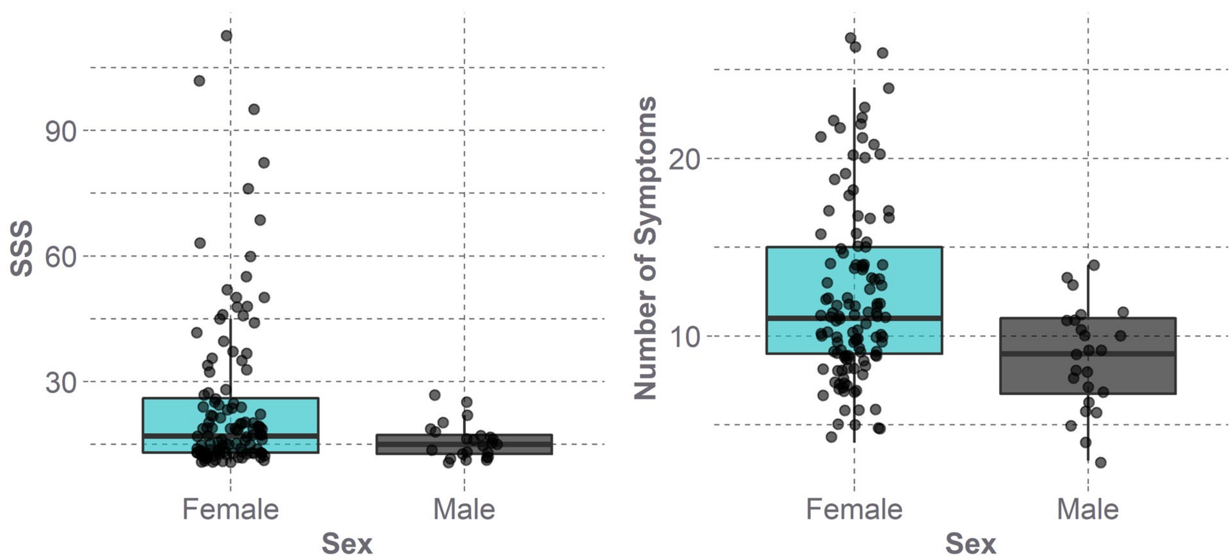

Figure 6.2. Boxplots with data points for SSS and number of symptoms for elevated surveys. Outliers from the box plots were not pictured so that those data points were not plotted twice. Although the central tendencies do not seem to vary greatly between females and males, the upper end of both SSS and the number of symptoms reported is higher in females, highlighting a difference in distribution.

The males were more evenly distributed across the scores while more females tended to report on the higher end, skewing the distribution to the right.

The highest reported mean severity for a symptom for females was headache, followed by fatigue and drowsiness. The highest mean symptom score for the males was drowsiness, followed by fatigue and feeling in a fog. The females reported higher symptom severity overall (Figure 6.3). Of the 27 symptoms, females reported the maximum severity for 17 symptoms and the males only reported maximum severity for one symptom.

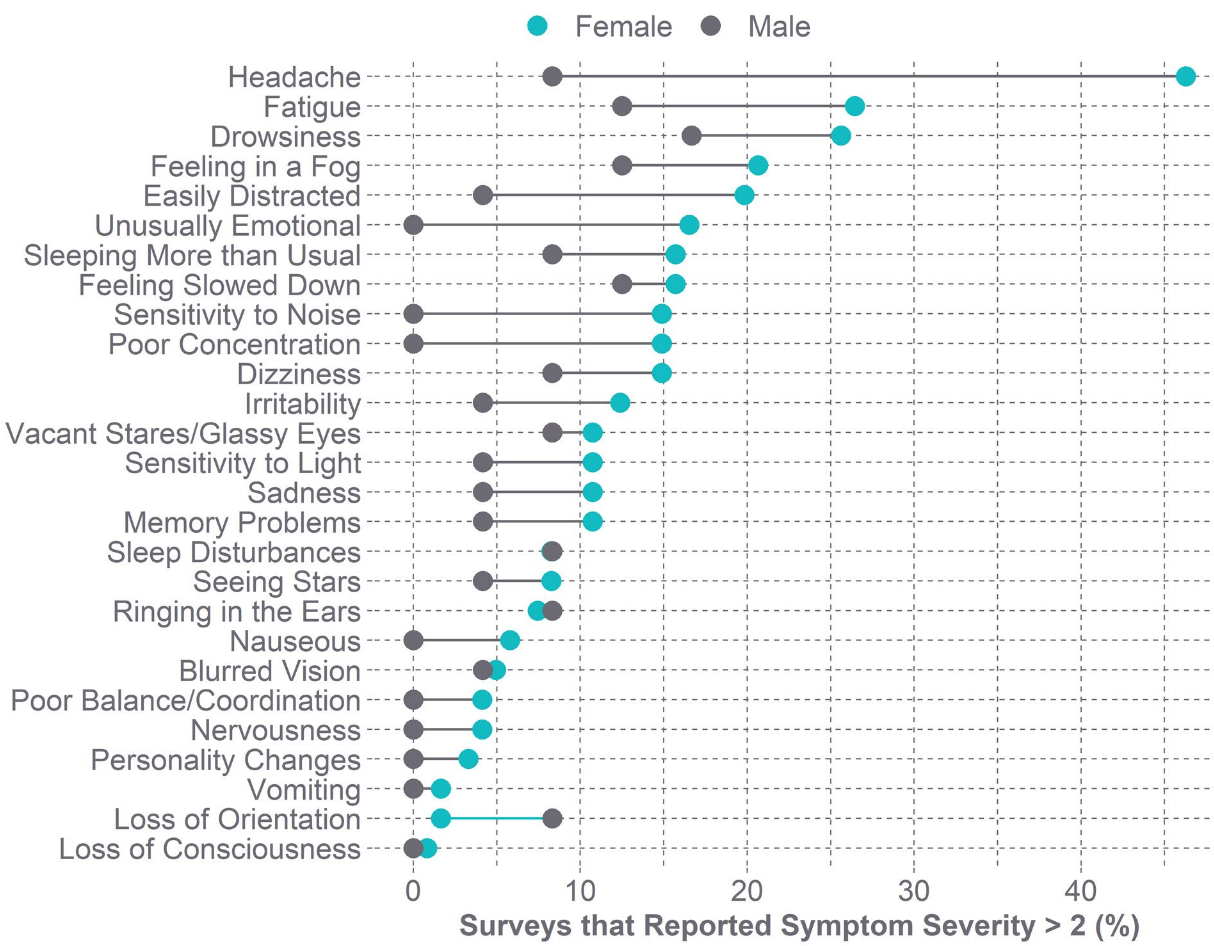

Figure 6.3. Plot of differences in the percentage of elevated surveys that report the given symptom with moderate or greater severity (> 2) between sexes. A higher proportion of females reported all symptoms with a severity greater than two except loss of orientation (-6.7%), ringing in the ears (-0.9%), and sleep disturbances (-0.1%). The other symptoms' mean difference was 8.5%, ranging between 0.8% and 16.5%, except for headache (37.9%).

When grouping the symptoms into subtypes, most surveys (51.2% of females' surveys and 45.8% of males' surveys) indicated diffuse presentation of symptom subtypes – identifying the presentation of more than one subtype – for both males and females. 16.5% of females' surveys indicated one predominant subtype, and 80.0% of those predominant subtypes were Anxiety/Mood. Cognitive was never reported as the predominant subtype for either sex. The 49 surveys (32.2% of females' surveys and 41.7% of males' surveys) that did not have any subtype with symptoms greater than 2 generally reported low-level severity for multiple symptoms.

Concussion Symptom Presentation

There were 14 diagnosed concussions in the dataset. The median and max SSS and number of symptoms for the diagnosed athletes and elevated surveys are summarized in Table 6.4. The females' survey results showed differences between elevated and concussed SSS ($p < 0.005$, mean difference of 28.1 [95% CI: 3.0, 53.2]) and number of symptoms reported ($p = 0.001$, mean difference of 6.6 [95% CI: 2.2, 10.9]). But the men did not have a difference in SSS ($p = 0.97$, mean difference of 1.12 [95% CI: -10.6, 12.9]) nor in number of symptoms reported ($p = 0.35$, mean difference of 1.96 [95% CI: -3.9, 7.8]).

Table 6.4. Summary of symptom presentation in athletes who were diagnosed with a concussion by clinical staff and those that reported elevated SSS. Two female athletes sustained concussions twice; the rest of the concussions are from unique athletes. Females report more symptoms with a higher severity than their male counterparts post-concussion.

Sex	Category	Survey Count	SSS Median (Max)	# of Symptoms Median (Max)
Female	Concussion	10	46 (113)	17.5 (27)
	Subconcussion	92	16 (102)	10 (26)
Male	Concussion	4	15 (27)	10.5 (14)
	Subconcussion	21	15 (25)	9 (13)

DISCUSSION

The rugby players commonly reported concussion symptoms in-season in the absence of diagnosed concussion, but at lower severities than those associated with a diagnosed concussion.[42,46] Previous work has identified cognitive and neuroimaging changes in post-season testing in various sports, but in-season symptoms have not been monitored before.[3,5,7,8,17,19-21,47-50] The elevated symptom cases we identified in our cohort may be the subconcussion injuries thought to cause the post-season changes previously measured. Sex-specific differences were also noted: females generally reported more symptoms with higher severity than their male counterparts. More females' surveys were categorized as elevated, and females more commonly reported symptoms of headache, anxiety, and mood.

While most athletes reported 0 symptoms at baseline, consistent with the literature,[51] we observed that those who did report symptoms at baseline were more likely to report symptoms in-season, potentially indicating reporting tendencies. This pattern was stronger in the male athletes ($p < 0.004$, 95% CI: 1.8, 112.2) than the female athletes ($p = 0.315$, 95% CI: 0.5, 27.1). Females reported higher in-season symptoms compared to their baseline and higher than males in-season. These results are consistent with other studies that indicate females report more baseline symptoms with higher severity.[22,28]

To identify a potential accumulation of symptoms, the number of weeks of recurrent elevated symptoms were quantified. The results did not vary significantly by sex, which is of note because previous work has identified post-concussion symptoms lasting longer in female athletes than their male counterparts.[28,52,53] Of the males that reported recurrent elevated symptoms in this study, their elevated surveys made up a higher percentage of their total surveys compared to the females. One explanation for this is that the male athletes were more likely to fill out a survey if they were experiencing symptoms.

Headache has been the most frequently reported symptom in other studies,[31] similar to the females in our study. Females have a higher frequency for pre-existing headache[54] which may explain a more frequent or severe reporting in-season or post-concussion.[55] The other most commonly reported symptoms by both sexes with moderate severity included fatigue and drowsiness. Both could be more reflective of a cohort of collegiate subjects and not specific to contact-sport athletes. A higher percentage of surveys from female athletes reported symptoms with moderate severity, and females reported maximum severities for more symptoms than males did (17 vs 1). These sex-specific patterns could be a systematic difference in reporting or a difference in experiences; we cannot determine from these data.

Surveys that had mentioned confounding reasons for symptom presentation were excluded. However, the symptoms included in the symptom checklist are not exclusive to concussions, and likely many more surveys are affected by outside factors beyond rugby. For this study, we were seeking to understand patterns in presentation between male and female collegiate rugby players and understand that the results presented may not be specific to sport-related head impacts.

Our analysis results showed mostly diffuse presentation of symptoms across several subtypes, or no subtype presentation at all. Strong evidence has supported cluster-based approaches to sport-related concussion management, identifying the most common clusters as migraine, cognitive-emotional and sleep-emotional, but acknowledged changes over recovery and overlap in the clusters.[56] Interestingly, of the 20 female surveys that reported a dominant subtype, 16 of those were Anxiety/Mood presentation. This is consistent with studies that show females with higher levels of anxiety than males.[57] Two limitations with the subtype categorization are that not all subtypes and associated conditions are mutually exclusive, and they are not all equally represented in standard post-concussion surveys, potentially skewing categorization to the subtypes that are more reflected in surveys.[58]

There were 14 diagnosed concussions in the dataset and 9 additional athletes with suspected concussions, i.e. they reported a suspected concussion to research staff but not to medical personnel. These suspected concussions were included in the subconcussion dataset, as they were not clinically diagnosed and had a SSS >= 11. The female athletes showed differences between the subconcussive and concussive levels, but the men did not. This sex-specific difference could be a result of the males' concussion severities being lower than the females' or that males experience higher level subconcussive events in-season. Post-concussion symptoms present themselves on a different timeline for each individual, and those differences are likely highlighted. As each week is treated in isolation, we may have missed delayed presentation of symptoms.

