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Video Confirmation of Head Impact Sensor Data From High School Soccer Players

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Abstract

Background—Recent advances in technology have enabled the development of head impact sensors, which provide a unique opportunity for sports medicine researchers to study head kinematics in contact sports. Studies have suggested that video or observer confirmation of head impact sensor data is required to remove false positives. In addition, manufacturer filtering algorithms may be ineffective in identifying true positives and removing true negatives.

Purpose—To (1) identify the percentage of video-confirmed events recorded by headband-mounted sensors in high school soccer through video analysis, overall and by sex; (2) compare video-confirmed events with the classification by the manufacturer filtering algorithms; and (3) quantify and compare the kinematics of true- and false-positive events.

Study Design—Cohort study; Level of evidence, 2.

Methods—Adolescent female and male soccer teams were instrumented with headband-mounted impact sensors (SIM-G; Triax Technologies) during games over 2 seasons of suburban high school competition. Sensor data were sequentially reduced to remove events recorded outside of game times, associated with players not on the pitch (ie, field) and players outside the field of view of the camera. With video analysis, the remaining sensor-recorded events were identified as an

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impact event, trivial event, or nonevent. The mechanisms of impact events were identified. The classifications of sensor-recorded events by the SIM-G algorithm were analyzed.

Results—A total of 6796 sensor events were recorded during scheduled varsity game times, of which 1893 (20%) were sensor-recorded events associated with players on the pitch in the field of view of the camera during verified game times. Most video-confirmed events were impact events (n = 1316, 70%), followed by trivial events (n = 396, 21%) and nonevents (n = 181, 10%). Female athletes had a significantly higher percentage of trivial events and nonevents with a significantly lower percentage of impact events. Most impact events were head-to-ball impacts (n = 1032, 78%), followed by player contact (n = 144, 11%) and falls (n = 129, 10%) with no significant differences between male and female teams. The SIM-G algorithm correctly identified 70%, 52%, and 66% of video-confirmed impact events, trivial events, and nonevents, respectively.

Conclusion—Video confirmation is critical to the processing of head impact sensor data. Percentages of video-confirmed impact events, trivial events, and nonevents vary by sex in high school soccer. Current manufacturer filtering algorithms and magnitude thresholds are ineffective at correctly classifying sensor-recorded events and should be used with caution.

Keywords

head injuries/concussion; pediatric sports medicine; football (soccer); injury prevention

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In any given sport, the potential for concussion is related to the number of opportunities for head impact[11]; therefore, the ability to quantitatively monitor the occurrence and severity of head impacts is an important methodologic approach for sports medicine researchers. Recent advances in technology have enabled the development of head impact sensors, which facilitate the study of head impact kinematics of athletes in vivo. Various head impact sensors are currently available, such as instrumented helmets, skull caps, headbands, mouthguards, and skin patches,[10] which have been used to investigate head impact kinematics in sports such as soccer,[2,7,9,12] lacrosse,[3,13] and American football.[4,6,8,14]

Since head impact sensor data are collected during game play, rather than in a carefully controlled setting of a laboratory, it is often contaminated with false-positive results, and several studies have suggested that video or observer confirmation of head impact sensor data is required to remove such inaccuracies.[3,12] Press and Rowson[12] used the xPatch (X2 Biosystems) to quantify head impact exposure in female collegiate soccer games and found that only 8% of sensor-recorded events were video-confirmed head impacts. Lamond et al[7] investigated head impacts in female collegiate soccer players using the SIM-G (Triax Technologies) and identified that 31% of sensor-recorded events were observer-confirmed head impacts. Cortes et al[3] investigated male and female high school lacrosse players; however, given the different equipment requirements of the 2 sports, the male players wore the helmet-mounted GForceTracker (GForceTracker, Inc) and the female players wore the skin-affixed xPatch. Of the sensor events recorded by the GForceTracker, 65% were video-confirmed head impacts, whereas the xPatch demonstrated twice as many false-positive readings, as 32% of sensor-recorded events were video-confirmed head impacts.

