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Distribution of position-specific head impact severities among professional and Division I collegiate American football athletes during games

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ABSTRACT

Objective To compare the severity of head impacts between professional and Division I (D-I) collegiate football games for the purpose of improving protective equipment.

Methods A total of 243 football players from the National Football League (NFL) and from D-I of the National Collegiate Athletic Association (NCAA) were equipped with instrumented mouthpieces capable of measuring six degrees-of-freedom head kinematics. Head impacts were processed using a custom algorithm and combined with game period descriptors to produce a curated dataset for analysis. Head impact severity distributions for several kinematic-based metrics were compared within position groupings between leagues.

Results A total of 11 038 head impacts greater than 10 g from 1208 player-games were collected during 286 player-seasons (2019–2022). No significant differences were found between leagues in the distributions of kinematic-based metrics for all investigated position groupings (p≥0.320). The median and IQRs for peak linear acceleration for NFL and NCAA were 17.2 (9.3) g and 17.0 (8.6) g for linemen, 20.7 (13.8) g and 20.0 (13.5) g for hybrid and 21.0 (17.0) g and 20.8 (15.5) g for speed position groupings, respectively.

Conclusion The absence of statistically significant differences in the distributions of head impact severity between professional and D-I collegiate football players indicates that these data can be combined for the purpose of understanding the range of loading conditions for which new protective equipment, such as position-specific helmets, should be designed. This observation underscores the potential for knowledge transfer regarding biomechanical factors affecting head loading across professional and D-I college football, highlighting crucial implications for innovation in protective equipment.

WHAT IS ALREADY KNOWN ON THIS TOPIC

⇒ Quantifying the number and severity of head impacts in American football is important for enhancing player safety through improved protective equipment, education and rule changes.
⇒ Limited studies characterising the head impact experience among professional football players leave a research gap to drive interventions at this level.
⇒ To address this gap, researchers have extrapolated data from the collegiate level; however, the assumption that the severity of head impacts sustained in collegiate and professional football is similar has never been thoroughly evaluated.

WHAT THIS STUDY ADDS

⇒ The first quantification of six degree-of-freedom head impact measurements in professional football players using instrumented mouthpieces, a gold standard method of measuring head impact severity.
⇒ The first direct comparison of the distributions of head impact severity experienced by professional and Division I (D-I) collegiate football players during games using the same head impact sensor.
⇒ The head impact severity distributions within position groupings were not significantly different between levels of play (p≥0.320).

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY

⇒ Head impact severity measurements from D-I collegiate football players during games may serve as a proxy for professional player head impact severity game data in future analyses.
⇒ Combining game head impact severity data from professional and D-I collegiate football levels will significantly enhance the data available for the development and evaluation of protective equipment, such as position-specific helmets.
⇒ The findings from this study highlight potential opportunities for knowledge transfer between different levels of play, driving interventions in helmet safety innovation.

INTRODUCTION

American football is a collision sport during which head impacts are often caused by player-to-player and player-to-ground contacts. Protective equipment, such as a helmet, is worn to reduce the magnitude of head impacts, while player education and rule changes aim to reduce both the magnitude and likelihood of such impacts.[1–4] Identifying the intervention that may yield the best result and evaluating the efficacy of that intervention require data that accurately quantify the severity (six degrees-of-freedom (6DOF) kinematics) and frequency of head impacts sustained by players during play.

For over 60 years, there have been efforts to collect head impact severity data in American football utilising instrumented equipment.[5 6] Early attempts were considered largely unsuccessful due to the technical challenges.[7] The introduction of the Head Impact Telemetry (HIT) System transformed on-field data collection, being the first commercially available helmet sensor for use in American football.[8] The HIT System has been used to record over one million events in American football, including collegiate,[9 10] high school[11 12] and youth levels.[13 14] In addition to the HIT System, other systems have been deployed to measure the severity of head impacts sustained by football players.[15 16] Laboratory validation studies have demonstrated limited accuracy of the kinematics measured by these helmet-mounted systems attributed in part to the relative movement between the head and helmet.[17–19]

As a result, instrumented mouthpieces (IMs) have emerged as the preferred method to monitor head impact severity experienced by athletes. IMs have been found to offer greater accuracy compared with other head impact systems due to improved sensor-skull coupling.[20 21] While IMs provide the most accurate head impact severity data, professional American football players are not required to wear a mouthpiece and those who voluntarily wear mouthpieces may wear ones that are too small to be instrumented. Thus, collecting data during play via an IM at this level represents operational and feasibility challenges. As a result, IM-based head impact datasets examining professional American football players do not exist while interventions derived from head impact data at this level have measured head kinematics from video reconstructions with limited sample sizes and suboptimal accuracy.[22 23]