In this study, we have shown that rugby players report concussion-like symptoms in the absence of diagnosed concussion during the course of a season. The consequences of these symptom reports is unclear as they might represent undiagnosed concussions, subconcussive tissue changes, or transient subclinical effects. How they contribute to overt injury still needs to be determined. Recent work from the Concussion Assessment, Research and Education (CARE) consortium demonstrated a relationship between the amount of head impact exposure during the season and subsequent concussion.[59] A relationship between measured head impact exposure and these "ambient" symptoms is of great interest and may offer insight into undiagnosed concussions. In this sample, female rugby players reported elevated symptom frequencies with greater severities than the males during the season, consistent with other findings. However, both males and females reported considerable levels of symptoms throughout the course of a season. Further strategies for addressing these in-season symptom responses should be considered.

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CHAPTER 7: DUAL-TASK GAIT PERFORMANCE FOLLOWING HEAD IMPACT EXPOSURE IN MALE AND FEMALE COLLEGIATE RUGBY PLAYERS

ABSTRACT

Decreased postural control and gait impairments have been well studied in concussed athletes. However, the effect of subconcussive impacts on gait is not well understood. As concussions affect parts of the brain responsible for cognitition as well as motor control, it is of interest to study the relationship between head impact exposure and its effect on gait, and identify potential sex-specific differences. Dual-task gait assessments, when a cognitive task is added to a walking task, can help amplify deficits in gait, and are representative of tasks in everyday life. Dual-task cost is the difference in performance going from walking (single-task) to walking with a cognitive load (dual-task). The objective of this study was to quantify differences between sexes dual-task gait metrics, gait metric changes from pre-season to post-concussion and post-season, and the dual-task costs associated with gait metrics. 77 female athlete-seasons and 64 male athlete-seasons from the Virginia Tech club rugby teams participated in this study. Subjects wore inertial sensors and completed walking trials with and without a cognitive test before the season began, after the season ended, and after a concussion (if applicable). Females athletes showed improvement in cadence (increase), double support time (decrease), gait speed (increase), and stride length (increase) in both task conditions over the course of the season ($p < 0.030$). Male athletes showed no differences in the metrics over the course of the season, with the exception of faster gait speeds and longer stride lengths in the dual-task condition ($p < 0.034$). In all four gait characteristics, at baseline and post-season, females had higher dual-task costs ($p < 0.003$) than the males. This study showed that there is little evidence suggesting a relationship between repetitive head impact exposure and gait deficits, but there are sex-specific differences that should be considered during the diagnosis and management of sports-related concussion.

Keywords: Dual-task, Gait, Sex-Specific, Subconcussion

INTRODUCTION

Concussions are a diffuse injury to the brain,[1] affecting a variety of brain functions, including neurocognition and motor control.[2] Gait research has advanced the understanding of the effect of concussions on motor control, and altered gait patterns have been observed as a result of sports related concussion.[3-6] Dual-task walking involves locomotion while performing a concurrent cognitive task. Concussions usually affect both motor and cognitive functions, so the divided attention required in dual-tasks may be more sensitive to post-concussion impairments than single-tasks.[7] The addition of a cognitive load while walking also allows for the evaluation of more subtle motor impairments due to the increase in processing demands required, and decrease in available attention.[8,9] It is of interest to quantify the change in a specific variable with the addition of the load, or the change in the variable from single task to dual task, known as dual-task cost.[10] Assessing the effects of dual task is also advantageous as most sport and daily living activities require both a motor and cognitive component, and understanding their interaction in concussion may provide useful information in injury recovery.

Researchers have observed that a full recovery in gait performance post-concussion required months to years, especially when the participant's attention is divided.[3,4,11,12] More traditional markers of recovery, like symptom surveys or neurocognitive test performance, typically recover on a shorter timeline.[13,14] Assessing gait is advantageous because it is a non-novel task and can be objectively measured,[3,4,12,15] unlike more obsolete methods of measuring balance[16,17] or less mobile methods.[18] Gait can be measured in-lab, but also on-field, using portable inertial measurement units.[19,20]

Accelerometry can be used to quantify gait, and the incorporation of accelerometers into these body-worn portable sensors allow for an assessment of gait that allows for widespread use.[19] Including a gait assessment in post-concussion protocols may provide an objective and sensitive measurement that can be assessed throughout return-to-play, to monitor progress and management. Limited sex-specific normative data exist for single and dual task gait characteristics,[7,21] and baseline measurements are recommended[22] as gait is unique to individuals, and varies based on body size,[23] concussion history,[6,24] and sex.[25] Females generally report more symptoms post-concussion[26] and take a longer time to fully recover[27] than males. Because of the differences in presentation of concussions, it is of interest to understand any sex-specific gait changes as well. Understanding the effect of sex on presentation and recovery of concussion will hopefully provide useful information to drive sex-specific interventions.

Athletes with a history of concussion have been shown to have a more conservative pattern in their gait,[6] with decreased walking speed, decreased cadence, decreased stride length, and increased double-leg support time compared with control subjects during dual-task walking.[12] It is not known how a season worth of cumulative head impacts in a contact sport in absence of a concussion affects gait. The objective is to explore the differences between sexes in 1) dual-task gait metrics in 2) gait metric changes from pre-season to post-concussion and post-season and 3) the dual-task costs associated with gait metrics.

METHODS

Study Participants

In the spring and fall of 2019 and spring of 2020, athletes from women's and men's club rugby teams were recruited. Written informed consent was obtained from each participant after explaining the purpose, associated benefits, and risks of the study with accordance to the ethical guidelines of the Virginia Tech Institutional Review Board (IRB). 77 female athlete-seasons (age: 20.7 ± 1.2 years, height: 1.7 ± 0.1 m, weight: 75.1 ± 17.6 kg) and 64 male athlete-seasons (age: 21.0 ± 1.2 years, height: 1.8 ± 0.1 m, weight: 89.5 ± 17.5 kg) participated in the study. If an athlete participated for two seasons, their data are treated as two unique athlete-seasons. Athletes reported suspected concussions to the research team. Not all concussions were clinically diagnosed.

Dual-Task Gait Protocol

The gait protocol was completed pre-season (baseline), post-season, and post-concussion (if applicable). Athletes were not tested if they had a lower extremity injury. Those who sustained concussions were evaluated an average of 2.7 days after injury (range = 1 - 4 days). There were no post-season data collected for Spring 2020, as the season was interrupted due to COVID-19.

The gait protocol included two conditions: walking without a cognitive task (single-task walking) and walking while completing a cognitive task (dual-task walking). Five trials were completed for each condition.[21] The subject walked at a self-selected, comfortable pace, barefoot or in socks. They were instructed to walk towards an object 8 m in front of them, walk around it, and return to the starting point.[21] For the dual-task trials, the test administrator explained the task prior to the start of the walk, and the athlete began walking when cued by an auditory beep. The test administrator did not instruct the athlete to prioritize the motor or cognitive task, just to continue walking while responding to the task as best as possible.[21] The dual task consisted of a Mini-Mental Status Examination (MMSE), which has been shown to detect differences in dual-task walking after concussion.[28] The MMSE contained three different tasks: spelling a 5-letter word backwards,[15,29] subtracting by 6s or 7s from a randomly presented 2-digit number,[30] and reciting the months in reverse order starting from a randomly chosen month.[31] This cognitive test is similar to the Standardized Concussion Assessment Tool, Version 3, which is used for on-field concussion diagnosis.[22,32] The tasks were randomly ordered to reduce learning effects from one trial to the next.

During the walking protocols, athletes wore inertial measurement units (Opal Sensor, APDM Inc. Portland, OR) attached with an elastic strap on the lumbar spine, at the lumbosacral junction, and on the dorsal surfaces of the left and right feet (Figure 7.1). This system has been validated[33] and utilized in clinical evaluations of gait through the completion of motor tasks.[20] Data were collected at a sampling frequency of 128 Hz and wirelessly synced to a computer during each trial. Temporal-distance measurements were calculated using Mobility Lab software[20] and variables of interest included gait speed, cadence, double support time, and stride length, previously shown to differentiate healthy from concussed subjects.[21,28,34]

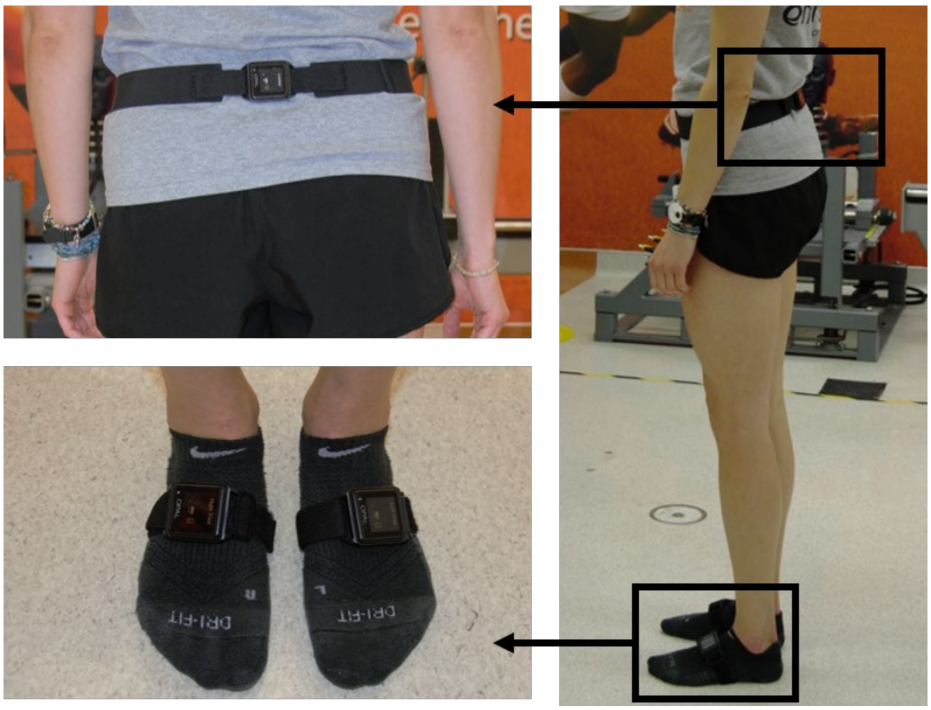

Figure 7.1. Opal Sensors attached to elastic straps around the athlete's waist and feet to measure gait characteristics.

Outcome Variables

Gait speed, cadence, double support time, and stride length were measured for each athlete under both tasks at each time point. Gait speed was calculated as the average velocity for the left and right foot across all gait cycles in each trial. Cadence was defined as the rate of steps per minute. Double support time is the percentage of time that both feet were on the ground in each gait cycle, reported as percent of gait cycle time (%GCT). Stride length is the average distance for each foot between consecutive steps in each trial. The changes in each metric were computed from baseline to post-season and baseline to post-concussion (if applicable). Dual task cost, the percent change between single and dual-task conditions, was computed for each athlete to normalize their individual dual-task performance to their single-task performance.[34,35] Dual task cost was calculated as (dual-task value – single-task value)/(single-task value) and reported as a percentage. Dual-task cost was measured for each gait characteristic of interest.

Statistical Analysis

Shapiro-Wilk tests were used to confirm normality of the gait metrics. Paired Welch two-sample t-tests were used to compare the magnitudes and estimate the effect size and precision of cadence, double support time, gait speed, and stride length from baseline to post-season within each task condition. The same paired comparisons were done for athletes with baseline and post-concussion time point data. These comparisons were paired per athlete and compared within sex. Welch two-sample t-tests were completed to compare the differences in metrics between sexes from baseline to post-season for each task condition. Because there was only one concussion for the males, only females' data were compared from baseline to post-concussion time points.

Dual-task costs were not normally distributed, so paired Wilcoxon rank-sum tests were used to compare dual-task cost from baseline to post-season within sex for each gait characteristic. Welch two-sample t-tests were used to estimate effect size and precision. Unpaired Wilcoxon rank-sum tests compared dual-task cost for each metric at each time. Again, only the females' data were compared for the differences in baseline to post-concussion change, and between sex differences were not. Welch two-sample t-tests were used to estimate effect size and precision of the comparisons.

RESULTS

Gait metrics are presented from both task conditions at each time point (where applicable) for all athletes (Table 7.1). All comparisons within sex were paired, i.e. only athletes that had both time points were included in the particular analysis.

Table 7.1. Summary table for the mean values ± the standard deviation for the four primary gait metrics from all athletes from baseline, post-concussion (CX), post-season, and at both single and dual task conditions. Count is the number of athlete-seasons in each category.