In an attempt to address the presence of false-positive results, some head impact sensors have a processing algorithm provided by the manufacturer to filter and remove “spurious” events; for example, the Head Impact Telemetry System (Simbex) compares the sensor-recorded kinematics to the expected acceleration signals for rigid body head acceleration,[4] whereas other sensors simply apply a magnitude-based filter. Although most processing algorithms are proprietary, some manufacturers allow the algorithm to be deactivated (eg, xPatch and SIM-G). Nevins et al[9] used video analysis to investigate the classification of 116 sensor-recorded events in male high school soccer players and found that the xPatch algorithm incorrectly classified 15% of video-confirmed impact events as spurious. In addition, 83% of sensor-recorded events determined to be nonevents by video analysis were incorrectly classified as valid by the algorithm. In a similar study of female collegiate soccer players, Press and Rowson[12] found that the xPatch algorithm incorrectly classified 57% of nonevents, but only 4% of video-confirmed impact events were incorrectly classified. Such findings suggest that manufacturer filtering algorithms may be ineffective in identifying true-positive results and removing true-negative ones.

The percentage of false-positive results is likely dependent on sensor model, sensor attachment method, sport, and athlete behavior, the last of which may vary by sex and nature of the sporting environment—for instance, lacrosse has different rules and equipment for females and males. However, to our knowledge, the percentage of false-positive readings within a head impact sensor data set has not been evaluated previously for males and females in the same sport with the same sensor. Furthermore, quantification of the characteristics of the kinematics of false-positive events may provide insight into possible processing strategies to improve filtering algorithms for future sensor designs. Therefore, the aim of the current study was to illustrate the importance of video confirmation methodologies in the processing of head impact sensor data by (1) identifying the percentage of video-confirmed events recorded by headband-mounted sensors in high school soccer, overall and by sex; (2) comparing video-confirmed events with the classification by the manufacturer filtering algorithm; and (3) quantifying and comparing the kinematics of true- and false-positive events.

METHODS

A prospective observational study of adolescent female varsity, male varsity, and male junior varsity soccer teams from a suburban high school (grades 9–12) was conducted. Athletes were instrumented with headband-mounted SIM-G impact sensors during competitive games for the 2017 and 2018 seasons. The current study was approved by the Children’s Hospital of Philadelphia Internal Review Board (IRB-17–013875 and IRB-18–015265). The SIM-G device comprises a triaxial gyroscope, for measurement of angular velocity, and a high- and low-g triaxial accelerometer, for measurement of linear acceleration with a measurement range of 3 to 150g and a trigger threshold of 16g.[17] For each impact, the sensor records linear acceleration and angular velocity time histories at 1000 Hz in all 3 unique axes and stores time series data from 10 ms preimpact to 52 ms after impact. The sensor device is mounted in a neoprene headband (Figure 1), which can be worn in helmeted and unhelmeted sports, and is positioned just above the greater occipital protuberance. Data are transmitted from the sensor via Bluetooth to the SKYi box up to 135 m away for up to 63 players per box. If a player is out of transmission range, up to 140 impacts can be stored on the sensor until the player returns within range.

Sensors were assigned to individual players throughout the entire season and were linked to a SKYi box. As each sensor was turned on before each game, connection with the respective SKYi box was confirmed. Sensors were distributed before the players began warm-ups. The SKYi box was placed near the midpoint of the pitch (ie, field), and recording of sensor data on the SKYi box was typically initiated during warm-ups. In the case of away games, the SKYi box and sensors were sometimes turned on earlier (eg, on the way to the game) because of staffing limitations. After the game, collection of sensor data on the SKYi box ceased, and sensors were returned to study staff and deactivated. Headbands were washed, and the sensors and SKYi box were charged between games.

Video footage from games was captured from a single-camera view (Sony HD Camcorder CX405) located close to the midpoint of the pitch from as high a vantage point as possible. Video footage was recorded in high-definition 1080p with a 16:9 aspect ratio at 60 frames per second. Before the start and end of each half, a few seconds of a world clock website was filmed,[16] which provided a timestamp for the video footage to align with that of the sensor data. Recording was done such that approximately one-third of the soccer pitch was shown in the field of view and the videographer panned the camera to follow the action of the ball.

