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Evaluation of Brain Injury Metrics in Automotive Head Impacts

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Abstract

Traumatic brain injury (TBI) remains a significant concern in automotive safety, necessitating accurate injury metrics for predicting brain tissue deformation under impact conditions. Traditional kinematics-based injury criteria provide measurable indicators of head motion but do not directly quantify internal brain strain. In contrast, strain-based metrics derived from finite element (FE) simulations offer a more detailed assessment of brain tissue responses. However, the extent to which kinematics-based metrics accurately predict strain-based injury risk remains unclear.

This study evaluates the correlation between kinematics-based and strain-based injury metrics using a dataset of 498 head impact cases from the National Highway Traffic Safety Administration (NHTSA) and previous research. Finite element simulations were conducted using the KTH head model to estimate brain strain. Statistical analyses, including linear regression, were applied to assess the predictive capabilities of various kinematics-based metrics.

The results indicate that certain kinematics-based metrics, particularly DAMAGE and UBrIC, exhibit the strongest correlations with strain-based metrics, suggesting their potential suitability for estimating brain tissue deformation in automotive impacts. In contrast, traditional regulatory metrics such as HIC, HIP, and GAMBIT showed weaker correlations, highlighting their limitations in predicting diffuse brain injuries. The findings underscore the need to refine injury prediction models by incorporating rotational kinematics and strain-based assessments.

This study contributes to the ongoing development of more accurate head injury criteria and highlights the potential for integrating strain-based modeling into regulatory crash testing frameworks. Future research should explore nonlinear predictive models, machine learning-based injury risk assessment, and expanded datasets covering a broader range of impact conditions. By improving the understanding of brain injury mechanisms, this research supports the development of safer vehicles and enhances injury prevention strategies in automotive safety.

Keywords

Traumatic Brain Injury, Kinematics-Based Injury Metrics, Strain-Based Injury Metrics, Finite Element Simulations, Automotive Safety, Head Injury Criterion, Biomechanics

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Sammanfattning

Traumatiska hjärnskador är en betydande utmaning inom trafiksäkerhet och kräver tillförlitliga skadekriterier för att förutsäga hjärnvävnadens deformation vid kollisioner. Traditionella kinematikbaserade skadeindikatorer ger mätbara parametrar för huvudets rörelse men kvantifierar inte direkt den interna belastningen på hjärnvävnaden. I kontrast till detta ger de belastningsbaserade metoderna, härledda från finita element-simuleringar en mer detaljerad analys av hjärnans respons vid yttre krafter. Hur väl kinematikbaserade skadekriterier kan förutsäga belastningsbaserade skador är dock fortfarande oklart.

Denna studie undersöker korrelationen mellan sex kinematikbaserade och två belastningsbaserade skadekriterier genom analys av 498 huvudkollisioner hämtade från National Highway Traffic Safety Administration (NHTSA) och tidigare forskning. Finita element-simuleringar genomfördes med KTHs huvudmodell för att beräkna hjärnans belastning, medan statistiska analyser, inklusive linjär regression, användes för att utvärdera de kinematikbaserade kriteriernas förmåga att förutsäga belastningsbaserade skador.

Resultaten visar att vissa kinematikbaserade skadekriterier, särskilt DAMAGE och UBrIC, uppvisar starkast korrelation med belastningsbaserade mått, vilket tyder på att dessa kan vara bättre lämpade för att förutsäga hjärnvävnadsdeformation vid bilolyckor. Däremot visade traditionella regleringskriterier, såsom HIC, HIP, och GAMBIT svagare korrelationer, vilket belyser deras begränsningar i att förutsäga diffusa hjärnskador. Dessa resultat understryker behovet av att förbättra skademodeller genom att inkludera rotationskinematik och belastningsbaserade analyser.

Denna studie bidrar till den pågående utvecklingen av mer exakta skadekriterier för huvudtrauma och betonar vikten av att integrera belastningsbaserade metoder i regulatoriska krocktester. Framtida forskning bör undersöka icke-linjära prediktionsmodeller, maskininlärningsbaserade skadebedömningar samt utökade dataset som täcker en bredare variation av kollisionstyper. Genom att förbättra förståelsen av hjärnskademekanismer stöder denna forskning utvecklingen av säkrare fordon och effektivare skadeförebyggande åtgärder inom trafiksäkerhet.

Keywords

Traumatiska hjärnskador, Kinematikbaserade skadekriterier, Belastningsbaserade skadekriterier, Finita element-simuleringar, Trafiksäkerhet, Biomekanik

List of Abbreviations

ATD – Anthropomorphic Test Device
BrIC – Brain Injury Criterion
CFC – Channel Frequency Class
CSDM – Cumulative Strain Damage Measure
DAI – Diffuse Axonal Injury
DAMAGE – Diffuse Axonal Multi-Axis General Evaluation
FE – Finite Element
GAMBIT – Generalized Acceleration Model for Brain Injury Threshold
HBM – Human Body Model
HIC – Head Injury Criterion
HIP – Head Impact Power
LS-DYNA – Explicit Finite Element Software used for impact simulations
MPS – Maximum Principal Strain
NHTSA – National Highway Traffic Safety Administration
OLS – Ordinary Least Squares (Regression Method)
PMHS – Post-Mortem Human Surrogate
SAE – Society of Automotive Engineers
SDH – Subdural Hematoma
TBI – Traumatic Brain Injury
UBrIC – Universal Brain Injury Criterion

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Contents

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1 Introduction

One of the first biomechanical experiment took place in 1939 at the bottom of an elevator shaft, where neurosurgeon Dr. E. Stephen Gurdjian and engineer Louis Lissner dropped steel balls onto a human skull [2]. Their goal was to understand the forces behind skull fractures. Decades later, biomechanics continues to play a crucial role in addressing brain injuries, particularly in motor vehicle collisions. The experimental methods have been refined since 1939 and data collected from biomechanical experiments have laid the groundwork for developing brain injury metrics that quantify the forces and strains associated with traumatic brain injuries.

Traumatic brain injury (TBI) is a complex condition that affects multiple brain structures through diverse pathologies. Each year, between 100 and 300 new cases of TBI occur per 100,000 individuals worldwide, but the true prevalence is likely much higher due to unreported or undiagnosed cases [3]. TBI is a significant concern in automotive crashes due to the severe and often lasting effects it has on individuals [4]. To reduce or prevent injuries, it is essential to understand injury mechanisms, which allows the development of effective tolerance criteria. Although it is qualitatively understood that the severity of TBI depends on factors such as the form, magnitude, direction, and duration of the external force, the exact pathway from external impact to tissue strain - and ultimately to the onset of the injury - remains elusive.

Biomechanical injury metrics are quantitative measures used to assess the risk and severity of injuries resulting from mechanical forces, particularly in scenarios like vehicle collisions, sports impacts, and falls. These metrics are essential in fields such as automotive safety, sports science, and biomechanics, as they inform the design of protective equipment, establish safety standards, and enhance our understanding of injury mechanisms [5]. By identifying the thresholds at which injuries are likely to occur, these metrics provide valuable guidance to implement preventive measures and design effective interventions in diverse settings.

However, the complex anatomy of the head and the varied forces involved in an impact present significant challenges to biomechanical injury metrics, highlighting their current limitations. These limitations include that some metrics are context-specific and may not be applicable across different scenarios, such as varying sports or accident types. In addition, many metrics do not fully capture the complex, multi-factorial nature of injuries, which can result in oversimplified assessments [6]. A deeper understanding of brain injury biomechanics and further assessment of currently used metrics is crucial to developing more accurate brain injury criteria. This thesis addresses these limitations by evaluating kinematics- and tissue strain-based metrics, providing insights into their applications and future potential, as detailed in Section 1.1.

1.1 Objective

The primary objective of this study is to analyse brain dynamics in automotive impact simulations to assess neurotrauma risk, evaluating both tissue-based and kinematics-based injury metrics.

1.1.1 Supporting objectives

To achieve the primary objective, the following supporting objectives are outlined:

- Develop an automated method to identify relevant impacts from online databases and extract time-history curves of head kinematics from real experimental data.
- Design and implement a processing pipeline to integrate head impact kinematics into a simulation program.
- Perform impact simulations using a finite element head model, processing computational results to identify neurotrauma risks.
- Compare the predictive capability of tissue strain-based metrics with kinematics-based head injury criteria.

1.2 Scope and Limitations

This thesis focuses on non-penetrating brain injuries caused by impulsive loading, such as those encountered in traffic-related scenarios. Injuries involving skull penetration or other trauma mechanisms are not considered. The analysis does not distinguish between specific impact angles, velocities, or loading conditions, simplifying the scope to focus on overall trends. Additionally, the research is limited to traffic data, which may reduce its applicability to other contexts like sports or falls.

These limitations reflect the necessary focus and constraints of this work, with opportunities for future research to explore these aspects further.

2 Background

Biomechanics is a field that investigates how biological systems, particularly the human body, respond to external forces. This field is critical for understanding injuries in various scenarios, from sports and falls to vehicle collisions. Impact biomechanics focuses on short-duration forces that act on the body, generally lasting less than a second [7]. These forces are encountered in various impact scenarios and can be used to understand and mitigate injury risks, particularly brain injuries. This chapter provides background on how biomechanics contributes to understanding brain injury mechanisms, focusing on impact biomechanics, and introduces the metrics and models used to evaluate neurotrauma risk, laying the groundwork for the analyses in this study. Moreover, the chapter provides an introduction to the databases used in the study.

2.1 Biomechanics of Traumatic Brain Injury

TBI is a complex neurological condition typically caused by external forces or sudden head movements, leading to structural damage and potential disruption of brain function. TBI is commonly acquired through falls or traffic accidents [8]. The main forces involved in these injuries are inertial forces that include translational acceleration, rotational acceleration, and angular acceleration [9]. Translational acceleration occurs when an object, such as the brain's center of mass, moves in a straight line without rotation. In contrast, rotational acceleration involves the brain's center of mass remaining stationary while the head rotates around it. Angular acceleration combines both aspects, involving motion along an angular path that integrates translational and rotational components [10]. TBIs are typically classified by the nature and extent of the damage they cause, with the two primary categories being focal brain injuries and diffuse brain injuries.