Sex	Time Point	Task	Count	Cadence (step/min)	Double Support Time (%GCT)	Gait Speed (m/s)	Stride Length (m)
Female	Baseline	Dual	77	105.5 ± 10.1	22.3 ± 3.2	0.9 ± 0.2	1.1 ± 0.1
		Single	77	113.0 ± 9.0	20.1 ± 2.9	1.1 ± 0.2	1.1 ± 0.1
	Post-CX	Dual	14	102.4 ± 11.1	23.2 ± 3.2	0.9 ± 0.2	1.1 ± 0.1
		Single	14	110.3 ± 11.1	20.8 ± 3.0	1.1 ± 0.2	1.1 ± 0.1
	Post-Season	Dual	39	106.9 ± 10.3	21.8 ± 3.5	0.9 ± 0.2	1.1 ± 0.1
		Single	39	114.5 ± 9.2	19.4 ± 3.3	1.1 ± 0.2	1.2 ± 0.1
Male	Baseline	Dual	64	102.3 ± 7.0	22.3 ± 3.0	0.9 ± 0.1	1.1 ± 0.1
		Single	64	106.5 ± 5.6	20.8 ± 2.7	1.0 ± 0.1	1.1 ± 0.1
	Post-CX	Dual	1	90.6	25.1	0.8	1.1
		Single	1	96.1	24.2	0.9	1.1
	Post-Season	Dual	37	102.4 ± 7.5	22.4 ± 2.7	1.0 ± 0.1	1.1 ± 0.1
		Single	37	106.3 ± 6.1	21.0 ± 2.5	1.1 ± 0.1	1.2 ± 0.1

At baseline and post-season, females walked with faster cadences at both task conditions than males ($p < 0.032$). Males walked with longer stride length in dual-task conditions at baseline and post-season ($p < 0.023$) and greater double support time in single-task conditions at baseline ($p = 0.020$). All other conditions were similar between sexes. The addition of the dual task negatively impacted all gait metrics for both sexes at each time point ($p < 0.001$). Mean percent differences and 95th percentile confidence intervals between sex are shown in Figure 7.2.

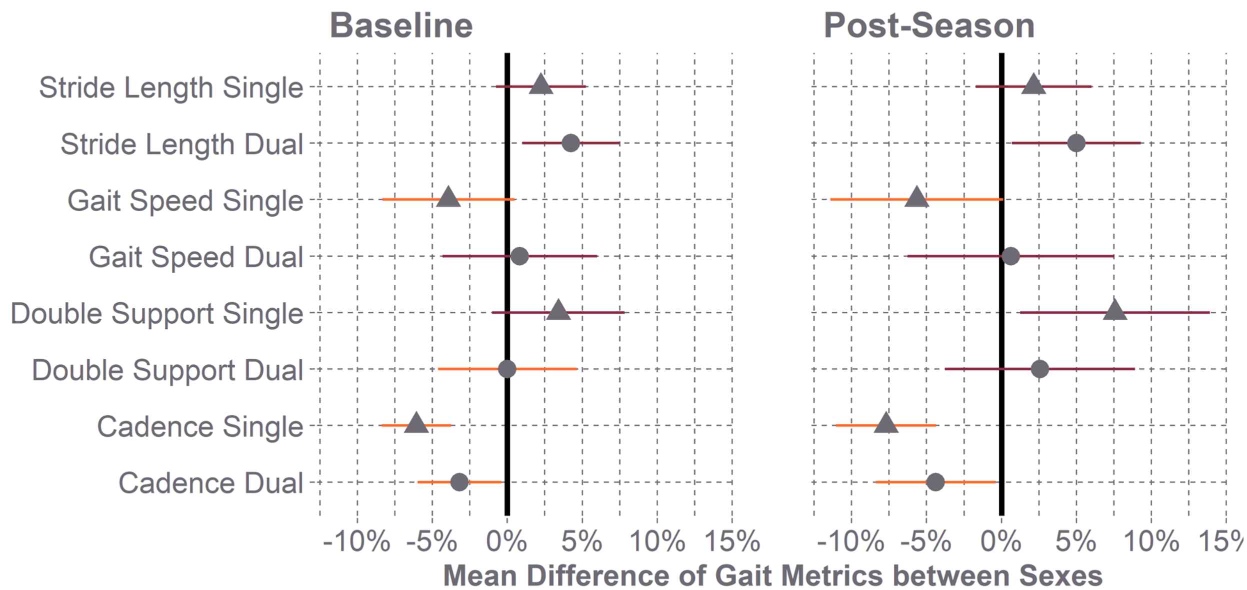

Figure 7.2. The mean difference of the female gait characteristic at the specified task from the males'. The females walked with greater cadence and a shorter stride length for the males in both task conditions. Mean differences are normalized to the males' mean for each so that each gait metric could be scaled for the sake of visualization. The tails of each point represent the 95% CI from a t-test. Maroon tails indicate a positive difference – that the males' mean was greater than the females'. Orange tails indicate a negative difference – that the males' mean was less than the females'. Triangles indicate single task condition; circles indicate dual task condition. All baseline and post-season data that were collected were included in this comparison.

Paired t-tests showed improvement in cadence (increase), double support time (decrease), gait speed (increase), and stride length (increase) in both task conditions among the female athletes over the course of the season (Table 7.2) ($p < 0.030$). No change was seen in stride length from baseline to post-season in dual task ($p = 0.071$). The same tests for the males showed no differences in the metrics over the course of the season, with the exception of faster gait speeds and longer stride lengths in the dual-task condition by the end of the season ($p < 0.034$). Mean percent differences and 95th percentile confidence intervals between time points are shown in Figure 7.3.

Table 7.2. Summary table for changes in the four primary gait metrics and the 95% confidence interval from athletes who completed both baseline and post-season gait tests. The change is the difference from baseline to post-season. In general, cadence, gait speed, and stride length increase while double support time decreases by the end of the season, showing improvement in all characteristics.

Sex	Task	Count	Δ Cadence (step/min)	Δ Double Support Time (%GCT)	Δ Gait Speed (m/s)	Δ Stride Length (m)
Female	Dual	39	3.3 [1.2, 5.4]	-0.8 [-1.6, -0.1]	0.1 [0.0, 0.1]	0.0 [0.0, 0.0]
	Single	39	2.1 [0.5, 3.6]	-0.7 [-1.1, -0.2]	0.0 [0.0, 0.1]	0.0 [0.0, 0.0]
Male	Dual	37	0.9 [-0.8, 2.5]	-0.2 [-0.6, 0.3]	0.0 [0.0, 0.1]	0.0 [0.0, 0.0]
	Single	37	0.1 [-1.3, 1.5]	0.0 [-0.4, 0.5]	0.0 [0.0, 0.0]	0.0 [0.0, 0.0]

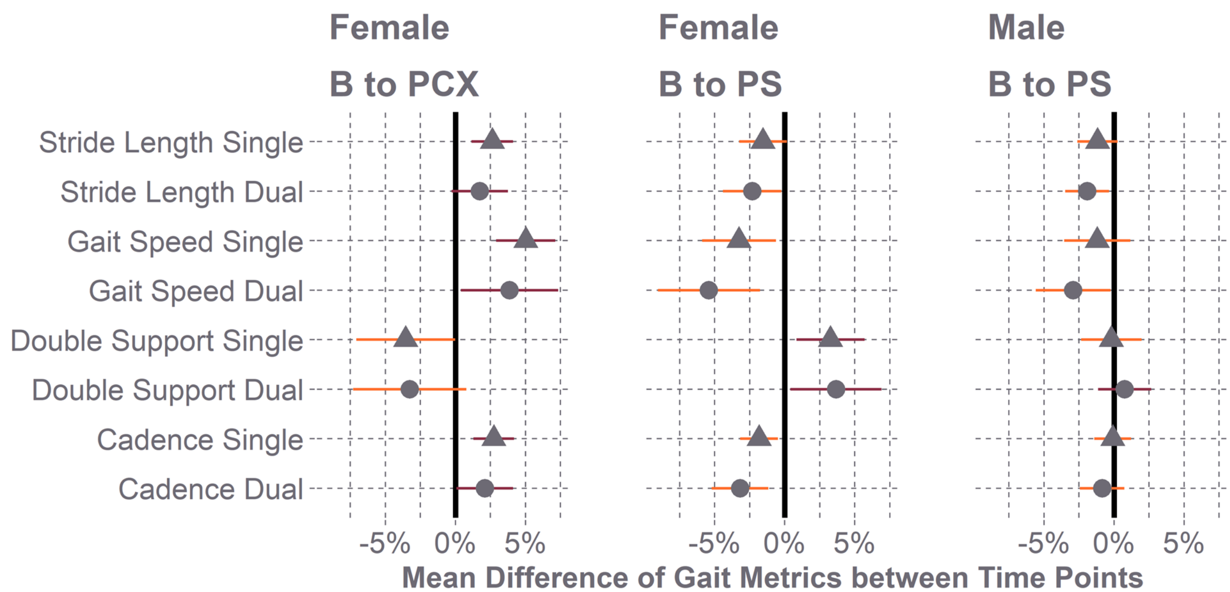

Figure 7.3. The mean difference of the post-season (and post-concussion, for the females) gait characteristics at the specified task from the baseline timepoint. Females showed greater improvement in all gait metrics over the course of the season compared to males. Post-concussion, the females performed worse in each metric. Mean differences are normalized to the baseline mean for each so that each gait metric could be scaled for the sake of visualization. The tails of each point represent the 95% CI from a paired t-test. Maroon tails indicate a positive difference – that the baseline mean was greater than the post-season (and post-concussion). Orange tails indicate a negative difference – that the baseline mean was less than the post-season (and post-concussion). Triangles indicate single task condition; circles indicate dual task condition. Only athlete-paired data were included in this comparison (Appendix Table A1).

To provide context to the changes over the course of the season, the metrics from baseline to post-concussion were similarly compared (Figure 7.3). The changes seen post-concussion (Table 7.3) are opposite in magnitude to those seen in post-season (Table 7.2) with cadence, gait speed, and stride length increasing, and most double support times decreasing. All characteristics showed deficits in the females in both task conditions ($p < 0.042$) with the exceptions of double support time and stride length during the dual task condition ($p > 0.083$). It is not possible to generalize about the males' responses because post-concussion gait data were only collected from one male athlete.

Table 7.3. Summary table for changes in the four primary gait metrics and the 95% confidence interval from athletes who completed both baseline and post-concussion gait tests. Consistent with prior literature, cadence, gait speed, and stride length decrease while double support time increases after concussion.

Sex	Task	Count	Δ Cadence (step/min)	Δ Double Support Time (%GCT)	Δ Gait Speed (m/s)	Δ Stride Length (m)
Female	Dual	14	-2.2 [-4.3, -0.1]	0.7 [-0.2, 1.6]	0.0 [-0.1, 0.0]	0.0 [0.0, 0.0]
	Single	14	-3.1 [-4.8, -1.4]	0.7 [0.0, 1.4]	-0.1[-0.1, 0.0]	0.0 [0.0, 0.0]
Male	Dual	1	-6.5	1.7	-0.1	0.0
	Single	1	-5.8	1.9	-0.1	-0.1

The costs for cadence, gait speed, and stride length are all negative and double support time is positive, because gait becomes more conservative with the addition of the cognitive load in the form of the dual-task condition (Table 7.4). In all four gait characteristics, at baseline and post-season, females had higher dual-task costs ($p < 0.003$) than the males (Figure 7.4).

Table 7.4. Summary table for mean dual task-cost (%) of four gait metrics in athletes at each time point.