After the game, the SKYi box was connected to a wireless network, and the data were uploaded to the cloud and processed by proprietary manufacturer software, which transformed linear acceleration data from the device location to the center of gravity of the head via the following equation:

$$a_{\mathrm{CG}} = a_{\mathrm{S}} + \omega \times (\omega \times r) + \omega' \times r,$$

where a_{CG} is linear acceleration of the center of gravity of the head, a_{S} is linear acceleration of the sensor, ω is angular velocity recorded by the sensor, ω' is angular acceleration recorded by the sensor, and r is the distance between the sensor and the center of gravity of the head for a 50th-percentile male. Resultant linear acceleration and angular velocity were calculated from axis-specific data. Angular acceleration is calculated; however, given the errors associated with numerical differentiation of gyroscopic impact data,[1] only angular velocity was analyzed in the current study. In addition, the proprietary manufacturer software labeled each sensor-recorded event as either a “valid” or “spurious” impact. For each sensor-recorded event, the summary data comprised a unique event identifier, timestamp, peak linear acceleration, peak angular velocity, and impact direction. In addition to the summary data, axis-specific time series data for each kinematic profile were recorded.

Initially, sensor-recorded events outside of scheduled game times were removed. However, games did not always start according to scheduled times (eg, 16:05 instead of 16:00). Therefore, the timestamp in the video footage was used to determine the time points associated with the start and end of each half, as indicated by the whistle of the referee, and sensor data outside of verified game times were excluded. Next, the video was inspected to identify time points where substitution of specific players occurred, and a list of players on the pitch by time of game was compiled. Any sensor-recorded events associated with players who were not on the pitch at the time were excluded. Last, any sensor-recorded event associated with a player who was out of frame of the camera at the time was excluded. The remaining sensor-recorded events were associated with players on the pitch and in the field of view of the camera during verified game times (hereafter, the final data set).

Remaining sensor-recorded events associated with a player who was in the field of view of the camera at the time were analyzed to categorize each event as an impact event (eg, player heading the ball), trivial event (eg, player adjusting the headband), or nonevent (eg, player stationary and not touching the headband). The mechanism of identified impact events was coded as ball to head (eg, unintentional ball impact to the face of an unsuspecting player), head to ball (eg, purposeful heading of the ball), fall (eg, player makes contact with the ground after losing balance), or player contact (eg, elbow of opposing player impacting the head during aerial contest). Data were summarized overall and by sex.

Percentages of event type (nonevents, trivial events, and impact events) and impact type (ball to head, fall, player contact, and head to ball) were calculated. Adjusted residual post hoc analyses of chi-square tests of independence with Bonferroni adjustment were performed to determine significant differences ($P < .05$) in the distribution of event types and impact types between female and male varsity players. The analyses were repeated to compare the distribution of event types and impact types between male varsity and junior varsity. Percentage correct classifications by the SIM-G algorithm of video-confirmed event types were calculated. Mean peak linear accelerations and angular velocities were calculated for the 3 event types, and significant differences ($P < .05$) between female and male varsity players for each kinematic outcome were assessed with the Student *t* test. To identify whether event types could be classified by differences in magnitude, unadjusted linear regressions were performed to assess significant differences ($P < .05$) in peak linear acceleration and angular velocity among the 3 event types (eg, impact events, trivial events, and nonevents) for female and male players.

RESULTS

Sensor data were recorded for 72 adolescent soccer players: 23 female varsity players and 49 male players (31 varsity and 18 junior varsity). Of the 65 varsity games during the 2017 and 2018 soccer seasons, 51 games (78%; 25 female and 26 male team games) had sensor data, and 54 (71%; 26 female and 28 male team games) had video data. A total of 41 varsity games (18 female and 23 male team games) had both sensor and video data. An additional 4 male junior varsity games from the 2017 season had both sensor and video data.