2.1.1 Focal Injuries

Focal brain injuries refer to damage localized to a specific area of the brain, often resulting from direct impact or localized force. Examples include subdural hematoma (SDH), that occurs when blood collects between the dura mater and the arachnoid mater, typically due to the rupture of bridging veins caused by rotational head movements. During such motion, the brain lags behind the skull, creating inertial forces that stress the veins and surrounding brain tissue [11]. This stress leads to vein rupture and hematoma formation and contributes to damage within the brain parenchyma. SDH is a catastrophic injury with a mortality rate of approximately 66 % [12]. Contusions are characterized by hemorrhagic lesions resulting from a combination of necrosis, pulping, infarction, hemorrhage, and edema. Translational forces often cause contusions when accompanied by skull fractures, while angular forces can induce contusions without fracture [8].

2.1.2 Diffuse Injuries

Diffuse brain injuries are characterized by widespread, global disruption of the brain tissue across multiple regions. This category includes conditions like concussion, where an acceleration causes the brain to deform within the skull, leading to temporary disruptions in normal brain function. The main force involved in the kinematics of concussion is rotational acceleration [13]. Diffuse Axonal Injury (DAI) is a significant type of TBI. It primarily affects the parasagittal white matter, corpus callosum, and brainstem, caused by rotational motion that shears axonal structures. These injuries often lead to immediate unconsciousness and long-term cognitive deficits, such as memory and processing impairments [14].

2.2 Brain Injury Metrics

To better understand and quantify the risk of traumatic brain injury under various impact conditions, researchers have developed a range of brain injury metrics that assess the forces and strains experienced by brain tissue during inertial loading events. As mentioned in section 1, they play a critical role in assessing the safety of vehicles, protective gear, and the establishment of safety standards. Depending on their purpose, these metrics may emphasize individual kinematic variables, like linear or rotational acceleration, or combine multiple factors to improve their accuracy in predicting injury risk [15]. An important distinction is whether the injury metric or criteria is kinematics-based or tissue strain-based.

2.2.1 Kinematics-based injury metrics

Kinematics-based injury metrics evaluate brain injury risk by examining the motion of the head in response to external forces. These criteria rely on measurable quantities, such as acceleration and velocity, to understand how the head responds during impacts [15]. Unlike tissue strain-based approaches, they do not directly model internal brain deformations but instead provide a practical method for estimating injury potential. Their simplicity and focus on measurable data make them useful in situations where detailed biomechanical modeling is not practical. However, some kinematic-based metrics, such as BrIC, DAMAGE, and UBrIC, are indirectly dependent on FE models, as their critical thresholds or strain predictions are derived from FE simulations. This hybrid nature means they are not purely kinematic criteria but incorporate biomechanical modeling to enhance their predictive capabilities.

The Head Injury Criterion (HIC), developed in the 1960s and 1970s, is one of the most widely used kinematic-based injury metrics today due to its effectiveness in predicting head injury risk based on acceleration data [16]. This widespread use persists despite the criterion's initial development focusing on predicting skull fractures [17]. The HIC is calculated as the maximum value of a time-weighted integral of translational acceleration, as defined by equation 2.1.

$$\mathrm{HIC} = \max \left[\frac{1}{t_2 - t_1} \int_{t_1}^{t_2} a(t)\, dt \right]^{2.5} (t_2 - t_1) \tag{2.1}$$

In this formulation, t_1 and t_2 represent the time interval (in seconds) over which the acceleration $a(t)$ (measured in $\mathrm{m/s^2}$) is evaluated [18]. The exponent of 2.5 reflects the non-linear relationship between acceleration and injury severity, as described by the Wayne State University tolerance curve, emphasizing the significant increase in injury risk as acceleration levels rise. In this study, HIC15 was utilized, which evaluates head acceleration over a 15-millisecond window and is commonly applied in automotive crash testing [19].

The Head Impact Power (HIP) kinematic criterion, proposed by Newman et al. in 2000 [20], evaluates brain injury risk by linking head motion to the power (in Watts) of the impact. This metric is based on the hypothesis that head injuries occur when the head's power surpasses a critical value [20]. HIP combines linear and rotational accelerations, making it one of the few metrics designed to account for both translational and rotational contributions to head impacts [15][21]. The computation of HIP is defined by the following equation 2.2, which integrates the head's linear acceleration, a, and rotational acceleration, α, as functions of time about each axis.

$$\begin{aligned}\text{HIP} = 4.5a_x \int a_x\,dt + 4.5a_y \int a_y\,dt + 4.5a_z \int a_z\,dt \\ + 0.016\alpha_x \int \alpha_x\,dt + 0.024\alpha_y \int \alpha_y\,dt + 0.022\alpha_z \int \alpha_z\,dt\end{aligned} \tag{2.2}$$

In this equation, a_x, a_y, and a_z represent the linear accelerations along the head's local axes, while α_x, α_y, and α_z denote the rotational accelerations. The coefficients correspond to the head's mass properties and moments of inertia, reflecting the directional sensitivities to impact forces [22]. Notably, Kleiven (2003) attempted to fit HIP for subdural hematoma (SDH) prediction and found that individual scaling coefficients were necessary for different impact directions to improve prediction accuracy [23].

The Generalized Acceleration Model for Brain Injury Threshold (GAMBIT), introduced by James Newman in 1985 [24], predicts brain injury risk by combining translational and rotational accelerations. It treats head motion like engineering stress analysis, where combined forces determine failure [25]. The model uses equation 2.3 that weights these accelerations empirically to assess whether an impact exceeds a critical threshold.

$$GAMBIT = \left[\left(\frac{a(t)}{a_c}\right)^n + \left(\frac{\ddot{\phi}(t)}{\ddot{\phi}_c}\right)^m\right]^{\frac{1}{k}} \tag{2.3}$$

In equation 2.3, $a(t)$ represents the translational acceleration as a function of time, and a_c is the critical threshold for translational acceleration. Similarly, $\ddot{\phi}(t)$ denotes the rotational acceleration as a function of time, while $\ddot{\phi}_c$ is the critical threshold for rotational acceleration. The parameters n, m, and k are empirical constants determined from experimental data to fit the injury prediction model. Studies, including musculoskeletal simulations, have validated GAMBIT under different impact conditions, such as vehicle crashes and sports collisions [25].

The Brain Injury Criterion (BrIC) is a kinematics-based metric developed to assess brain injuries caused by rotational motion. Unlike previous head injury metrics that relied on angular acceleration, BrIC is based on angular velocity components, as research has shown that peak change in angular velocity better correlates with strain levels in brain tissue [26]. Studies have demonstrated that for purely rotational impulses, peak angular velocity change shows a stronger relationship with tissue deformation than angular acceleration or other traditional injury metrics [27]. Additionally, angular velocity components have been found to be more predictive of mild traumatic brain injury (mTBI) than angular acceleration [27]. These findings laid the foundation for BrIC, which quantifies brain injury risk based on peak rotational velocities in multiple directions [28]. By incorporating rotational motion across multiple axes, BrIC helps capture the complex nature of brain deformation during impacts. BrIC is calculated using directional peak rotational velocities as defined in equation 2.4.

$$\mathrm{BrIC} = \sqrt{\left(\frac{\omega_x}{\omega_{xC}}\right)^2 + \left(\frac{\omega_y}{\omega_{yC}}\right)^2 + \left(\frac{\omega_z}{\omega_{zC}}\right)^2} \tag{2.4}$$

In this equation, ω_x, ω_y, and ω_z are the peak angular velocities about the head's local axes, and ω_{xC}, ω_{zC}, and ω_{zC} are the corresponding critical thresholds derived from experimental and computational data [21]. BrIC provides a practical means to assess the rotational kinematics of head impacts, which are strongly associated with some brain injuries.

While BrIC is often described as a kinematic criterion, it is fundamentally dependent on finite element models. The critical thresholds used in BrIC are derived from strain-based finite element simulations, making it a hybrid approach rather than a purely kinematic one. This means that BrIC indirectly accounts for strain-related brain injury mechanisms despite being computed from kinematic inputs alone [21]. As a result of this dependence on FE-derived thresholds, BrIC's applicability is inherently linked to the accuracy and assumptions of the FE models used in its calibration.

The Diffuse Axonal Multi-Axis General Evaluation (DAMAGE) is a brain injury metric designed to predict maximum brain strain during head impacts using rotational kinematics. DAMAGE is based on a second-order mechanical system that incorporates directionally dependent angular acceleration time histories to estimate brain deformation [29]. Unlike other kinematic metrics, DAMAGE accounts for multiaxial rotational motion, improving its predictive power for strain-related brain injuries like diffuse axonal injury. The model was validated against a large dataset of 1,747 head impacts and demonstrated a high correlation with finite element brain strain simulations, making it a reliable tool for rapid assessment of head impact severity [29].

$$DAMAGE = \beta \max_t \left\{ \vec{\delta}(t) \right\} \tag{2.5}$$

Equation 2.5 demonstrates DAMAGE, where β is a scaling coefficient that adjusts the magnitude of the predicted strain response, and $\vec{\delta}(t)$ represents the approximated strain response of the brain, fitted to the Global Human Body Models Consortium (GHBMC) head model using both angular acceleration and angular velocity inputs. The equation takes the maximum strain value over time, ensuring that the metric captures the peak deformation experienced by the brain during an impact [29]. Since DAMAGE is empirically fitted to finite element model strain data, it is not a purely kinematic metric, but rather a strain-informed approach.

