Brain strain and anatomy: correlating sports impact strain with brain measures

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ABSTRACT

Brain strain calculated by biomechanical models is used as a biomechanical marker of brain injury. Under the same head kinematics, different individuals may sustain different values of brain strain due to the difference of brain anatomy. In this study, we explored the effect of sex and brain anatomy on brain strain using multiple real-world sports impacts of different severities. We selected representative subjects with differences in brain anatomy. Three key anatomical measures were extracted for each subject: total cerebrum volume (TCV), ventricular cerebrospinal fluid volume (CSFV), and mean cortical thickness (mCT). These measures were converted to centile scores using the Brain Chart database, and six subjects were selected as a small and a large representation of each measure. Subject-specific finite element (FE) models were generated for these subjects, using segmentation and meshing techniques. Four rugby impacts, selected based on both peak rotational acceleration and whole brain strain at moderate and high severity, were simulated on each FE model. After each simulation, 90th percentile maximum principal strain (MPS) in the whole brain (WB), sulci and brain stem were extracted for analysis. We found that TCV has the strongest linear correlation with WBMPS, but the correlation coefficient varied with impact severity. Sulci and brain stem MPS ranking by subject has no significant difference. Sex has no significant effect on brain strain. Our results highlight that the relationship between brain anatomy and brain strain can be different with different impact severity.

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INTRODUCTION

Traumatic brain injury (TBI) is a serious condition that occurs when an external force disrupts brain function, typically caused by a blow, jolt, or penetrating injury (Centers for Disease Control and Prevention [CDC], 2021). The leading causes of TBI are high-impact events such as falls and motor vehicle collisions, which can result in life-threatening injuries (Giza & Hovda, 2014). However, the majority of reported TBIs are mild, often referred to as mild TBIs, which are commonly associated with rapid head movements resulting from blunt impacts, such as those occurring in sports-related collisions.

Biomechanics plays an important role in understanding how these sports-related impacts affect the brain by analysing factors like rotational forces, accelerations, and impact duration (Meaney & Smith, 2011). Researchers have developed brain biomechanical models to enhance injury prediction and offer a more detailed understanding of kinematic exposure beyond head movements (Ji et al., 2022). These models are designed to estimate brain responses using head kinematics observed in various environment including sports and automotive (Donat et al., 2021, Ghajari et al., 2017, Kimpara et al., 2006, Mao et al., 2013, Sahoo et al., 2014, Takhounts et al., 2008). These models can simulate brain biomechanics with high accuracy *in silico*, enabling the analysis of tissue-level responses based on physical principles. This allows for more precise injury risk assessment and insights into specific injury characteristics, such as location and severity of structural damage.

Most of these brain models are developed using physics-based finite element (FE) method from the brain anatomy of an average demographic, usually a 50th percentile male subject. While relying on demographic-specific is effective, these models overlook the anatomical differences within the population and how these variations impact the brain biomechanical response. Consequently, the relationship between brain anatomy and brain deformation are unclear. To address this limitation, subject-specific brain models have been developed using non-linear image registration techniques (Giudice et al., 2020; Li et al., 2021; Duckworth et al., 2022; Menghani et al., 2023). These models capture the brain anatomical differences and be used to understand how these differences affect biomechanical response.

Previous research using subject-specific models has primarily focused on the correlation between head size and brain deformation (Kleiven & von Holst, 2002; Li et al., 2021; Reynier et al., 2022; Liu et al., 2022). These studies consistently found that smaller brains experience less deformation under the same impact conditions. Building on this finding, machine learning models have been developed to predict acute brain responses across different individuals (Wu et al., 2022; Lin, Wu & Ji, 2023). However, these studies used a range of subject-specific models to simulate impacts under a limited set, potentially limiting the generalisability of the relationship between brain size and brain deformation. Additional work is required to investigate whether this relationship holds across a broader range of kinematic conditions.

This objective of this paper is to statistically quantify the effect of brain anatomical measures to brain response using subject-specific brain models. Subjects were selected based on the centile scores calculated from a large brain scan database span across infant to seniors, representing smallest and largest of each brain anatomical measure. On-field sports impacts at different levels of severity were simulated on these subject-specific models, to investigate which anatomical measure are most related to brain deformation, with considering the effect of impact severity. Understanding such relationship can inform the accuracy of subject-specific machine learning model for brain response prediction, as well as the development of sports injury prevention guidelines, injury risk functions and clinical diagnosis.

