Investigating the relationship between kinematic-based brain injury metrics and brain tissue strain for a football helmet test standard

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Abstract

American football athletes experience frequent head impacts that place them at risk of concussion. Although football helmet performance standards have been effective at reducing traumatic brain injuries, concussions remain prevalent, suggesting that current evaluation criteria may not adequately represent mechanisms associated with concussive injury. Maximum principal strain (MPS) is widely used as a strain-based predictor of brain injury; however, computational cost limits its application in helmet certification. As a practical alternative, helmet standards rely on kinematic-based brain injury metrics derived from head acceleration data, though their ability to represent brain tissue strain under standardized test conditions is unclear. The purpose of this study was to investigate the relationship between kinematic-based brain injury metrics and MPS using data obtained from NOCSAE standard impact tests. Youth and adult helmet models were tested using wire-guided drop and pneumatic ram impacts. Linear and rotational head kinematics were recorded and used to calculate six brain injury metrics (GSI, HIC, HIP, GAMBIT, BrIC, and UBrIC). Impact kinematics were applied to the University College Dublin Brain Trauma Model v2.0 to determine MPS. Linear, multiple, and random forest regression models were used to examine correlations of metrics with MPS and evaluate predictive performance. Kinematic brain injury metrics demonstrated poor correlations with MPS ($R^2 < 0.4$) and poor predictive capacity. Prediction accuracy improved substantially when multiple peak kinematic variables and their directional components were incorporated into multiple and random forest regression models. These findings suggest that current helmet evaluation criteria do not adequately represent brain tissue strain. Incorporating multiple kinematic variables to predict brain tissue strain may provide a more biologically meaningful approach for assessing concussive injury risk during NOCSAE football helmet testing.

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List of Abbreviations

AE: Athletic Exposure

BrIC: Brain Injury Criterion

CSDM: Cumulative Strain Damage Measure

DAI: Diffuse Axonal Injury

FE: Finite Element

GAMBIT: Generalized Acceleration Model for Brain Injury Threshold

GSI: Gadd Severity Index

MEP: Modulated Elastomer Programmer

HIC: Head Injury Criterion

HIP: Head Impact Power

MPS: Maximum Principal Strain

NCAA: National Collegiate Athletic Association

NFL: National Football League

NOCSAE: National Operating Committee on Standards for Athletic Equipment

PCS: Persistent Concussive Syndrome

PRLA: Peak Resultant Linear Acceleration

PRRA: Peak Resultant Rotational Acceleration

PRRV: Peak Resultant Rotational Velocity

RMSE: Root Mean Squared Error

TBI: Traumatic Brain Injury

UBrIC: Universal Brain Injury Criterion

UCD2: University College Dublin Brain Trauma Model v2.0

WSTC: Wayne State Tolerance Curve

1. Introduction

American football is a fast-paced contact sport with frequent high-energy collisions, placing athletes at elevated risk of concussion due to frequent head impacts (Dick et al., 2007; Gessel et al., 2007; Hootman et al., 2007; Willigenburg et al., 2016). These injuries can have lasting cognitive, physical, and emotional consequences that can prolong an athlete's return to play, impair performance, and reduce long-term quality of life (Bailes & Cantu, 2001; Daneshvar et al., 2011; Decq et al., 2016; J. C. Edwards & Bodle, 2014; June et al., 2020), and repetitive concussive and sub-concussive impacts can increase risk of neurodegenerative diseases (Baugh et al., 2012; Decq et al., 2016; McAllister & McCrea, 2017; McKee et al., 2013; Stern et al., 2011).

The National Operating Committee on Standards for Athletic Equipment (NOCSAE) regulates helmet safety through laboratory tests using drop rigs and pneumatic rams to simulate football head impacts. The resulting dynamic response data is then used to assess the ability of the helmet to meet the performance standard. Although the football helmet performance standard has nearly eliminated the occurrence of traumatic brain injuries (Cantu & Mueller, 2000), concussions remain prevalent in this sport (Dompier et al., 2015; Kerr et al., 2017; Nathanson et al., 2016; O'Malley et al., 2024; Pankow et al., 2022). This may present an opportunity to improve the protective capacity of football helmets against concussive injury.

Maximum Principal Strain (MPS), a finite element (FE) measure of brain tissue strain, is used as a predictor of brain injury as it has been associated with structural and functional impairments (Bain & Meaney, 2000; McAllister et al., 2012; Zou et al., 2007). The use of FE modeling in helmet certification, however, remains limited due to time and cost inefficiency. As a more feasible alternative, metrics estimating brain injury risk from kinematic measures are utilized by standards committees to evaluate football helmet performance; however, their ability to predict strain-based brain injury risk under NOCSAE test conditions is not well understood.

The purpose of this study was to investigate the relationship between kinematic-based brain injury metrics and MPS using kinematic data obtained from NOCSAE football helmet standard test methods. Additionally, multiple regression and random forest regression models were developed to predict MPS directly from kinematic variables with the aim of enhancing the efficiency and accuracy of helmet performance evaluation. By identifying which metric best captures brain tissue strain under NOCSAE test conditions, this research aims to provide a stronger biological foundation for helmet performance evaluation criteria, ultimately contributing to improved protection against concussion in football.

2. Literature Review

2.1 Incidence of Concussion in American Football

The high-speed, physical nature of American football is conducive to high-energy collisions between players, which can cause a number of injuries from simple bruising to spinal cord injury (T. Edwards et al., 2018; Mall et al., 2012; Matusak et al., 2023; Smart et al., 2016). Across all age groups, concussions are among the most common injuries in this sport (Dick et al., 2007; Gessel et al., 2007; Hootman et al., 2007; Willigenburg et al., 2016). In the National Football League (NFL), concussions have been estimated to average between 0.30 and 0.61 occurrences per game, or 6.61-7.04 per 1000 athletic exposures (AE) (May et al., 2023; Nathanson et al., 2016; O'Malley et al., 2024). An analysis of reported concussions in National Collegiate Athletic Association (NCAA) football over the 2012-13 and 2013-14 seasons revealed that concussions accounted for 8.0% of all in-game injuries with a frequency of 3.74/1000 AEs (Dompier et al., 2015). Rates in high school athletes are estimated to be slightly lower, occurring at rates between 0.78 and 2.01/1000 AEs, while youth have been estimated to experience between 1.15 and 2.38 concussions per 1000 AEs (Dompier et al., 2015; Pankow et al., 2022). Compared to other sports, American Football consistently reports among the greatest concussion frequencies. In an analysis of nine sports over the 2005-06 season by Gessel et al. (2007), football exhibited the highest concussion frequency and incidence rates of all American high school and collegiate sports. More recently, Kerr et al. (2017) found football to have the second-highest concussion incidence rate across NCAA sports, behind only men's wrestling. In youth, Tsushima et al. (2019) showed football to have the third-highest relative risk of concussion; however, football had the highest absolute frequency due to the high participation rate. These studies demonstrate that American football carries a high risk of concussion compared to other sports; therefore, further action is required to improve player safety in this sport.

Many efforts have been made to reduce concussion incidence in football, including modifications to gameplay regulations and practice structure, and the implementation of awareness programs for coaches and athletes. McCrea et al. (2021) found that, from 2015 to 2019, concussions in the NCAA most frequently occurred during the preseason and practices. Although two-a-day preseason practices were banned in 2017, this rule change was not effective in reducing total head impact exposures, which are associated with increased concussion incidence, likely due to increased practice intensity (Stemper, Shah, Harezlak, Rowson, Duma, et al., 2019; Stemper, Shah, Harezlak, Rowson, Mihalik, et al., 2019). In 2018, the NCAA reduced on-field preseason activities from 29 to 25 per team; however, total head impact exposure did not significantly change as a result of increased contact practice duration and intensity (Stemper et al., 2020). In high school athletes, limiting the amount and duration of full-contact activities during practice resulted in a significant reduction of in-practice head impact exposures and concussions; however, in-game concussion rates did not decline (Broglio et al., 2016; Pfaller et al., 2019). These results suggest that, while practice modifications may reduce athletes' total head impact burden over a season, they have little effect on in-game concussion incidence. On the other hand, training interventions that promote safe tackling technique and implement a player safety coach have been shown to reduce head impact exposure and concussion incidence in high school football (Champagne et al., 2019; Kerr et al., 2016; Shanley et al., 2021; Swartz et al., 2019). Gameplay rule changes have also been shown to influence in-game concussion incidence. The implementation of targeting rules that penalize players for hits with or directed at the head was found to decrease the total number of concussions per year in the NFL (May et al., 2023), while modifications to kickoff rules have had less clear effects in terms of concussion rates (Puga et al., 2025; Whelan et al., 2023; Wiebe et al., 2018).

Despite these interventions, concussion incidence remains elevated (May et al., 2023; O'Malley et al., 2024; Pankow et al., 2022; Pfaller et al., 2019; Stemper et al., 2020; Tsushima et al., 2019). While this may in part be due to the poor efficacy of the implemented changes, it may also be a result of increased awareness and updated definition of concussion. In 1986, loss of consciousness and retrograde amnesia were the primary symptoms associated with concussive injuries (Cantu, 1986). In the 3rd consensus statement on concussion in sport, McCrory et al. (2009) claimed that "concussion typically results in the rapid onset of short-lived impairment of neurologic function that resolves spontaneously" (p.756), adding headaches, visual disturbances, nausea, dizziness, sleep disturbances, and memory problems as symptoms. The most recent consensus statement specifies that "symptoms and signs may present immediately, or evolve over minutes or hours, and commonly resolve within days, but may be prolonged" (Patricios et al., 2023, p.697). By including additional, less severe symptoms in revisions of concussive injury definitions, these revisions may have led to the increased diagnosis of concussions that would not have been diagnosed historically. In addition, the ever-expanding body of research regarding the consequences of these injuries has led to a surge in awareness and caution, which likely also contributes to increased diagnosis (Macpherson et al., 2014; Schallmo et al., 2017). Regardless, the consistent prevalence of concussions in football suggests further need to understand their causes in this sport and how to mitigate risk.