The Universal Brain Injury Criterion (UBrIC) is a kinematic-based metric designed to predict brain strain responses more accurately across a broad range of head impact conditions. Developed by Gabler et al. (2018), UBrIC is grounded in the physics of a second-order mechanical system and models brain deformation based on both angular velocity and acceleration [30]. It accounts for both angular velocity and angular acceleration, adapting dynamically based on impact duration. Short-duration impacts primarily depend on angular velocity, while long-duration impacts are influenced by angular acceleration. This transition is captured using an exponential function that ensures the metric responds appropriately across different types of impacts [25]. UBrIC is computed by normalizing rotational kinematics along three axes and summing their contributions with a weighting function, as can be seen in equation 2.6.

$$UBrIC = \left\{ \sum_i \left[\omega_i^* + (\alpha_i^* - \omega_i^*) e^{-\frac{\alpha_i^*}{\omega_i^*}} \right]^r \right\}^{\frac{1}{r}} \tag{2.6}$$

In this equation, ω_i^* represents the normalized peak angular velocity in direction i, and α_i^* is the normalized peak angular acceleration in the same direction. The exponential term governs the transition between velocity- and acceleration-dominant responses, ensuring that for short-duration impacts. The summation accounts for contributions from all three anatomical axes ($i = x, y, z$), and the exponent r controls the weighting of these contributions in the overall metric. Since UBrIC was fitted to strain responses derived from FE model simulations, it is similarly not a purely kinematic metric but an empirically calibrated one, dependent on strain-based predictions.

2.2.2 Tissue strain-based injury metrics

Tissue strain-based injury metrics are used to assess the risk of injury by analyzing how the brain tissue deforms when subjected to external forces. They focus on how mechanical forces cause strain in the brain tissue, leading to potential damage. Normal and shear strain in brain tissue occurs when forces cause the tissue to stretch, compress, or twist [9]. Strain-based injury criteria rely on determining critical thresholds for strain beyond which brain tissue damage is likely to occur.

One commonly used tissue strain-based injury criteria is the Maximum Principal Strain (MPS). MPS quantifies the highest strain experienced by a material point within a structure, indicating the maximum elongation or compression along a specific direction [31]. In the context of brain injuries, MPS measures the maximum strain experienced by brain tissue and identifies the regions of the brain undergoing the most significant deformation. Finite element models are normally used to calculate MPS, simulating how brain tissue deforms under various impact scenarios. Studies using accident reconstructions have demonstrated that MPS can reliably predict injury thresholds, making it a valuable tool for designing safety systems and analyzing traumatic brain injuries [32]. Additionally, research has shown that the injury areas predicted by finite element analysis closely match those observed in CT imaging, as demonstrated in previous studies on accident reconstructions and FE model validation [33] [34] [35] [36].

The Cumulative Strain Damage Measure (CSDM) quantifies the volume fraction of brain tissue that experiences strain exceeding a specified threshold during an impact event. This metric is calculated by integrating strain data over time to track the accumulation of tissue experiencing strains above critical levels [37]. The CSDM captures not only the magnitude of the strain but also its spatial distribution within the brain [38]. This cumulative approach allows researchers to evaluate the progressive nature of strain damage, identifying regions more vulnerable to deformation under specific loading conditions [39]. As with the MPS, the calculations are performed using FE simulations. CSDM is typically calculated using the first principal Green-Lagrange strain, as originally proposed in Takhounts et al. (2003) [37], and this study follows the same convention. In this analysis, CSDM is defined as the fraction of brain volume experiencing a first principal Green-Lagrange strain exceeding 0.10.

2.2.3 Evaluation of metrics

Brain injury metrics, whether kinematics-based or tissue strain-based, provide valuable insights into the mechanisms of head trauma. Each metric offers unique advantages but also faces limitations, highlighting the need for a comprehensive evaluation.

Kinematics-based metrics have proven to be invaluable tools for assessing head injury risk due to their simplicity, ease of implementation, and reliance on measurable external data like acceleration and velocity. Their ability to provide a broad estimate of injury likelihood makes them widely applicable in safety evaluations. However, they do not account for the specific tissue-level responses of the brain or pinpoint the locations of potential injuries [40]. This gap underscores the need for complementary approaches to provide a more detailed understanding of brain injury mechanisms.

Tissue strain-based injury metrics have demonstrated improved injury predictability in studies, particularly in their ability to quantify localized brain tissue responses [41][42][15]. However, implementing tissue strain-based criteria presents challenges. Accurately modeling the complex geometry and material properties of the brain requires sophisticated computational resources.

Another challenge with these metrics lies in their varying interpretations of impact severity. Studies comparing kinematics-based injury criteria against brain strain have found that impacts producing identical values for kinematics-based metrics can result in significantly different brain strains for varying impacts [43]. Furthermore, non-injurious brain strain levels may correspond to much higher risk predictions based on kinematics-based metrics [44][45].

Given these differences, directly comparing the predictive capabilities of tissue strain-based metrics and kinematics-based head injury criteria is critical for advancing the understanding of their relative effectiveness. This analysis will identify the specific strengths and limitations of each approach and provide valuable insights into their applicability across diverse impact scenarios.

2.3 Data Sources and Relevance

The National Highway Traffic Safety Administration (NHTSA), a division of the U.S. Department of Transportation, has been dedicated to improving roadway safety in the United States since 1970. Its mission is to reduce fatalities, injuries, and economic losses resulting from motor vehicle crashes [46]. To support research and innovation in vehicle safety, the NHTSA provides open-access databases, including the Vehicle

Crash Test Database and the Biomechanics Test Database [47], [48]. The Vehicle Crash Test Database contains engineering data from compliance crash tests and the New Car Assessment Program (NCAP), detailing the performance and response of vehicles and structures under impact conditions. The Biomechanics Test Database is a repository for experimental data to develop anthropomorphic test devices (ATDs) and injury criteria. This dataset, widely utilized by researchers, the automotive industry, and policymakers, aids in advancing automobile safety and mitigating injuries. Due to its comprehensive nature, the biomechanics data extends beyond vehicle safety applications, finding relevance in sports medicine, space travel, aircraft safety, and military impact research. The available data from 1970 to 2024 includes time-history curves of translational acceleration and angular velocity recorded via sensors placed on the heads of crash test dummies and other experimental subjects. These measurements are instrumental in simulating and assessing traumatic brain injuries, contributing to advancements in injury biomechanics and safety regulations.

Östh et al. (2023) also provided a dataset of impact kinematics used for head injury assessment based on crash tests and accident reconstructions. Their study evaluated multiple head injury criteria by correlating crash-induced six-degree-of-freedom head kinematics with brain strain responses in a finite element head model [1]. This dataset includes head kinematics from crash tests with THOR-50M and WorldSID-50M ATDs and 19 human body model (HBM) accident reconstructions, enabling further assessment of brain injury risk metrics in automotive safety research.

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3 Methodology

This chapter outlines the methodology used to evaluate brain injury metrics through finite element simulations and statistical analysis. The process begins with data collection and preparation, ensuring the inputs for simulations are accurate and standardized. It then details the setup and execution of finite element simulations, followed by the calculation of tissue-strain and kinematics-based metrics. Finally, statistical methods are applied to compare and validate these metrics. The overall methodology is summarized in Figure 1, providing a flowchart of the key steps.

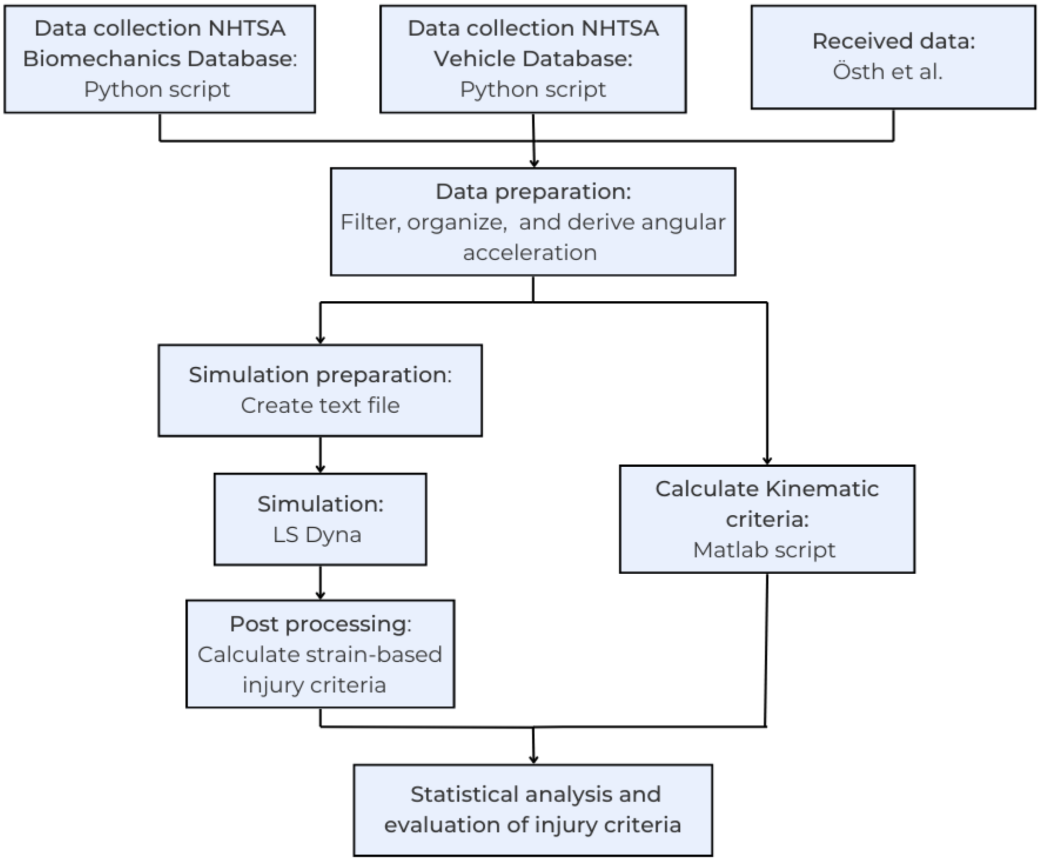

Figure 1: Overview of the methodology used in this study, illustrating the key steps.