One primary intervention for enhanced head protection in football is the development of improved protective equipment, such as helmets. Laboratory methodologies provide a foundation for evaluating and driving improvements in helmets and the development of these methodologies relies on knowledge of the underlying distribution of the head impact severities sustained on-field. One proposed strategy to augment head impact severity data available at the professional level for this effort was to combine them with data from collegiate football. To have confidence in equipment interventions derived from a combined dataset, it must be ensured that the distributions of head impact kinematics between the two leagues are not significantly different. While previous studies have assumed that the severity of head impacts sustained in collegiate and professional football is similar,[24] this hypothesis has not been thoroughly evaluated. The aim of this study was to compare the distributions of kinematic parameters, measured by an IM, for head impacts collected during games in the National Football League (NFL) and the National Collegiate Athletic Association (NCAA) Division I (D-I) football to determine whether head impact severity data from these two levels can be combined and collectively used to improve player protective equipment.

METHODS

This study adheres to the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) cohort and the Consensus Head Acceleration Measurement Practices (CHAMP) 2022 reporting guidelines.[25 26] Reporting checklists for STROBE and the CHAMP on-field deployment and validation of wearable head acceleration measurement devices are provided in online supplemental tables 1 and 2, respectively.

Participants

Study participants included professional (n=99) and collegiate (n=144) male American football players. Professional players, aged between 21 and 35 years, were recruited from 12 NFL clubs during the 2019–2022 seasons. All players on these teams were eligible to participate, though participation was optional. Player interest was evaluated by study staff and club personnel. Collegiate players, aged between 18 and 24 years, were recruited from eight teams within the NCAA D-I Power Five conferences during the fall 2021 and 2022 seasons. Based on the NFL experience, collegiate recruitment was directed towards linemen, hybrid and speed position groups, and up to 40 players were eligible to participate at each team. The final set of participants consisted of starters and backups across various playing positions (table 1). Informed written consent was obtained from each player prior to data collection. The study protocols for professional and collegiate players received approval from the Mount Sinai Health System Institutional Review Board (IRB) (STUDY-19-NFL12) and the IRB of each participating university (provided in online supplemental table 3), respectively. Collegiate players received financial incentives for their participation in the study in line with research participation in a study lasting several months. The amount and timing of the distribution of incentives at each university were determined by the university's research staff, with approval from the site's athletic department based on regulations for collegiate athletics.

Equity, diversity and inclusion statement

The study population was adult, male collegiate and professional American football players that include a variety of different races and ethnicities. All players on participating teams were given an opportunity to voluntarily participate in the study. Additional details on the player recruitment process are provided in the

Table 1 Player and head impact counts by league and position

Position	Player-positions*		Player-games		Head impacts†	
	NFL	NCAA	NFL	NCAA	NFL	NCAA
OL	33 (32)	22 (15)	183 (33)	99 (15)	2387 (46)	1087 (19)
DL	22 (22)	17 (12)	142 (26)	105 (16)	1403 (27)	1232 (21)
TE	7 (7)	17 (12)	34 (6)	80 (12)	193 (4)	638 (11)
LB	12 (12)	39 (27)	65 (12)	200 (30)	394 (8)	1925 (33)
RB	5 (5)	12 (8)	44 (8)	49 (7)	519 (10)	304 (5)
DB	14 (14)	24 (16)	43 (8)	78 (12)	187 (3)	524 (9)
WR	8 (8)	15 (10)	36 (7)	50 (8)	124 (2)	121 (2)
Total	101	146	547	661	5207	5831

*Totals include two players in both leagues that changed positions during the study. There were no players that collected data in both leagues.
† Values indicate head impacts greater than 10 g. Values in parentheses are percentages of the column total.
DB, defensive backs; DL, defensive line; LB, linebackers; NCAA, National Collegiate Athletic Association; NFL, National Football League; OL, offensive line; RB, running backs; TE, tight ends; WR, wide receivers.

Participants section. The authors were both male and female, come from various institutions, consist of a variety of disciplines and include junior, mid-career and senior researchers.