2.2 Biomechanics of Brain Injury

To understand why concussions occur in American football and how efforts can be made to mitigate risk, it is necessary to first recognize how brain injuries occur, as well as the factors influencing their type and severity. The following section provides an overview of the existing body of knowledge surrounding the biomechanical mechanisms through which brain injuries are produced.

2.2.1 Brain Injury Classification

When the head is impacted directly, energy is transferred to the soft tissues of the scalp, skull, and brain, damaging these tissues and causing injury. Depending on the type of tissue damaged and its extent, various forms of injury can occur. There exist two primary classifications of head trauma: focal injuries and diffuse injuries. Focal traumatic brain injuries (TBI), such as skull fracture, cerebral contusion, and intracerebral hematoma, are localized and tend to be more severe in nature, with extreme cases being fatal (Gennarelli et al., 1972; Gurdjian, 1961, 1975, 1976; Gurdjian et al., 1968; Kleiven, 2003). Diffuse injuries such as subdural hematoma and concussion, on the other hand, manifest over a more widespread area. Characterized by bleeding within the subdural space due to rupture of the bridging veins or cortical arteries (Bailes & Hudson, 2001; Forbes et al., 2014; Gennarelli & Thibault, 1982; Matsuyama et al., 1997), subdural hematoma is one of the leading causes of fatal head injury in football (Canseco et al., 2022; Cantu & Mueller, 2003; Kucera et al., 2017). Lower on the severity spectrum, symptoms commonly associated with concussive injuries include headache, dizziness, disorientation, incoordination, anxiety, depression, poor concentration, and altered sleep patterns (Kutcher & Giza, 2014). These typically resolve within 7-30 days (Mah et al., 2025; Patricios et al., 2023); however, persistent concussive syndrome (PCS) can occur, in which symptoms can persist for months to years (Quinn et al., 2018). While the exact factors determining whether an individual will experience PCS, as opposed to transient concussion, are not yet clear, higher severity impacts (increased magnitude and/or duration) and greater brain deformation values are associated with PCS (Hoshizaki et al., 2013; Post et al., 2015; Quinn et al., 2018). Evidence also supports those with PCS demonstrate structural, functional, and/or metabolic irregularities in the brain that are more severe and last longer than a transient concussion (Biagianti et al., 2020). Although acute concussion itself is not fatal, sustaining multiple concussions before the brain heals can increase the risk for a fatal condition termed second-impact syndrome (Bailes & Cantu, 2001; Dessy et al., 2015). In addition, the accumulation of concussive or sub-concussive head impacts over one's lifetime can cause the buildup of dysfunctional tau proteins around the brain's blood vessels and brain atrophy, accelerating the development of chronic traumatic encephalopathy (CTE) and leading to memory loss, mood and behaviour changes, and motor incoordination (Baugh et al., 2012; Decq et al., 2016; McAllister & McCrea, 2017; McKee et al., 2013; Stern et al., 2011). Diffuse axonal injury (DAI) is a diffuse brain injury characterized by axonal degeneration that can occur with a single high-magnitude event, leading to altered hormonal and temperature regulation, memory and information processing deficits, and coma (Meythaler et al., 2001). These injuries can be classified according to their severity, the structures damaged, and the biomechanical mechanisms through which they occur (Hoshizaki et al., 2013). The unique characteristics of a given impact (i.e. magnitude, location, duration, and mass) affect the kinematic response of the head, principally the linear and rotational accelerations (Karton et al., 2013; Post, 2013; Post et al., 2013b, 2014; Post, Hoshizaki, Gilchrist, & Cusimano, 2017; Taylor et al., 2020; Walsh et al., 2011). These variables influence the mechanism of injury, thereby dictating the type and severity of the resulting brain injury (Gennarelli et al., 1971, 1972; Ommaya & Hirsch, 1971; Unterharnscheidt, 1971).

2.2.2 Linear Acceleration

Focal TBIs are primarily associated with direct head impacts of high magnitude and short duration which produce high linear accelerations. These impacts can cause skull/brain relative motions and intracranial pressure gradients, resulting in focal injuries such as epidural hematomas and cerebral contusions (Gennarelli et al., 1971, 1972; Gurdjian, 1961; Gurdjian & Gurdjian, 1975; Patrick et al., 1963). Such injuries can occur either at the site of impact (coup) or in the area distal to the impact (contrecoup) (Gurdjian & Gurdjian, 1975). Coup contusions may be a result of high impact force producing inward skull deformation, causing the skull to damage the brain tissue and cerebral blood vessels directly underneath (Gurdjian & Gurdjian, 1975). Relative motions between the skull and brain resulting from impacts can also cause shear strains on the cerebral blood vessels, leading to cerebral hematoma if rupture occurs (Kleiven, 2003). This relative motion produces an area of increased intracerebral pressure at the coup site and an area of reduced pressure at the contrecoup site (Gurdjian & Gurdjian, 1975), causing shear strains that damage local brain tissue and result in contusion (Gurdjian et al., 1968). While intracerebral pressure gradients are thought to be a major contributor to coup injuries, contrecoup contusions are most likely the result of the brain moving relative to bony prominences on the interior of the skull (Gurdjian & Gurdjian, 1975). Gennarelli et al. (1971, 1972) produced only focal injuries in animal subjects with pure horizontal translation of the head. This suggests that, although linear acceleration is an influential factor in producing risk of focal TBI, it alone is insufficient for creating concussion risk, which is more dependent upon rotational components.

2.2.3 Rotational Acceleration

Neurological injuries more diffuse in nature, such as DAI and concussion, are primarily associated with rotational head motions. Holbourn (1943) initially suggested that, due to neural tissue's high tolerance for compression and low resistance to shear, rotational accelerations that produce greater shearing forces are more likely to cause brain damage than linear accelerations producing high compressive forces. Subhuman primate research by Ommaya & Hirsch (1971) estimated that rotation accounted for approximately half of the potential for brain injury, with impact phenomena accounting for the remainder. Gennarelli et al. (1971, 1972) found diffuse injuries to occur in subhuman primates only with the presence of a rotational component. Unterharnscheidt (1971) hypothesized that, while translation of the head is closely associated with focal injuries, rotation produces diffuse damage to brain tissue due to the widespread shearing force from relative motion between the skull and brain. This theory has been supported by later research demonstrating a high correlation between rotational head motion, brain tissue strain, and concussion (Kimpara & Iwamoto, 2012; Kleiven, 2007; Zhang et al., 2004). Head rotation produces focal shear stresses and strains at points where the relative brain-skull motion is restricted, as well as in regions where adjacent tissues have different densities and inertial properties, resulting in axonal strains and cerebral vasculature damage (Bradshaw et al., 2001; Kleiven, 2003; Ommaya & Gennarelli, 1974). Axonal strain can cause swelling, electrophysiological impairment, morphologic changes, altered membrane permeability, microtubule disintegration, and axotomy (Adams et al., 1989; Ommaya & Gennarelli, 1974; Povlishock, 1992; Smith et al., 1999; Tang-Schomer et al., 2010), leading to the neurological symptoms characteristic of concussive injury and DAI (Blumbergs et al., 1994; Povlishock, 1992; Wilde et al., 2008; Wright & Ramesh, 2012).

2.2.4 Impact Conditions

Although experimental studies have shown focal and diffuse injuries to occur with isolated linear and rotational accelerations, respectively, it is unlikely for linear and rotational head accelerations to occur separately outside of laboratory conditions (Post & Hoshizaki, 2012). While strains due to intracranial pressure gradients are largely dependent upon linear accelerations and shear strains from brain motion are dependent upon rotational acceleration, it has been proposed that the combination and interaction of linear and rotational kinematics is what dictates the type and severity of the resulting injury (Post & Hoshizaki, 2012). Studies evaluating the correlation between linear and rotational head accelerations have determined that certain impact conditions (i.e. impact mass, velocity, duration, and location) may influence the relationship between these variables (Gimbel & Hoshizaki, 2008; Hoshizaki, Post, et al., 2017; Karton et al., 2013; Karton & Hoshizaki, 2018; Post, 2013; Post et al., 2013b, 2013a, 2014; Post, Hoshizaki, Gilchrist, & Cusimano, 2017; Taylor et al., 2020; Walsh et al., 2011). These results demonstrate that measuring peak linear or rotational acceleration alone is not sufficient for estimating brain injury risk (Post & Hoshizaki, 2015).

Animal, human, and finite element (FE) experiments have shown impact location to significantly affect injury outcomes. While lateral impacts may increase risk of concussion and DAI (Gennarelli et al., 1982, 1987; Hodgson et al., 1983; Zhang et al., 2001; Zwahlen et al., 2007), other TBIs such as subdural hematoma may be more sensitive to loading in the anterior-posterior directions (Kleiven, 2003). This relationship has also been demonstrated in FE analyses of football event reconstructions (Post et al., 2014, 2018; Taylor et al., 2020; Zhang et al., 2004). Post et al. (2018) concluded that impacts to the side of a football helmet produced the greatest strains in the grey matter, white matter, and brainstem, while correlations between kinematics and brain tissue strain were variable across locations. Furthermore, the anisotropy of white matter causes the amount of axonal strain resulting from a given stress to depend on the loading direction. These results are reflected in epidemiological studies finding impact location and direction to influence concussive injury outcomes in football (Broglio et al., 2010; Crisco et al., 2010; Kerr et al., 2014; Liao et al., 2016; Pellman, Viano, Tucker, Casson, Waeckerle, et al., 2003).