Sex	Time Point	Count	Cadence Cost (%)	Double Support Cost (%)	Gait Speed Cost (%)	Stride Length Cost (%)
Female	Baseline	77	-6.6 ± 4.0	11.3 ± 7.7	-12.9 ± 6.8	-6.9 ± 4.3
	Post-Concussion	14	-7.2 ± 2.9	11.9 ± 6.2	-13.0 ± 5.4	-6.2 ± 3.6
	Post-Season	39	-6.7 ± 3.7	12.5 ± 5.8	-13.4 ± 5.9	-7.4 ± 3.9
Male	Baseline	64	-4.0 ± 3.6	7.4 ± 5.5	-8.6 ± 6.0	-4.9 ± 3.7
	Post-Concussion	1	-5.7	3.7	-8.8	-3.6
	Post-Season	37	-3.6 ± 4.2	6.7 ± 5.6	-7.7 ± 6.8	-4.5 ± 3.7

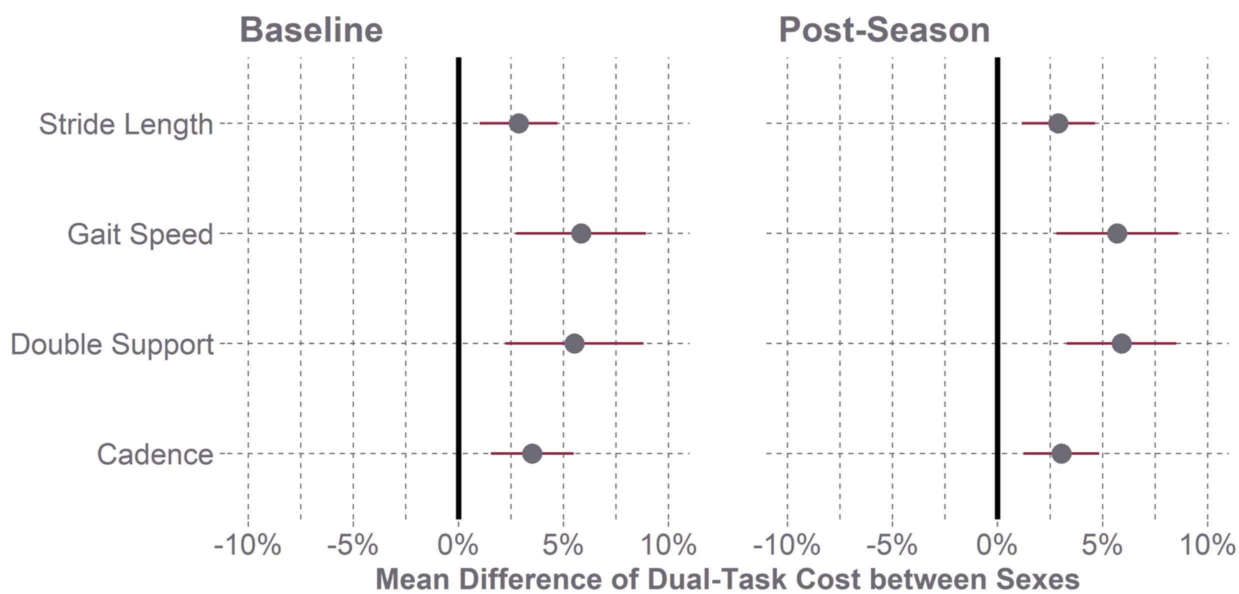

Figure 7.4. The mean difference of the female dual-task cost at the specified gait variable from the male. Females had greater cost for each gait metric both at baseline and post-season. The tails of each point represent the 95% CI from a t-test. The absolute value of double support time was taken as the cost for the females was greater in magnitude, but a negative value. Maroon tails indicate a positive difference – that the males' mean cost was greater than the females'. All baseline and post-season data that were collected were included in this comparison (Table 7.4).

Paired Wilcox test showed cadence and gait speed had higher dual-task costs at baseline compared to post-season for both males and females ($p < 0.049$) (Figure 7.5). Across all conditions, gait speed had the highest cost. Dual-task cost for double support time and stride length were not different at baseline or post-season for males or females ($p > 0.059$) (Figure 7.5). When comparing the post-concussion data to the paired baseline data for the females, there were no differences in cost between the two time points ($p > 0.384$) (Figure 7.5).

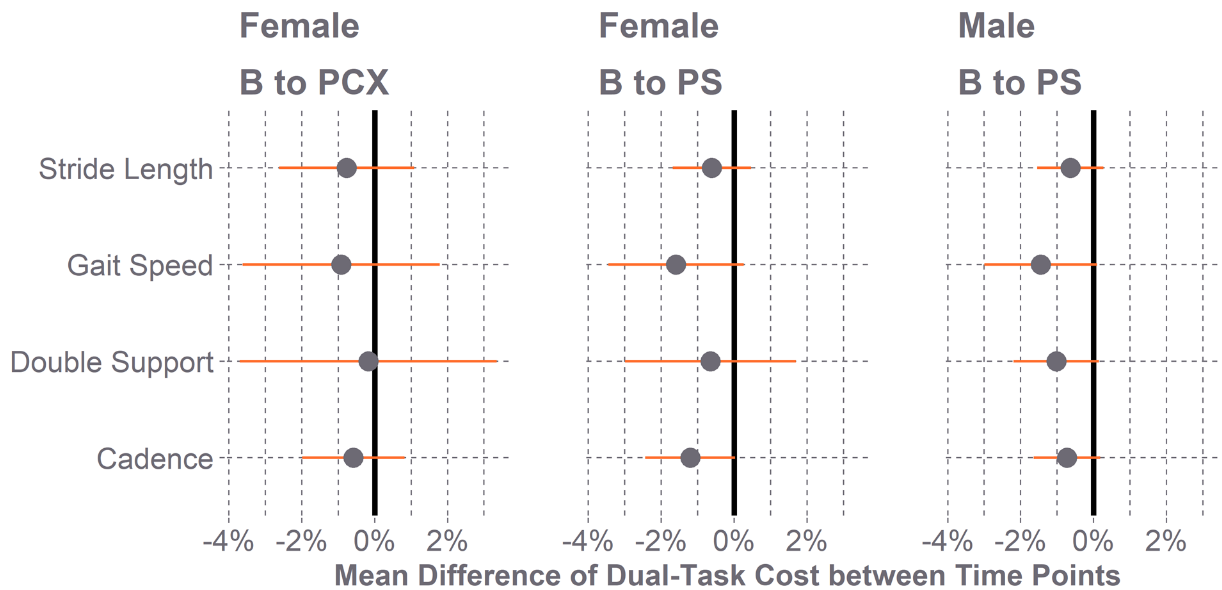

Figure 7.5. The mean difference of the post-season (and post-concussion, for the females) dual-task cost at each gait characteristic from the baseline timepoint. Dual-task cost did not change much from baseline to post-season or post-concussion for either sex. The tails of each point represent the 95% CI from a paired t-test. The magnitude of double support was taken to be consistent with the other metrics. Orange tails indicate a negative difference – that the baseline mean was less than the post-season (and post-concussion). Only athlete-paired data were included in this comparison (Appendix Table A2).

DISCUSSION

The objective of the introduction of a dual task into gait tests is to identify deficits that may not be as prevalent when the attention is focused on gait. In our study, the addition of the mental load decreased cadence, gait speed, and stride length, and increased double support time for both sexes at each time point, in line with other studies.[21] Compared to the males, females walked with faster cadences and shorter stride length, similar to previous research.[7,34] It has been suggested that female's dual-task gait velocity is higher because females may be better at executing two tasks at once, compared to their male counterparts.[36] This also may explain the females' improvement in all four gait variables over the course of the season, with the exception of stride length in dual task. Males improved in their gait speed and stride length in dual task only, the rest of their metrics were not different from their baseline values. In this study, collegiate rugby players did not exhibit similar deficits in gait post-season to those they, or other studies have shown, post-concussion.[12,37-40] Compared to a similar study by Howell, the athletes in our study spent much less time in double support (mean range 34.0 – 38.2 for concussed and control males and females),[34] but there lacks a body of sex-specific normative value to compare to.

The changes the females showed post-concussion are consistent with post-concussion gait tests in literature.[7,34] Their cadence, gait speed, and stride length increased, and most double support times decreased. Previous work has shown a decrease in these metrics post-concussion,[34,35] indicating a more conservative gait pattern, with the athletes walking slower with smaller steps post-concussion.

At baseline and post-season, females had higher dual-task costs than the males in all four variables. Across the board, gait speed had the largest dual-task cost. Dual-task costs for gait speed have been used as a predictor in prolonged recovery time in concussed athletes.[41] Previous literature has shown a greater cadence cost in females compared to males post-concussion.[34] In the same study, they did not notice any dual-task cost difference between male and female controls[34] which is not consistent with our results at baseline. They did not see a difference in dual-task cost from control males to concussed males either,[34] which follows the same trend as our male athletes at baseline and post-season.

Although we expected females to have higher cost, we also expected cost to be higher with post-concussion, similar to other studies.[4,35,42] The additional cognitive load was expected to reflect functional changes post-concussion and decreased interhemispheric brain connectivity,[43] forcing the brain to reorganize to perform the challenging task while simultaneously proving resources for walking. In concussed athletes, we would except this resource allocation to be hindered,[44,45] and appropriately reflected in dual-task costs. However, there were no difference in cost in the baseline and post-concussion paired data. Previous work has shown dual-task deficits at days 5-6,[46] or in the year following,[40] which is after all of the athletes in this study were tested. Additionally, based on the performance of the athletes, improving over the season, it is unsurprising that cadence and gait speed had higher dual-task costs at baseline compared to post-season for both males and females. No study has quantified cost after a season of impacts to compare with.

The overall improvement in gait and decrease in dual-task cost could be the result of a learning effect of the tests, but there does not appear to be a deficit in gait or more conservative gait pattern that accumulated over the season. A study looking at acute postural control effects after a simulated match load of rugby impacts also suggested no changes following subconcussive impacts.[47] The learning effect is likely more noticeable in our study as we had athletes complete the protocol multiple times in a season, and many participate in multiple seasons. Other studies compared concussed athletes to controls,[34,35] which reduces the overall number of times an athlete would complete the dual-task protocol. Additionally, a season worth of exercise and training in their sport may have also contributed to these numbers improving.

There were several limitations to this study. Namely, only one male post-concussion time point was collected, making it impossible to generalize about males' responses post-concussion, compare them to the females at post-concussion, or compare them to males at baseline and post-season. Additionally, we did not consider age, height, weight, or prior concussion history on the comparisons in our analysis. Although likely the differences in sizes between males and females may contribute to the four gait variables, body mass indices (BMIs) from the two groups are similar, and the dual-task cost normalizes performance in an individual manner. The environment in which the tests were conducted were not always consistent. They were conducted in the lab or the hallway, but sometimes the lab was busier than others, and the other distractions may have confounded the subject's attention. However, we chose not to check for accuracy of these dual-task tests, because the divided attention should be enough to elucidate differences, their performance on the MMSE should not matter. It has been shown that females prioritize the accuracy of their answers over their gait, compared to their male counterparts.[48]

Although the results of this study are mixed, dual-task gait can be used to uncover functional deficits in athletes who may be asymptomatic and do not exhibit neuropsychological dysfunction,[45] but it is important to use it in the context of other diagnostic tools. Dual-task gait assessment is especially relevant given the implication of concussion on musculoskeletal injuries,[49] and therefore should be incorporated into future clinical assessments and sex-specific interventions post-concussion.

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APPENDIX

Table A1. Summary table for the mean values for the four primary gait metrics at both task conditions from athletes who completed both a baseline and post-season, and baseline and post-concussion, tests in the same season. Count is the number of athlete-seasons in each category.

Sex	Time Point	Task	Count	Cadence (step/min)	Double Support Time (%GCT)	Gait Speed (m/s)	Stride Length (m)
Female	Baseline	Dual	39	103.6 ± 10.2	22.6 ± 3.2	0.9 ± 0.2	1.1 ± 0.1
		Single	39	112.4 ± 8.9	20.1 ± 3.1	1.1 ± 0.2	1.1 ± 0.1
	Post-Season	Dual	39	106.9 ± 10.3	21.8 ± 3.5	0.9 ± 0.2	1.1 ± 0.1
		Single	39	114.5 ± 9.2	19.4 ± 3.3	1.1 ± 0.2	1.2 ± 0.1
Male	Baseline	Dual	37	101.6 ± 7.2	22.6 ± 2.8	0.9 ± 0.1	1.1 ± 0.1
		Single	37	106.2 ± 5.6	21.0 ± 2.7	1.0 ± 0.1	1.2 ± 0.1
	Post-Season	Dual	37	102.4 ± 7.5	22.4 ± 2.7	1.0 ± 0.1	1.1 ± 0.1
		Single	37	106.3 ± 6.1	21.0 ± 2.5	1.1 ± 0.1	1.2 ± 0.1
Female	Baseline	Dual	14	104.6 ± 11.4	22.5 ± 3.2	1.0 ± 0.2	1.1 ± 0.1
		Single	14	113.4 ± 10.7	20.1 ± 2.8	1.1 ± 0.2	1.2 ± 1.2
	Post-CX	Dual	14	102.4 ± 11.1	23.2 ± 3.2	0.9 ± 0.2	1.1 ± 0.1
		Single	14	110.3 ± 11.1	20.8 ± 3.0	1.1 ± 0.2	1.1 ± 0.1

Table A2. Summary table for the mean dual task-cost (%) of four gait metrics from athletes who completed both a baseline and post-season test in the same season. Count is the number of athlete-seasons in each category.