For varsity game days, 40,352 sensor events were recorded. A total of 9503 sensor events were recorded during scheduled game times (Table 1; Appendix Figure A1, available in the online version of article); however, when verified game times were accounted for (eg, game started 5 minutes late), the number of sensor-recorded events was reduced to 6796. The number of sensor-recorded events was further reduced to 2775 after exclusion of data from players who were not on the pitch and to 1893 after exclusion of data from players not in the field of view of the camera at the time when the sensor recorded the event. The final data set of sensor-recorded events represented 20% of the sensor-recorded impact events during scheduled game times.

Of the 1893 sensor-recorded events in the final data set, video confirmation revealed that 1316 (70%) were impact events, 396 (21%) were trivial events, and 181 (10%) were nonevents. Females had significantly higher ($P < .05$) percentages of nonevents (15%) and trivial events (37%) than males (7% and 14%, respectively), whereas females had a significantly lower ($P < .05$) percentage of impact events (49%) than males (78%). Of the 1316 sensor-recorded impact events, most were head-to-ball impacts (78%), for which the head intentionally impacts the ball, followed by player contact (11%) and falls (10%). Very few sensor-recorded events were ball-to-head impacts (<1%), for which the head is impacted by the ball unintentionally. No significant differences in impact event types were observed between males and females.

To compare level of play, a data set of 4 male junior varsity games comprising 96 video-confirmed sensor-recorded events was examined, of which 68 (71%) were impact events, 16 (17%) were nonevents, and 12 (13%) were trivial events. Male junior varsity teams had a significantly higher ($P < .05$) percentage of nonevents than male varsity teams. Of the 68 sensor-recorded impact events, most were head to ball (74%), followed by falls (12%), player contact (10%), and ball to head (4%).

The SIM-G algorithm correctly classified 78% and 68% of all video-confirmed impact events as valid impacts for female and male players, respectively (Table 2). Similarly, the SIM-G algorithm correctly classified 63% and 69% of all video-confirmed nonevents as spurious impacts for female and male varsity players. For video-confirmed trivial events, the SIM-G algorithm was less accurate, correctly identifying 43% and 61% as spurious impacts for female and male varsity players.

When kinematics were compared across impact types for females, the mean peak linear acceleration of nonevents was significantly lower ($P = .01$) than that of impact events, whereas the mean peak angular velocity of trivial events was significantly higher ($P < .001$) than that of impact events (Table 3). Similarly for males, the mean peak linear acceleration of nonevents was significantly ($P < .001$) lower than that with impact events. The mean peak angular velocity for trivial events and nonevents for males was significantly higher ($P < .001$) and lower ($P < .001$) than that for impact events, respectively.

Within some categories of event types and impact types, significant differences in sensor-recorded peak kinematics were found between females and males. For nonevents, females had significantly higher ($P = .004$) mean peak linear acceleration and angular velocity values than males (Figures 2 and 3). In contrast, females had a significantly lower ($P = .037$) mean peak linear acceleration for trivial events than males. No significant differences ($P < .05$) were found between females and males for impact events.

DISCUSSION

With the proliferation of head impact sensors as an advantageous and accessible methodology for sports medicine researchers to study head impact kinematics in sports, the importance of identifying sensor-recorded events as head impacts with video or observer confirmation is critical. The percentage of false-positive results is likely dependent on athlete behavior, which may vary by sex; therefore, it is important to explore such a phenomenon by sex. To investigate such issues, the current study used a sample of head impacts recorded by a headband-based sensor worn by high school female and male soccer teams. We found that approximately 1 in 5 sensor events recorded during scheduled game times were associated with players on the pitch and within the field of view, of which 70% were video confirmed as impact events. The proportions of event type varied by sex, as females had a significantly lower percentage of impact events (49%) than males (78%). In addition, the SIM-G algorithm incorrectly classified approximately one-third of sensor-recorded events.