METHODS

Subjects and subject-specific models

Magnetic Resonance Imaging (MRI) scans from a cohort of healthy human subjects (N=211) was acquired at Hammersmith Hospital, Imperial College (Parker et al., 2023). Each brain scan was processed using FreeSurfer's *recon-all* pipeline to segment and parcellate brain structures (Fischl et al., 1999). From these scans, we extracted key anatomical measures for each subject, namely total cerebral volume (TCV), ventricular cerebrospinal fluid volume (CSFV), and mean cortical thickness (mCT). To contextualise these brain measures, we referenced them against the Brain Chart database of over 110,000 human subjects (Bethlehem et al., 2022) to calculate centile scores for each subject. These scores indicate how an individual's brain measures compare to others within their age and sex group.

Using these centile scores, we selected representative subjects for brain biomechanics modelling. Specifically, we identified three pairs of subjects, ensuring that each pair represented opposite extremes of a given brain measure while maintaining similar centile scores for the other two measures. Additionally, we derived estimated total intracranial volume (eTIV) as a complementary measure of total brain volume alongside TCV (Klasson et al., 2018).

To control for age-related effects, all selected subjects were between 23 and 35 years old, aligning with the typical age range of elite or professional athletes. Details of the three pairs of selected subjects including age, sex, and brain measures with their centile scores are provided in Table 1, the brain measure to compare is highlighted in bold text.

Table 1: Subject details with brain measures and centile scores

Subject	Age	Sex	eTIV *[cm^3]*	TCV *[cm^3]* (Centile)	mCT *[mm]* (Centile)	CSFV *[cm^3]* (Centile)
Sub0175	33	M	1481	**979 (0.16)**	2.47 (0.61)	18.57 (0.39)
Sub0183	35	M	1875	**1265 (0.96)**	2.46 (0.58)	18.72 (0.37)
Sub0188	30	F	1357	976 (0.46)	**2.43 (0.17)**	8.91 (0.13)
Sub1770	23	F	1457	990 (0.49)	**2.53 (0.82)**	16.18 (0.32)
Sub1998	30	F	1528	1004 (0.68)	2.37 (0.75)	**16.55 (0.02)**
Sub0184	34	M	1668	1116 (0.66)	2.60 (0.80)	**23.1 (0.97)**

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Finite element (FE) models were generated for each subject. The MR images were segmented into brain structures using FAST and BET segmentation (Zhang, Brady & Smith, 2001; Smith, 2000). A composite segmented image was then created by combining these structures, and any missing voxels were filled. FE meshes were subsequently generated from the segmented images and smoothed to develop subject-specific FE brain models (Duckworth et al., 2022). These models are shown in Figure 1.

Impact simulation

We simulated real-world sports impacts on the subject-specific models. The impact kinematics data were collected by the validated Protecht instrumented mouthguards (Jones et al., 2023). Impacts were selected based on peak rotational velocity (PRV) and the peak whole-brain 90th percentile of maximum principal strain (WBMPS). The MPS values were estimated using the detailed Imperial College (IC) FE model of brain biomechanics, developed from an average healthy male subject (Ghajari, Hellyer & Sharp, 2017).

From a dataset of 1,701 elite male rugby impacts, we selected impacts at the 50th percentile (moderate severity) and 90th percentile (high severity) for both PRV and WBMPS. Four representative impacts were then chosen for simulation on each subject-specific model. After each simulation, MPS values were extracted for the whole brain, brainstem, and sulci using region-specific binary masks.