Sex	Time Point	Count	Cadence Cost (%)	Double Support Cost (%)	Gait Speed Cost (%)	Stride Length Cost (%)
Female	Baseline	39	-7.8 ± 4.6	13.2 ± 8.7	-15.1 ± 7.1	-8.0 ± 4.5
	Post-Season	39	-6.7 ± 3.7	12.5 ± 5.8	-13.4 ± 5.9	-7.4 ± 3.9
Male	Baseline	37	-4.4 ± 4.0	7.7 ± 5.3	-9.2 ± 6.4	-5.2 ± 3.7
	Post-Season	37	-3.6 ± 4.2	6.7 ± 5.6	-7.7 ± 6.8	-4.5 ± 3.7
Female	Baseline	14	-7.8 ± 4.5	12.1 ± 6.5	-13.9 ± 7.6	-7.0 ± 4.3
	Post-CX	14	-7.2 ± 2.9	11.9 ± 6.2	-13.0 ± 5.4	-6.2 ± 3.6

CHAPTER 8: CONCUSSION CASE REPORTS IN COLLEGIATE MEN'S AND WOMEN'S RUGBY: CONSIDERATIONS FOR FUTURE DATA COLLECTION

ABSTRACT

The previous on-field data collection has worked to quantify concussion biomechanics, based mostly in helmeted, male athletes. Data from unhelmeted and female athletes still needs to be collected and quantified to understand how concussion tolerance varies amongst these populations. Pairing clinical data with biomechanics allows research to more holistically understand the negative effects of head impact exposure on other domains of an athlete's health. The goal of this study was to instrument collegiate rugby players with head impact sensors embedded in mouthguards and to report concussive biomechanics with symptom presentation and dual-task gait changes from pre-season to post-concussion. Over four seasons of data collection, four males and 15 females sustained suspected concussions. We did not require a clinical diagnosis in attempt to reduce underreporting. Kinematics were collected for two of the males' concussions and three of the females' due to different challenges with the instrumentation. A post-concussion symptom survey was collected after each, and corresponding gait data were collected in most cases. Not enough data were collected to generalize about sex-specific or unhelmeted athlete concussion tolerance, but the following reports may provide foundational and reference cases for future work.

Keywords: Concussion, Female, Linear Acceleraion, Rotational Velocity

INTRODUCTION

On-field data collection in contact sport athletes presents a unique opportunity to study human tolerance to brain injury.[1] By non-invasively measuring skull acceleration and velocity, researchers are able to correlate impacts to the inertial response of the brain. The basis of on-field data collection comes from mounted accelerometer arrays in the helmets of male football players.[2-6] These helmet-mounted sensors helped researchers understand the head impact tolerance of elite male athletes and build concussion risk functions to predict injury.[7] However females are underrepresented in concussion research, despite plenty of evidence suggesting that presentation and outcome of concussion is sex-specific.[8-13] These differences are likely due to a combination of biomechanical, physiologic, and psychosocial factors that vary between female and male populations. Since females have smaller heads and weaker necks, it has been suggested that they are more likely to experience greater head accelerations for a given impact than males, thus increasing concussion risk.[14-17] From a physiologic standpoint, hormonal differences between sexes, where estrogen and progesterone act as neuroprotectants, may contribute to the differences in presentation, outcome, and tolerance of concussion.[12,18,19] Moreover, studies have pointed to psychosocial factors that lead females to be more honest in reporting concussions due to concerns about the effects of injury on their future health and males less likely to report concussions due to cultural tendencies which encourage male athletes to play despite injuries.[8,14,20]

The lack of female biomechanical data is partially due to the amount of research on football and the ability to instrument helmets with relative ease. As the sensor market progressed, smaller sensors that could be worn independently of a helmet were developed, allowing populations like females and unhelmeted athletes to be studied. By comparing real-world biomechanical data with clinical outcomes, concussion tolerance can be better understood. The mechanics of concussions are still unknown due to the variability in subject population, type of sensor used and the need for large datasets to make conclusions on concussive thresholds.[5]

Rugby is an ideal population to study, as it is a contact sport with a high exposure to head impact and concussion, is played by the same rules for both sexes, and does not require the use of protective headgear.[21-24] The objective of this study is to report concussions in collegiate rugby players and their corresponding symptom presentation and changes in gait that we observed over a two year study. Not enough concussive biomechanics were captured for a concussion-specific analysis, but there is still value in sharing and making these data available for researchers to use in the future.

METHODS

Subjects

A total of 107 male-seasons (age: 20.6 ± 1.3 years, height: 70.7 ± 3.0 in, weight: 197.0 ± 34.3 lbs) and 114 females-seasons (age: 20.6 ± 1.3 years, height: 65.3 ± 3.1 in, weight: 162.3 ± 38.7 lbs) from the Virginia Tech men's and women's club rugby team participated in the study which was conducted from Fall 2018 – Spring 2020. All participants provided written informed consent in this study approved by the Virginia Tech Institutional Review Board (IRB).

Biomechanical Data

Each athlete was instrumented with a custom-fit mouthguard that housed linear accelerometers and angular rate sensors to measure head kinematics with six degrees of freedom. The athletes wore their mouthguards for each game and contact practice. The Prevent Biometrics Impact Monitoring Mouthguard and Wake Forest mouthguard (Figure 8.1) have both been validated in laboratory testing.[25-27]

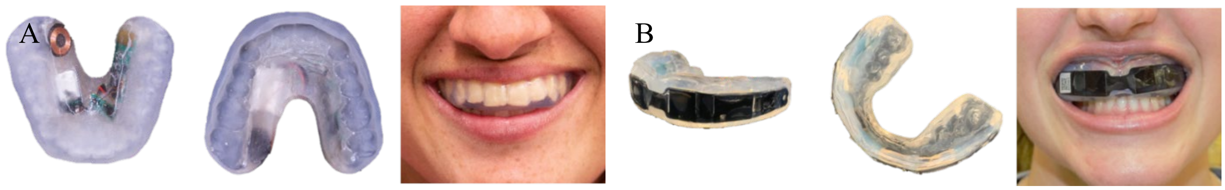

Figure 8.1. (A) Wake Forest University Mouthguard with instrumentation along the upper palate and (B) Prevent Biometrics mouthguard with instrumentation along the teeth.

Prevent Biometrics' device had a sampling rate of 3,200 Hz. When a buffering accelerometer measurement exceeded 5 g on a single axis, 10 ms of pre-trigger and 50 ms of post-trigger data were collected and stored on local memory. The Prevent iOS app downloaded the data in real-time. A low-pass filter of channel frequency class (CFC) 240 was used to filter the data. To avoid possible data loss, Prevent Biometrics' algorithm to remove suspected false-positive impact events was deactivated. A generalized transformation formula was used to transform accelerations to the head's center of gravity (CG).

Wake Forest's device sampled the accelerometers at 4,684 Hz and the gyroscope at 1,565 Hz. When a buffering accelerometer measurement exceeded 5 g on a single axis, 15 ms of pre-trigger and 45 ms of post-trigger data were collected and stored on local memory. Wake Forest's device had a low-pass filter of CFC 2000 to filter the acceleration data and CFC 270 to filter angular rate data. The device required 300 ms of turnover time in-between events. Facial landmarks of each athlete were used to estimate the CG location to apply subject-specific transformations.[27] Instrumentation of each team varied by season.

Clinical Data – Symptom Checklists

Athletes were emailed a survey with a Graded Symptom Checklist (GSC) and an open-ended question before the season start and at the end of each week in-season. The GSC consisted of 27 symptoms which could be graded on a scale of 0-6, with 0 meaning a symptom was not present and 6 meaning the most severe presentation (Table 8.1).[28] The total symptom frequency score (maximum of 27) and the aggregate score, computed as the Symptom Severity Score (SSS) (maximum of 162), were quantified for the after the concussion.

Table 8.1. List of 27 concussion symptoms in the Graded Symptom Checklist that subjects grade on a scale of 0 to 6. Total scores are determined for the numbers of symptoms reported and total SSS.

Blurred Vision	Loss of Consciousness	Sadness
Dizziness	Loss of Orientation	Seeing Stars
Drowsiness	Memory Problems	Sensitivity to Light
Easily Distracted	Nauseous	Sensitivity to Noise
Fatigue	Nervousness	Sleep Disturbances
Feeling "In a Fog"	Personality Changes	Sleeping More than Usual
Feeling "Slowed Down"	Poor Balance/ Coordination	Unusually Emotional
Headache	Poor Concentration	Vacant Stares/Glassy Eyes
Irritability	Ringing in the Ears	Vomiting

Clinical Data – Dual-Task Gait Protocol

The gait protocol was completed pre-season and post-concussion. Post-concussion tests were conducted an average of 2.7 days after injury (range = 1-4 days). The athletes were tested in two conditions: walking without a cognitive task (single-task walking) and walking while completing a cognitive task (dual-task walking). Five trials were completed for each condition.[29] The subject walked at a self-selected pace while barefoot or in socks. They walked towards an object 8 m in front of them, around it, and returned to the starting point.[29] For the dual-task trials, the test administrator explained the task prior to the start of the walk, and the athlete began walking when cued by an auditory beep. The dual task consisted of a Mini-Mental Status Examination (MMSE), which has been shown to detect differences in dual-task walking after concussion.[30] The MMSE contained three different tasks: spelling a 5-letter word backwards,[31,32] subtracting by 6s or 7s from a randomly presented 2-digit number,[33] and reciting the months in reverse order starting from a randomly chosen month.[34] This cognitive test is similar to the Standardized Concussion Assessment Tool, Version 3, which is used for on-field concussion diagnosis.[35,36] The tasks were randomly ordered to reduce learning effects from one trial to the next.

During the walking protocols, athletes wore inertial measurement units (Opal Sensor, APDM Inc. Portland, OR) attached with an elastic strap on the lumbar spine, at the lumbosacral junction, and on the dorsal surfaces of the left and right feet (Figure 8.2). This system has been validated[37] and utilized in clinical evaluations of gait through the completion of motor tasks.[38] Data were collected at a sampling frequency of 128 Hz and wirelessly synced to a computer during each trial. Temporal-distance measurements were calculated using Mobility Lab software[38] and variables of interest included gait speed, cadence, double support time, and stride length, previously shown to differentiate healthy from concussed subjects.[29,30,39] Gait speed was calculated as the average velocity for the left and right foot across all gait cycles in each trial. Cadence was defined as the rate of steps per minute. Double support time is the percentage of time that both feet were on the ground in each gait cycle. Stride length is the average distance for each foot between consecutive steps in each trial.

Gait speed, cadence, double support time, and stride length were measured for each athlete under both tasks at each time point. The changes in each metric were computed from baseline to post-concussion. Dual task cost, the percent change between single and dual-task conditions, was computed for each athlete to normalize their individual dual-task performance to their single-task performance.[39,40] Dual task cost was calculated as (dual-task value – single-task value)/(single-task value) and reported as a percentage. Dual-task cost was measured for each gait characteristic of interest.

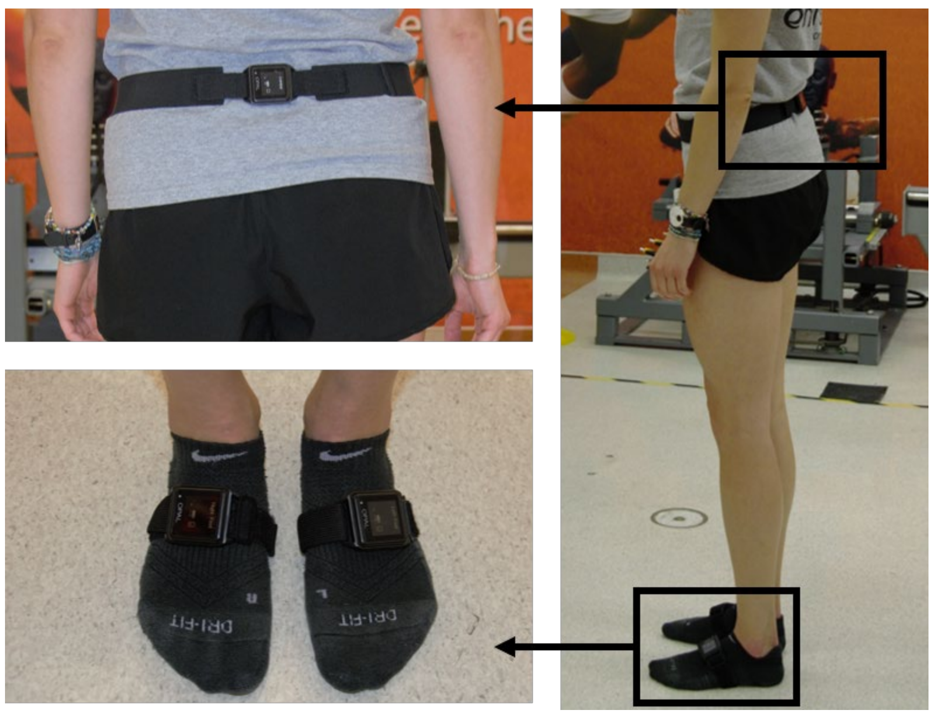

Figure 8.2. Opal Sensors attached to elastic straps around the athlete's waist and feet to measure gait characteristics.

Concussion Identification

Athletes reported suspected concussions to the research team, though not all concussions were clinically diagnosed. The athlete worked with the research team to describe the concussive event (or events) the situation surrounding it. Together, the staff and athlete identified the impact(s) on film. Time-synced video from each session was used to verify if an acceleration event recorded for the event (or events) of interest. PLA and PRV were quantified for each athlete. A time trace of the acceleration pulse was extracted and studied. Mechanism of injury was characterized. For concussive impacts for which no biomechanical data was recorded, a description of the event and potential reason for lack of data is documented.