Data collection

Participants were provided custom-fit mouthpieces instrumented with triaxial linear (±400 g) and angular (±20 krad/s^2) accelerometers (figure 1). The IM measures 6DOF kinematics and was validated in both laboratory and on-field studies to accurately quantify the count and severity of head impacts sustained in American football.[27 28] In the current study, data were collected using IMs consisting of two different form factors: a mouthguard and a retainer. Both options consist of a flexible electronics board (Diversified Technical Systems, Seal Beach, California) embedded in thermoplastic materials; however, there was an additional 0.3 mm of thermoplastic material between the board and teeth in the mouthguard. Both form factors showed similar performance in laboratory tests.[27–29] Each participant could choose which form factor they preferred. Additionally, the flexible electronics board underwent three annual hardware revisions during this study, which were aimed at improving the durability, memory and battery life: the sensing components remained unchanged (Analog Devices, Wilmington, Massachusetts). Mouthpieces were manufactured for each player based on three-dimensional scans of the upper dentition (OPRO, Hemel Hempstead, UK).

During the study period, IMs were deployed to collect head impact severity data in practices and games. This study focuses on the data collected during games. Before each game, IMs were checked to ensure functionality and configured for data collection. Kinematic data were recorded when the magnitude of linear acceleration in any of the three cartesian axes exceeded 10 g for more than 1.92 ms (event trigger). The kinematic data were sampled at a rate of 5.5 kHz for a duration of 70 ms (20 ms pretrigger and 50 ms post-trigger). Events were recorded with a corresponding timestamp synchronised to Coordinated Universal Time (UTC) based on the IM internal clock. After the completion of a game, data were downloaded from the IMs and uploaded to a secure cloud database, where they underwent postprocessing and storage for further analysis (Amazon Web Services, Seattle, Washington).

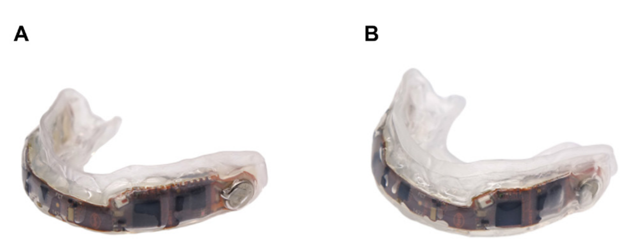

Figure 1 Examples of the custom-fit IMs used in the study, including options for (A) the retainer and (B) the mouthguard. IMs, instrumented mouthpieces.

Data postprocessing

The kinematic data collected by the IMs were postprocessed to determine the number and severity of head impacts. The data were debiased using the mean of the pretrigger signal and filtered using a zero-phase shift, four-pole, digital infinite impulse response filter with a low pass frequency of 300 Hz (channel frequency class 180). The acceleration data were numerically integrated using the trapezoidal method to calculate linear and angular velocities. The kinematics measured at the IM were transformed to a local head coordinate system through a rigid body transformation defined by the geometry of a medium-sized male headform.[27 28 30]

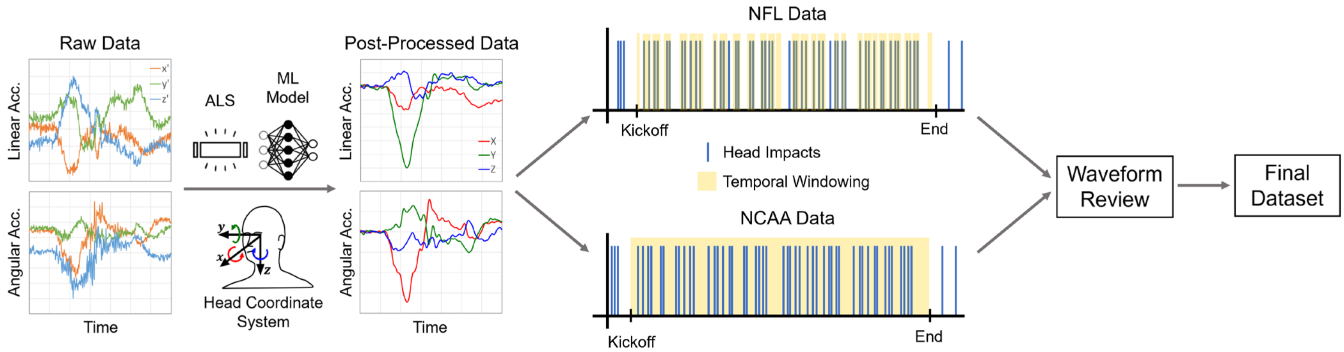

Figure 2 Schematic of the process used to determine the final dataset of head impacts for analysis. ALS represents the ambient light sensor used to detect the placement of the mouthpiece in the mouth. ML represents the machine learning model. NCAA, National Collegiate Athletic Association; NFL, National Football League.