The duration of the impact, or the acceleration pulse, has also been shown to interact with magnitude and influence head injury risk (Gennarelli, 1983; Gurdjian et al., 1954; Hoshizaki, Post, et al., 2017; Kleiven, 2005; Post, Hoshizaki, Gilchrist, & Cusimano, 2017; Willinger et al., 1994). By manipulating the duration of pressure applied to the dural sac of mongrel dogs, Gurdjian et al. (1954) discovered that shorter time durations required higher pressure to result in concussion, whereas the longer the time duration, the lower the pressure necessary to produce a concussive effect. Based on mathematical modeling of human car crashes, Willinger et al. (1994) proposed that short duration events (5-15ms) resulted in vascular stretching and contact between the skull and brain due to relative motion between the two, whereas the primary injury mechanism of longer duration events (15-20ms) is large intracerebral stresses and strains as the brain moves with the skull. More recent studies examining this interaction via FE modeling have produced similar conclusions (Gilchrist, 2003; Kleiven, 2005; Post, Hoshizaki, Gilchrist, & Cusimano, 2017). These results suggest that impacts with unique characteristics may lead to different types of brain injury. The broad range of brain injuries, all with different mechanisms and conditions under which they occur, provide a unique challenge for developing protective equipment standards that reflect overall safety across concussion, PCS, TBI, and neurodegenerative disease.

2.2.5 Trauma in the Developing Brain

In comparison to adults, children demonstrate anatomical, physiological, and biomechanical differences that may influence how they experience brain trauma (Kirkwood et al., 2006). While total cerebral volume reaches approximately 95% of its maximum by age 6, brain size continues to increase until approximately 14.5 years and 11.5 years in males and females, respectively (Giedd et al., 1996). During this time, the mechanical properties of brain tissues also change with the myelination of axons and the restructuring of grey and white matter, which can continue into the second or third decade of life (Lenroot & Giedd, 2006; Prange & Margulies, 2002). Because grey matter is isotropic while white matter is anisotropic (Prange & Meaney, 2000), age-related differences in the structure of these tissues may affect how the brain responds to loading from impacts. Thibault & Margulies (1998) demonstrated that the resistance of brain tissue to shear forces increases with age; therefore, the developing brain may be more susceptible to concussive injuries as smaller forces are required to produce the same amount of shear stress (Bauer & Fritz, 2004). This is supported by research showing children sustained concussions at lower impact kinematics and brain tissue strains than adults (Dawson et al., 2020; Koncan et al., 2020). Differences in physical characteristics such as body size, neck strength, and head-to-body ratio also affect head impact conditions and may influence the relationship between kinematics and injury outcomes (Eckner et al., 2014; Mihalik et al., 2011; Olvey et al., 2006; Parkinson & Reed, 2026; Vickers & Stuart, 1943). Furthermore, youth exhibit more severe concussive symptoms and prolonged recovery periods (typically around 30 days) compared to adults (Chauhan et al., 2023; Davis et al., 2017; Lee et al., 2013; Mah et al., 2025; Williams et al., 2015; Zuckerman et al., 2012). It is therefore important to consider age-related differences in impact conditions and the brain's response when assessing risk of brain injury.

2.3 Brain Injury Metrics

2.3.1 Strain-Based Metrics

Finite element (FE) brain modeling is a widely used tool to mathematically calculate Maximum Principal Strain (MPS) of the brain tissue to estimate risk of brain injury. MPS can be defined as the largest normal strain experienced by a material, occurring on a plane where the shear strain is zero. In the context of brain tissue, this measure refers to the maximum elongation of a tissue relative to its original length. The amount of brain tissue strain and the rate of onset relate directly to the disruption of axonal cell signalling and increases in cell death, impairing brain function (Bain & Meaney, 2000; Galbraith et al., 1993; Mao et al., 2006; Morrison et al., 2000, 2003). Axonal fibers within the brain are particularly susceptible to strain, and excessive deformation can impair axonal transport, alter membrane permeability, and disrupt neuronal signaling, leading to the neurological symptoms characteristic of concussions (Blumbergs et al., 1994; Povlishock, 1992; Smith et al., 1999; Tang-Schomer et al., 2010; Wilde et al., 2008; Wright & Ramesh, 2012). MPS provides a measure of the peak deformation experienced by brain tissue and is therefore widely used to approximate the biomechanical conditions associated with concussive injury.

MPS has been shown to correlate with concussive injuries (Kleiven, 2007; Patton et al., 2013; Viano et al., 2005; Willinger & Baumgartner, 2003; Zhang et al., 2004) and is commonly used for predicting brain injury in reconstructions of on-field football impacts (Cournoyer & Hoshizaki, 2021; Ghazi et al., 2021; Kleiven, 2007; McAllister et al., 2012; Patton et al., 2013; Post et al., 2018; Taylor et al., 2019, 2020; Zhang et al., 2004). Studies have reported MPS values between 0.15 and 0.32 in the grey matter to represent 50% risk of concussion (Kimpara & Iwamoto, 2012; Kleiven, 2007; Patton et al., 2013; Zhang et al., 2004), with strains between 0.48

and 0.62 associated with risk of loss of consciousness and persistent post-concussion symptoms (Cournoyer & Hoshizaki, 2021; Koncan et al., 2020; Post et al., 2015). Although there is a lack of youth-specific injury thresholds, Koncan et al. (2020) found a strain threshold of 0.26 in the grey matter to predict concussion risk in children. 50% risk of severe brain injuries, such as DAI, hematomas, and skull fractures, occurs at strains of 0.81 to 0.89 (Post, 2013; Takhounts et al., 2008, 2013). Karton et al. (2020) found over 90% of all impacts experienced by NFL linemen to produce MPS values between 0.08 and 0.17, demonstrating how football impacts frequently produce strains within the concussive range.

MPS is limited, however, due to it only representing the axis with the greatest strain, thereby overlooking important directional information. White matter is anisotropic (Prange & Margulies, 2002; Prange & Meaney, 2000); therefore, strain aligned with axonal fiber tracts may have different injury implications than strain perpendicular to them. As a non-directional scalar value, MPS is unable to capture the influence of strain direction on neurological injury. In addition, it does not account for the region of the brain in which the maximum strain occurs, which has been shown to affect the symptoms produced by a given strain (Post et al., 2014). Despite these limitations, FE measures of brain tissue strain are a valuable tool for estimating brain injury risk (Madhukar & Ostoja-Starzewski, 2019). This is because these measures account for both the linear and rotational head kinematics, as well as the event duration, impact location, and brain tissue properties (Post & Hoshizaki, 2012). Models can vary in number of elements, the tissues represented, and the material model used to calculate the response of each tissue type to movement, resulting in varying performance (Dixit & Liu, 2017; Madhukar & Ostoja-Starzewski, 2019). Outputs were validated against cadaveric studies to determine model accuracy (Alshareef et al., 2018; Hardy et al., 2001; Nahum et al., 1977); however, challenges remain in accurately replicating the unique material properties of brain tissues and the complexity of biological responses to impact (Madhukar & Ostoja-Starzewski, 2019; Tierney, 2021). In addition, using these models comes at a high computational cost and is very time consuming, taking hours or even days to simulate a single head impact, limiting their use outside of research applications (Horgan & Gilchrist, 2003; Lu et al., 2019; Mao et al., 2013; Miller et al., 2016). As a feasible alternative, the automotive and sporting industries estimate brain injury risk from simplified functions using impact kinematics to inform safety standards.

2.3.2 Impact Kinematics

Prior to technological advances permitting the development of FE models, thresholds for brain injury had been proposed based on single peak resultant kinematic values. The Wayne State Tolerance Curve (WSTC) was one of the first functions for estimating brain injury, plotting peak resultant linear acceleration as a function of impact duration (Gurdjian et al., 1966). At long durations (≥10ms), approximately 90g was estimated to result in brain injury (Gurdjian et al., 1966). The curve boundary represented the threshold for brain injury; however, this function was based on skull fracture in animal and cadaveric experiments from direct frontal head impacts, limiting its applicability to other brain injuries with different mechanisms, non-contact scenarios, and impacts to other locations (Gurdjian et al., 1953, 1955). As a result, the WSTC has been shown to be a poor predictor of concussive injuries, which are primarily associated with rotational kinematics (Hoshizaki, Post, et al., 2017). Ommaya & Hirsch (1971) proposed a rotational acceleration injury threshold of 18000 rad/s^2 based on head impacts and whiplash events in subhuman primates, suggesting rotational acceleration is more closely related to concussion. Since these initial estimates, additional studies have proposed updated threshold values. Fernandes & Sousa (2015) present a review of proposed brain injury thresholds, with values as low as 65g and 1800 rad/s^2 suggested to represent 50% risk of concussion. Although these provided a useful starting point, peak kinematic values do not fully represent the characteristics of an impact and the complexities of the head and brain's response (Goldsmith, 1981; Greenwald et al., 2008; Post, Hoshizaki, Gilchrist, & Cusimano, 2017). This has led to the development of metrics using multiple kinematic variables to estimate likelihood and severity of brain injury from a given head impact.