3.1 Data Collection and Preparation

3.1.1 Automated Data Extraction

To facilitate the retrieval of large datasets, an automated Python script was developed to download relevant time-history curves from the NHTSA Biomechanics database. The script utilizes the Selenium library to navigate the website, simulate user actions, and interact with the web elements. It systematically searches for and downloads head kinematics data related to translational acceleration and angular velocity, which is then saved to a designated local folder for further processing.

Table 1: Download Conditions for Head Kinematics Data. Download is initiated if one item per column describes the file.

Sensor Type	Sensor Attachment	Axis Direction of Sensor	Units	Data Status
Accelerometer Angular Velocity Transducer	Head Head CG Head Other Head 9-array	X-local Y-local Z-local	G's Degrees/s	As Measured

The script begins by configuring browser settings to automatically download files to a specified folder. After loading the NHTSA biomechanics database page, it conducts a search, iterates through available test results, and identifies the relevant files based on sensor type, attachment location, axis direction, and measurement units. the conditions for finding a match can be seen in Table 1, where the script recognized a match if one of the items per column is identified as information about the file. When a matching file is found, the script initiates the download and renames each file according to the specific test number associated to the experiment to facilitate organization and later analysis. It also includes mechanisms to handle potential errors, such as retries for intercepted clicks and automated pagination to proceed through multiple search result pages.

The script was then adjusted to work for the NHTSA Vehicle database, ensuring compatibility with the different data structure and formats used in this repository. These adjustments included refining the search parameters, updating the file parsing logic, and modifying the output processing to accommodate variations in data organization. By adapting the script, the workflow could seamlessly extract and prepare vehicle-specific kinematics data for subsequent simulation and analysis.

The resulting data contains 6 ASCII files for each test number, 3 files (X, Y, and Z direction) for translational acceleration and 3 files (X, Y, and Z direction) for angular velocity.

3.1.2 Data Preparation for Simulation

After the data collection a script was created in Matlab to reformat the ASCII files for preparation for inclusion to LS Dyna and calculation of injury metrics. The script first groups all files by test number, checking for completeness of data by ensuring the presence of six files (three for linear acceleration and three for angular velocity, corresponding to the X, Y, and Z axes). For each test, the script applies an eighth-order low-pass Butterworth filter to reduce high-frequency noise. The translational accelerations were filtered to channel frequency class (CFC) 1000, corresponding to a cutoff frequency of 1650 Hz, and the angular velocities were filtered to CFC 60, corresponding to a cutoff frequency of 100 Hz. All filtering was made according to the standard SAE J211: Instrumentation for Impact Test [49], using the Matlab code filterJ211 [50]. After filtering, the angular velocity data was converted from degrees per second to radians per second. Adjustments where made by inverting the Y and Z axes to align the coordinate system from the NHTSA local system [51] to the local coordinate system of the FE model.

To calculate angular acceleration, the script differentiates the filtered angular velocity data over time, producing angular acceleration values for each axis. The resulting data, including time, translational acceleration, angular velocity, and angular acceleration, is saved into structured .mat files. Lastly, a Matlab script was constructed to iterate trough the files and create a folder for each with a textfile containing the data arranged to work with the main files used for simulation.

3.2 Simulation and Model Setup

3.2.1 Finite Element Model Description

The finite element model of the human head used in the project is the KTH head model developed by Svein Kleiven [52]. It integrates detailed anatomical and biomechanical features to simulate head injury dynamics accurately. This model encompasses the scalp, skull, meninges, cerebrospinal fluid, and brain, including representations of gray and white matter, and anatomical features like the falx cerebri, tentorium, ventricles, and eleven pairs of parasagittal bridging veins. The brain tissue is modeled using hyperelastic and viscoelastic constitutive laws to account for its nonlinear and rate-dependent properties.

The model is designed with a parameterized mesh of over 16,000 nodes, enabling high-resolution analysis while maintaining computational efficiency. It has undergone extensive validation against experimental data, including skull fracture, intracranial pressure, and relative brain motion experiments. Key features such as the differentiation of tissue layers, sliding interface conditions between brain and skull, and the inclusion of biomechanical material properties enhance its capability to replicate the physical response under various loading scenarios, including both translational and rotational kinematics.

This model's robustness and fidelity make it a critical tool for evaluating brain injury mechanisms and predictors, facilitating insights into localized strains, pressures, and injury thresholds across different regions of the brain under various impact conditions [52]. Using only the head when simulating with forces affecting only the head saves computational power while still giving accurate results [30].

3.2.2 Simulation Execution

The impact simulations were performed using LS-DYNA [53] to model the dynamic response of the head under various impact conditions. The simulation setup required three key input files: two pre-defined files specifying the model components, material properties, boundary conditions, and loading conditions, along with a third file generated from the processed kinematic data from section 3.2.

Each simulation was executed with a runtime of 300 milliseconds, ensuring that both the impact event and subsequent brain response were captured. The applied boundary conditions were based on the head kinematics extracted from experimental datasets, ensuring that the simulated motions accurately reflected real-world impact scenarios. The simulation outputs included nodal displacement, strain, and intracranial pressure, forming the basis for further metric calculations.

3.3 Post-Simulation Processing

3.3.1 Calculation of Tissue-strain Based Metrics

This study considered two key tissue-strain-based metrics: the MPS and the CSDM.

Using a custom Python script, the 95th percentile MPS was calculated by post-processing simulation output (d3plot files). The script provided by Zhou (2020) was used with some modifications. The script utilizes the Green Lagrange strain, extracting the strain data from each element within the finite element model and identifying the maximum strain values experienced during the simulation. These values represent the peak deformation along the principal axes within the brain tissue, offering insights into regions of high vulnerability.

The CSDM was computed using the post-processing program LS-PrePost. The d3plot files were imported into LS-PrePost, where the volume for each element of the FE model was extracted. A Matlab script was created to load the GL strain and volume data, align element IDs, and identify elements where strain exceeds 0.1, which was chosen as the threshold. It then computes the total volume and the volume of elements exceeding the strain limit and calculates CSDM as the ratio of exceeding volume to total volume.

3.3.2 Calculation of Kinematics Based Metrics

The kinematics-based injury metrics were computed using the filtered translational acceleration and angular velocity data prepared in section 3.1.2. These metrics include HIC, HIP, BrIC, DAMAGE, GAMBIT, and UBrIC. The calculations were performed using Matlab scripts developed in prior studies, with adaptations where necessary. Each script utilized the time-history data of the head's motion along the X, Y, and Z axes, integrating acceleration and velocity profiles over time to compute respective injury metrics.

3.3.3 Statistical Analysis

Statistical analysis was performed to evaluate the predictive capabilities of the computed injury metrics and to identify relationships between kinematics-based and tissue-strain based approaches. Linear regression analysis was used to assess the relationship between kinematics-based metrics and tissue-strain metrics. Ordinary least squares (OLS) regression was applied to quantify the strength of these relationships. The coefficient of determination (R^2) was calculated to measure how well each metric explained the variance in brain strain data obtained from the simulations. The regression models were evaluated for statistical significance, with p-values computed to assess the reliability of each relationship. A significance threshold of 0.05 was used to determine whether the observed correlations were statistically meaningful.

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4 Results

This chapter presents the results of the finite element simulations and statistical analyses conducted to evaluate brain injury metrics in automotive head impacts. A total of 498 cases were analyzed, sourced from the NHTSA Biomechanics, NHTSA Vehicle, and Östh et al. datasets. From this point forward, these datasets will be referred to as Dataset 1, Dataset 2, and Dataset 3, respectively. The distribution of cases across these datasets is shown in Table 2.

Table 2: Database, dataset, and number of cases

Database	Dataset	No. of cases
NHTSA Biomechanics	Dataset 1	184
NHTSA Vehicle	Dataset 2	154
Östh et al.	Dataset 3	160
Total	-	498

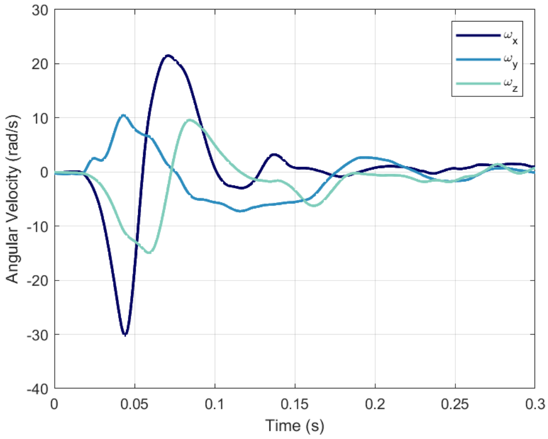
The results begin with a case illustration, providing a detailed example of how the computed injury metrics apply to a specific impact scenario. This is followed by a general overview of trends and distributions across all cases, summarizing key findings from the dataset. The subsequent sections present detailed analyses of individual injury metrics, including statistical evaluations of their relationships. Finally, regression models are used to assess how well kinematics-based metrics predict tissue strain-based metrics, offering insights into their relative predictive capabilities.

4.1 Case Illustration

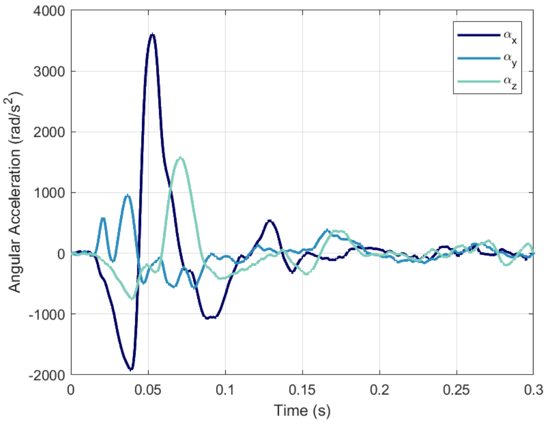
To provide a clear example of the methodology and analysis used in this study, a representative case, Case 14098 from Dataset 2, has been selected for detailed examination. This case was chosen as it exhibits typical impact conditions found in automotive head collisions and serves as an illustrative example of how kinematics-based and tissue strain-based injury metrics interact in a real-world scenario.