The analysis in the current study identified several methodological steps that are critical to implement in studies with data from head impact sensors, including verifying game time and limiting data to players on the pitch. The majority (76%) of the 40,352 sensor events recorded on game days were excluded because they occurred outside of scheduled game times. This was attributed to the practical logistics of implementing a sensor program within a sports team, such as the sensors being turned on well before a game, handled and inserted into headbands, and adjusted and worn during warm-ups. Similarly, after the game, the headbands were removed by the players, and the sensors were removed from the headbands and collected before being deactivated.

A total of 9503 sensor events were recorded during scheduled game times; however, less than three-quarters (72%) were recorded during verified game times. Therefore, it is essential to verify game time and not rely on scheduled game time. In addition, approximately 60% of sensor events recorded during verified game times were associated with players not on the pitch. Therefore, if the intent is to study head kinematics in live sports, it is crucial to limit the final data set to players on the pitch. It is possible for player-to-player interaction to occur on the sideline, as in a celebratory manner, which may result in loading of the head; however, it is more plausible that events occurring off the pitch are associated with players manipulating their sensors (eg, hitting the headband on the knee as a repetitive behavior) or placing their sensors on their persons (eg, winding the headband around the wrist) as they move about the sideline. Regardless of the cause, sensor-recorded events associated with players not in active play are typically not the focus of head impact biomechanics studies. Practically, to exclude such data, the timing of specific player substitutions needs to be recorded via video or visual observations.

After video analysis was used to reduce data for verified game time and players on the pitch, most sensor-recorded events were confirmed to be impact events (70%), indicating that head impact sensors do indeed capture valuable data if rigorous methodological steps are followed. Video analysis also identified 1 in 5 sensor-recorded events as trivial events and 1 in 10 as nonevents. As trivial events involve movement of the sensor, it is expected that the sensor record such events. Nonevents may also involve some sensor movement; however, this was not discernable by video. Therefore, it is encouraging that <10% of events recorded by the SIM-G in the final data set may be artifacts of the system.

To illustrate the importance of the methodological steps in the current study, consider how the percentage of the 1316 video-confirmed impact events changes from 3.3% when the 40,352 sensor events recorded on game days were used as the denominator to 70% when the 1893 sensor-recorded events in the final data set were used as the denominator. Lamond et al[7] found that a similarly low percentage of sensor events recorded on game days for female collegiate soccer players were observer-confirmed direct head impacts (6.1%). If removing sensor-recorded events occurring outside scheduled game times is the only method used to reduce data, approximately 1 in 7 (14%) events recorded by the sensor in the current study was a video-confirmed impact event. However, if verified game times are used to reduce sensor-recorded data, then approximately 1 in 5 (19%) events recorded by the sensors were associated with a video-confirmed impact event.

As athlete behavior influences the percentage of false-positive readings in head impact sensor data, the methodological steps in the current study were explored by sex and level of play. The percentages of event type differed between females and males: females experienced a higher percentage of trivial events and nonevents and therefore a lower percentage of impact events as compared with males. There were no significant differences between the percentages of impact events for male junior varsity players and male varsity players. Such findings may be due to game differences between males and females (eg, playing style) or other factors (eg, headband fit) rather than competition level. Video data exist for trivial events; however, no formal observations regarding the nature of the events were recorded (eg, player adjusted headband), and such observations may give insight into the higher percentage of trivial events for females. Interestingly, of the video-confirmed impact events, there were no significant differences in the percentages of impact types (ie, head to ball, player contact, fall) between females and males.

The current study compared the video classification of sensor-recorded events with that of the SIM-G algorithm. Only 70% of video-confirmed impact events were correctly classified as valid impacts by the SIM-G algorithm; therefore, 30% of video-confirmed impact events would be removed by the algorithm. In male high school soccer players, Nevins et al[9] reported that 85% of video-confirmed impact events were correctly classified as valid impacts by the xPatch algorithm. In addition, Nevins et al reported that only 17% of video-confirmed nonevents were correctly classified as spurious events by the xPatch algorithm. Although 66% of video-confirmed nonevents were correctly classified as spurious events by the SIM-G algorithm in the current study, the remaining 34% of video-confirmed nonevents would be included in a data set as impact events if video confirmation were not used. In addition, almost half of all video-confirmed trivial events (48%) would be included as false-positive results in the absence of video confirmation. Such findings highlight the caution that should be used with manufacturer filtering algorithms and the need for video confirmation of sensor-recorded events. Quantification of the characteristics of the kinematics of false-positive events may provide insight into possible processing strategies that may improve filtering algorithms for future sensor designs. One strategy to discriminate true-positive from false-positive results is the implementation of a magnitude threshold.