2.3.3 Kinematic-Based Metrics

Among the first kinematic brain injury metrics was the Gadd Severity Index (GSI), developed by Gadd (1966) based on the WSTC, incorporating impact duration and a power-weighing factor into the equation:

$$GSI = \int_{t_0}^{t} \vec{a}^{2.5} dt$$

where *a* is the peak linear acceleration vector of the headform's center of gravity in standard gravitational units (g) to the power-weighting factor of 2.5, integrated over the impact duration *t* in seconds (s). Solving this equation results in a single numeric value that can be interpreted in reference to a specified injury threshold value, with a value of 300 thought to represent the concussive threshold (Pellman, Viano, Tucker, Casson, Waeckerle, et al., 2003). The GSI and WSTC, however, only account for linear acceleration and impact duration, thereby overlooking impact characteristics that may influence the risk of brain injury, such as rotational kinematics and loading curve shape (Hoshizaki et al., 2013; Post et al., 2012; Post, Hoshizaki, Gilchrist, & Cusimano, 2017; Post & Hoshizaki, 2015; Yoganandan et al., 2008). In addition, the WSTC was developed to predict skull fracture during frontal impacts; therefore, predictions may not be accurate for other brain injuries and impact locations (Hoshizaki, Post, et al., 2017). To improve upon the GSI, Head Injury Criterion (HIC) was proposed by Versace (1971). The HIC formula expands upon that of the GSI by multiplying the linear acceleration by the time interval, as shown in the equation:

$$HIC = (t - t_0)\left[\left(\frac{1}{t - t_0}\right)\int_{t_0}^{t} \vec{a}^{2.5} dt\right]^{2.5}$$

where *a* and *t* are the same as in the GSI equation, and $(t - t_0)$ denotes the time interval over which the HIC value is maximized, typically restricted to a length of 15ms. This allows the HIC to represent impacts of longer duration and low acceleration compared to the GSI. Researchers have proposed that there is a 50% risk of concussion with a HIC value between 200 and 240 (Duma et al., 2005; Newman et al., 2000; Zhang et al., 2004), while values of 533 and 1032 represent 50% risk of moderate and severe neurological injury, respectively (Marjoux et al., 2008). Similar to GSI, however, HIC does not account for rotational kinematics, impact location, and direction. HIC remains widely used within the automotive industry (Gabler et al., 2016; Osth et al., 2023; Westrom et al., 2024; Wu et al., 2021).

Newman (1986) proposed the first brain injury metric combining both linear and rotational accelerations: the Generalized Acceleration Model for Brain Injury Threshold (GAMBIT).

$$GAMBIT = \left[\left(\frac{\vec{a}(t)}{\overrightarrow{a_c}}\right)^{m} + \left(\frac{\vec{\alpha}(t)}{\overrightarrow{\alpha_c}}\right)^{n}\right]^{\frac{1}{s}}$$

In this formula, $a(t)$ is the instantaneous linear acceleration at time *t*; $\alpha(t)$ is the instantaneous angular acceleration at time *t*; a_c is the critical value for linear acceleration; α_c is the critical value for angular acceleration; and *m*, *n*, and *s* are empirical constants set to 1 for a linearly weighted model or 2 for an elliptical model. Time *t* is chosen such that the GAMBIT value is maximized. A value of 0.4 is proposed to reflect 50% risk of concussion (Newman et al., 2000). Developed based on stress/strain theory and hospital records of car accidents, GAMBIT has been shown to correlate poorly with measures of brain tissue strain (Gabler et al., 2016; Levy et al., 2021). Recognizing the limitations of GAMBIT, Newman & Shewchenko (2000) developed Head Impact Power (HIP) from reconstructions of helmeted football head impacts. This equation is based on the rate of change of kinetic energy entering the head with the mass and inertia of a 50th percentile adult male head and incorporates directional components. It can be defined as:

$$HIP = m \sum a_i(t) \int a_i(t)dt + \sum I_i \alpha_i(t) \int \alpha_i(t)dt$$

where I_i are the principal moments of inertia of the head, with mass *m*, about the anatomical axes (I = x, y, z). Newman & Shewchenko (2000) proposed HIP values of 4.7, 12.79 and 20.88 kW to represent 5%, 50%, and 95% risk of concussion, respectively. Despite including directional sensitivity, HIP does not describe whether impact location, or one of the other variables in the formula, plays a role in differing results since the output is a singular value. In addition, this model assumes that the head is a rigid body with no deformation and is treated as a single mass at the center of gravity.

Using reconstructions of automobile impacts via pendulum and occupant crash tests, the Brain Injury Criterion (BrIC) was developed by Takhounts and colleagues (2013). They concluded that angular velocity alone was sufficient to predict FE measures of brain tissue strain. The resulting equation was:

$$BrIC = \sqrt{\sum \left(\frac{\omega_i}{\omega_{ic}}\right)^2}$$

where ω_i are the peak angular velocity components of the three principal axes (I = x, y, z) and ω_{ic} are their respective critical values. Based on the risk curve for concussions in college football players developed by Rowson et al. (2012), 50% probability of concussive injury was set at a BrIC value of 0.50 (Takhounts et al., 2013). This metric is limited to DAI type brain injuries and may not accurately predict other types of TBI, such as skull fractures, focal lesions, and contusions, given their association with linear acceleration (Gennarelli et al., 1971, 1972; Gurdjian, 1961; Gurdjian & Gurdjian, 1975; Takhounts et al., 2013). Gabler et al. (2018) proposed an updated version of BrIC, the Universal Brain Injury Criterion (UBrIC), which includes angular acceleration and improved critical values. The UBrIC formula is:

$$UBrIC = \sqrt{\sum \left[\omega_i^* + (\alpha_i^* - \omega_i^*)e^{-\frac{\alpha_i^*}{\omega_i^*}}\right]^2}$$

where ω_i^* and α_i^* are the peak angular velocity and acceleration in the three axes (I = x, y, z). Each are normalized by a critical value, *cr* ($\omega_i^* = \omega_i/\omega_{icr}$ and $\alpha_i^* = \alpha_i/\alpha_{icr}$). When calculated for 1600 head impacts under conditions representing automotive and American football events using dummies, cadavers, and human volunteers, UBrIC consistently outperformed BrIC in predicting MPS (Gabler et al., 2018). Similar to BrIC, however, predictions were poorer for high-strain impacts, limiting its effectiveness for severe TBI prediction (Gabler et al., 2018). Although injury thresholds have yet to be established for this metric, the UBrIC's accuracy in predicting lower-range MPS can be useful as a tool for informing the design of protective equipment (Gabler et al., 2018).

Many kinematic-based metrics have been compared to FE measures of tissue strain in the context of automotive and sporting impacts to determine the best predictors of brain injury

(Fernandes & Sousa, 2015; Gabler et al., 2016; Kimpara et al., 2011; Kimpara & Iwamoto, 2012; Levy et al., 2021). For 672 laboratory reconstructions of hockey impacts, Levy et al. (2021) analyzed correlations between seven kinematics-based brain injury metrics, including GSI, HIC, GAMBIT, BrIC, and UBrIC, and $CSDM_{20}$, another common FE measure of strain. It was found that rotation-based metrics, such as BrIC and UBrIC, correlated better with $CSDM_{20}$ ($R^2 = 0.83$ and 0.85, respectively) than linear-based metrics such as GSI, HIC, and GAMBIT ($R^2 = 0.34$, 0.49, and 0.31, respectively) (Levy et al., 2021). In the context of automotive head impacts, Gabler et al. (2016) had similar results, with BrIC correlating best with MPS ($R^2 = 0.778$). Interestingly, Levy et al. (2021) found peak rotational velocity to predict $CSDM_{20}$ equally as well as UBrIC ($R^2 = 0.85$), whereas it performed more poorly ($R^2 = 0.593$) in the study by Gabler et al. (2016). In addition, overall predictive capacity was notably worse for automotive impacts than hockey. This highlights the effects of different impact conditions on the predictive capacity of peak kinematics and injury metrics. The current study utilizes FE measures of brain tissue strain produced during standardized football helmet impact testing to compare the correlations of kinematic metrics with MPS for this protocol.

2.3.4 Machine Learning Models

Limitations of kinematic-based metrics to estimate brain tissue strain (Gabler et al., 2016; Kleiven, 2007; Knowles & Dennison, 2017; Levy et al., 2021) and the feasibility of using FE models (Horgan & Gilchrist, 2003; Lu et al., 2019; Mao et al., 2013; Miller et al., 2016) have given rise to the use of regression and machine learning models for predicting strain from kinematic data (Deck et al., 2023; Ghazi et al., 2021, 2022; Greenwald et al., 2008; Kleiven, 2007; Rowson & Duma, 2013; Zhan et al., 2021). Kleiven (2007) proposed a linear regression model combining HIC and peak resultant rotational velocity to predict MPS in American football impacts. In 2008, Greenwald et al. used principal component analysis to develop a model including GSI, HIC, and peak resultant linear and rotational acceleration. Furthermore, multivariate logistic regression of peak resultant linear and rotational acceleration has been employed to predict risk of concussion experienced by football athletes following a head impact (Rowson & Duma, 2013). Most recently, Ghazi et al. (2021, 2022) created a convolutional neural network to instantly estimate peak MPS for each element of the entire brain during automotive and football events. On a sample of 144 American football impacts, this model was able to predict element-wise peak MPS with 98.6% accuracy and R^2 values for whole-brain peak MPS and CSDM of 0.977 and 0.980, respectively (Ghazi et al., 2022). Machine learning models show a promising future for improving the accuracy, efficiency, and feasibility of predicting brain injury risk in American football (Gabler et al., 2016; Ghazi et al., 2022); however, a model for predicting MPS has yet to be developed specific to the methods used for testing helmets. This research develops multiple regression and random forest regression models to predict MPS produced during standardized football helmet impact testing, then compares the prediction accuracy of these models to linear regression and random forest regression models of kinematic brain injury metrics.

2.4 Head Protection in American Football

Given that the predictive capacity of kinematic metrics and machine learning models may vary depending on the head impact characteristics represented within a dataset, it is important that this research use standardized helmet testing impact conditions to compare predictive performance between models. The following section provides a summary of how head impacts occur in American football, as well as how they are represented in standardized helmet testing procedures.

