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HEAD IMPACT SENSOR STUDIES IN SPORTS: A SYSTEMATIC REVIEW OF EXPOSURE CONFIRMATION METHODS

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Abstract

To further the understanding of long-term sequelae as a result of repetitive head impacts in sports, *in vivo* head impact exposure data are critical to expand on existing evidence from animal model and laboratory studies. Recent technological advances have enabled the development of head impact sensors to estimate the head impact exposure of human subjects *in vivo*. Previous research has identified the limitations of filtering algorithms to process sensor data and observer and/or video confirmation of sensor-recorded events is crucial to remove false positives. The purpose of the current study was to conduct a systematic review to determine the proportion of published head impact sensor data studies that used filtering algorithms, observer confirmation and/or video confirmation of sensor-recorded events to remove false positives. Articles were eligible for inclusion if collection of head impact sensor data during live sport was reported in the methods section. Descriptive data, confirmation methods and algorithm use for included articles were coded. The primary objective of each study was reviewed to identify the primary measure of exposure, primary outcome and any additional covariates. A total of 168 articles met the inclusion criteria, the publication of which has increased in recent years. The majority used filtering algorithms (74%). The majority did not use observer and/or video confirmation for all sensor-recorded events (64%), which suggests estimates of head impact exposure from these studies may be imprecise.

Keywords

general sports trauma; head injuries/concussion; injury prevention; pediatric sports medicine

Introduction

Debate continues regarding the potential for long-term sequelae as a result of repetitive head impacts in sports. Participation in contact and collision sports has been associated with increased risk of long-term problems in memory and cognition;²⁴ however, recent concern regarding repetitive head impacts and policies developed to minimize head impact exposure may have unintended consequences for sports participation.²¹ To further the understanding of repetitive head impacts, *in vivo* exposure data are critical to expand on existing evidence relating repetitive head impacts to biomechanical and neurophysiological outcome from animal model and laboratory studies.^{10,34,35,40,41}

Recent technological advances have enabled the development of head impact sensors to estimate the head impact exposure of human subjects *in vivo*.³¹ A wide variety of head impact sensors is currently available, such as instrumented helmets (e.g. GForceTracker),^{5,7,26} headbands (e.g. SIM-G),^{18,32,43} mouthguards (e.g. MIG)^{16,46} and skin patches (e.g. xPatch).^{23,28,33} Increasingly, research studies have used such technology to collect head impact data in sports, commonly American football.³⁰ Validation of kinematics recorded by head impact sensors in laboratory settings has typically used anthropometric test devices,⁴⁴ cadavers¹⁷ and human volunteers.⁴⁷ Furthermore, field studies have evaluated the accuracy of sensors to measure head impact exposure using video analysis.^{7,16,28,32,33} Such previous research has identified that the absence of observer and/or video confirmation of sensor-recorded events to remove false positives may result in substantial overestimation of head impact exposure.^{7,18,32,33} Although filtering algorithms attempt to remove false positives in an automated fashion, some investigations suggest such approaches are imprecise, inaccurate and not a valid replacement for observer and/or video confirmation.^{28,32,33} Therefore, the absence of rigorous confirmation methods or use of a filtering algorithm may result in estimates of head impact exposure that are imprecise. To understand the prevalence of this issue in the literature, the purpose of the current systematic review was to determine the proportion of head impact sensor data studies published in the last two decades that used filtering algorithms, observer confirmation and/or video confirmation of sensor-recorded events to remove false positives.

Methods

A systematic literature review was conducted and reported as per the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) statement.^{27,39}

Search Strategies

The primary search strategy involved searching the PubMed database, which is maintained by the United States National Library of Medicine at the National Institutes of Health and primarily accesses citations from the MEDLINE database in addition to other biomedical

literature. A Boolean combination of keyword search terms were used: ‘head impact sensor’, ‘acceler*’, ‘gyroscope’, ‘head impact telemetry’, ‘xpatch’, ‘x-patch’, ‘smart impact monitor’, ‘gforcetracker’ and ‘vector mouthguard’, where an asterisk represents truncation. The primary search strategy sequentially assessed the titles, abstracts and full texts to identify potentially relevant articles. In addition to the primary search strategy, a secondary search strategy assessed the reference lists of initially included articles to identify additional articles, which also met the inclusion criteria listed below.