The time-history curves of angular velocity, angular acceleration, and translational acceleration for this case are presented in Figure 2. Key observations include a peak angular velocity of 38 rad/s occurring approximately 10 ms post-impact, indicating significant rotational movement. Also, a peak angular acceleration of 3000 rad/s^2, suggesting a strong likelihood of rotational brain strain. The peak translational acceleration of 700 m/s^2, which is within the range associated with moderate traumatic brain injuries. These kinematic trends suggest a combination of translational and rotational forces.

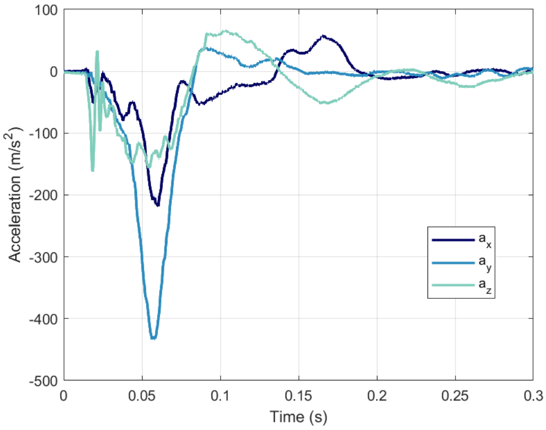
Figure 3 illustrates the Green Lagrange strain for three different elements of the model from the simulation. Element with id 5695 is at the frontal lobe. It experienced a peak strain of 0.35, suggesting significant deformation in the anterior brain.



(a)

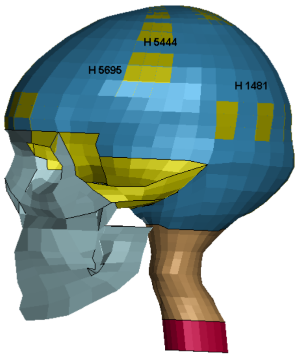


(b)

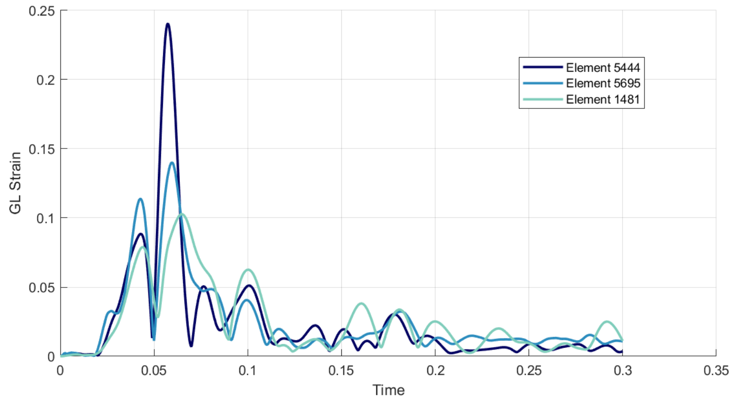


(c)

Figure 2: Loading curves of case 14098 from Vehicle database. a) Shows the angular velocity, b) the angular acceleration, and c) the translational acceleration.



(a)



(b)

Figure 3: a) Three elements from the head model. b) Green Lagrange Strain for the three different elements.

Element with id 5444 showed a strain of 0.28, aligning with typical patterns seen in diffuse axonal injuries. An lastly element id 1481 near the brainstem exhibited a strain of 0.22. Table 3 summarizes the injury metrics calculated for this case. Notably, none of the illustrated elements in Figure 3 exhibit the highest recorded strain values within the model.

Table 3: Summary of injury metrics for case 14098.

HIC	DAMAGE	BrIC	HIP	HIP (kW)	UBrIC	$CSDM_{0.1}$	MPS
200.7	0.314	0.602	19.56	0.315	0.252	0.612	0.565

4.2 General Overview

The initial analysis provides an overview of the key metrics evaluated across the 498 cases included in the study. The peak values of the analyzed metrics, summarized in Table 4, reveal substantial variability across cases. For instance, the average peak rotational velocity was 29.8 rad/s, with a standard deviation of 13.2 rad/s, while the average peak translational acceleration was 635.1 m/s², exhibiting a higher degree of variability with a standard deviation of 1914.7 m/s². Similarly, MPS and CSDM demonstrated notable differences in their distributions, suggesting variability in the tissue-level response to impacts.

Table 4: Average and standard deviation of peak values for all 498 cases.

Peak Metrics	Average	Standard Deviation
Peak Rotational Velocity (rad/s)	29.8	13.2
Peak Rotational Acceleration (rad/s^2)	2618.9	1914.7
Peak Translational Acceleration (m/s^2)	635.1	1193.5

A comprehensive overview of the head injury metrics, detailed in Table 5, provides insight into their central tendencies and variability across the dataset. The table presents the average, median, and standard deviation for each kinematics-based and tissue strain-based injury metric, considering only data between the 1st and 99th percentiles to mitigate the influence of extreme outliers. The inclusion of median values helps to account for potential skewness in the distributions, while standard deviations indicate the degree of variability in the dataset.

Table 5: General assessment of the average, standard deviation (SD), and the median for each head injury metric. Including data between the 1st and 99th percentiles.

Head Injury Metric	Average	Median	Standard Deviation
HIP (kW)	21.3	21.3	16.0
BrIC	0.59	0.56	0.23
HIC	233.2	172.0	384.6
DAMAGE	0.26	0.25	0.13
UBrIC	0.27	0.27	0.11
GAMBIT	0.25	0.23	0.17
MPS	0.229	0.165	0.157
$CSDM_{0.1}$	0.295	0.115	0.335

Figure 4 presents histograms depicting the distribution of kinematics-based injury metrics across all cases. The variation in these distributions highlights differences in how each metric responds to different impact conditions. Some metrics, such as DAMAGE and BrIC, exhibit a relatively uniform spread, while others, like HIC and

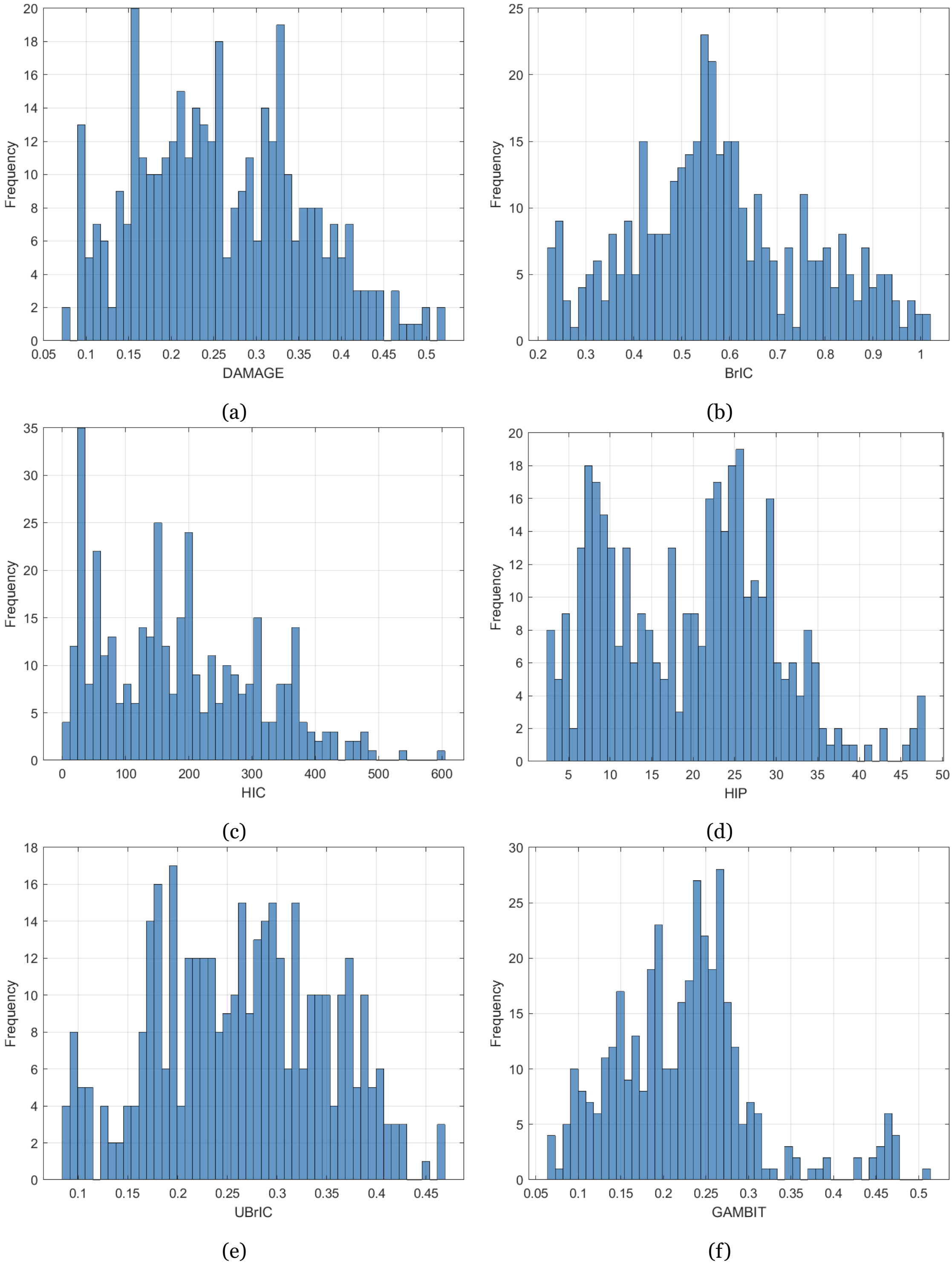


Figure 4: Histograms showing the distribution of results for (a) DAMAGE, (b) BrIC, (c) HIC, (d) HIP, (e) UBrIC, and (f) GAMBIT.