2.4.1 Head Impact Events

Head impacts in football primarily occur due to collisions between players or falls to the ground. Pellman, Viano, Tucker, Casson, Waeckerle, et al. (2003) reported that 61% of NFL concussions result from head-to-head collisions, 16% from shoulder/arm-to-head, and 16% from falls to the ground. A later analysis found 37.8% of concussions to occur as a result of helmet-to-body contact, 32.4% from helmet-to-helmet, and 29.8% from helmet-to-ground (Clark et al., 2017). This reduction in head-to-head contacts may be a result of rule modifications made by the NFL, heavily penalizing players for making contact to the head and neck area (Clark et al., 2017). In addition to the different types of contact, frequency and magnitude of head impacts vary by player position. While linemen, running backs, and linebackers experience the greatest frequency of head impacts, running backs, wide receivers, and quarterbacks experience a larger proportion of high-magnitude impacts (Crisco et al., 2010, 2011; Karton et al., 2020). Impact location may also influence outcome, with impacts to the side of the head most frequently resulting in concussion (Clark et al., 2017; Greenwald et al., 2008; Kerr et al., 2014; Liao et al., 2016; Pellman, Viano, Tucker, Casson, Waeckerle, et al., 2003). Furthermore, 79% of impacts to the helmet strike above the head's centre of gravity, producing oblique impact angles that result in greater rotational accelerations and further contribute to the risk of brain injury (Pellman, Viano, Tucker, Casson, Valadka, et al., 2003). The variety of impact characteristics produced in the game of football demonstrates the potential for many types of brain injury to occur through different mechanisms, presenting a unique challenge for establishing equipment safety standards that encompass the full range from concussion to TBI.

2.4.2 Helmet Testing & Performance Standards

In 1975, the National Operating Committee on Standards for Athletic Equipment (NOCSAE) established the first American football helmet test protocol and performance standards with the aim of reducing the incidence of TBI (Hodgson, 1975). This test protocol consisted of twin-wire-guided drop impacts to the front, front boss, side, rear boss, rear, and top of helmeted headforms, with a GSI value of 1500 representing the pass/fail threshold (Hodgson, 1975). The introduction of these standards reduced fatal head injuries by 51% and cranial fractures by 65% (Hodgson, 1980); however, the incidence of concussion did not change significantly (Casson et al., 2010). Although a good predictor for TBI, the GSI was not intended to predict concussion and has been shown to correlate poorly with these injuries (Gadd, 1966; Hoshizaki, Post, et al., 2017). In addition, the GSI threshold was much higher than the later proposed threshold of 300 for concussion (Pellman, Viano, Tucker, Casson, Waeckerle, et al., 2003). Furthermore, drop impacts produce a kinematic head response dominated by linear acceleration; therefore, the initial NOCSAE test protocol and performance criteria did not assess the performance of helmets under conditions reflecting the mechanisms and risks associated with concussions (Hoshizaki et al., 2004; Hoshizaki, Karton, et al., 2017; Post et al., 2013a, 2018).

To better represent the mechanism of concussive injury, pneumatic ram impacts were added to the NOCSAE protocol in 2016, and a peak resultant rotational acceleration threshold of 6000 rad/s^2 was established (NOCSAE, 2023, 2024a, 2024b). Although this addition more closely represents the mechanisms of concussion (Hoshizaki, Karton, et al., 2017), incidence remains high in football (Canseco et al., 2022), suggesting that concussive risk is not fully predicted by performance evaluation criteria. This may be because peak rotational acceleration alone is not an accurate predictor of concussive risk (Goldsmith, 1981; Greenwald et al., 2008;

Post, Hoshizaki, Gilchrist, & Cusimano, 2017). Furthermore, although the GSI criteria for drop impacts was lowered to 300 for the lowest velocity condition, this metric continues to correlate poorly with concussive injury risk (Hoshizaki, Post, et al., 2017). Therefore, the measures currently used to evaluate football helmet performance may not be suitable for assessing a helmet's ability to mitigate brain injuries other than TBI. This research aimed to determine whether different kinematic brain injury metrics associate with measures of brain tissue strain and can be employed to more effectively assess protection against concussive injury.

There exist additional limitations within NOCSAE test protocols that restrict the ability of standard test impacts to represent common on-field head impacts. Impacting surfaces are generally less compliant than would be a typical player-to-player collision, resulting in shorter impact durations and greater magnitudes than may be experienced on the field (Hoshizaki et al., 2014; Pellman, Viano, Tucker, Casson, Waeckerle, et al., 2003). Furthermore, test impacts are conducted at velocities between 3.46 and 6.00 m/s (NOCSAE, 2023, 2024a, 2024b), whereas Pellman, Viano, Tucker, Casson, Waeckerle, et al. (2003) found average impact velocity of concussive events in the NFL to be 9.30 m/s. As a result, these methodological limitations may further inhibit the ability of NOCSAE protocols to assess the capacity of football helmets to reduce concussive injury risk in real-world events. Although the purpose of this study is not to evaluate the methods used in NOCSAE standard helmet testing, it is important to note potential limitations of these protocols. Therefore, the current research is not intended to represent in-game impacts, but to further our understanding of the relationship between various kinematic metrics and brain tissue strain produced during NOCSAE helmet performance evaluation tests.

2.5 Summary

Football helmets have been effective at mitigating the risk associated with TBI but remain limited in their ability to prevent concussion (Hoshizaki et al., 2004, 2014). As a result, the occurrence of TBI has been drastically reduced, while incidence of concussion remains a concern (Canseco et al., 2022; Cantu & Mueller, 2003; Casson et al., 2010; Dompier et al., 2015; Hodgson, 1980; May et al., 2023; O'Malley et al., 2024; Pankow et al., 2022). One reason for this may be that helmet performance evaluation criteria primarily reflect the risks for TBI over concussion (Hodgson, 1975; Hoshizaki et al., 2017). Although FE modeling of brain tissue strain has been associated with risk of concussion (Bain & Meaney, 2000; Kleiven, 2007; McAllister et al., 2012; Patton et al., 2013; Post et al., 2015), its cost and complexity limit its application in certification settings. The predictive capacity of more practical kinematic-based brain injury metrics within NOCSAE test protocols has not been established; therefore, there is a need to identify which of these metrics best associates with strain-based measures of injury risk under standardized helmet test conditions. Moreover, it remains unknown whether combining multiple kinematic variables in a machine learning model could further improve strain prediction under these conditions. The current research addresses this gap by comparing the correlations of kinematic brain injury metrics with MPS calculated through FE modeling of NOCSAE-standard impacts, as well as the ability of linear, multiple, and random forest regression models to predict MPS using kinematic data obtained from these impacts. In doing so, this study identifies evaluation criteria to more accurately reflect the biological mechanisms of concussion, informing the improvement of football helmet performance standards.

3. Research Design

This study was designed to address the following: 1. Describe the relationship between kinematic brain injury metrics and MPS for youth and adult NOCSAE football helmet standard test conditions; and 2. Develop multiple regression and random forest regression models to predict MPS using kinematic data obtained from NOCSAE standard impacts.

The independent variables included the test methods, impact velocities, and impact locations specified by NOCSAE test standards. The peak resultant linear and rotational acceleration, peak resultant rotational velocity, peak directional components (x, y, z) of linear acceleration, rotational acceleration, and rotational velocity, and kinematic brain injury metrics (GSI, HIC, HIP, GAMBIT, BrIC, and UBrIC) resulting from each impact were defined as intermediate variables. MPS was the sole dependent variable examined.

It was hypothesized that correlations with MPS would differ between kinematic brain injury metrics for both youth and adult test protocols. It was also hypothesized that predictive performance would differ between linear, multiple, and random forest regression models of kinematic brain injury metrics and peak kinematic variables.

4. Methodology

4.1 Impact Testing Equipment

4.1.1 Helmets & Headform

For adult impact tests, Riddell Speed Classic Icon, Speedflex, and Axiom helmets were equipped to a size medium NOCSAE-certified headform with a mass of 4.90 kg. Youth-model Riddell Victor, Speed Classic, and Speedflex helmets were equipped to a size small NOCSAE-certified headform with a mass of 4.12 kg for youth impact tests (NOCSAE, 2024b). Images of each helmet can be found in Appendix A. Headforms were equipped with Diversified Technical Systems 6DX PRO and SLICE NANO data acquisition system (DTS, Calabasas, CA) to collect linear and rotational acceleration and rotational velocity data from each impact. Accelerometer signals were sampled at a rate of 20 kHz through a TDAS Pro Lab system (DTS, Calabasas, CA) and filtered with a CFC180 filter using TDAS software.

4.1.2 Wire-Guided Drop Rig

The drop rig used in NOCSAE impact tests consisted of a drop carriage, to which the headform was attached, and a steel-base anvil with a 0.5-inch modular elastomer programmer (MEP) pad (Appendix B). An electric winch attached to a top plate approximately 10 ft above the anvil allowed for the raising of the carriage to the appropriate heights, and twin wires attached to the carriage via nylon bushings guided the carriage’s fall to the anvil. The coupler that connected the headform to the carriage could be adjusted to the various head impact positions required by NOCSAE standards.

4.1.3 Pneumatic Ram

The apparatus used to carry out the pneumatic ram impacts consisted of a pneumatic linear impactor and a sliding table to which the headform was attached (Appendix B). The frame of the impactor held an air canister, piston, and aluminum impactor arm (13.1 kg) attached to rails via ball bearings. Once pressurized to the appropriate PSI for a desired impact velocity, the piston horizontally propelled the impacting arm along the rails toward the headform, which was mounted on the sliding table (12.78 kg) via a Hybrid III 50th percentile neckform (5th percentile for youth). The connection between the neckform and sliding table was adjustable with 5 degrees of freedom, allowing the headform to be positioned for the NOCSAE-standard impact locations. The sliding table was attached to rails on a height-adjustable aluminum shelf via ball bearings. Upon head impact, the sliding table would move along the rails until it was stopped after 0.65 m by stop pads. For the adult protocol, the end of the impactor arm was equipped with a 2.3 kg hemispherical aluminum cap and 1.5-inch MEP shore type 43A tip, as specified by NOCSAE (2023). The total combined mass of the impactor arm and cap was 15.4 kg. For youth, the impactor head was equipped with 1.0 inch of MEP shore type 43A with a nylon cap and mass of 0.9 kg, resulting in a total impacting mass of 14.0 kg. This is greater than the 6.88 kg impacting mass outlined in NOCSAE protocols to represent youth below high school age (NOCSAE, 2023); however, an impacting arm of lower mass was not accessible for use in this research. Karton et al. (2013) demonstrated that increasing impacting mass from 6.3 kg to 14.3 kg resulted in increases of approximately 30 g and 1.4 krad/s^2 in linear and rotational acceleration, respectively. As a result, the results of this study take into consideration that youth impact magnitudes may be greater than would be expected with a lower impacting mass.