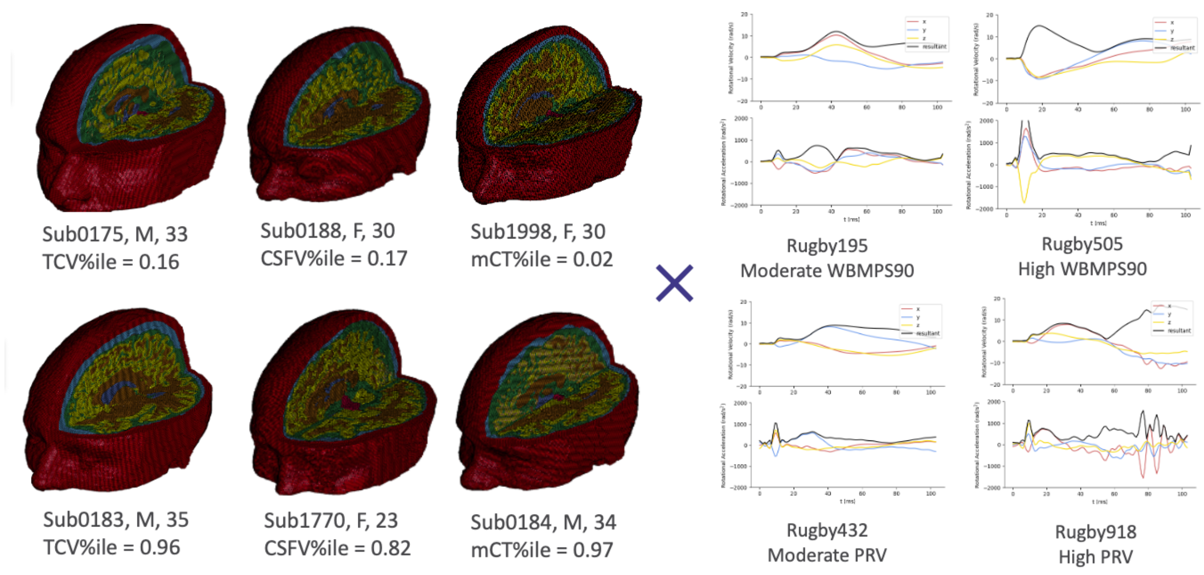

Figure 1: Subject-specific brain FE models and representative sports impacts. Each impact was simulated on each model.

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Statistical analysis

The effects of age and sex on WBMPS were assessed using analysis of variance (ANOVA). Within each impact, Pearson's correlation coefficient (r) was used to evaluate the linear relationship between WBMPS and each brain measure. To determine whether MPS values in critical brain regions differed significantly among subjects, Spearman's correlation coefficient was used to assess the ranking of brainstem and sulci MPS values across all subjects within each impact.

RESULTS

The simulation results for all subjects on each representative impact are presented in Table 2. The WBMPS estimated by the IC FE model was at the higher end of the WBMPS range observed across all subjects. Overall, the WBMPS sustained by different subjects showed minimal variation, with the largest difference of 0.023 observed in the high-MPS impact. ANOVA revealed no significant differences in WBMPS based on sex ($F = 0.008$, $p > 0.1$).

Among the three brain measures, TCV and eTIV showed the strongest linear relationship with WBMPS, followed by CSFV and mCT (Table 2). Notably, the correlation between TCV and WBMPS varied with the level of WBMPS, suggesting that the relationship between TCV and WBMPS may change depending on the severity of the impact.

Table 2: WBMPS ranges and correlations with brain measures

Impact severity	**PRV (rad/s)**	**WBMPS (IC FE)**	**WBMPS range (subjects n=6)**	**Correlation coefficient (r)**			
				TCV	eTIV	CSFV	mCT
Moderate-PRV	8.8	0.053	0.042-0.055	0.87	0.83	0.33	-0.08
High-PRV	17.02	0.066	0.055-0.067	0.83	0.83	-0.06	-0.24
Moderate-MPS	11.93	0.070	0.054-0.071	0.83	0.76	0.33	-0.10
High-MPS	15.02	0.153	0.130-0.153	0.79	0.71	0.36	-0.03

Figure 2 illustrates the strain distribution following each impact for subjects *Sub0175* and *Sub0183*, who have small and large TCV centile scores, respectively. Although there is a visible difference in the magnitude of strain between the subjects, the MPS distribution follows a similar pattern. Spearman rank correlation analysis revealed no significant difference between the ranking of brainstem MPS and sulci MPS across all subjects within each impact ($p > 0.05$ for all four

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impacts), suggesting that the strain distribution patterns in the brainstem and sulci are not significantly different.