HIP, show a wider range of values with higher frequency clustering at lower magnitudes. This suggests that while certain metrics are more evenly distributed across impacts, others are influenced more strongly by extreme cases.

4.3 Correlation Results of Kinematic- and Tissue-Based Metrics

To evaluate the relationships between kinematics-based and tissue strain-based metrics, linear regression analysis was performed. This statistical approach quantifies the extent to which variations in kinematics-based metrics can predict tissue strain responses. By examining these relationships, the analysis provides insights into how well external kinematic measures correlate with localized brain tissue deformations.

The regression models utilized OLS methods to calculate coefficients and coefficients of determination (R^2) for each metric pairing. This allowed for a systematic comparison of the predictive power of different metrics in estimating tissue strain under diverse impact scenarios. To improve the robustness of the analysis and reduce the influence of extreme outliers, data below the 1st percentile and above the 99th percentile were removed before performing the regression.

4.3.1 Maximal Principal Strain Linear Regression

The linear regression analysis between kinematics-based metrics and MPS reveals varying degrees of correlation, as summarized in Table 6 and visualized in Figure 5. Each kinematic metric—DAMAGE, BrIC, HIP, HIC, UBrIC, and GAMBIT—was assessed for its predictive capability in estimating tissue strain, with particular attention given to the strength and nature of the relationships.

Among the assessed metrics, DAMAGE exhibited the highest correlation with MPS, with an R^2 value of 0.608, indicating that approximately 60 % of the variance in MPS can be explained by DAMAGE. Since DAMAGE is fitted to the strain of the GHBMC head model, this correlation reflects how well the KTH strain approximates the GHBMC strain as represented by DAMAGE. This suggests that DAMAGE's predictive capability is influenced by its original formulation based on GHBMC-derived strain patterns. The positive regression slope of 0.7217 further supports this relationship, suggesting that increases in DAMAGE are consistently associated with higher MPS values. UBrIC also demonstrated a strong correlation (R^2 = 0.558), reinforcing its relevance as a predictor of strain-based brain injury metrics.

In contrast, GAMBIT displayed the weakest correlation with MPS, with an R^2 value of 0.149, indicating that it explains only a small portion of the observed variance. HIP and HIC showed moderate correlations, with R^2 values of 0.253 and 0.359, respectively, suggesting a limited but measurable relationship with MPS. BrIC exhibited an R^2 of 0.348, positioning it between the stronger predictors (DAMAGE and UBrIC) and the weaker ones (HIP and GAMBIT).

None of the regression models indicated non-significant results, with all p-values below 0.05, confirming the statistical significance of the observed relationships.

4.3.2 Cumulative Strain Damage Measure Linear regression

The linear regression analysis between kinematics-based metrics and the CSDM provides further insights into the predictive capabilities of these metrics for cumulative tissue strain effects. The results, summarized in Table 7 and visualized in Figure 6, reveal a range of correlations.

Among the evaluated metrics, DAMAGE exhibited the strongest correlation with

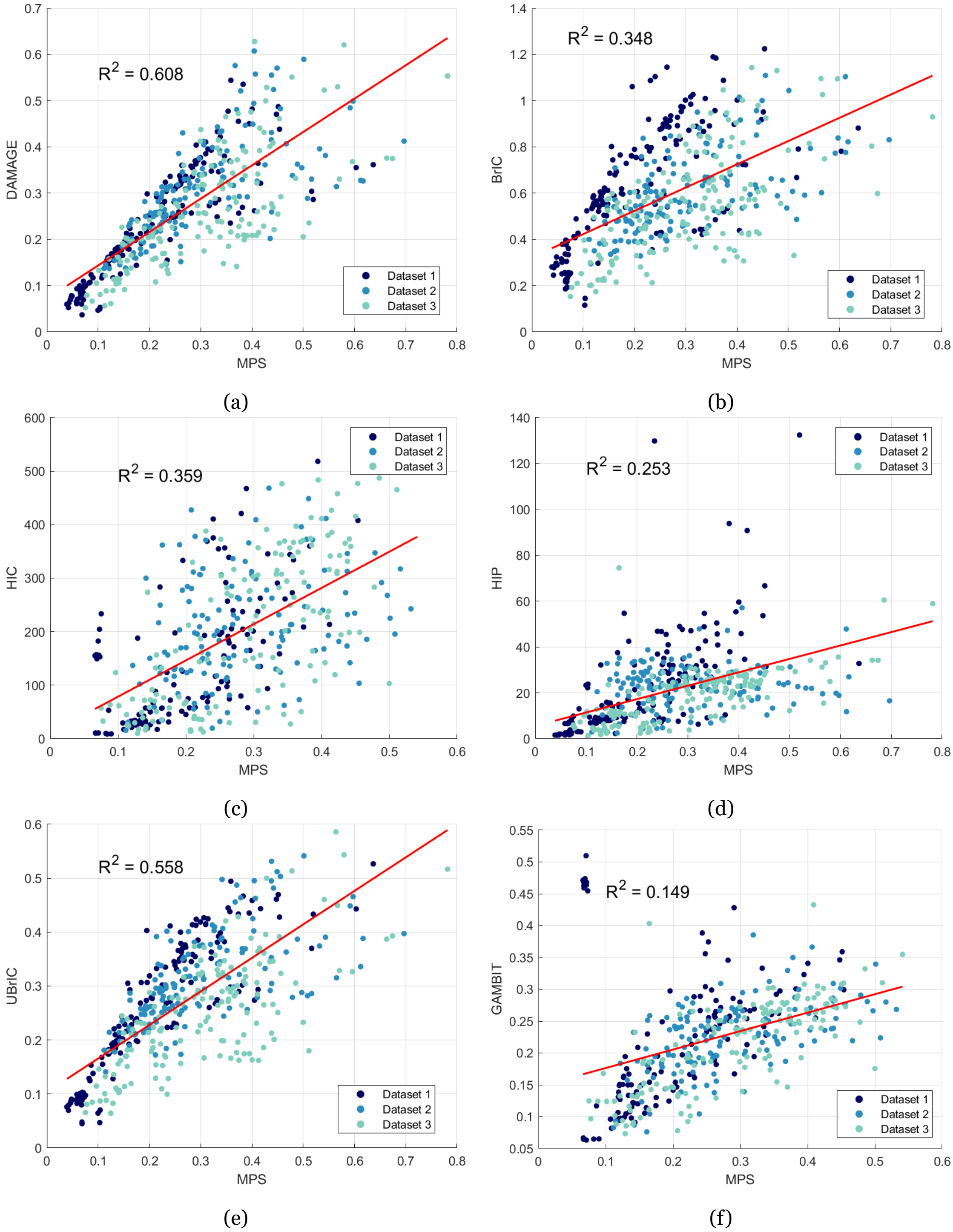


Figure 5: Scatter plots showing correlations between kinematics-based metrics and MPS: (a) DAMAGE and MPS, (b) BrIC and MPS, (c) HIC and MPS, (d) HIP and MPS, (e) UBrIC and MPS, and (f) GAMBIT and MPS.

CSDM, with an R^2 value of 0.747, indicating that approximately 75 % of the variance in CSDM can be explained by DAMAGE. As DAMAGE is derived from the GHBMC head model strain, this strong correlation suggests that the KTH strain exhibits a similar pattern, reinforcing the applicability of DAMAGE in capturing cumulative brain strain effects across different modeling approaches. The regression slope of 0.3759 suggests a proportional relationship, reinforcing DAMAGE's robustness in

Table 6: Linear regression parameters for MPS with different kinematic metrics.

Kinematic Metric	Intercept	Slope	$\mathbf{R^2}$
DAMAGE	0.0714	0.7217	0.608
BrIC	0.3221	1.006	0.348
HIP	5.557	58.460	0.253
HIC	10.876	677.27	0.359
UBrIC	0.1036	0.6214	0.558
GAMBIT	0.1474	0.2898	0.149

Table 7: Linear regression parameters for CSDM with different kinematic metrics.

Kinematic Metric	Intercept	Slope	$\mathbf{R^2}$
DAMAGE	0.1185	0.3759	0.747
BrIC	0.3895	0.5175	0.416
HIP	9.507	29.985	0.298
HIC	80.337	284.512	0.377
UBrIC	0.1137	0.3241	0.691
GAMBIT	0.1822	0.1185	0.130

capturing cumulative brain strain effects. UBrIC also demonstrated a strong correlation, with an R^2 value of 0.691, further supporting its predictive capability for cumulative strain accumulation.

BrIC and HIC showed moderate correlations with CSDM, with R^2 values of 0.416 and 0.377, respectively, indicating a measurable but weaker relationship compared to DAMAGE and UBrIC. The regression slopes of 0.5093 for BrIC and 284.815 for HIC reflect differences in how these metrics scale with cumulative strain.

Among the evaluated metrics, GAMBIT displayed the weakest correlation with CSDM, with an R^2 value of 0.130, suggesting limited predictive power for cumulative strain effects. HIP also demonstrated a lower correlation ($R^2 = 0.298$), indicating that translational acceleration alone may not adequately capture cumulative strain accumulation.

All regression models yielded statistically significant results, with p-values below 0.05, confirming the relevance of these relationships.