Inclusion Criteria

Peer-reviewed English-language journal articles published from 1st January 2000 to 31st December 2019, were considered for inclusion; therefore, conference proceedings, theses and books were excluded. Review articles were also excluded; however, the reference lists of such articles were reviewed as part of the secondary search strategy. Articles were eligible for inclusion if collection of head impact sensor data during live sport was reported in the methods section. For the purposes of the current systematic review, head impact sensor data were defined to include any combination of the following measurements: head impact frequency, direction and/or peak kinematics (i.e. linear acceleration, angular velocity or angular acceleration), false negative rate, false positive rate and kinematic profile and algorithm detection accuracy. Articles describing results of laboratory-based studies of head impact sensors were excluded (e.g. controlled soccer ball heading by human subjects) unless head impact sensor data were also collected during live sport (e.g. soccer training and/or games).

Data Collection

Initially, descriptive data were coded for each article including gender, sport, age, competition level and sensor type. Algorithm use and confirmation methods were coded from the text of the articles and/or references to previous studies. Algorithm data were coded ‘all events’ if an article reported that all sensor-recorded events were processed through a device algorithm designed to remove events considered spurious. Observer confirmation was defined as an observer (or observers) monitoring sensor data to visually determine if sensor-recorded events were head impacts in real time. Video confirmation was defined as a reviewer (or reviewers) using video to determine if sensor-recorded events were head impacts. Confirmation data were coded ‘all events’ if an article reported that all sensor-recorded events were observer- and/or video-confirmed. If confirmation was only performed for some sensor-recorded events, confirmation was coded as ‘conditional’ and the specific criterion was noted. For example, if a study reported that video confirmation was only performed for sensor-recorded events above 40 g, video confirmation data were coded as ‘conditional’ with the condition being ‘>40 g’. Algorithm use and/or confirmation methods were coded ‘none’ if an article reported that algorithm use and/or confirmation methods were not used, respectively. Algorithm use and/or confirmation methods were coded as ‘not reported’ if not specifically reported in the article.

To characterize how head impact sensor data was analyzed, two members of the research team independently reviewed the primary objective described by each article to identify the primary measure of exposure, primary outcome and any additional covariates. An exposure

was defined as an independent variable that affected the outcome of interest. Exposure variables had to meet criteria for causality (e.g. temporality, biologic plausibility, evidence of a dose-response relationship, consistency of association, coherence and specificity).¹⁹ The outcome was defined as the primary dependent variable of the study and the measure for which the primary analyses were presented. Covariates were classified as additional variables or factors of interest that were considered analytically to affect the relationship between the exposure and outcome of interest. Classification was limited to the primary aim or analysis described by each article and did not code the exposures or outcomes of secondary aims or analyses. For example, the purpose of the study by Broglio et al.² was to “compare the number and magnitude of head impacts resulting from games, contact practices, and noncontact practices and to estimate the effect of limiting contact practices on head impact exposure in high school football.” Session type (i.e. game, contact practice, or non-contact practice) was classified as the exposure and head impact kinematics were classified as the primary outcome. In addition, the article described collecting and analyzing data regarding player position, which was coded as a covariate. In the event of discrepancies between the two reviewers, a third reviewer was consulted to reach a consensus.

Descriptive statistics were calculated and reported. Although some articles may use the same underlying dataset and associated methods as they are part of larger studies, calculations were performed with equal weighting to all articles.

Results

Initially, 251 articles were identified from the PubMed keyword search strategy (Figure 1). After review of the title, abstract and full text, 84 articles remained using the primary search strategy. The secondary search strategy identified an additional 84 articles; therefore, a total of 168 head impact sensor articles met the inclusion criteria (Supplemental Table). Publication of articles describing the collection of head impact sensor data have increased in recent years (Figure 2).