The severity of each head impact was assessed through various kinematic-based metrics calculated from the postprocessed data. These metrics include peak linear acceleration (PLA), peak angular acceleration (PAA) and peak angular velocity (PAV), which are the maximum values of the resultant time histories.[27] Additionally, metrics currently used to assess the safety of helmets worn in the NFL were computed.[1] These include the Head Injury Criterion (HIC),[31] Diffuse Axonal Multi-Axis General Evaluation (DAMAGE)[32] and Head Acceleration Response Metric (HARM).[1] These metrics use the full-time history of head kinematics to quantify the contribution of both linear and angular kinematics to head impact severity.

A multifaceted approach, incorporating head impact classification, spatial and temporal windowing and human review of high severity waveforms, was used to distinguish head impacts from spurious events (figure 2). Head impacts from the IM were time-synchronised to video consisting of sideline and endzone views (720p, 60fps). A previously developed machine learning (ML) model, described by Gabler *et al*, was updated for the current study.[28] The ML model predicts whether the sensor event recorded by the IM is identified as a head impact compared with what a human reviewer would have identified as a head impact on video. The original ML model was developed using a subset of video-verified head impacts (via expert-trained human reviewers) collected from IMs worn by D-I collegiate players during games.[28] Following additional data collection and video review, the original ML model, incorporating the same descriptive features, was retrained. This retraining used head impacts that were verified on video from games and practices in both leagues during the broader study period. Additionally, the IM was equipped with an ambient light sensor (ALS); the ALS was used to determine whether an event occurred while the IM was worn by the player. An IM event was classified as a head impact when the probability output from the ML model exceeded a threshold for head impact, and readings from the ALS fell below a threshold for ambient light.

Data collected from NFL players were synchronised with player tracking data obtained from a league-wide tracking system, Next Gen Stats (NGS), to determine active time periods for every player-play in every game (Zebra Technologies, Lincolnshire, Illinois).[33 34] For NCAA players, data were synchronised with player tracking data from each team's tracking system (Catapult, Melbourne, Australia). Data for temporal windowing for NCAA games varied by site. The start (ie, kickoff) and end times were recorded for every game, the breaks during halves were recorded for 97% of player-games (640 of 661), the breaks between quarters were recorded for 94% of player-games (622 of 661), while possession drives were recorded in 30% of player-games (198 of 661). Additionally, daily participation was logged at each NCAA site, and data from players listed as not participating on gameday were excluded from the analysis. The NCAA data were further combined with game day analytics to remove data from players that did not play (Pro Football Focus, PFF). For NFL players, participation was known at the play level for every play through NGS. Player tracking systems were synchronised to UTC prior to the start of each game. Events recorded by the IM that occurred outside of activity periods or from inactive players were removed from the final dataset.

Following recommended best practices,[35] time histories corresponding to the top 10% severity impacts by PLA, PAA and HARM, as determined by each league separately, were reviewed (ie, waveform review). This review aimed to confirm the accuracy of signals within the uppermost tail of the head impact severity distributions. For the NFL, the top 10% impacts were reviewed relative to time-synchronised game video to confirm that the head impact occurred at the corresponding time and that the direction of observed head motion on video was consistent with the 6DOF time histories. For the NCAA, only the time histories of the top 10% impacts were reviewed, as time-synchronised game videos were not available. Head impacts with obvious error or false positives were then excluded from the final dataset.

Data analysis

Head impacts in the final dataset were grouped by player-position and compared across leagues. Three separate position groupings were formed: linemen (encompassing offensive and defensive line), hybrid (including tight ends, linebackers and running backs) and speed (comprising wide receivers and defensive backs). Head impact severity distributions were calculated for each kinematic-based metric and for each position grouping. Player-positions were determined at the game level from rosters available through PFF, which were verified using rosters provided by the NFL and NCAA teams.