RESULTS

There were 4 male concussions and 15 female concussions (Table 8.2). One male sustained two concussions (M-2 and M-3), and one female sustained two concussions (F-8 and F-13) (both in different seasons). This corresponded to 3.7% of male athlete-seasons concussed, and 13.2% of female athlete-seasons concussed. Three of the men's concussions were clinically diagnosed, and the fourth (M-3) was not reported to a clinician because it was during the last minutes of the last game of the season. Nine of the women's concussions were reported to clinical staff. This corresponds to 25% of the male concussions and 40% of the female concussions as unreported. Three of the females (F-4, F-7, and F-12) identified two impacts as the cause of the concussion, and were only tested after sustaining the second one. The most common reason for not reporting a potential concussion to clinical staff was that the athlete wanted to play in the next game.

Biomechanical data were collected for two male concussions and three female concussions. Data are missing for a variety of reasons: a false negative impact, mouthguard died, mouthguard would not connect to Bluetooth, mouthguard settings were not correct, mouthguard failure, and that the impact before happened in too close of a time window, and the impact of interest occurred in the turnover time.

The median number of symptoms reported was 17 (range: 3-24) for women and the 10.5 (range: 6-14) for men. The median SSS reported was 27 (range: 5-95) for women and the 15 (range: 9-25) for men. Most athletes showed a decrease in cadence, gait speed, and stride length, and an increase in double support time post-concussion (Table 8.3).

Table 8.2. Biomechanical summary of concussions for male and females.

Athlete	Reported	Mouthguard	PLA (g)	ΔRV (rad/s)	Mechanism	Skull Region	Event
M-1	Yes	Prevent	109.7	28.7	Head	Facial	Game
M-2*	Yes	Prevent	NA	NA	Head	Frontal	Game
M-3*	No	Wake	81.6	18.5	Ground	Occipital	Game
M-4	Yes	Prevent	NA	NA	Head	Occipital	Practice
F-1	Yes	Prevent	NA	NA	Ground	Occipital	Game
F-2	Yes	Prevent	NA	NA	Knee	Frontal	Game
F-3	Yes	Prevent	NA	NA	Knee	Frontal	Game
F-4	No	Prevent	NA	NA	Foot	Occipital	Practice
	Yes	Prevent	NA	NA	Ground	Occipital	Game
F-5	No	Wake	54.6	9.7	Knee	Frontal	Game
F-6	No	Wake	NA	NA	Foot	Frontal	Game
F-7	No	Wake	NA	NA	Forearm	Occipital	Game
	Yes	Wake	NA	NA	NA	NA	Game
F-8^	No	Wake	NA	NA	Shoulder	Temporal	Game
F-9	No	Wake	NA	NA	Elbow	Temporal	Practice
F-10	Yes	Wake	NA	NA	Head	Temporal	Practice
F-11	No	Wake	NA	NA	Ground	Parietal	Game
F-12	NA	Wake	43.3	9.7	Knee	Frontal	Practice
	Yes	Wake	71.7	6.3	Elbow	Facial	Practice
F-13^	Yes	Wake	NA	NA	Ground	Temporal	Game
F-14	Yes	Wake	24.0	5.4	Ball	Facial	Game
F-15	No	Wake	NA	NA	Head	Parietal	Game
	No	Wake	NA	NA	Knee	Frontal	Game

Table 8.3. Clinical summary, including symptom scores and changes in four gait metrics, associated with the concussions.

Athlete	Number of Symptoms	SSS	Task	Changes from Baseline to Post-Concussion (%) Cadence	Double Support Time	Gait Speed	Stride Length
M-1	6	9	NA	NA	NA	NA	NA
M-2*	14	16	NA	NA	NA	NA	NA
M-3*	13	25	Dual	-6.7	7.2	-9.8	-4.0
			Single	-5.7	8.7	-10.7	-5.1
M-4	8	14	NA	NA	NA	NA	NA
F-1	6	9	NA	NA	NA	NA	NA
F-2	24	95	Dual	4.9	-10.4	4.8	0.0
			Single	2.8	-8.9	-0.9	-3.6
F-3	20	46	Dual	-5.0	9.7	-8.5	-3.9
			Single	-3.2	6.1	-4.7	-2.1
F-4	NA	NA					
	17	46	Dual	2.7	-1.0	7.0	4.5
			Single	-5.6	13.3	-11.0	-5.9
F-5	16	27	NA	NA	NA	NA	NA
F-6	21	48	Dual	-5.6	9.2	-13.3	-7.6
			Single	-3.9	9.8	-10.2	-6.7
F-7	17	44	NA	NA	NA	NA	NA
	18	50	Dual	-4.5	7.2	-6.3	-2.0
			Single	-3.7	0.4	-9.0	-5.1
F-8^	10	10	Dual	-3.4	10.8	-9.7	-6.6
			Single	-5.5	4.8	-8.6	-3.4
F-9	13	21	Dual	0.8	2.6	-1.5	-2.1
			Single	0.8	-1.4	-2.7	-3.2
F-10	20	37	Dual	-6.7	1.0	-7.4	-0.7
			Single	-6.2	5.2	-7.3	-1.6
F-11	4	5	Dual	-3.2	1.8	0.1	3.5
			Single	-3.8	2.9	-0.4	3.3
F-12	NA	NA					
	17	19	Dual	1.0	-3.9	0.2	-0.8
			Single	-0.2	-1.5	-1.1	-1.0
F-13^	22	76	Dual	0.4	-4.3	1.1	0.8
			Single	-3.0	-2.0	-4.7	-2.2
F-14	13	27	Dual	-4.5	10.0	-8.5	-4.0
			Single	-2.0	8.0	-5.4	-3.6
F-15	NA	NA					
	3	8	Dual	-0.9	6.1	0.6	1.1
			Single	-1.0	8.6	-0.2	0.7

Individual Male Concussions

M-1 – This athlete was running at an opponent and as he went into for a tackle, he hit his face on his opponent's head. His impact registered 109.7 g and had a change in rotational velocity of 28.7 rad/s (Figure 8.3). He suffered a clinically diagnosed concussion and facial fracture. He reported 6 symptoms with an SSS of 9. Gait assessments were not yet part of study protocol.

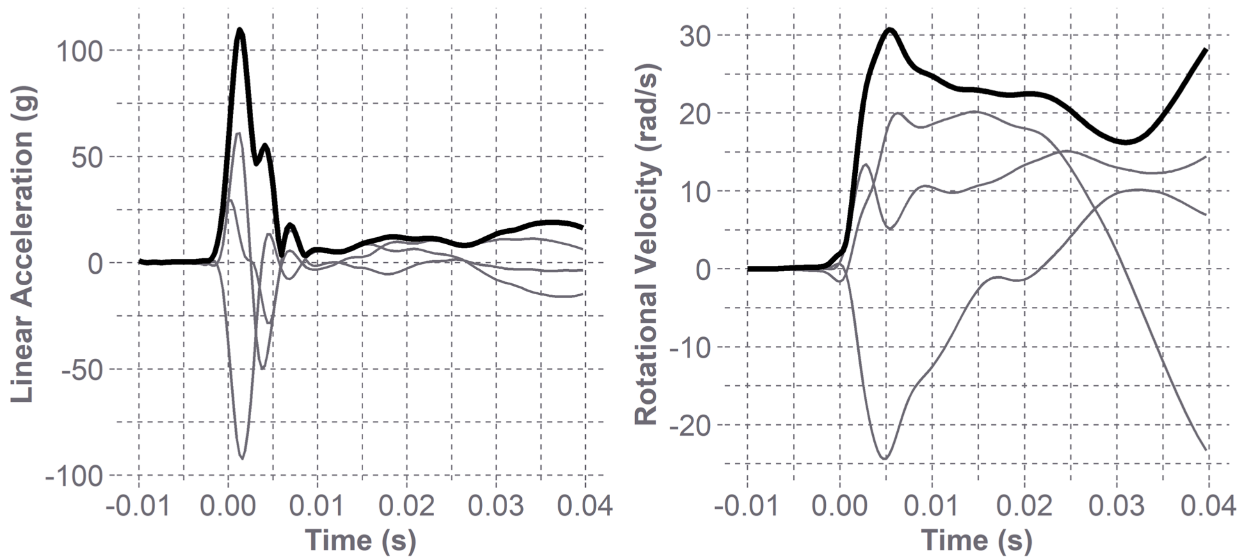

Figure 8.3. Linear acceleration and rotational velocity traces for a concussion M-1 on the men's team. The linear acceleration curve's narrow width and sharp peak is reflective of the head to head impact. The rotational velocity curve is also very steep and potentially indicative of the relatively rapid and severe impact. Resultant trace is black and axis specific traces are gray.

M-2 – A male athlete was going into a tackle during a game, and as his teammate went in for the same tackle, they collided heads, impacting the athlete of interest in the frontal region of his head, on the right side. He reported that his head hurt going into that tackle, but he saw a bright light after the impact and subbed himself out of the game. He was clinically diagnosed with a concussion. His teammate did not sustain a concussion. Due to issues with the time stamps on the Prevent mouthguard data, no kinematics were collected. He reported 14 symptoms with an SSS of 16 and said that he felt more tired than usual and had a very hard time focusing on school work. Gait assessments were not yet part of study protocol.

M-3 – The same athlete from the previous concussion tackled an opponent in the last minutes of a game in the following season, swung his opponent around and brought him to the ground but hit the occipital region of his head on the ground in the process. The impact was 81.6 g and 18.5 rad/s (Figure 8.4). He said that he does not remember the end of the game, was sensitive to light and noise, and his headache increased in intensity. He did not report this impact to an athletic trainer because it was the last game of the season. He reported 13 symptoms with an SSS of 25. He completed his gait test 4 days post-concussion and saw decreases in his cadence, gait speed, and stride length, and increase in double support time, consistent with previous post-concussion literature.[39]

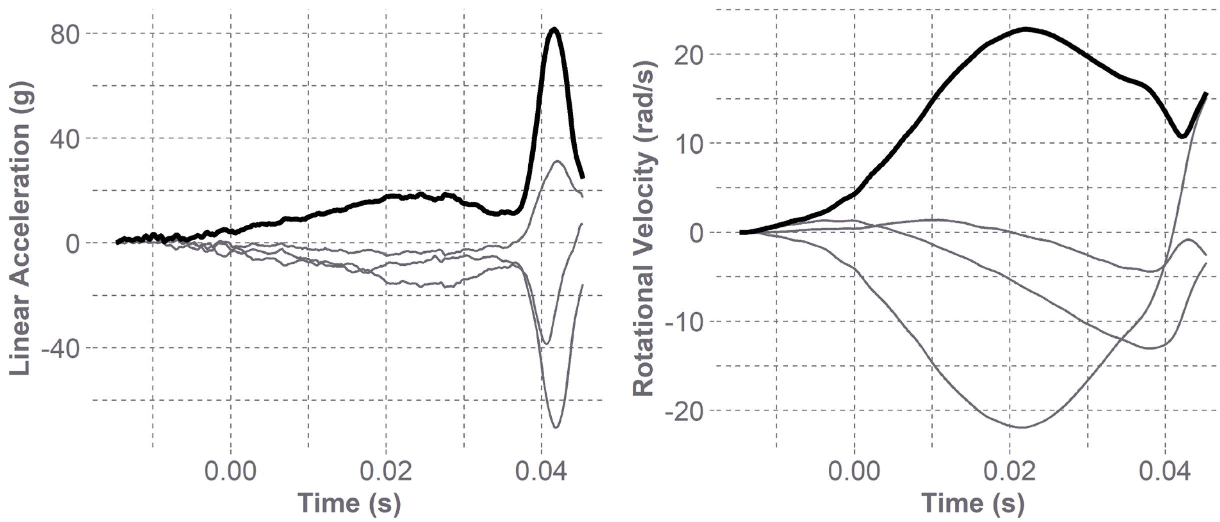

Figure 8.4. Linear acceleration and rotational velocity traces for a concussion M-3 on the men's team. It is likely that the rotational velocity measured is associated with the body impact that happened before the head to ground impact, and the change in rotational velocity associated with the head impact was not captured. Resultant trace is black and axis specific traces are gray.

M-4 – This male athlete sustained a clinically diagnosed concussion while doing a tackling drill at practice. His teammate's forehead collided with the occipital region of his head. There were no kinematic data collected for this impact; Prevent hypothesized that the oblique rear impact did not generate an acceleration at the center of gravity high enough to trigger data acquisition. He reported 8 symptoms with an SSS of 14. There were no gait data collected after this concussion.

Individual Female Concussions

F-1 – This female athlete picked a loose ball up during a game, was picked up and slammed on her back, and her head snapped back and hit the ground. Due to issues with the time stamps on the Prevent mouthguard data, no kinematics were collected. She reported 6 symptoms with an SSS of 9 and was clinically diagnosed with a concussion. Gait data were not yet part of study protocol.