Demographics, Settings and Study Designs

Most articles reported solely on male athletes (134, 80%), whereas 14 (8.3%) reported solely on females and 20 (12%) reported sensor data for both male and female athletes (Table 1). Some articles reported data for multiple sports, competition levels and/or using multiple sensor types; therefore, the following categories are not mutually exclusive. The majority of articles reported on sensor data in American football (104, 62%), followed by ice hockey (20, 12%) soccer (19, 11%), lacrosse (15, 8.9%), rugby league or union (6, 3.6%), Australian football (5, 3.0%) and boxing (2, 1.2%). In addition, there were single articles describing sensor data in BMX racing, downhill mountain bike racing, flag football, hurling, skiing and snowboarding, taekwondo, water polo and wrestling. Almost half of all articles reported on sensor data at the collegiate level (80, 48%), followed by high school (62, 37%), youth (37, 22%) and adult (amateur, 11, 6.5%; professional, 1, 0.6%). The majority of articles reported use of helmet-mounted sensors (107, 64%), followed by skin- (40, 24%), mouthguard- (11, 6.5%), headband- (7, 4.2%), headgear- (2, 1.2%), cap- (2, 1.2%), ear- (1, 0.6%) and mouthpiece-mounted (1, 0.6%) sensors.

Head impact sensor data were the primary outcome in 105 (63%) articles and the primary measure of exposure in 58 (35%) articles (Table 2). Head impact sensor data were a covariate in 4 (2.4%) articles. Head impact sensor data were not able to be categorized as the primary outcome, primary measure of exposure or covariate in the article by Gwin et al.¹¹ as data were collected, described and compared to laboratory impact testing results, but not analyzed. For the 58 articles in which head impact sensor data were the primary measure of exposure, 53 articles (91%) reported clinical measures (e.g. neuroimaging, concussion, etc.) as the primary outcome, whereas the remaining articles reported tissue strain (4, 6.9%) and sports performance metrics (1, 1.7%) as the primary outcomes.

Filtering Algorithms

The majority of articles (74%) reported the use of filtering algorithms to remove false positives or suspected spurious sensor-recorded events. Cortes et al.⁷ used two sensors and reported using the xPatch filtering algorithm, but did not report using a filtering algorithm for the GForceTracker; therefore, the article was coded as ‘conditional’ algorithm use. In addition, nine articles described further filtering methods such as excluding data below acceleration thresholds (e.g. sensor records events greater than 10 g, but analysis excludes events below 30 g),^{3,29,42} for players with high numbers of sensor-recorded events,^{20,45,48} for players with more than 15% of data missing,^{37,38} or from multiple sensor-recorded events for single timestamps.⁴³ Two articles reported using engineering filtering solutions, which included infrared device placement measurements in a mouthguard-mounted sensor⁴⁶ and cross-checking sensor data with global positioning system (GPS) data to establish location of sensor-recorded events.⁹

Of the 105 articles in which head impact sensor data were the primary outcome, filtering algorithms were used in 79 (75%). Similarly, 43 (74%) of the 58 articles in which head impact sensor data were the primary measure of exposure used filtering algorithms. No significant difference in filtering algorithm use was found between articles in which head impact sensor data were the primary outcome and the primary measure of exposure ($p=0.88$).

Confirmation Methods

Of the 168 included articles, 61 (36%) described observer and/or video confirmation for all sensor-recorded events (Table 1). Video- and observer-confirmation for all sensor-recorded events were described by 34 and 29 articles, respectively. Two articles described the use of both observer and video confirmation for all sensor-recorded events. Conditional video confirmation was used by an additional 24 articles, of which 9 only video-confirmed impacts associated with concussion, 9 only video-confirmed impacts above specific linear acceleration thresholds, which ranged from 30 to 150 g. Six articles used various other conditional video confirmation criteria, such as limiting confirmation to purposeful headers in soccer or tackles in rugby union. Five of the articles describing conditional video confirmation also described using observer confirmation for all events. For the most commonly studied sport, American football, 19 (18%) and 18 (17%) of the 104 articles used observer and video confirmation for all events, respectively.