We employed a two-sample Kolmogorov-Smirnov (KS) test to assess differences between the distributions of head impact severity between leagues. While a generalised linear mixed effects model would allow for hypothesis testing on the league differences at the mean level while accounting for repeated measures on the same player,[36] the KS test allows for detecting differences in the distribution of impact severity when comparing the two leagues that may not be captured by the first moment of their distributions alone. Shapiro-Wilk tests of normality were performed, which confirmed strong non-normality in every case ($p<1\times10^{-7}$). Due to the head impact severity distributions involving repeated measures on the same player, the empirical null distribution (H_0:no league difference) of the KS test was generated through permutation of the league label at the player level for a total of 10 000 permuted datasets along with their corresponding KS test statistics.[37] This procedure was repeated for each kinematic-based metric and player-position grouping combination leading to 18 total tests. Thus, p values were adjusted to account for multiple testing using the Benjamini-Hochberg procedure, controlling for a false discovery rate (FDR) of 20%.[38] Note that there is positive correlation between many kinematic-based metrics and our FDR control, therefore, represents a conservative correction and 20% can be seen as an upper bound. Head impacts with a PLA below 10 g were excluded from the analysis to eliminate non-impact head accelerations due to other dynamic everyday movements.[39]

RESULTS

Impact classifier performance

The ML model developed by Gabler *et al*[28] was retrained using sensor recordings corresponding to 3060 definitive head impacts and 750 definitive non-impacts, all verified on video.[28] Approximately 91% of the definitive head impacts and 61% of the definitive non-impacts were recorded during games. For the updated model using game data, the precision (positive predictive value) was 98.3% with a 95% CI of (96.6%, 98.9%) while recall (sensitivity) was 96.4% with a 95% CI of (94.9%, 98.2%).

Final dataset

In the NFL, data were recorded on 101 player-positions (99 unique players) across 547 player-games (table 1). The final dataset for the NFL comprised a total of 6289 head impacts, of which 5207 exceeded 10 g. In the NCAA, data were recorded on 146 player-positions (144 unique players) across 661 player-games (table 1). The final dataset for the NCAA comprised a total of 6866 head impacts, of which 5831 were greater than 10 g.

Head impact severity

After accounting for multiple comparisons, the distributions of all head impact kinematic-based metrics were not significantly different between the NFL and NCAA ($p\geq0.320$ for all comparisons made, table 2, online supplemental file 4). Combining all position groups, the magnitudes of the median differences (95% CIs) between the two leagues for PLA, PAA, PAV, HIC, DAMAGE and HARM were 0.6 (−0.4, 1.6) g, 0.02 (−0.93, 1.26) krad/s^2, 0.4 (−0.3, 1.1) rad/s, 0.6 (−0.6, 1.6), 0.005 (−0.001, 0.011) and 0.10 (−0.02, 0.20), respectively. The initial comparisons involving DAMAGE and HARM for the speed position grouping were the only ones that yielded significant between-league differences: median difference (95% CI) 0.015 (0.001, 0.029), p=0.029 and median difference (95% CI) 0.29 (0.02, 0.56), p=0.036, respectively; however, these results did not hold after adjusting for multiple comparisons (p=0.320 for both metrics). Distributions for PLA, PAA and HARM for the three position groupings are shown in figure 3. The median differences and 95% CIs for each metric reported above and in table 2 were of a severity that is within the range of values reported in studies involving volunteers undergoing everyday activities and therefore do not represent clinically meaningful differences.[39]

DISCUSSION

This study provides the first comparison of head impact severity in D-I collegiate and professional football, rigorously measured by IMs, considering multiple kinematic parameters and different player-positions. When comparing the distributions of head impact severity across kinematic-based metrics and position groupings, the magnitudes of the median differences between the leagues were within 13% of the NFL median values and statistically non-significant after adjusting for multiple comparisons, suggesting that the distributions of head impact severity in games from each league may serve as a reliable proxy for the other. These findings emphasise the potential opportunities for knowledge transfer between different levels of play for driving innovation in protective equipment.