In general, the mean peak head kinematics was significantly lower for nonevents than for impact events. Mean peak linear acceleration was approximately 10*g* less, and mean peak angular velocity was 2 rad/s less—both of which were more exaggerated for males as compared with females. Although such findings suggest that simple magnitude thresholds could be used to separate impact events from nonevents, the regression models that include event type explain <3% of the variability in peak linear acceleration, which suggests that discrimination among event types is more complex. Interestingly, trivial events were characterized by significantly greater angular velocity when compared with impact events but similar peak linear accelerations. Angular velocity is likely elevated for trivial events because of the range of activities and sensor manipulation (eg, adjusting the headband). The sensor may truly be experiencing elevated angular velocities during trivial events, that are not representative of head kinematics owing to poor coupling with the head. The complex relationship between the magnitude of linear acceleration and angular velocities among impact events (eg, those of interest to study), trivial events, and nonevents suggests that a window of angular velocities would be required to accurately discriminate true-positive from false-positive readings.

Comparing kinematics between females and males revealed interesting findings. Most important, no significant differences in mean peak linear acceleration and angular velocity for impact events were found between females and males, which is consistent with laboratory studies.[5,15] Such a finding has implications regarding differing rates of concussion for females and males in sports. In terms of false-positive events, females had significantly lower and higher mean peak linear accelerations than males for trivial events and nonevents, respectively. Females also demonstrated a significantly higher mean peak angular velocity than males for nonevents. The cause of significant differences in mean peak kinematics between female and male trivial and nonevents is unknown.

Several limitations of the current study exist. First, only a single-camera view was used for video confirmation. The field of view encompassed approximately one-third of the soccer pitch at any one time; therefore, a portion of sensor-recorded events were unable to be observed. Although the video footage was recorded in high-definition 1080p with a 16:9 aspect ratio at 60 frames per second, some impacts in the far corners of the pitch were difficult to observe. However, none of the unobserved sensor-recorded events involved the ball (ie, head to ball or ball to head), as the camera panned to follow the play and always contained the ball within the field of view. Impact events involving the ball compose nearly 80% of all video-confirmed sensor-recorded impact events. Therefore, some unobserved events may be falls and player contact; however, verification cannot be performed owing to the lack of video data. Multiple camera views would assist in minimizing the number of unobserved sensor-recorded events and potentially provide additional information for sensor-recorded events observed within the fields of view.

In addition, the current study investigated a single sensor in a single high school sport. The results of the current study compare well with investigations in female and male high school lacrosse with the xPatch and GForceTracker,[3] respectively, and female collegiate soccer with the xPatch[12] and SIM-G.[7] It should be noted that, in addition to soccer, the SIM-G has been used to investigate head impacts in lacrosse[13] and American football[8,14]; however, video confirmation and the SIM-G algorithm were not assessed. It is possible that performing the same study in different sports may yield different results owing to differences in equipment, game play, and contact levels. For example, American football players wear helmets, do not purposefully head the ball, and are allowed to block and tackle opposing players. In addition, some sensors have advanced design features to remove false-positive results, such as mouthguard sensors with infrared detection designed to record data only in the presence of teeth within the mouthguard,[6] which would be useful to reduce the number of trivial events and limit the reliance on video confirmation. However, while the percentages of impact events and impact types may vary by sport and sensor, the concepts illustrated herein are critical to implement in any study using sensors to investigate head impact biomechanics.

It is important to note that the current study did not establish the percentage of false-negative results (ie, kinematics experienced by the head that were not captured by the head impact sensor). Such analysis is difficult, as video needs to be observed independently by multiple reviewers to code head contacts. In addition, the severity of an impact cannot be accurately ascertained from video to determine if a given impact was over the recording threshold of the sensor. Therefore, identifying false-negative results was outside the scope of the current study.