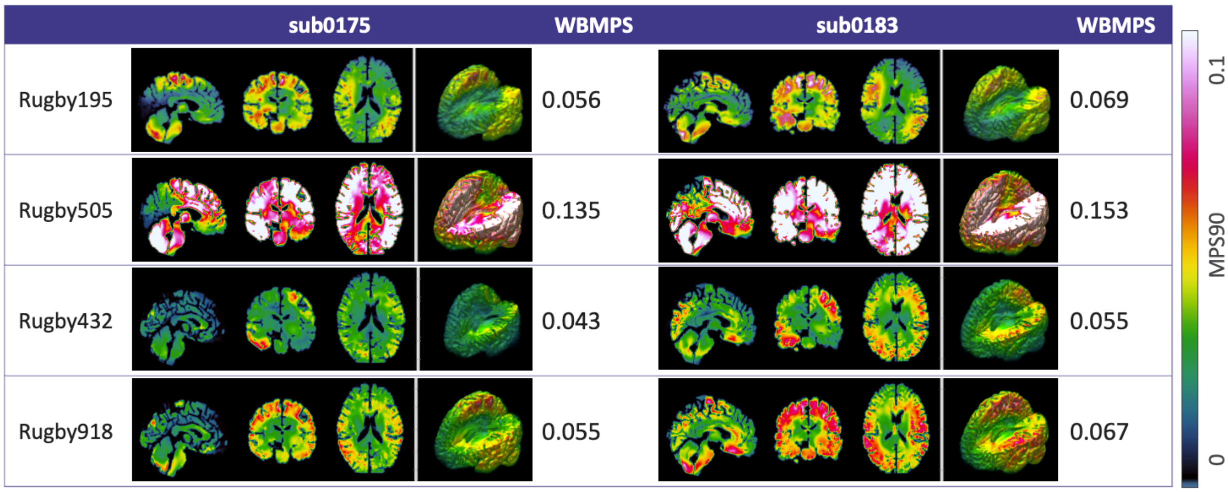

Figure 2: Strain distribution of subjects sub0175 (with small TCV) and sub0183 (with large TCV) after each impact. The WBMPS values for each subject and impact were shown aside.

DISCUSSION

This study used subject-specific models selected based on Brain Chart centile scores, ensuring each brain measure spanned from the smallest to the largest based on data from 110,000 individuals, capturing broad anatomical variation in brain strain analysis. Our findings show that strain is correlated with brain volume (i.e., TCV and eTIV), which aligns with previous research (Wu et al., 2022; Li et al., 2020; Reynier et al., 2022). However, our preliminary results highlight that this correlation is not constant and varies with impact severity. To investigate this, we simulated four real-world rugby impacts representing different levels of impact severity, assessed through both kinematic and biomechanical metrics. Our results demonstrate that the linear correlation between brain volume and strain shifts as impact severity changes, highlighting the need for a more nuanced approach when modelling brain deformation.

This finding has implications for predictive modelling. Prior research introduced scaling factors based on brain volume to enhance the accuracy of machine learning models in predicting brain strain across individuals, but these models were developed using data from a single impact scenario. Our results suggest that impact severity should also be incorporated into these scaling factors, as it significantly influences the volume-strain relationship. Integrating impact severity into predictive models may improve their ability to generalise across a wider range of real-world conditions.

We also examined the distribution MPS in key brain regions. By assessing the ranking differences of MPS in the brainstem and sulci, we found that if one of these regions exhibits higher

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strain in a subject compared to another, the same pattern holds for the other region. This suggests that, under the same impact severity, while the absolute magnitude of MPS may vary across individuals, the relative distribution of high- and low-strain regions remains consistent. Clinically, this may be relevant as strain in specific brain regions is often linked to symptoms and injury outcomes (Post et al., 2017; Zimmerman et al., 2023). Future research should expand on this by analysing additional brain regions and conducting voxel-wise comparisons to better understand individual differences in strain distribution.

This study has limitations. Although we analysed four different impact scenarios, all were derived from rugby, which may limit the generalisability of our findings to other sports with distinct impact kinematics and strain patterns. Future studies should explore a broader range of sports to account for varying impact dynamics. Additionally, our study only included male athletes, whereas previous research suggests that female athletes may experience higher kinematic loads under similar conditions (Abbasi Ghiri et al., 2025). Expanding the dataset to include both sexes will provide a more comprehensive understanding of sex-based differences in brain strain. Finally, the study focused on young athletes, preventing us from examining how age-related anatomical changes influence strain responses. Future research should incorporate a wider age range to determine whether age is a significant factor in brain biomechanics.

CONCLUSIONS

This study investigated the relationship between brain anatomy and brain strain using kinematic data from multiple sports impacts. Our findings confirm that brain strain correlates with brain volume, consistent with previous research. However, we observed that this correlation varies with impact severity, highlighting the need to consider impact conditions when modelling strain responses. We also found that while individual differences in whole-brain MPS values exist, the ranking of high-strain regions, particularly in the brainstem and sulci, remains consistent across individuals. This could have clinical implications for associating strain patterns with injury risk and post-impact symptoms.

The preliminary results of this study provide insight into how anatomical variations influence brain strain in sports impacts, which could inform the development of more individualised strain prediction models. Future research should expand on these findings by incorporating diverse impact scenarios and broader demographic groups.

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