4.2 Impact Attenuation Tests

Each helmet model underwent 25 drop tests, as described in NOCSAE (2025b). Impact locations included the front, front boss, side, rear boss, rear, and top of the helmet, as well as a random location within the defined impact area (Appendix C). All locations were tested at impact velocities of 3.46 and 5.46 m/s, with two 5.46 m/s impacts, while the front and side locations underwent additional impacts at 4.23 and 4.88 m/s. Impact velocity and location summary tables can be found in Appendix C. An electronic time gate with a sampling rate of 20 kHz recorded the inbound velocity of the helmet and carriage rig momentarily before impact using National Instruments VI-logger software (National Instruments, Austin, TX). Velocities were verified to ensure all impacts were within 3% of the required velocity. The same drop protocol was conducted for youth helmets as for adult, with the exception of headform size and helmet models. In accordance with NOCSAE (2025a, 2025b), 7 pneumatic ram impacts were conducted per helmet at the front, front boss, side, rear boss centric, rear boss non-centric, rear, and random locations. Impact velocities were 6.0 m/s for adult models and 5.0 m/s for youth (Appendix C). As with the drop tests, an electronic time gate was used to verify that impact velocities were within 3% of the required values.

4.3 Data Analysis

4.3.1 Kinematic Brain Injury Metrics

Once accelerometer data for each impact was recorded, it was exported to a custom Microsoft Excel sheet that retrieved the peak resultant linear acceleration (PRLA), rotational acceleration (PRRA), and rotational velocity (PRRV) values, and calculated the GSI and HIC metrics. Using Rstudio coding software (Posit PBC, Boston, MA), a custom script was used to calculate the HIP, GAMBIT, BrIC, and UBrIC values for each impact. The constraints and critical values used to calculate each metric are presented in Appendix D.

4.3.2 Finite Element Model

Using ABAQUS computer software (Dassault Systemes, Vélizy-Villacoublay, France), the linear and rotational acceleration time histories of each impact were applied to the University College Dublin Brain Trauma Model v2.0 (UCD2) at the centre of gravity to determine MPS of the grey matter. This model, initially developed by Horgan & Gilchrist (2003, 2004), was created based on the geometry of a human male cadaver obtained via computed tomography scans, magnetic resonance tomography scans, and sliced contour photographs. The scalp, skull, pia, falx, tentorium, cerebrospinal fluid, grey and white matter, cerebellum, and brain stem were represented. The original version has since been updated by Trotta et al. (2020) to include sliding contact properties between the scalp and skull, accelerometer elements at the centre of gravity to more accurately represent a surrogate headform, and whole-head mesh refinement, resulting in over 184,000 elements. In addition, the dura mater, falx, and tentorium were modeled as hyperelastic rather than the linear viscoelastic model originally used, improving model performance (Trotta et al., 2020). Mechanical properties used in the UCD2 can be found in Trotta et al. (2020). The UCD2 has been validated against cadaveric impact intracranial pressure data by Nahum et al. (1977), as well as brain motion data from Hardy et al. (2001); however, these experimental studies contained only adult male cadavers. Given the differences between adult and youth brain structures and material properties, the UCD2 may not accurately represent the brain tissue response of a youth (Coats et al., 2007; Danelson et al., 2008; Dawson et al., 2020; Koncan et al., 2020; Lenroot & Giedd, 2006; Prange & Margulies, 2002; Reiss et al., 1996; Thibault & Margulies, 1998). Previous research has scaled adult models to youth dimensions (Dawson et al., 2020; Doorly & Gilchrist, 2006; Klinich et al., 2002; Meliambro et al., 2022; Post, Hoshizaki, Gilchrist, Koncan, et al., 2017); however, FE models have mostly been validated against adult cadaveric data as there is a lack of experimental data that can be used to validate youth FE models. Therefore, the UCD2 model was scaled to the 95th percentile for the youth helmet impacts, recognizing the limitations in representing this demographic. This is consistent with previous research reconstructing youth football impacts (Meliambro et al., 2022).

4.3.3 MPS Prediction Models

The following analyses were conducted on youth and adult datasets separately. Mean MPS was first calculated for drop and pneumatic ram impacts separately, as well as the overall mean across both conditions, to provide insight into the range of brain trauma produced by NOCSAE test protocols. Using Rstudio, each peak resultant kinematic variable and kinematic brain injury metric was linearly regressed against MPS for every impact conducted. Each regression model's coefficient of determination (R^2) was used to compare correlations with MPS between models. R^2 values can range from 0 to 1, with higher values indicating a greater amount of variance explained by the model; however, there are no universally accepted thresholds for 'good' model performance, as interpretation depends on the application and inherent variability of the data. For this study, R^2 values below 0.4 were defined as “poor”, values between 0.4 and 0.7 were defined as “moderate”, and “high” values were those above 0.7. These categories were chosen based on the range of R^2 values achieved in previous studies examining the relationship between kinematic brain injury metrics and measures of brain tissue strain for various head impact events (Gabler et al., 2016, 2019; Kimpara et al., 2011; Kimpara & Iwamoto, 2012; Levy et al., 2021).

Once correlations between each metric and MPS were determined, 10-fold cross validation was then performed to assess the ability of each regression model to predict MPS from unseen data. Each kinematic variable and metric was regressed against MPS using 90% of the collected NOCSAE impact data, as opposed to the entire dataset. The remaining 10% of the dataset was then used to test model performance, whereby the resulting regression lines were used to predict MPS from the appropriate kinematic variable or metric. This was performed 10 times for each model, using different random samples of the dataset each time, and average R^2 and root mean squared prediction error (RMSE) across all 10 folds were recorded. This method was chosen to minimize sampling bias and provide a robust estimate of out-of-sample predictive performance. RMSE, in units of MPS, represents the average magnitude of error in predictions compared to actual MPS values, with lower values indicating greater performance. RMSE can also be expressed as a percentage of the standard deviation of MPS within the dataset to contextualize the magnitude of the prediction error relative to the natural variability in the data. As with R^2, there are no universally accepted ranges to quantify “good” RMSE; therefore, this study uses RMSE solely as a means for relative comparison between models.

Following the development of linear regression models, the same cross-validation process was then repeated using random forest models to predict MPS from each kinematic variable and metric. Each model comprised 500 decision trees, in which the single predictor variable (the kinematic variable or metric of interest) was recursively split at thresholds that minimized the variance of MPS within the resulting nodes. Tree growth stopped when a terminal node contained fewer than five samples, and new observations reaching that node were assigned the mean MPS of the training samples within it. MPS estimated by each tree was then averaged across the entire forest to obtain the model's final MPS estimate. Again, average R^2 and RMSE of each model across all 10 folds were recorded for comparison between variables, as well as between regression types.

Correlation and cross-validation results were then examined to gain insight into the relationship between kinematic brain injury metrics and MPS for NOCSAE football helmet test protocols. Poor model performance indicated the presence of additional factors influencing MPS during testing that were not being captured by these metrics. Given the known influence of impact location on strain, it was hypothesized that including directional information would improve predictions, as NOCSAE testing includes multiple impact locations. Consequently, three multiple regression models were developed to predict MPS from kinematic variables. The first included the three peak resultant kinematic variables (PRLA, PRRA, and PRRV) as predictors, thereby not including directional information. Loading direction was implicitly modeled in the second multiple regression model, which predicted MPS from all the peak kinematic components (peak x, y, and z components of linear acceleration, rotational acceleration, and rotational velocity) resulting from each impact. All peak resultant kinematics and peak kinematic components were modeled as predictor variables in the final multiple regression model. Each model's predictive performance was assessed via 10-fold cross-validation, as outlined above.

Finally, three random forest models were developed using the same three kinematic variable combinations as predictors. Random forests were chosen due to their ability to flexibly model multivariable relationships without requiring assumptions of linearity, independence, or additivity of predictors, unlike multiple linear regression models. The relationship between linear and rotational kinematics, and their influence on MPS, is likely non-linear and depends on multi-directional and region-specific loading characteristics. It was hypothesized that a random forest model would be able to better capture these interactions than a linear model, thereby improving performance. Random forests are also relatively robust to multicollinearity among predictors because predictions are generated from the combination of many decorrelated decision trees. As a result, the model is less sensitive to the correlations between kinematic variables. Compared to other machine learning techniques, random forests provide a strong balance between predictive flexibility, robustness to multicollinearity, and implementation simplicity, without requiring significant hyperparameter optimization and a very large training dataset. Consistent with the previous random forest models, each model consisted of 500 decision trees, with a minimum node size of 5. All predictor variables were considered as candidates for splitting at each node before selecting the predictor that minimized the variance of MPS within the resulting nodes when split. As with each previous model, 10-fold cross-validation was performed to assess the ability of these random forest models to predict MPS using kinematic data obtained from NOCSAE standard football helmet impact tests.

5. Results

5.1 Maximum Principal Strain

Impacts under adult NOCSAE test conditions produced MPS values ranging from 0.180 to 0.641 (M = 0.386, SD = 0.112). Drop impacts (M = 0.399, SD = 0.119) resulted in slightly greater mean MPS than pneumatic ram impacts (M = 0.340, SD = 0.064). Under youth impact conditions, MPS ranged from 0.182 to 0.582. Consistent with adult protocols, mean MPS was greater for drop impacts (M = 0.399, SD = 0.103) than pneumatic ram impacts (M = 0.323, SD = 0.056). Mean MPS values are summarized in Table 1.