In summary, the current study illustrated necessary methodological steps critical to the processing of head impact sensor data from athletes during play. Sensors are increasingly being used as investigative tools by sports medicine researchers; therefore, it is important to emphasize approaches to extract valuable and accurate data from head impacts in a live sport setting. First, a series of necessary methodological steps were highlighted, including the exclusion of data recorded outside verified game times and from players not on the pitch—both of which can be achieved via video analysis. Such data reduction resulted in a final data set that was 20% of the original data set collected during scheduled game times. Second, video confirmation is necessary to discriminate head impacts from false-positive readings (ie, trivial events and nonevents). After such exclusion procedures were implemented, the percentage of verified head impact events recorded by headband-mounted sensors in high school soccer with video analysis was 70% of all sensor-recorded events. The percentage of impact events, trivial events, and nonevents were significantly different between females and males, with more trivial events and nonevents recorded for females. Manufacturer algorithms represent an alternative approach to reduce false-positive results; however, the current study highlighted that the SIM-G algorithm incorrectly classified a third of sensor-recorded events. Therefore, it is recommended that manufacturer filtering algorithms be avoided. Last, kinematic magnitudes did not provide a convenient approach to discriminate between true-positive and false-positive results, given the complex relationship of peak linear acceleration and angular velocity among head impact events, trivial events, and nonevents.

Head impact sensors are a valuable research tool in sports medicine research, including their potential use in rigorous study designs to monitor head impacts during live play and evaluate the effectiveness of interventions such as rule changes, coaching strategies, and behavioral interventions. Using head impact sensor data without video verification may lead to a biased estimate of head impacts, thus biasing the evaluated effect of the targeted intervention. Sports medicine researchers should be aware of the limitations of head impact sensors and employ methodologies to minimize such limitations, which include performing video or observer confirmation of sensor-recorded events and avoiding manufacturer filtering algorithms. The findings of any clinical study not employing such methodologies may result in overestimation of impact frequency and magnitude and should be interpreted with caution.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Figure 1.
SIM-G impact sensor device (center), neoprene headband (right), and SKYi box (left).

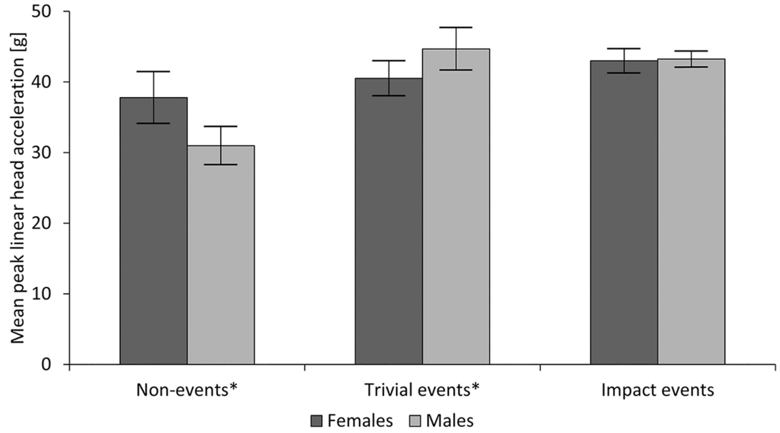

Figure 2.
Mean peak linear head accelerations for sensor-recorded event types. Error bars represent 95% CIs. *Significant difference ($P < .05$) between males and females.