F-2 – This athlete recalled several hard impacts during this game, but most notably one when an opponent hit her down, and she hit the right frontal region of her head on a knee. She held her head after the impact and reported 24 symptoms with an SSS of 95. She was clinically diagnosed with a concussion. No kinematics were collected for this impact or the day in general, likely due to an unidentifiable device failure.

Her gait was tested two days post-concussion and her cadence increased and her double support time decreased in both tasks.

F-3 – Similar to the previous female athlete, this player identified a rough game with the most significant impact happening when she was tackled, spun around, and flung onto her teammate's knee on the way to the ground. She hit the front of her head and was clinically diagnosed with a concussion. She reported 20 symptoms with an SSS of 46. She completed his gait test 3 days post-concussion and saw decreases in cadence, gait speed, and stride length, and increase in double support time, consistent with previous post-concussion literature.[39] Her mouthguard recorded impacts during the warm-up, but none during the game, likely due to another device failure.

F-4 – She reported two impacts causing her concussion, after the second occurred. The first was at practice, when she was kicked in the back of the head during a ruck. The following Saturday during a game, she was trying to tackle someone and was stiff-armed, knocking her to the ground where she hit the back right side of her head. Her Prevent mouthguard seemed to be functioning fine, other impacts were recorded for her on both days but not for these two impacts, leaving them as false negative impacts with no resulting kinematics. She took her symptom survey after the Saturday game, and reported 17 symptoms with an SSS of 46. Her concussion was clinically diagnosed by an athletic trainer. Her single-task gait variables matched other post-concussion results (decrease in cadence, gait speed, and stride length and an increase in double support time), but her dual-task gait variables were the exact opposite – an increase in cadence, gait speed, and stride length and a decrease in double support time. Her gait was tested two days after the second impact.

F-5 – This female attributed her diagnosed concussion to a series of events during a game, but most significant was an impact that occurred when she brought an opponent down and hit the right frontal part of her head on someone's knee. This registered a 54.6 g and 9.7 rad/s impact (Figure 8.5). She reported 16 symptoms with an SSS of 27. She told me about the concussion, but did not report it to a clinician. There were no gait data collected after this concussion.

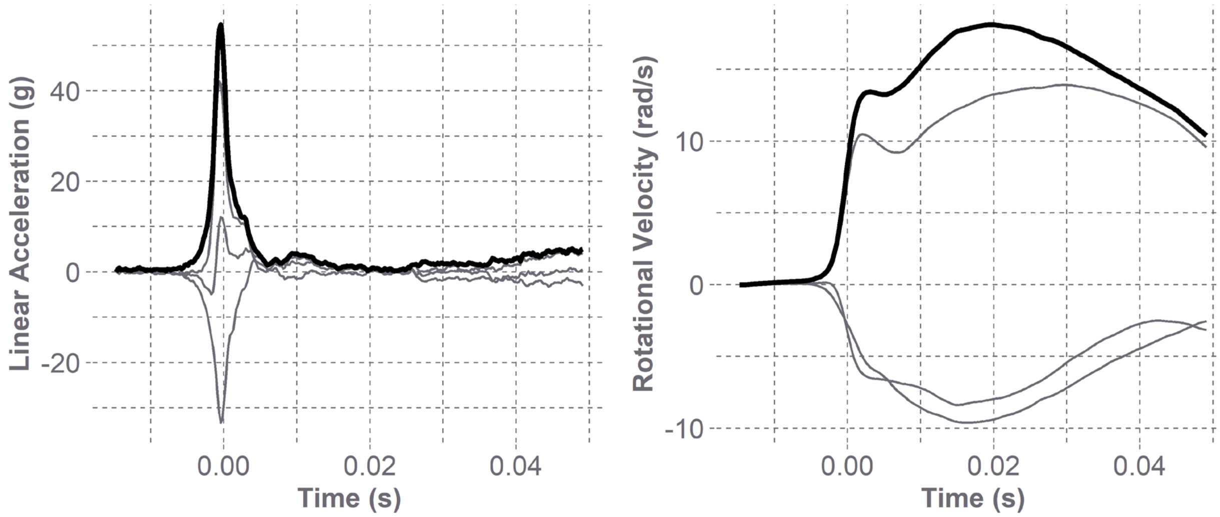

Figure 8.5. Linear acceleration and rotational velocity traces for concussion F-5 on the women's team. These traces have similar shapes to those seen in lab impacts and the short duration is consistent with an impact to a knee. Resultant trace is black and axis specific traces are gray.

F-6 – This athlete was kicked in the frontal region of her head during a game. The kinematics collected were from the impact just prior, when she dove to the ground in the try zone. The second impact happened in the time window when the device was preparing to trigger the next event, and therefore classified as a false negative. She reported 21 symptoms was an SSS of 48, and that she did not want to report anything officially because of a big game the following weekend. Both task conditions in her gait tests, three days later, were consistent with literature for concussions (decrease in cadence, gait speed, and stride length and an increase in double support time).

F-7 – This female athlete sustained two impacts on the same day before being clinically diagnosed with a concussion. The first was during the A side game, when she rolled her opponent off of her which resulted in her opponent hitting her in the back of the head with her forearm. This impact was a false negative and no kinematics were collected. The second impact occurred during the B side game, which she was not instrumented for, but she described the effects of as her "vision turned funny and colors washed out into a haze" but she continued to play through. She was diagnosed by an athletic trainer and reported 18 symptoms with an SSS of 50. Both task conditions in her gait tests, which she took four days after the second impact, were consistent with literature for concussions (decrease in cadence, gait speed, and stride length and an increase in double support time).

F-8 – This female athlete went to tackle her opponent during a game and who dropped her shoulder into the side of this athlete's face who then fell back. Her mouthguard died midway through the game so no kinematic data were collected. She did not report this to a clinician, but reported 10 symptoms with an SSS of 10 on her survey. She said that “at first felt like I blacked out and I felt dizzy and my head hurt. I kept playing, and had burry vision ten minutes after.” Both task conditions in her gait tests, which she took two days later, were consistent with literature for concussions (decrease in cadence, gait speed, and stride length and an increase in double support time).

F-9 – This female was impacted in a practice that she was not instrumented in. She took out opponent’s legs to tackle her; she was then elbowed in the left side of the head while her opponent rolled over her and the rucker kneed her in the left side of the jaw. She did not report her symptoms to a clinician, but reported 13 symptoms with a severity of 21. After the impact, she was dizzy, slow to get up, and nauseous, but continued to play. Both her temple and jaw bruised. One day after her concussion, she took her gait test where her cadence was slightly increased, and her gait speed and stride length were slightly decreased. Her double support time increased for the dual task, but decreased for the single task.

F-10 – This female was also impacted in a practice that she was not instrumented in. Her teammate tackled her head on to the left side of her head. She reported 20 symptoms with an SSS of 37. She said that right after it happened it felt like her head exploded and she fell down. She woke up several times that night and was nauseous. Her headache lingered and she felt sensitive to light. and that her symptoms resolved in a few days. The athletic trainer said she had signs on a concussion. Both task conditions in her gait tests, which she took one day later, were consistent with literature for concussions (decrease in cadence, gait speed, and stride length and an increase in double support time).

F-11 – This athlete was tackled during a game, and impacted the parietal region of her head on the ground. The acquisition settings of her device were wrong and no kinematic data were collected. She reported 4 symptoms with an SSS of 5, and did not notify clinical staff. She said that she “greyed out” at the time of impact and saw stars, but did not notice other symptoms until the following days, with a constant headache, increased fatigue, and inability to do homework. She continued to play and practice that week. She took her gait test four days later, and showed a decrease in cadence and increase in double support time, consistent with post-concussion gait tests. However, her stride length increased, and her gait speed barely changed.

F-12 – This player sustained two impacts at practice that she attributes to her clinically diagnosed concussion. In the first, a teammate was running at her with a ruck pad during a drill and she tripped on her own foot and dove below the pad, hitting the front of her head on the pad holder’s knee. The kinematics associated with this impact were 43.3 g and 9.7 rad/s (Figure 8.6). The second impact occurred when she was the pad holder and a teammate was running toward her, and hit her in the left eye with her elbow. The kinematics associated with this impact were 71.7 g and 6.3 rad/s (Figure 8.6). She had a lot of neck pain associated with the impacts, in addition to nausea, headache, and difficulty sleeping. She reported 17 symptoms with an SSS of 19. She took the post-concussion gait test two days later, and her results were mixed. She showed a slight increase in cadence and gait speed during dual task, but a slight decrease in both during single task. Her double support time and stride length both decreased.

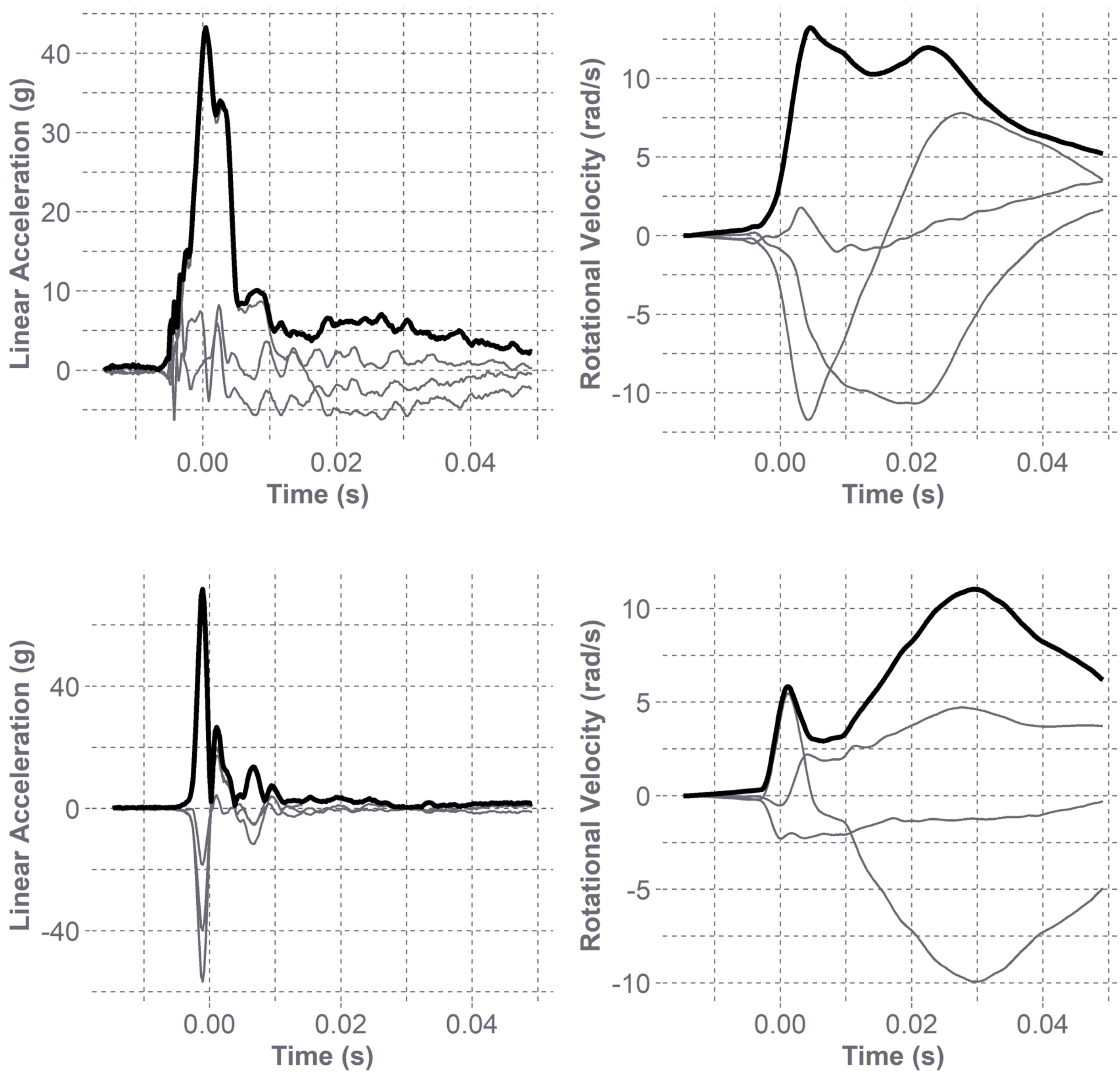

Figure 8.6. Linear acceleration and rotational velocity traces for concussion F-12 on the women's team. The top two traces are from the first impact, and the bottom two traces are from the second impact. These traces similar shapes to those seen in lab impacts and the short duration is consistent with an impact to a knee and head. Resultant trace is black and axis specific traces are gray.