Of the 105 articles in which head impact sensor data were the primary outcome, 43 (41%) reported observer and/or video confirmation of all events, whereas 17 (29%) of the 58 articles in which head impact sensor data were the primary measure of exposure reported observer and/or video confirmation of all events. No significant difference in confirmation methods was found between articles in which head impact sensor data were the primary outcome and the primary measure of exposure ($p=0.32$).

Discussion

In vivo head impact exposure data is required to further the understanding of potential long-term sequelae from repetitive head impacts. Advancements in head impact sensor technology has enabled the measurement of head impact exposure in live sport and the publication of studies reporting the use of such technology has increased in recent years. Such data has been used in sports, including American football, to drive changes in sport policy, rules and protective equipment. In the current review, filtering algorithms designed to remove false positives were used to remove sensor-recorded events in approximately three-quarters of articles. Some filtering algorithms have been trained and validated using field data,⁴⁶ other filtering algorithms not using such an approach have previously been reported to have limited accuracy.^{28,32,33} In addition, the current review demonstrated that the majority of studies (64%) did not use observer and/or video confirmation for all sensor-recorded events, which is a critical methodologic step to minimize false positives and ensure accurate data.^{7,18,32,33}

Filtering Algorithms

Most head impact sensors have a processing algorithm provided by the manufacturer to filter and remove 'spurious' events. The development of some processing algorithms has been reported. For example, HITS (Simbex, Lebanon, NH) compares the sensor-recorded kinematics to the expected acceleration signals for rigid body head acceleration,⁸ whereas others remain proprietary (e.g. SIM-G and xPatch). When a processing algorithm can be deactivated, it is possible to compare the classification of sensor-recorded events compared to video review. Nevins et al.²⁸ used video analysis to investigate the classification of 116 unfiltered sensor-recorded events in male high school soccer and found that the xPatch algorithm incorrectly classified 15% of video-confirmed impact events as spurious. In addition, 83% of unfiltered sensor-recorded events determined to be non-events by video analysis were incorrectly classified as valid by the algorithm. In a similar study of female collegiate soccer games, Press et al.³³ found that the proprietary xPatch filtering algorithm incorrectly classified 43% of non-events, but only 4% of video-confirmed impact events were incorrectly classified. McIntosh et al.²³ reported the xPatch algorithm incorrectly classified 38% and 28% of video-confirmed impact events and non-events, respectively, in adult amateur Australian football. Patton et al.³² evaluated unfiltered data from the SIM-G in male and female high school soccer games using video review and reported that 30% of the algorithm-determined impact events were incorrectly classified, whereas 44% of the algorithm-determined non-events were incorrectly classified. Together, such studies indicate that the current state of filtering algorithms remain inadequate, despite prevalent use.

Some studies used published, non-proprietary thresholds as filters (e.g. removing all impacts surpassing 200 g peak linear acceleration).^{29,42} As an example, for data collected in collegiate American football by the NCAA-DOD CARE Consortium, one of the largest data collection efforts using head impact sensors to date, Stemper et al.⁴² removed all impacts surpassing 10 krad/s² peak angular acceleration. Brokaw et al.³ filtered out sensor-recorded events for collegiate lacrosse with high linear acceleration and low time duration by removing events with Head Injury Criterion (HIC) values less than 15. Similarly, Rich et al.³⁶ incorporated a duration requirement into the trigger for a custom mouthpiece sensor used in youth soccer, which recorded data when linear acceleration above 5 g was detected on any axis for longer than 3 ms. In contrast, several studies raised the linear acceleration trigger threshold to 20 g in an attempt to reduce low magnitude false positives.^{5-7,14,22,26,29} Press et al.³³ found that the positive predictive value of the xPatch algorithm increased from 16% to 66% when the threshold was increased from 10 g to 20 g, respectively. Similarly, Carey et al.⁴ evaluated the xPatch during adult semi-professional male rugby league games and determined 31% of sensor-recorded events above 10 g were false positives from video confirmation, which decreased to 6% for events above 20 g.