Research/policy implications

Combining NCAA and NFL data would leverage the tremendous resources required to collect such information by providing a much larger dataset for analyses that identify, prioritise or evaluate interventions aimed at reducing the severity of head impacts. These data can enhance injury prevention initiatives, such as evaluating and improving player protective equipment through the design of improved test methodologies and on-field

Table 2 Descriptive statistics for kinematic-based metrics by league and position grouping

	Percentile	PLA (g) NFL	PLA (g) NCAA	PAA (krad/s²) NFL	PAA (krad/s²) NCAA	PAV (rad/s) NFL	PAV (rad/s) NCAA
Linemen	10	11.4	11.6	0.71	0.72	7.3	7.5
	25	13.6	13.6	0.92	0.91	10.1	10.3
	50	17.2	17.0	1.21	1.18	13.5	14.0
	75	22.9	22.2	1.68	1.56	17.6	17.9
	90	29.9	28.5	2.30	2.08	21.9	22.3
	IQR	9.3	8.6	0.76	0.65	7.6	7.7
	MD (95% CI)	0.2 (–0.7, 1.1)		0.03 (–0.10, 0.16)		–0.5 (–2.2, 1.2)	
	P value	(0.654, 0.762)		(0.658, 0.762)		(0.550, 0.762)	
Hybrid	10	12.0	11.8	0.77	0.74	7.6	7.0
	25	15.5	14.8	0.98	0.98	10.9	10.4
	50	20.7	20.0	1.37	1.34	14.9	14.6
	75	29.4	28.3	1.97	1.91	20.4	19.8
	90	40.7	38.0	2.78	2.66	25.5	25.5
	IQR	13.8	13.5	0.99	0.93	9.4	9.4
	MD (95% CI)	0.7 (–1.2, 2.6)		0.03 (–0.20, 0.26)		0.3 (–0.5, 1.1)	
	P value	(0.454, 0.762)		(0.795, 0.797)		(0.477, 0.762)	
Speed	10	12.1	11.6	0.83	0.79	8.7	7.8
	25	14.6	14.5	1.13	1.03	11.7	11.0
	50	21.0	20.8	1.58	1.44	17.1	15.3
	75	31.7	30.0	2.30	2.08	22.8	21.6
	90	41.1	40.4	3.00	2.85	29.1	26.6
	IQR	17.0	15.5	1.17	1.05	11.1	10.6
	MD (95% CI)	0.2 (–0.4, 0.8)		0.14 (–0.11, 0.39)		1.8 (–0.8, 4.3)	
	P value	(0.531, 0.762)		(0.272, 0.762)		(0.155, 0.762)	

	Percentile	HIC NFL	HIC NCAA	DAMAGE NFL	DAMAGE NCAA	HARM NFL	HARM NCAA
Linemen	10	3.0	3.0	0.061	0.060	1.02	1.04
	25	4.5	4.6	0.082	0.082	1.39	1.39
	50	8.0	7.7	0.107	0.111	1.82	1.87
	75	14.5	13.6	0.140	0.142	2.40	2.43
	90	24.9	23.7	0.177	0.178	3.08	3.04
	IQR	10.0	9.0	0.059	0.060	1.01	1.03
	MD (95% CI)	0.3 (–0.5, 1.1)		–0.004 (–0.023, 0.015)		–0.05 (–0.21, 0.11)	
	P value	(0.477, 0.762)		(0.391, 0.762)		(0.537, 0.762)	
Hybrid	10	3.5	3.1	0.067	0.060	1.12	1.03
	25	5.9	5.2	0.089	0.085	1.51	1.45
	50	12.4	10.8	0.121	0.120	2.11	2.08
	75	27.5	23.7	0.168	0.163	3.02	2.92
	90	53.1	44.9	0.216	0.211	4.10	3.89
	IQR	21.6	18.5	0.078	0.078	1.51	1.47
	MD (95% CI)	1.6 (–1.4, 4.6)		0.001 (–0.015, 0.017)		0.03 (–0.10, 0.16)	
	P value	(0.284, 0.762)		(0.678, 0.762)		(0.652, 0.762)	

Continued

 Gabler LF, *et al. BMJ Open Sp Ex Med* 2025;**11**:e002365. doi:10.1136/bmjsem-2024-002365

Table 2 Continued

	Percentile	HIC		DAMAGE		HARM	
		NFL	NCAA	NFL	NCAA	NFL	NCAA
Speed	10	3.3	2.9	0.069	0.067	1.20	1.13
	25	5.7	5.6	0.097	0.087	1.62	1.51
	50	12.5	12.7	0.137	0.122	2.41	2.12
	75	28.5	25.5	0.188	0.169	3.31	3.04
	90	53.6	52.1	0.230	0.213	4.33	3.84
	IQR	22.8	19.9	0.091	0.082	1.69	1.54
	MD (95% CI)	−0.2 (−1.7, 1.3)		0.015 (0.001, 0.029)		0.29 (0.02, 0.56)	
	P value	(0.797, 0.797)		(0.029, 0.320)		(0.036, 0.320)	