F-13 – This concussion was sustained by the same athlete that sustained concussion F-8. During a game, she caught the ball and was going into contact when her opponent hit me hard on the side, knocking her off my feet and the right side of her head hit to the ground. The mouthguard recorded the impact of her body hitting the ground; her head hit the ground in the time window when the device was preparing to trigger the next event, and therefore this concussion was classified as a false negative. She had an instant severe headache after, was slow to get up, and extremely emotional after. The following day she was sensitive to light, nauseous, had neck pain, and generally felt "out of it." She was clinically diagnosed and reported 22 symptoms with an SSS of 76. She did her gait test two days post-concussion; She showed a slight increase in cadence, gait speed, and stride length during dual task, but a larger decrease in all three during single task. Her double support time both decreased.

F-14 – During a game, this athlete took a punted ball to her left eye, and did not remember the impact. She was subbed out but later went back in. The kinematics were 24.0 g and 5.4 rad/s (Figure 8.7). She reported 13 symptoms with an SSS of 27. She said her headache did not start until after the game, and was bad in the following days. She had trouble falling asleep and doing work, and was sensitive to light and noise. An athletic trainer diagnosed her with a concussion. She took her post-concussion gait test two days after, and was consistent with literature for concussions (decrease in cadence, gait speed, and stride length and an increase in double support time) in both task conditions.

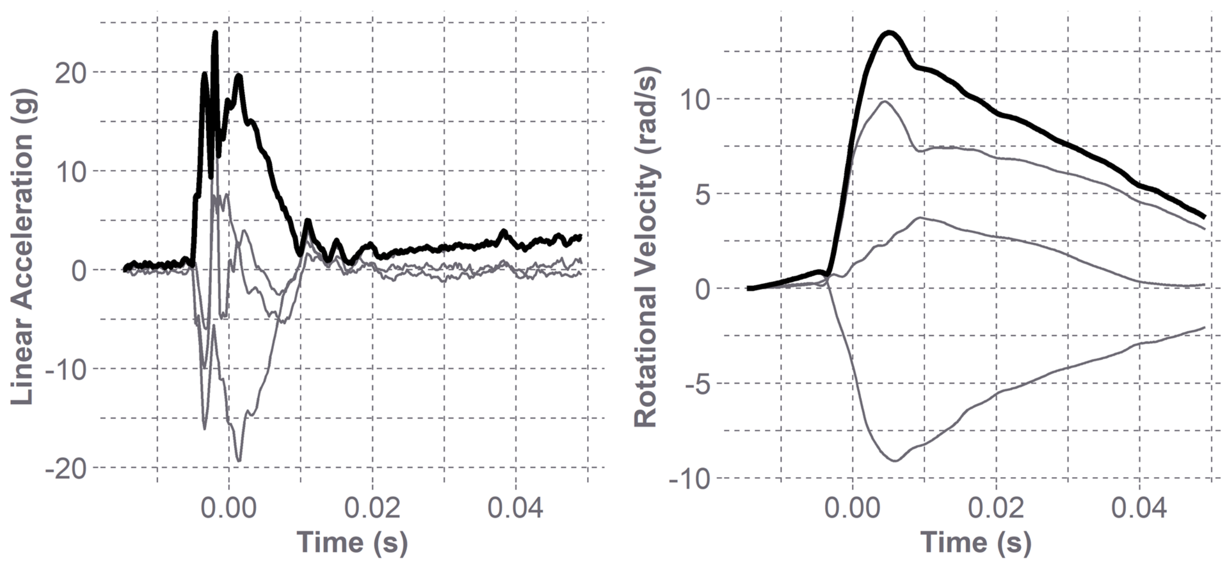

Figure 8.7. Linear acceleration and rotational velocity traces for concussion F-14 on the women's team. The linear acceleration pulse is wider, likely reflecting the compliant nature of the ball upon impact. Resultant trace is black and axis specific traces are gray.

F-15 – This athlete sustained two major impacts in the last game of the season: the first she was in a ruck and collided head-on with her opponent, and the second she was kneed in the head while defending a try. Her mouthguard would not connect to Bluetooth after the game and therefore we have no kinematics for these impacts. She filled out her survey right after the game, with 3 symptoms and an SSS of 8, but said that symptoms worsened into the week. She felt nauseous, “out of it”, dizzy, had a headache, and was sensitive to light and noise. She took her post-concussion gait test 4 days after the game and showed a slight decrease in cadence, slight increase in stride length, a larger increase in double support, and very small changes in gait speed.

DISCUSSION

Over the course of the study, more women sustained concussions than their male counterparts. Of those sustained, a higher proportion of males reported their symptoms to a clinician than the female athletes. It is well documented that underreporting is extremely common in athletes and complicates concussion diagnosis.[41-43] We were transparent with the athletes in that we wanted to know if they suspected they had a concussion, whether or not they reported their symptoms to an athletic trainer. Because of this, the number of concussions reported to a clinician is much lower than the number of events reported to the research staff, exemplifying the underreporting of concussion. This emphasizes the value of collecting weekly symptom data from the athletes, and providing them a mechanism of self-reporting. The athletes may be more aware of their symptoms in-season if they fill out a symptom survey each week, and may feel more comfortable being honest in a survey, compared to the pressure of reporting to a clinician. It is also interesting to note that three of the women identified two impacts contributing to their diagnosis, but did not report the first impact initially. Many athletes played through their impacts during practices or games, and did not acknowledge the severity of the impacts or report them until after the event was over. Previous work has shown that athletes are likely to not report a concussion because they think the impact was not as severe as a concussive impact.[42]

We were missing kinematic data from most events for a variety of reasons. For the data we have, the men’s impacts were sustained at higher kinematics, but we cannot generalize as so much data are missing. The concussive impacts for the men were measured at 109.7 g and 28.7 rad/s, and 81.6 g and 18.5 rad/s. This compares to average concussion linear accelerations of 104 ± 30 g from collegiate football players.[15] It is important to note that football players are helmeted, compared to unhelmeted rugby players, so we would expect lower concussive kinematics in rugby.

The women’s concussions occurred at 54.6 g and 9.7 rad/s, 43.4 and 9.7 rad/s and 71.7 g and 6.3 rad/s, and 24.0 g and 5.4 rad/s. While we cannot infer from the small sample of concussions we collected, we can provide context of our data through comparison to concussions measured in other studies. Previous work showed four female collegiate hockey players had an average concussive linear acceleration of 43.0 ± 11.5 g.[44] The magnitudes recorded in our study are all lower than the male concussions in our study, but comparable to the helmeted female hockey players. Data from potentially more severe impacts were missed, which may have had kinematics of a more similar magnitude to the men's.

Another head, a knee, and the ground were the most common things impacted. Going into a tackle and colliding head to head with an opponent, rucking or going for the ball, and being flung to the ground were the most frequent mechanisms for impacts with these three things respectively. These mechanisms are similar to observational studies in other rugby teams.[23] Several impacts happened with a teammate, suggesting that potential better communication or field awareness could help decrease the risk of concussion. Neck strengthening exercises may help mitigate the head acceleration when being tackled to the ground, and decrease the severity of those impacts. Proper tackling form should be reinforced during practices and games to reduce unnecessary risk of illegal and more dangerous tackles.[45] Additionally, protective soft-shelled headgear might reduce any force input to the head in these impacts. Headgear is infrequently worn by rugby players, and has raised much controversy over the years.[46-51]

The number of symptoms reported and the SSS for each athlete vary greatly. This could be partially attributed to differences in onset of symptoms per individual. Likely some athletes experienced a delay compared to others, or some might have resolved before taking the symptom survey. An SSS $\geq$ 21 has been associated with concussions in collegiate football players.[52,53] The women in our study in general reported a higher SSS (mean = 35.5) than the men (mean = 16). Sex may also play a role in perception of symptoms and the tendency to underreport the severity of symptoms.[54]

In general, gait results were consistent with other dual-task studies post-concussion.[39,55,56] We normalized changes in the four gait metrics to the individual's baseline measurements for comparison. Previous work has identified changes in cadence, double support time, gait speed, and stride length in post-concussion time points. Again, time could play a factor in the magnitude of changes in gait; all athletes were tested within four days but it is possible that the clinical effect of a mild concussion of gait has resolved by that time or, they have not presented yet. Previous work has shown dual-task deficits at days 5-6,[57] or in the year following the concussion,[58] which is after all of the athletes in this study were tested. Interestingly, the metrics of concussion F-2, showed all opposite of what we would expect post-concussion, and improved in all of her gait metrics.

In this study, the frequency of women's concussions is greater than the men's team but the kinematics of women's concussions seem to be lower than those of the men. Women also reported more symptoms with a higher severity, and increased gait deficits post-concussion. This dataset included a candid look into the underreporting of collegiate athletes by including events that resulted in an increase in self-reported symptoms. Some concussive kinematic data for women exist, but this is one of the first datasets comparing a matched cohort of unhelmeted athletes, allowing for a comparison of sex-specific biomechanics, incidence rates, and their clinical effects. Collecting these on-field kinematics is challenging and requires a comprehensive approach to device use and great attention to detail. In the future, thoughtful emphasis should be put on sensor validation, its sports-specific application, and its careful use to collect more on-field biomechanics of contact sport athletes. Ideally, this dataset can be a foundation of injury risk curves that are representative of women. Understanding the biomechanics of women's concussions will provide better understanding of concussion tolerance and hopefully pave the way for more sex-specific prevention and intervention strategies.

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CHAPTER 9: CLOSING REMARKS

SUMMARY OF RESEARCH

The research in this dissertation was to designed to help better understand head impact exposure and its clinical effects, with the overarching goal of learning more about concussions in unhelmeted and female populations. On-field biomechanical data collected with instrumented mouthguards from collegiate rugby players served as the basis of assessing head acceleration. Linear acceleration, rotational velocity, and impact duration were quantified for head impacts and body impacts and compared between sexes. The females in our study sustained fewer impacts per session than the males, but their impacts had similar linear acceleration magnitudes. The kinematics of the concussive male impacts were higher than the kinematics of the concessive female impacts.

Clinical measures such as routine symptom surveys and gait assessments provided a multi-faceted approach towards understanding potential changes athletes experience after a concussive impact, as well as over the course of a season of cumulative, subconcussive head impacts. The sex-specific presentation of severity and frequency of symptoms was collected on a weekly basis and elevated cases were identified. Females reported more symptoms with a higher severity in-season compared to males after subconcussive and concussive impacts. Both sexes reported concussion-like symptoms in the absence of diagnosed concussion during a season. This enforces the need for regular symptom monitoring in-season in attempt to identify unreported concussions. Dual-task gait assessments provided a motor-control perspective on the effect of cumulative subconcussive impacts over the course of a season. The gait changes from baseline to post-season were compared, and post-concussion data provided context for these values. Female athletes saw deficits in cadence, double support time, gait speed, and stride length post-concussion. The majority of athletes improved in their dual-task gait assessment by the end of the season, suggesting there may not be a negative effect on gait after an accumulation of subconcussive impacts.

As concussion tolerance varies with sex, utilizing appropriate evaluation methods, management strategies, and prevention tools based on sex may be necessary. The few concussions that were captured provide case study examples and serve as context and references for future data collection from unhelmeted athletes. The data that were collected will inform future bivariate concussion risk curves specific to women and unhelmeted athletes, contributing to the safety of all athletes. Additionally, the on-field data that were collected will be used to inform a rugby headgear testing protocol to better understand the energy mitigation abilities of these headgear in attempt to improve safety of the sport.

PUBLICATION PLAN

All research presented in this dissertation is expected to be published in peer-reviewed, scientific journals or conference proceedings. Table 9.1 specifies the publication location for each chapter as well as the conferences at which each chapter was presented.

Table 9.1. Publication plan for research

Chapter	Title	Journal *(Conference)*
2	On the Use of Wearable Sensors to Measure Head Impacts in Sports	Annals of Biomedical Engineering *(Biomedical Engineering Society Annual Meeting)*
3	A Two-Phased Approach to Quantifying Head Impact Sensor Accuracy: In-Laboratory and On-Field Assessments	Annals of Biomedical Engineering*
4	Using In-Mouth Sensors to Measure Head Kinematics in Rugby	*International Research Council on Biomechanics of Injury (IRCOBI)**
5	In-Season Concussion Symptom Presentation in Men's and Women's Collegiate Rugby	Biomedical Science Instrumentation* *(Rocky Mountain Bioengineering Symposium)*
6	In-Season Concussion Symptom Reporting in Male and Female Collegiate Rugby	American Journal of Sports Medicine^ *(Sports Concussion Conference)*
7	Dual-Task Gait Performance in Collegiate Rugby Athletes	Journal of Sports Engineering and Technology
8	Concussion Biomechanics and Clinical Outcomes in Rugby	International Journal of Sports Physical Therapy

* Published
^ Submitted