However, it is likely that the particular recording threshold of linear and angular acceleration magnitude and duration varies by sport and sensor. For example, a high linear acceleration recording threshold may result in the sensor not capturing relevant sport-specific head impacts (e.g. low severity repetitive head impacts to linemen in American football).^{25,36} Optimal recording thresholds can only be determined via comprehensive video confirmation approaches using unfiltered data.

Algorithms with more advanced machine learning processing approaches have shown promising results. Wu et al.⁴⁶ developed a processing algorithm for an instrumented mouthguard, which incorporated a support vector machine classifier that used model predictions of head-neck motions and biomechanical features from the time and frequency domains. The algorithm was trained on data from games and practices of collegiate American football and subsequently tested against 32 sensor-recorded events in youth American football, of which two (6%) were incorrectly classified. Future efforts using such advanced approaches should quantify measures such as precision and recall using video confirmation methods so that the reader can evaluate the accuracy of the algorithm.

Engineering solutions, such as infrared device placement measurements in a mouthguard-mounted sensor,⁴⁶ have shown promise in reducing the proportion of false-positives. Dickson et al.⁹ cross-checked sensor data with global positioning system (GPS) data to remove sensor-recorded events that did not occur on ski slopes. Such a technique may be useful for field-based sports to remove sensor-recorded events associated with players on the bench considering several sports use GPS tracking devices on athletes to analyze positioning and performance.

Confirmation Methods

Nearly two-thirds of the identified studies did not perform and/or report observer and/or video confirmation for all sensor-recorded events, which is a critical gap considering previous studies have found the absence of confirmation methodology can result in

substantial overestimation of head impact exposure.^{7,18,23,28,32,33,36} For example, Cortes et al.⁷ investigated male and female high school lacrosse players using two different sensors: male players wore the helmet-mounted GForceTracker (GForceTracker, Richmond Hill, ON), while female players wore the skin-affixed xPatch (X2 Biosystems, Seattle, WA). Of the sensor events recorded by the GForceTracker, 35% were false positives, whereas the xPatch demonstrated nearly twice as many false positives (68%). Additional studies have evaluated the xPatch in male high school soccer,³³ female collegiate soccer,²⁸ amateur adult Australian football²³ and semi-professional adult rugby league,⁴ with false positives identified via video confirmation comprising up to 92% of sensor data. In collegiate American football, Wu et al.⁴⁶ reported that 83% of events recorded by a custom-designed mouthguard sensor were false positives. Bari et al.¹ found that the Vector mouthguard (i1 Biometrics, Kirkland, WA) failed to reliably capture video-documented impacts in high school American football. Together, such studies indicate that as few as four, and as many as nine, out of ten events recorded by head impact sensors may be false positives. The extent of inaccuracies across sports and sensors raises concerns regarding overestimation of head impact exposure in many studies not implementing observer or video confirmation methods.

American football was the most frequently studied sport, representing nearly two-thirds of articles. Only 17% of American football articles reported performing video confirmation of all events. In addition, several American football articles reported video confirmation methods as eliminating sensor data for periods of time when players were not wearing helmets. For example, Kelley et al.¹³ stated that “video review of all practices and games was used to verify the times that the athletes were helmeted, but a systematic review of all impacts to visually confirm each individual data point was not completed”. In recent American football studies reporting head impact sensor studies, the absence of video confirmation was identified as a limitation and video confirmation was identified as a way to reduce false positives.^{20,42} There may also be limitations in the ability to accurately video-confirm head impacts due to the nature of American football, which was found to be the case in rugby union.¹⁵ However, multiple camera angles used to broadcast higher levels of play, such as division I collegiate, may provide adequate video evidence to verify impacts. Lastly, advanced engineering approaches have been used in American football to remove false positives. For example, Wu et al.⁴⁶ used video analysis to evaluate an instrumented mouthguard in American football and reported that 83% of sensor-recorded events were false positives, which decreased to 60% with the use of an infrared proximity sensor to identify when the mouthguard was being worn on the teeth. Although several of the HITS articles reviewed in the current systematic review reported confirmation methods, no article reported the proportion of false positives.