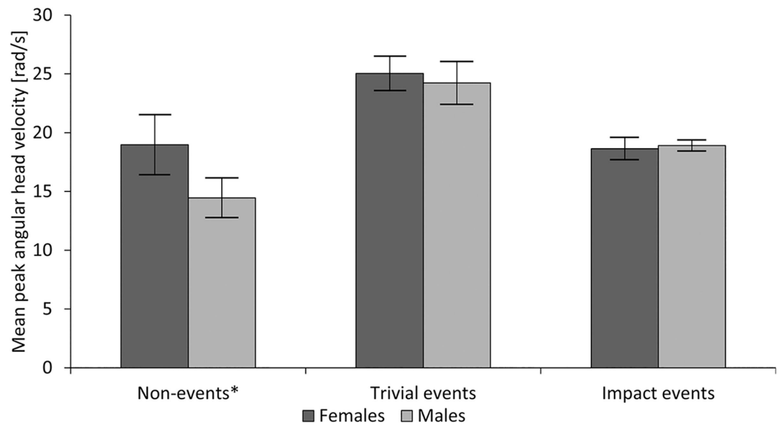

Figure 3.
Mean peak angular head velocities for sensor-recorded event types. Error bars represent 95% CIs. *Significant difference ($P < .05$) between males and females.

TABLE 1

Video Confirmation of Sensor-Recorded Events: Varsity[a]

	All (41 Games)		Female (18 Games)		Male (23 Games)	
	n	%	n	%	n	%
During game times						
Scheduled	9503		2331		7172	
Verified	6796	71.5	1758	75.4	5038	70.2
For players						
On the pitch (ie, field)	2775	29.2	1191	51.1	1584	22.1
In the field of view	1893	19.9	565	24.2	1328	18.5
Events						
Nonevents[b]	181	9.6	83	14.7	98	7.4
Trivial[b]	396	20.9	207	36.6	189	14.2
Impact[b]	1316	69.5	275	48.7	1041	78.4
Ball to head	11	0.8	2	0.7	9	0.9
Fall	129	9.8	18	6.5	111	10.7
Player contact	144	10.9	24	8.7	120	11.5
Head to ball	1032	78.4	231	84.0	801	76.9

[a]Male junior varsity results are not included. Ball-to-head impacts were excluded from chi-square test owing to small sample size.

[b]Significant difference ($P < .05$) between males and females per adjusted residuals post hoc analyses with Bonferroni adjustment.

TABLE 2

Classification of Sensor-Recorded Events by Video Analysis and the SIM-G Algorithm: Varsity[a]

	Events Correctly Classified by SIM-G, %		
Video-Confirmed Events	**All**	**Female**	**Male**
Impact (n = 1316)	70.1	77.5	68.0
Trivial (n = 396)	52.0	43.5	61.4
Nonevents (n = 181)	66.3	62.7	69.4
All (n = 1893)	65.9	62.8	67.2

[a]For impact events, the value corresponds to the percentage of impacts identified as “valid”; for trivial and nonevents, the value corresponds to the percentage of impacts identified as “spurious.”

TABLE 3

Unadjusted Multiple Regression Analysis for Kinematic Measures of the Head: Varsity[a]

	All (n = 1893)		Female (n = 565)		Male (n = 1328)	
	PLA, g	**PAV, rad/s**	**PLA, g**	**PAV, rad/s**	**PLA, g**	**PAV, rad/s**
Impact events (intercept) vs	43.2 ± 1.0	18.8 ± 0.5	43.0 ± 1.9	18.6 ± 1.1	43.3 ± 1.1	18.9 ± 0.5
Trivial events	−0.7 ± 2.0	5.8 ± 1.0[b]	−2.5 ± 2.9	6.4 ± 1.8[b]	1.4 ± 2.9	5.3 ± 1.3[b]
Nonevents	−9.1 ± 2.8[b]	−2.3 ± 1.4[c]	−5.2 ± 4.0[d]	0.3 ± 2.4	−12.2 ± 3.8[b]	−4.5 ± 1.8[b]
R^2, %	2.1	7.6	1.3	9.1	3.1	6.7
F (P value)	2.5 (<.001)	77.4 (<.001)	3.7 (.026)	28.1 (<.001)	21.1 (<.001)	47.4 (<.001)

[a] Values are presented as coefficient ± 95% CI. Intercept is the impact events condition, which is compared with the trivial events and nonevents conditions. PAV, peak angular velocity; PLA, peak linear acceleration.

[b] $P < .001$.

[c] $P < .01$.

[d] $P < .05$.