4.3.3 Summary of Correlations Between Kinematics-Based and Strain-Based Injury Metrics

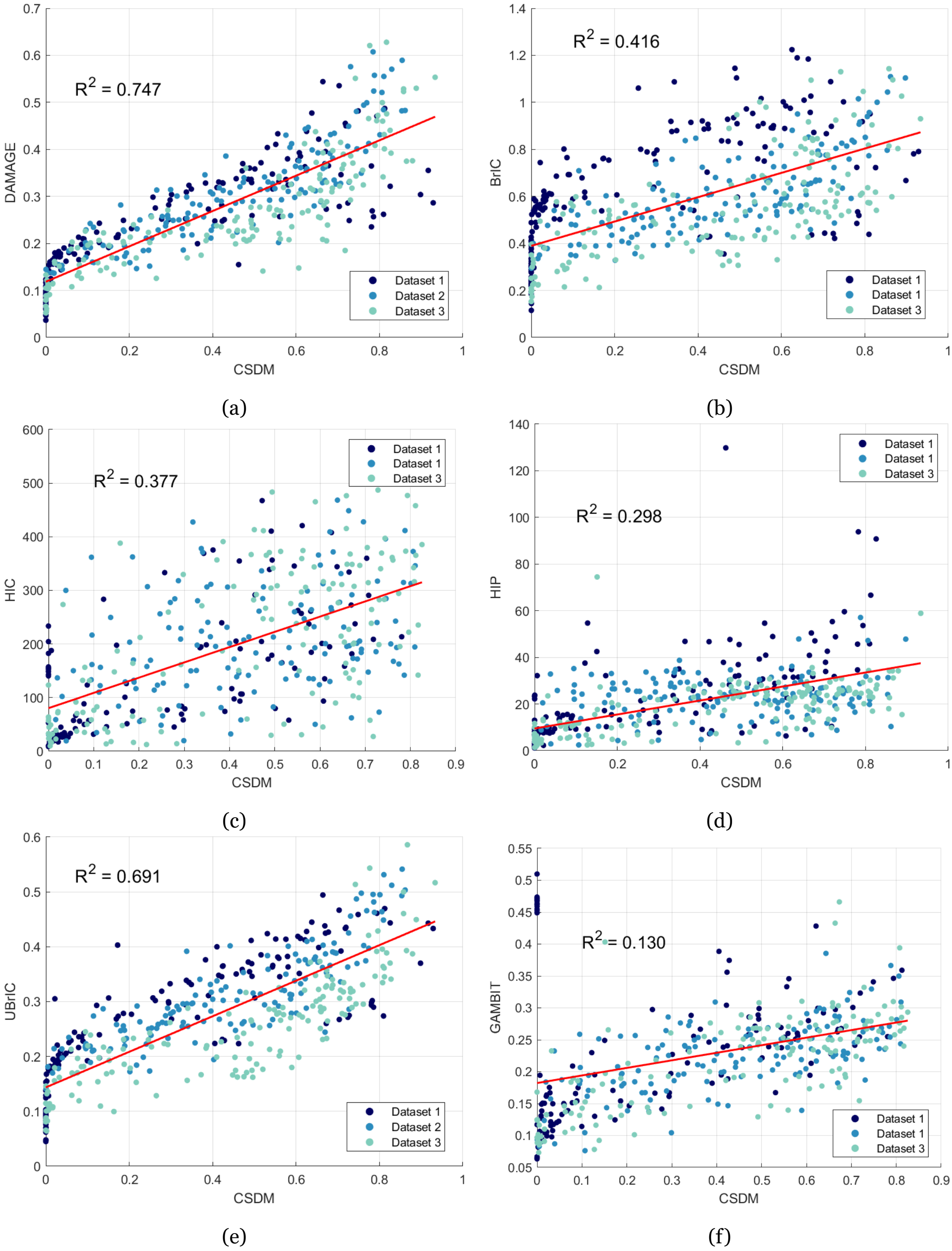


Figure 6: Scatter plots showing correlations between kinematics-based metrics and CSDM: (a) DAMAGE and CSDM, (b) BrIC and CSDM, (c) HIC and CSDM, (d) HIP and CSDM, (e) UBrIC and CSDM, and (f) GAMBIT and CSDM.

Figure 7 presents an overview of the coefficient of determination values for the relationships between kinematics-based injury metrics and strain-based metrics (MPS and CSDM), summarizing the findings from the previous sections. These values indicate how well each kinematics-based metric predicts variations in strain responses across the dataset.

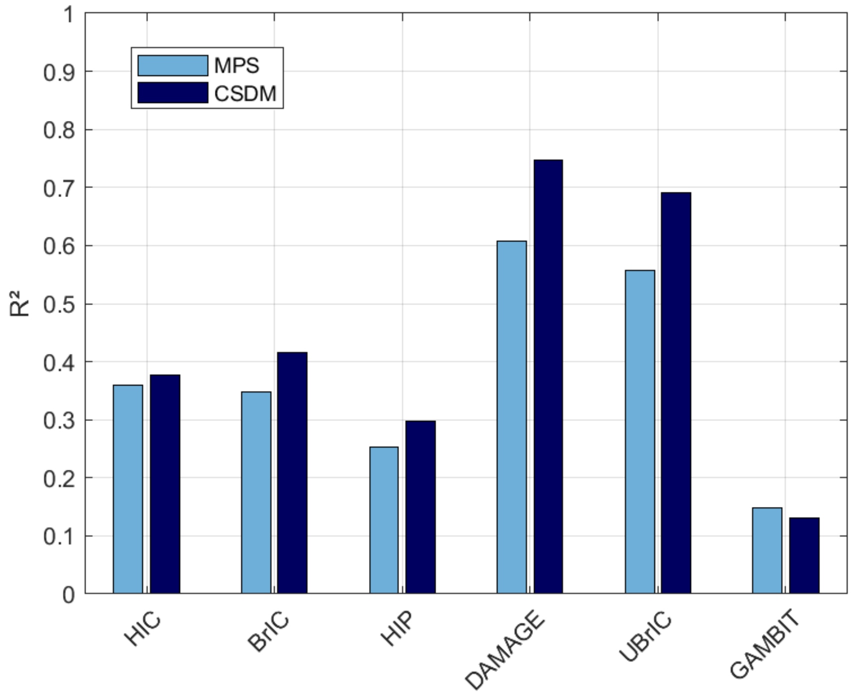


Figure 7: R^2 values comparing kinematics-based injury metrics with MPS and CSDM.

The results show that DAMAGE and UBrIC exhibit the strongest correlations with both MPS and CSDM, supporting their effectiveness in estimating strain-based injury risk. Since both DAMAGE and UBrIC are empirically fitted to FE model strain responses, their high correlations are expected, as they inherently incorporate strain-based injury mechanisms. BrIC and HIC demonstrate moderate correlations, capturing some aspects of strain response but with lower predictive strength. HIP and GAMBIT show the weakest correlations, suggesting that they are less effective in representing brain strain variations under impact conditions.

To further investigate potential differences across datasets, linear regression analyses for each dataset separately have been included in Appendix. These additional analyses provide insight into how dataset-specific variations influence the correlation between kinematics-based and strain-based injury metrics, offering a more detailed perspective of the findings.

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5 Discussion

The evaluation of brain injury metrics in automotive head impacts provides valuable insights into their predictive capabilities and limitations. By analyzing the relationships between kinematics-based and tissue strain-based metrics, this study contributes to the ongoing effort to refine injury prediction models used in automotive safety research. This section discusses the key findings, methodological considerations, and the broader implications of the results, while also addressing the limitations of the study.

5.1 Comparison of Kinematics-Based and Tissue Strain-Based Metrics

The results indicate notable differences in how kinematics-based and tissue strain-based metrics estimate brain injury risk. Among the kinematics-based metrics, DAMAGE and UBrIC consistently exhibited the strongest correlations with strain-based measures MPS and CSDM, suggesting their suitability for estimating localized brain deformation. Since DAMAGE is fitted to the strain of the GHBMC head model, its strong correlation with MPS and CSDM reflects how well the KTH strain approximates the GHBMC strain representation. This suggests that DAMAGE's predictive performance is inherently influenced by its original formulation, reinforcing its relevance in estimating strain-based injury risk. This aligns with previous studies indicating that injury metrics incorporating rotational kinematics tend to correlate more strongly with strain-based injury predictors. The high R^2 values for these metrics suggest that they capture critical aspects of brain motion and deformation, making them potential candidates for further refinement in injury risk assessment.

BrIC demonstrated moderate correlation with strain-based metrics, ranking below DAMAGE and UBrIC but still outperforming HIC and HIP. As a metric specifically designed to account for rotational velocity, BrIC captures an important aspect of brain motion relevant to traumatic brain injuries. However, its moderate R^2 values suggest that rotational velocity alone may not fully explain tissue-level strain responses. This may indicate that additional factors, such as strain rate, could further enhance its predictive power.

GAMBIT, on the other hand, exhibited the lowest correlation values among the evaluated metrics. This suggests that its empirical formulation may not effectively capture the complex interplay of translational and rotational kinematics that drive brain tissue deformation. Given its relatively low predictive performance, its applicability in estimating strain-based injury risk in automotive impacts appears limited.

HIC and HIP demonstrated moderate correlations with tissue strain-based metrics, indicating that they may not fully capture the complex deformation patterns of brain tissue. HIC, traditionally used in regulatory crash tests, relies solely on translational acceleration, which does not adequately account for the rotational forces known to contribute significantly to traumatic brain injuries. The results suggest that while HIC remains useful for assessing skull fractures and focal injuries, its ability to predict strain-based injuries is limited. Similarly, HIP, despite integrating both translational and rotational components, exhibited low correlation values, indicating that its weighting of kinematic parameters may not accurately reflect tissue strain response.

5.1.1 Dataset-Specific Trends

The results of the dataset-separated linear regression analysis (provided in Appendix) reveal some variation in correlation strengths across datasets. Certain kinematics-based metrics, such as DAMAGE and UBrIC, exhibited consistently strong correlations with MPS and CSDM across all datasets, while others, such as HIC and GAMBIT, showed greater variability in predictive performance. These differences may be influenced by dataset composition. The observed variations suggest that kinematics-based injury metrics may perform differently depending on impact conditions and data collection methods, which should be considered in future research and injury risk model development.