In the current review, the prevalence of both observer- and/or video-review methods was documented. Only one study reported the proportion of false positives using observer-confirmation. Lamond et al.¹⁸ investigated head impacts in female collegiate soccer games and practices using the SIM-G (Triax Technologies, Norwalk, CT) and identified that 31% of sensor-recorded events were observer-confirmed head impacts. Using the same sensor, Patton et al.³² found 49% of sensor-recorded events were video-confirmed in high school female soccer games; however, direct comparisons between observer and video confirmation methods have yet to be performed.

In addition to using video review to identify false positives, it has also been used to identify false negatives.^{4,12,16,36} Huber et al.¹² found that the SIM-G recorded 63% of head contacts identified from video review of six games of high school soccer. The head contacts not recorded by the sensor were thought to potentially involve peak linear accelerations below the 16 g recording threshold of the SIM-G. In a larger study, Kuo et al.¹⁶ identified 271 head contacts from two rounds of video review of 163 hours of collegiate American football games, of which 217 (80%) were recorded by the Stanford Instrumented Mouthguard (MIG) with a recording threshold of 10 g. Using a custom mouthpiece with a recording threshold of 5 g, Rich et al.³⁶ reported that the sensor recorded 72% of the head contact events identified from video of female youth soccer games. Carey et al.⁴ identified 2997 head contact events in semi-professional rugby league from game video. For a recording threshold of 10 g, the xPatch recorded 73% of head contact events, but only 24% when the recording threshold was increased to 20 g. Although it is difficult to identify false negatives owing to the challenges in objectively estimating impact severity from video review, such studies indicate that it may be another source of inaccuracies in head impact exposure data from sensors.

Study Design

The importance of appropriate methods for processing head impact sensor data was emphasized via the analysis of study design. Nearly two thirds of articles reported head impact sensor data as the primary outcome, which were typically biomechanical studies interested in describing the number and magnitude of head impacts. For the 105 such articles, approximately three of four used a filtering algorithm and less than half described the use of observer and/or video confirmation of all sensor-recorded events. When head impact sensor data were not the primary outcome, most articles focused on clinical outcomes with the number and/or magnitude of head impacts as a measure of exposure. Less than one third of the 58 articles in which head impact sensor data were the primary measure of exposure described the use of observer and/or video confirmation of all sensor-recorded events, but nearly three-quarters of the 58 articles reported the use of filtering algorithms. The presence of false positives, and removal of true positives, in head impact sensor data in these studies may lead to erroneous conclusions regarding associations between head impacts and clinical measures, which may misinform clinical decisions regarding head impacts in sports.

Limitations

The main limitation of the current systematic review is that a study may have performed observer and/or video confirmation on sensor-recorded events, but not provided a description of confirmation methods in the article. However, observer and video confirmation are time- and labor-intensive; therefore, it is reasonable to assume that the majority of studies that performed confirmation included a description of confirmation methods in published articles. In addition, although the current systematic review discriminated between the presence and absence of observer and/or video confirmation, the rigor of the confirmation methodology could not be ascertained (e.g. single or multiple reviewers). As there is no standardized method for observer and/or video confirmation, future efforts should consider developing a consensus statement of best practices for confirmation methods.