Table 1

Mean MPS by Inbound Velocity for NOCSAE Adult and Youth Football Helmet Impacts

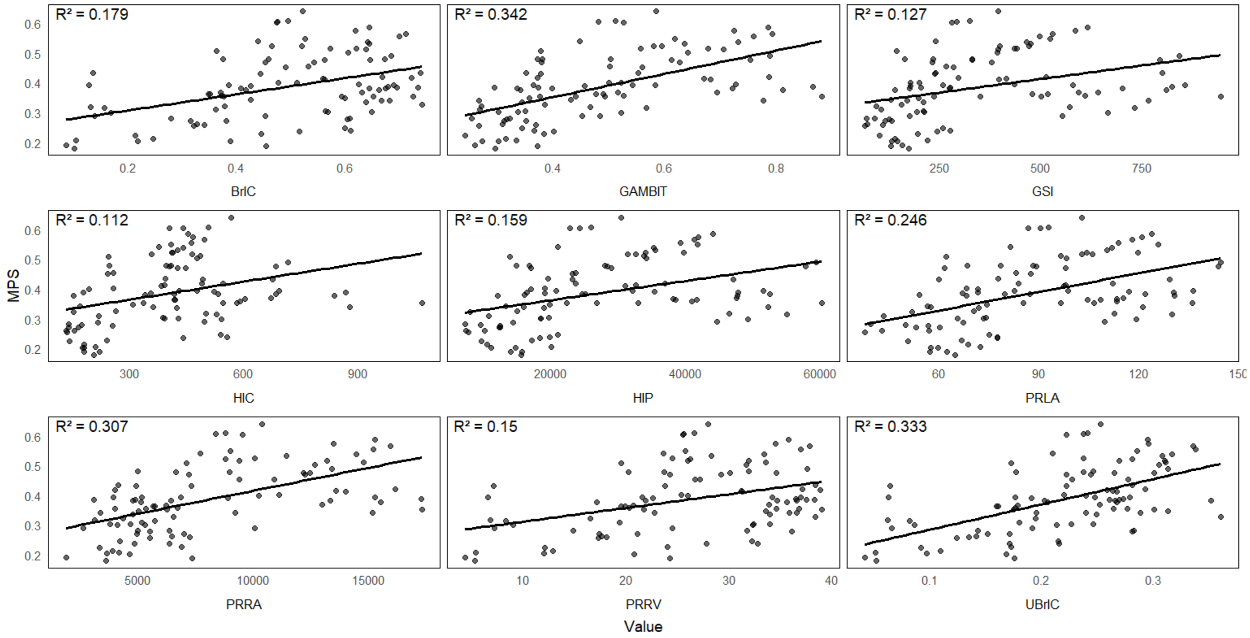
	Mean MPS (±SD)	
Inbound Velocity (m/s)	Adult	Youth
3.46	0.265 (0.068)	0.290 (0.062)
4.23	0.435 (0.071)	0.392 (0.055)
4.88	0.510 (0.075)	0.460 (0.054)
5.00	*N/A*	0.323 (0.058)
5.46	0.446 (0.094)	0.446 (0.089)
6.00	0.340 (0.065)	*N/A*
Overall	0.386 (0.112)	0.383 (0.100)

5.2 Linear Regression Correlations

Figure 1 presents the linear regressions and R^2 values of each kinematic brain injury metric and peak resultant kinematic variable against MPS during adult NOCSAE standard tests. GAMBIT revealed the highest correlation with MPS for adult testing protocols ($R^2 = 0.342$), followed by UBrIC ($R^2 = 0.333$). PRRA demonstrated the highest correlation of all peak resultant kinematic variables ($R^2 = 0.307$), followed by PRLA ($R^2 = 0.246$). BrIC ($R^2 = 0.179$) and HIP ($R^2 = 0.159$) showed slightly greater correlation with MPS than PRRV ($R^2 = 0.150$), although lower than the other peak resultant kinematic variables. The GSI had the second-lowest correlation ($R^2 = 0.127$), outperforming only HIC ($R^2 = 0.112$). A table summarizing the coefficient of determination and correlation strength of each metric for adult test data can be found in Appendix E.

Figure 1

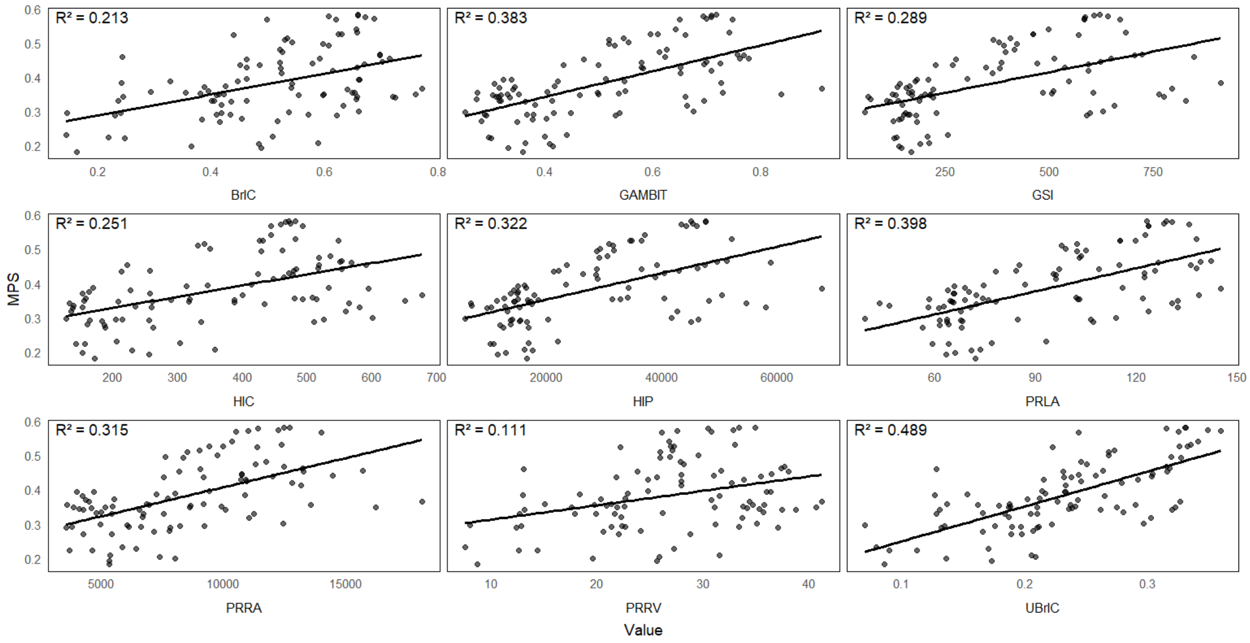
Linear Regressions of Peak Resultant Kinematics and Kinematic Brain Injury Metrics, Plotted Against MPS for NOCSAE Adult Football Helmet Impacts



Under youth impact testing conditions, UBrIC demonstrated the highest correlation with MPS ($R^2 = 0.489$). For the peak resultant kinematic variables, PRLA correlated best with MPS, with an R^2 value of 0.398. GAMBIT and HIP ($R^2 = 0.383$ and 0.322, respectively) marginally outperformed PRRA ($R^2 = 0.315$), whereas GSI, HIC, and BrIC ($R^2 = 0.289$, 0.251, and 0.213, respectively) only demonstrated greater correlations than PRRV ($R^2 = 0.111$). Youth regression results are shown in Figure 2. Appendix E contains a summary table of R^2 values and correlation strength for the youth dataset.

Figure 2

Linear Regressions of Peak Resultant Kinematics and Kinematic Brain Injury Metrics, Plotted Against MPS for NOCSAE Youth Football Helmet Impacts



5.3 Prediction of MPS

5.3.1 Kinematic Brain Injury Metrics

Figure 3 shows the prediction results using linear regression models for single peak resultant kinematic variables or kinematic metrics as a predictor of MPS under adult NOCSAE test protocols. Of all linear regression models, GAMBIT (R^2 = 0.332, RMSE = 0.092) and UBrIC (R^2 = 0.319, RMSE = 0.092) demonstrated the greatest predictive performance for adult testing, while BrIC (R^2 = 0.166, RMSE = 0.102), HIP (R^2 = 0.150, RMSE = 0.103), GSI (R^2 = 0.118, RMSE = 0.105), and HIC (R^2 = 0.102, RMSE = 0.106) achieved the worst results. Linear regression of PRRA (R^2 = 0.297, RMSE = 0.094) and PRLA (R^2 = 0.234, RMSE = 0.098) predicted MPS moderately better than BrIC, HIP, GSI, and HIC, while PRRV (R^2 = 0.137, RMSE = 0.104) outperformed only GSI and HIC.

When using a random forest regression model as opposed to linear regression, effects varied; however, performance remained largely the same. GSI ($R^2 = 0.292$, RMSE = 0.097), BrIC ($R^2 = 0.269$, RMSE = 0.098), HIC ($R^2 = 0.244$, RMSE = 0.103), PRRV ($R^2 = 0.193$, RMSE = 0.105), and HIP ($R^2 = 0.189$, RMSE = 0.108) demonstrated marginal improvements, whereas UBrIC ($R^2 = 0.263$, RMSE = 0.099), PRRA ($R^2 = 0.233$, RMSE = 0.103), GAMBIT ($R^2 = 0.232$, RMSE = 0.104), and PRLA ($R^2 = 0.170$, RMSE = 0.107) slightly decreased in predictive performance. Prediction results of random forest models using single peak resultant kinematic variables or kinematic metrics are shown in Figure 4.