5.2 Comparison with Previous Studies

In the study by Takhounts et al. (2013), the development of BrIC was based on its strong correlation with strain-based metrics, specifically CSDM and MPS [21]. The researchers found that BrIC correlates best with both CSDM and MPS, emphasizing that rotational velocity, rather than rotational acceleration, is the primary mechanism for brain injuries. The findings in this study however shows a moderate correlation with MPS (R^2 = 0.348) and CSDM (R^2 = 0.416). BrIC was outperformed by DAMAGE and UBrIC in predictive capabilities, its moderate correlation underscores the significance of rotational kinematics in brain injury prediction.

Gabler et al. (2016) conducted an assessment of kinematics-based injury metrics and found that GAMBIT exhibited the lowest correlation with strain-based measures, with MPS (R^2 = 0.032) and CSDM (R^2 = 0.041). These results suggest that GAMBIT's formulation may not effectively capture the complex relationship between head kinematics and brain tissue deformation [5]. The present findings align with this conclusion, as GAMBIT demonstrated the weakest correlation with both MPS (R^2 = 0.149) and CSDM (R^2 = 0.130). While these values are higher than those reported by Gabler et al. (2016), the consistently low correlations reinforce GAMBIT's limited predictive capability for strain-based brain injuries. This further emphasizes the importance of rotational velocity-based metrics, such as DAMAGE and UBrIC, which have demonstrated significantly stronger correlations with strain-based measures, underscoring their relevance in improving injury risk assessment.

It has previously been reported that UBrIC achieved an R^2 of 0.93 with MPS [54]. Though the results from the present study indicate a lower R^2 value of 0.558, this discrepancy may arise from differences in dataset composition, impact scenarios, or the finite element models used to derive strain metrics. The findings in this study still highlight UBrIC's strong predictive capability for brain strain, particularly compared to HIP, HIC, and GAMBIT, which demonstrated significantly weaker correlations with MPS.

Östh et al. investigated head injury criteria using head kinematics from crash tests and accident reconstructions, assessing their effectiveness in predicting brain injuries [1]. Their study emphasized the importance of rotational motion in head trauma analysis, aligning with the findings of this study. However, their results indicated a stronger correlation between rotational kinematics and brain strain than observed in the present study. This discrepancy may stem from downsampling, version of FE model, or from differences in injury metrics used. Despite this variation, both studies highlight the limitations of traditional translational-based metrics such as HIC and support the use of rotational velocity-based metrics for improved injury assessment.

These comparisons highlight the importance of incorporating rotational kinematics into brain injury assessment models. While traditional metrics such as HIC remain widely used in crash testing protocols, their lower correlation with brain strain underscores the need for more advanced injury criteria that better capture the mechanical response of brain tissue under rotational forces. The strong agreement between the present study and prior research strengthens the argument for integrating DAMAGE and UBrIC into future injury risk models and regulatory safety assessments.

5.3 Implications for Injury Prediction and Automotive Safety

The observed correlations between certain kinematics-based metrics and strain-based metrics have significant implications for the development of improved head injury criteria in automotive safety testing. Current regulatory standards predominantly rely on kinematics-based metrics such as HIC, but the findings suggest that integrating strain-based assessments could enhance injury prediction accuracy. This is particularly relevant given that diffuse brain injuries, such as DAI, are primarily associated with rotational motion, which is not well captured by traditional kinematics-based metrics.

These findings support the need for a more comprehensive approach to head injury assessment, potentially involving a hybrid metric framework that incorporates both kinematic predictors and finite element strain analyses. The strong correlation of DAMAGE and UBrIC with strain metrics suggests that they could serve as better proxies for brain tissue deformation, and their implementation in crash test dummies and computational simulations could improve real-world injury prediction.

Additionally, the variability in metric performance across datasets highlights the importance of considering case-specific factors, such as impact orientation, duration, and energy transfer mechanisms. The dataset used in this study included a diverse range of impact conditions, which strengthens the generalizability of the results. However, further validation is required across different biomechanical models, crash test setups, and human injury case studies to confirm the findings.

5.4 Methodological Considerations and Study Limitations

Kinematics-based metrics do not account for spatial variations in brain strain; they treat the head as a single rigid body, whereas strain-based metrics capture regional deformations within the brain. This means that kinematics-based metrics may perform differently depending on impact orientation—for example, a purely lateral impact may produce high rotational acceleration but result in relatively lower strain than a frontal impact with the same kinematic magnitude. The study did not explicitly analyze how impact directionality affects metric correlations, which could be a key factor in explaining why some kinematics-based metrics correlate better with strain than others.

While linear regression provided a systematic way to quantify the relationships between injury metrics, brain injury mechanics are inherently nonlinear. Alternative approaches, such as machine learning-based predictive models or higher-order regression techniques, could offer additional insights into injury prediction.

5.5 Ethics and Sustainability

This study addresses a critical societal issue by improving our understanding of traumatic brain injury mechanisms in automotive crashes. The findings contribute to the development of safer vehicles, improved protective systems, and enhanced injury risk assessment models, ultimately aiming to reduce the incidence of severe brain injuries on the road.

From an ethical perspective, the study aligns with the principles of harm reduction and public safety. By improving injury prediction models, the research supports efforts to minimize the human and economic costs of road traffic injuries, which remain a leading cause of disability and fatalities worldwide. Additionally, the study utilizes computational simulations rather than live human or animal testing, adhering to the 3R principles (Replacement, Reduction, Refinement) in ethical research by reducing the need for physical experiments.

From a sustainability perspective, the research contributes to the long-term goal of sustainable transportation safety. Road traffic injuries impose a significant environmental and economic burden, including medical costs, loss of productivity, and the resources required for emergency response and rehabilitation. By improving injury prevention strategies, the study promotes safer vehicle design, which can reduce the frequency and severity of crashes, ultimately leading to lower material consumption in vehicle manufacturing, fewer hospitalizations, and reduced societal costs.

5.6 Future work

This study provides a comparative assessment of kinematics-based and strain-based injury metrics in automotive head impacts. While the findings offer valuable insights, several areas require further research to enhance the accuracy, applicability, and impact of injury prediction models.

One key area for future research is to expand the analysis to higher-order regression techniques. The use of linear regression provides a straightforward means of quantifying correlations; however, brain injury mechanics are inherently nonlinear. The relationship between head kinematics and strain is influenced by complex factors such as impact duration, rotational acceleration magnitude, strain rate effects, and brain tissue heterogeneity. Future studies should explore alternative modeling approaches that better capture these complexities. Higher-order regression models, such as polynomial or exponential regression, could provide improved predictive accuracy. Additionally, machine learning techniques, including neural networks and decision tree-based models, may help identify nonlinear patterns in large-scale injury datasets that traditional statistical approaches may overlook.

Future studies should consider the development of hybrid metrics, a combination of kinematic and strain-based approaches could lead to improved injury risk prediction, particularly for rotational brain injuries that are not well captured by existing regulatory metrics. Furthermore, advanced data-driven approaches, such as machine learning or neural networks, could help refine the predictive capabilities of kinematics-based metrics by identifying nonlinear relationships in brain deformation patterns.

5.7 Conclusion

This study provides a detailed assessment of kinematics-based and strain-based injury metrics, evaluating their effectiveness in predicting brain tissue deformation in automotive crash scenarios. The findings highlight that while some kinematics-based metrics, such as DAMAGE and UBrIC, correlate strongly with strain-based predictors, others, such as GAMBIT and HIP, demonstrate limited predictive capability for tissue-level brain injuries. These results emphasize the need to reconsider how injury risk is assessed in automotive safety regulations, with a stronger emphasis on rotational kinematics and strain-based modeling.

These findings contribute to the ongoing evolution of injury assessment models, emphasizing the need for continued advancements in head injury criteria. Continued research in hybrid injury metrics, machine learning-based prediction models, and experimental validation will be essential in advancing the field of traumatic brain injury prevention. Ultimately, refining these metrics could lead to better safety standards, improved vehicle designs, and a reduced incidence of severe brain injuries in road traffic collisions.

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Appendix

A1 Correlation results separated into datasets

A1.1 Maximal Principal Strain Linear Regression

Table 8: Comparison of Linear Regression Parameters for MPS across Different Datasets

Kinematic Metric	Dataset 1			Dataset 2			Dataset 3		
	Intercept	Slope	R^2	Intercept	Slope	R^2	Intercept	Slope	R^2
DAMAGE	0.0478	0.8536	0.778	0.1071	0.6900	0.492	0.0650	0.6579	0.484
BrIC	0.2775	1.617	0.520	0.3408	0.9236	0.385	0.2144	1.117	0.404
HIP	-7.665	153.85	0.534	21.38	6.93	0.009	1.076	57.624	0.576
HIC	-22.41	1046.17	0.305	163.12	150.63	0.035	1.170	703.92	0.323
UBrIC	0.0582	0.9337	0.802	0.1673	0.5061	0.430	0.0839	0.5527	0.481
GAMBIT	0.1935	0.3869	0.040	0.1667	0.2171	0.253	0.0791	0.4633	0.601

A1.2 Cumulative Strain Damage Measure Linear regression

Table 9: Comparison of Linear Regression Parameters for CSDM across Different Datasets

Kinematic Metric	Dataset 1			Dataset 2			Dataset 3		
	Intercept	Slope	R^2	Intercept	Slope	R^2	Intercept	Slope	R^2
DAMAGE	0.1215	0.3564	0.746	0.1177	0.4240	0.762	0.1020	0.3641	0.700
BrIC	0.4245	0.6368	0.449	0.3670	0.5384	0.541	0.3046	0.5508	0.472
HIP	5.687	64.316	0.520	21.066	4.394	0.014	7.902	23.869	0.494
HIC	72.449	398.92	0.339	170.17	79.60	0.040	86.157	285.03	0.309
UBrIC	0.1418	0.3735	0.733	0.1673	0.3280	0.727	0.1154	0.3047	0.681
GAMBIT	0.2176	0.1816	0.062	0.1822	0.1015	0.248	0.1362	0.1809	0.548