Summary

Head impact sensors provide valuable head impact exposure data of athletes *in vivo*, which are required to further the understanding of potential long-term sequelae from repetitive head impacts, establish valid injury tolerance limits for concussion and develop relevant injury mitigation strategies. The current systematic review of head impact sensor studies revealed that the publication of such studies has increased in recent years, with American football being the most commonly studied sport. Filtering algorithms were used to remove sensor-recorded events in approximately three-quarters of head impact sensor articles, but previous investigations suggest that current approaches are imprecise and inaccurate. Algorithms with more advanced machine learning processing and engineering approaches to identify and remove false positives have shown promising results in American football. Almost two-thirds of articles did not report observer and/or video confirmation methods for all sensor-recorded events. The absence of observer or video confirmation of sensor-recorded events to remove false positives may result in substantial overestimation of head impact exposure.

Without furthering development of accurate filtering algorithms and performing the necessary observer and/or video confirmation of head impact sensor data, studies investigating associations between head impacts and clinical measures may misinform the understanding of how repetitive head impacts influence acute injury risk and long-term neurological outcomes. The current systematic review provides context in which to view previous head impact sensor studies and informs future studies regarding the importance of rigorous confirmation methods for all sensor-recorded events and effective filtering algorithms trained on field data. The field should consider adopting hardware and software sensitivity and specificity standards and best practice analytical methods to improve data quality and allow for cross-platform and cross-study comparisons.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Figure 1:
PRISMA flow chart.

Figure 2:
Confirmation methods of published articles reporting head impact sensor data by year of publication.

Table 1:

Summary of articles reporting head impact sensor data.

		Number	Percentage
All articles		168	
Gender	Males only	134	80%
	Females only	14	8.3%
	Females and males	20	12%
Sport	American football	104	62%
	Ice hockey	20	12%
	Soccer	19	11%
	Lacrosse	15	8.9%
	Australian football	5	3.0%
	Rugby league	4	2.4%
	Boxing	2	1.2%
	Rugby union	2	1.2%
	BMX	1	0.6%
	Downhill MTB	1	0.6%
	Flag football	1	0.6%
	Hurling	1	0.6%
	Skiing	1	0.6%
	Snowboarding	1	0.6%
	Taekwondo	1	0.6%
	Water polo	1	0.6%
	Wrestling	1	0.6%
Level of play	Collegiate	80	48%
	High school	62	37%
	Youth	37	22%
	Adult (Amateur)	11	6.5%
	Adult (Professional)	1	0.6%
Head impact sensor	HITS	92	55%
	xPatch	40	24%
	GFT	10	6.0%
	SIM-G	7	4.2%
	HITS (6DOF)	6	3.6%
	Vector	6	3.6%
	InSite	2	1.2%
	MIG	2	1.2%
	Prevent	2	1.2%
	BodiTrak	1	0.6%
	Custom Mouthpiece	1	0.6%

		Number	Percentage
	MV1	1	0.6%
	Novel	1	0.6%
	Shockbox	1	0.6%
	xGuard	1	0.6%
Sensor mount	Helmet	107	64%
	Skin	40	24%
	Mouthguard	11	6.5%
	Headband	7	4.2%
	Cap (skull/swim)	2	1.2%
	Headgear	2	1.2%
	Ear	1	0.6%
	Mouthpiece	1	0.6%
Filtering algorithm	Used	124	74%
	Conditional	1	0.6%
	None or not reported	43	26%
Confirmation	Observer and/or video (all events)	61	36%
	Observer (all events)	29	17%
	Observer (conditional)	1	0.6%
	Video (all events)	34	20%
	Video (conditional)	24	14%
	None or not reported	88	52%

Table 2:

Chi-squared analyses of confirmation methods and filtering algorithm use for articles reporting head impact sensor data as the primary outcome and measure of exposure.

		Head impact sensor data		Chi-squared
		Outcome (n=105)	Exposure (n=58)	p-value
Filtering algorithm	All events	79 (75%)	43 (74%)	0.73
	Conditional	1 (0.6%)	0 (0%)	
	None or not reported	25 (24%)	15 (26%)	
Observer and/or video confirmation	All events	43 (41%)	17 (29%)	0.32
	Conditional	12 (11%)	7 (12%)	
	None or not reported	50 (48%)	34 (59%)	