Values indicate various percentiles of the distribution of head impacts.
IQR = interquartile range (difference between 75th and 25th percentiles).
MD (95% CI) = median difference (NFL – NCAA) and corresponding 95% CI.
P values in parentheses indicate the outcome of the permutation test (left) and the adjustment for multiple comparisons (right).
DAMAGE, Diffuse Axonal Multi-Axis General Evaluation; HARM, Head Acceleration Response Metric; HIC, Head Injury Criterion; NCAA, National Collegiate Athletic Association; NFL, National Football League; PAA, peak angular acceleration; PAV, peak angular velocity; PLA, peak linear acceleration.

evaluations. For example, these data can be used, when paired with contextual data from video review, to inform efforts to develop test methods for evaluating position-specific helmets.[1 40] These findings also indicate that new helmet designs could be evaluated on-field using D-I collegiate game head impact severity data, which would expedite the rate of helmet innovation because more data are available. Similarly, by studying impacts in the top percentiles of severity, one could identify the scenarios that lead to those impacts and propose interventions to minimise the likelihood that such scenarios occur during game play.

One possible explanation for why the distributions of kinematics showed no significant differences between leagues may be due to the variation in head impact severity among individual players within a position. For example, among all linemen within a league, the player with the highest median value for PAA was 1.7 and 1.5 times greater than the player with the lowest median value in the NFL and NCAA, respectively. This finding underscores the variability among players within a position, suggesting that the mean or median severity of impacts for a position group may not accurately represent the impact distribution experienced by individual players, an approach used in previous studies.[24] The high variability within a position group also indicates opportunities to use these data to identify individual players who generate impacts with elevated kinematics, who may benefit from an individualised evaluation of their technique.

Limitations

There are several limitations of this study. The data were obtained from players who volunteered to wear the IM. This voluntary participation introduces a potential source of bias, as the head impacts experienced by the players wearing IMs may not fully represent the player population in both leagues. This could have contributed to unequal participation across positions. Specifically, there were fewer participants in the hybrid and speed position groupings compared with linemen, a difference that was more pronounced in the NFL. It is worth noting that while NCAA players were incentivised to participate, NFL players were not. The NCAA teams were from the Power Five conferences whose players regularly join NFL rosters such that the NCAA data may not be generalisable to all collegiate football teams. Future research should aim to recruit participants from a broader range of teams and playing styles.

The sample size in the smallest position grouping, speed, was sufficient to detect a median difference of 4g or more in PLA with 98.5% power, accounting for multiple comparisons (a 4g difference is based on previously published device error data).[27] This result lends further support to our findings that the distributions of kinematic-based metrics do not significantly differ between the two leagues and the lack of difference is not the result of a type II error.

Additionally, the results herein only evaluate head impact severity in games, and the conclusions cannot be extended to the frequency of head impacts, the practice environment or to other levels of football competition. Notably, the frequency of head impacts is an important parameter to consider when evaluating interventions and may provide additional useful information about the impact environment beyond the distributions of impact severity[41 42]; however, the development and evaluation of protective equipment do not require knowledge of impact frequency and can be based on the distributions of impact severity alone. A comparison of head impact frequency between the NFL and NCAA may benefit other types of interventions and should be investigated in the future.

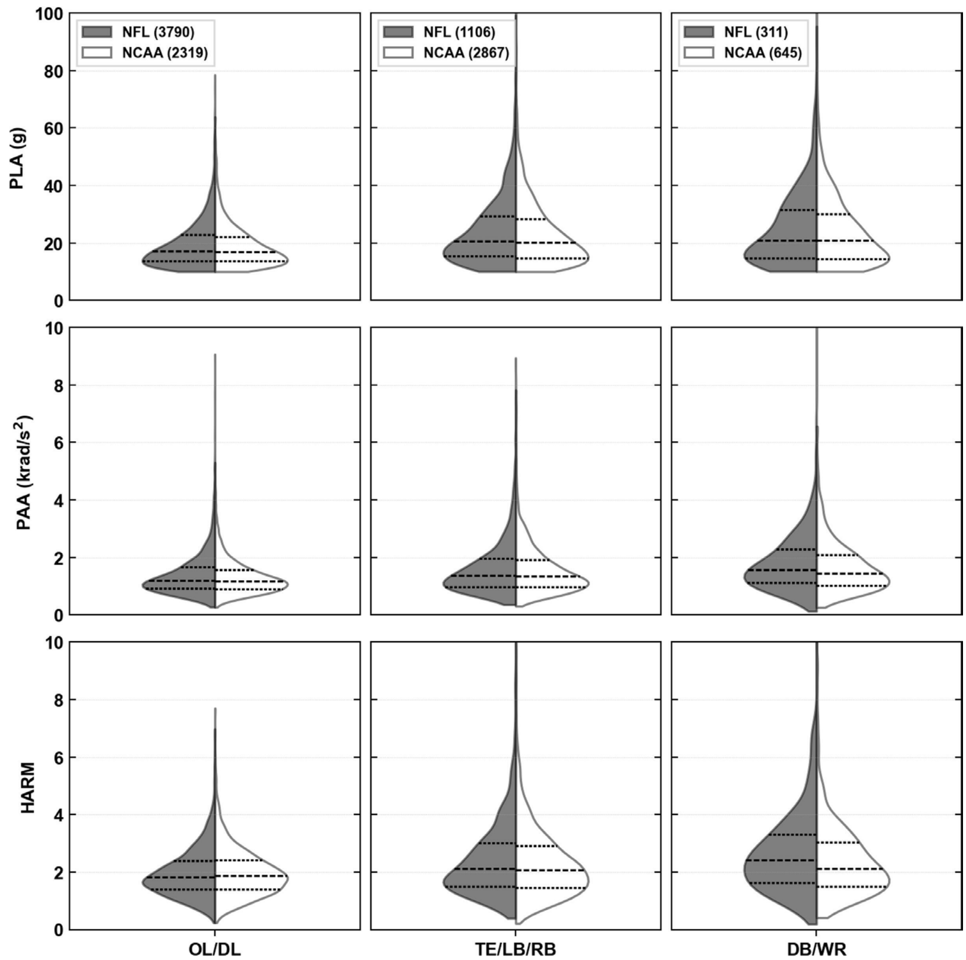

Figure 3 A comparison of the head impact severity distributions between the NFL and NCAA for position groupings (columns) and kinematic-based metrics (rows). Sample sizes (number of impacts) are indicated in parentheses in the legends at the top row. Medians (dashed lines), first and third quartiles (dotted lines) are shown on the distributions. Five impacts extend beyond the chart limits. DB, defensive backs; DL, defensive line; HARM, Head Acceleration Response Metric; LB, linebackers; NCAA, National Collegiate Athletic Association; NFL, National Football League; OL, offensive line; PAA, peak angular acceleration; PLA, peak linear acceleration; RB, running backs, TE, tight ends; WR, wide receivers.

While video verification greatly enhances the rigour of the dataset, it becomes impractical at scale.[43] Approximately 55% of the impacts in the NFL dataset were video verified since they were used to retrain the ML model. Despite the high precision and recall of the ML model used to classify head impacts (>95%), there remains the potential for false positives and false negatives.

It is also important to note that the head impact classifier used in video review may not have captured all head impacts. In the current study, the classifier defines a head impact as an event where there is clear contact with the player's helmet, resulting in a visible change in the trajectory of the helmet.[28] This definition specifically addresses direct contact to the head, as previously described.[44 45] While it is possible that indirect or inertial head acceleration events were included in the severity distribution, these events are typically of lower magnitude and are unlikely to have a significant influence on the distribution of head impacts exceeding 10 g.[39]

Finally, the current study did not involve head injury data; therefore, direct clinical implications are limited. However, the findings of non-significant differences between leagues will broaden the environments in which the clinical implications (eg, head injury reduction) of interventions that minimise the likelihood and severity of head impacts can be analysed.

CONCLUSIONS

Effective interventions aimed at reducing the number and severity of head impacts in American football require a large volume of accurate data given differences across player behaviour, game scenarios and levels of play. Data collected via IM represent the most accurate method for measuring head kinematics during live play, however, few studies have investigated the severity of head impacts in American football using IMs, and none have focused on the professional level. This study provides a valuable and novel dataset of head impacts measured by the same IM from both professional and D-I collegiate levels, indicating similarity in the distribution of head impact severity during games in both leagues. These findings suggest that combining these datasets could expedite the rate of protective equipment innovation through the development of improved test methodologies and underscore potential opportunities for transfer of game intervention knowledge between the collegiate and professional levels of play.

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