Figure 3

MPS Predicted by Linear Regressions of Kinematic Brain Injury Metrics and Peak Resultant Kinematics, Plotted Against Actual MPS Calculated from NOCSAE Adult Football Helmet Impacts

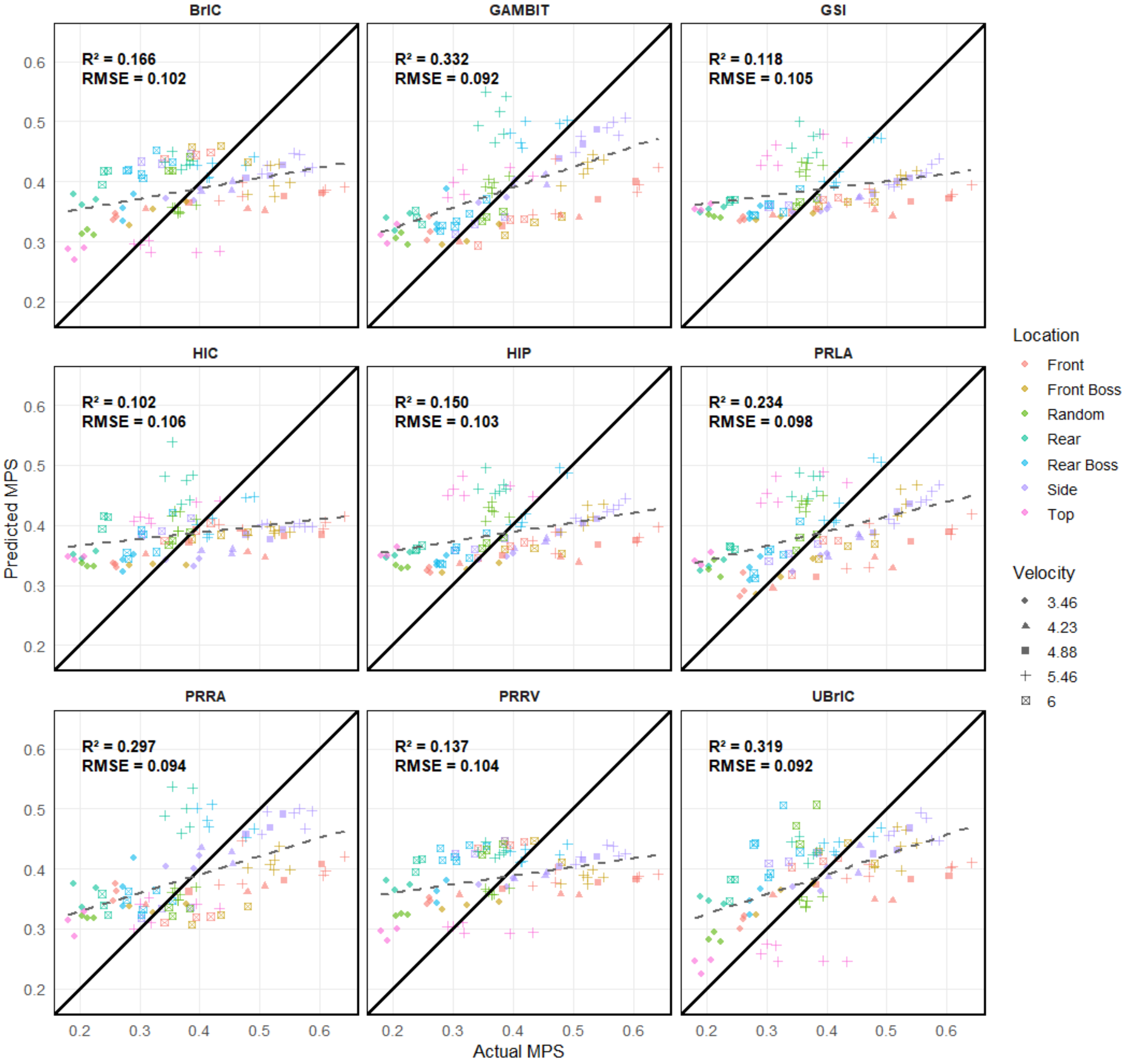
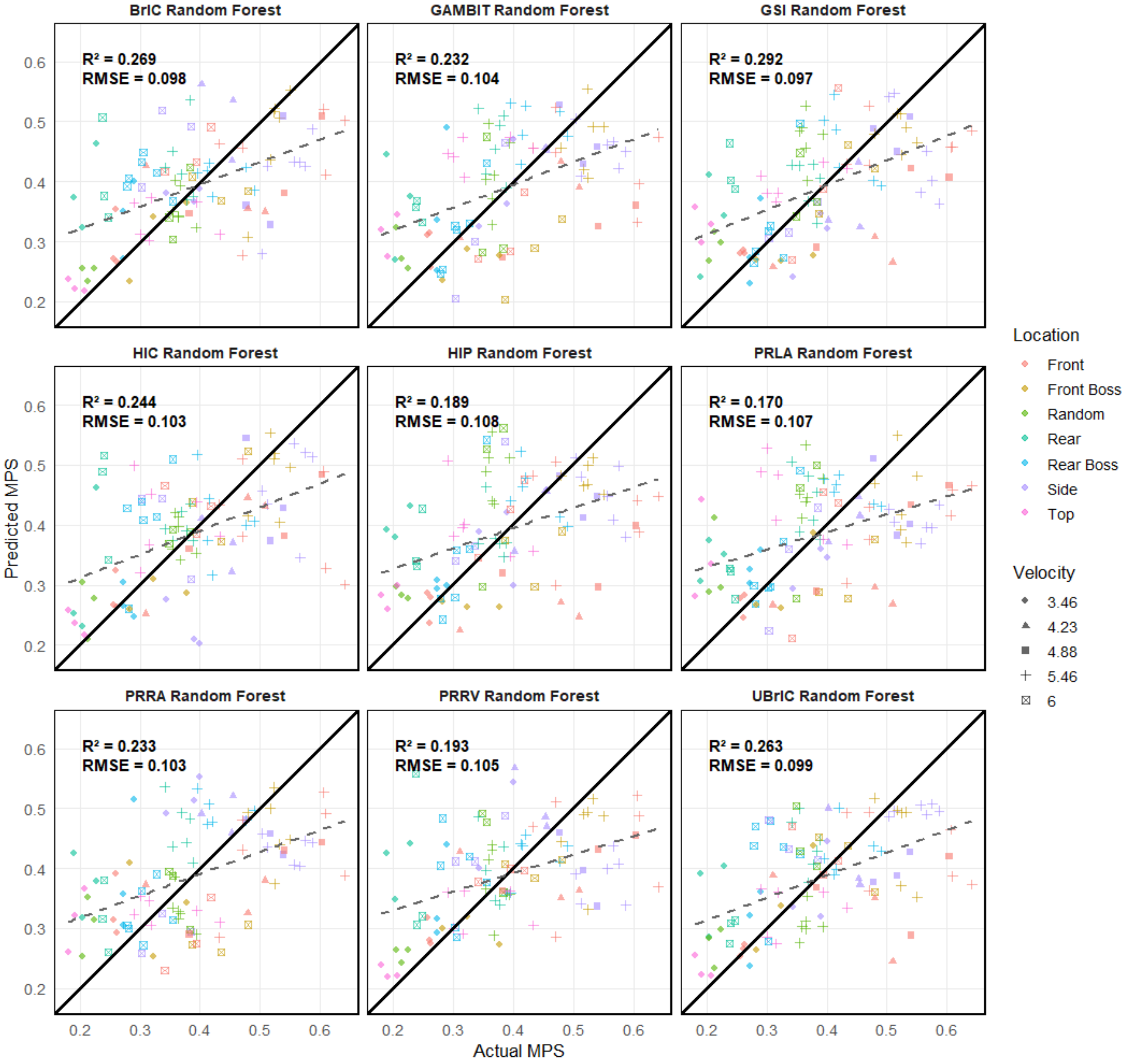


Figure 4

MPS Predicted by Random Forest Regressions of Kinematic Brain Injury Metrics and Peak Resultant Kinematics, Plotted Against Actual MPS Calculated from NOCSAE Adult Football Helmet Impacts



Regression models of kinematic metrics achieved similar predictive performance for youth testing protocols as for adult protocols (Figure 5). Linear regressions of UBrIC (R^2 = 0.467, RMSE = 0.073) and GAMBIT (R^2 = 0.358, RMSE = 0.080) achieved the greatest results of the kinematic brain injury metrics. HIP (R^2 = 0.246, RMSE = 0.088), GSI (R^2 = 0.231, RMSE = 0.088), HIC (R^2 = 0.217, RMSE = 0.089), and BrIC (R^2 = 0.196, RMSE = 0.090) demonstrated poorer performance. PRLA (R^2 = 0.369, RMSE = 0.080) predicted MPS with greater accuracy than other peak resultant kinematic variables, also outperforming all metrics except UBrIC. PRRA (R^2 = 0.285, RMSE = 0.085) achieved greater results than HIP, GSI, HIC, and BrIC, while PRRV (R^2 = 0.096, RMSE = 0.095) performed the worst of all models.

Similar to adult models, random forest regression produced negligible changes in model performance when applied to youth impact test data (Figure 6). Marginal performance improvements were observed in UBrIC (R^2 = 0.517, RMSE = 0.070), GSI (R^2 = 0.313, RMSE = 0.087), HIP (R^2 = 0.294, RMSE = 0.087), and HIC (R^2 = 0.248, RMSE = 0.091), while GAMBIT (R^2 = 0.351, RMSE = 0.083), PRLA (R^2 = 0.305, RMSE = 0.087), PRRA (R^2 = 0.246, RMSE = 0.091), PRRV (R^2 = 0.043, RMSE = 0.107), and BrIC (R^2 = 0.043, RMSE = 0.110) demonstrated slight decreases in predictive performance. Summary tables containing the performance measures of each kinematic metric-based prediction model can be found in Appendix F.

Figure 5

MPS Predicted by Linear Regressions of Kinematic Brain Injury Metrics and Peak Resultant Kinematics, Plotted Against Actual MPS Calculated from NOCSAE Youth Football Helmet Impacts

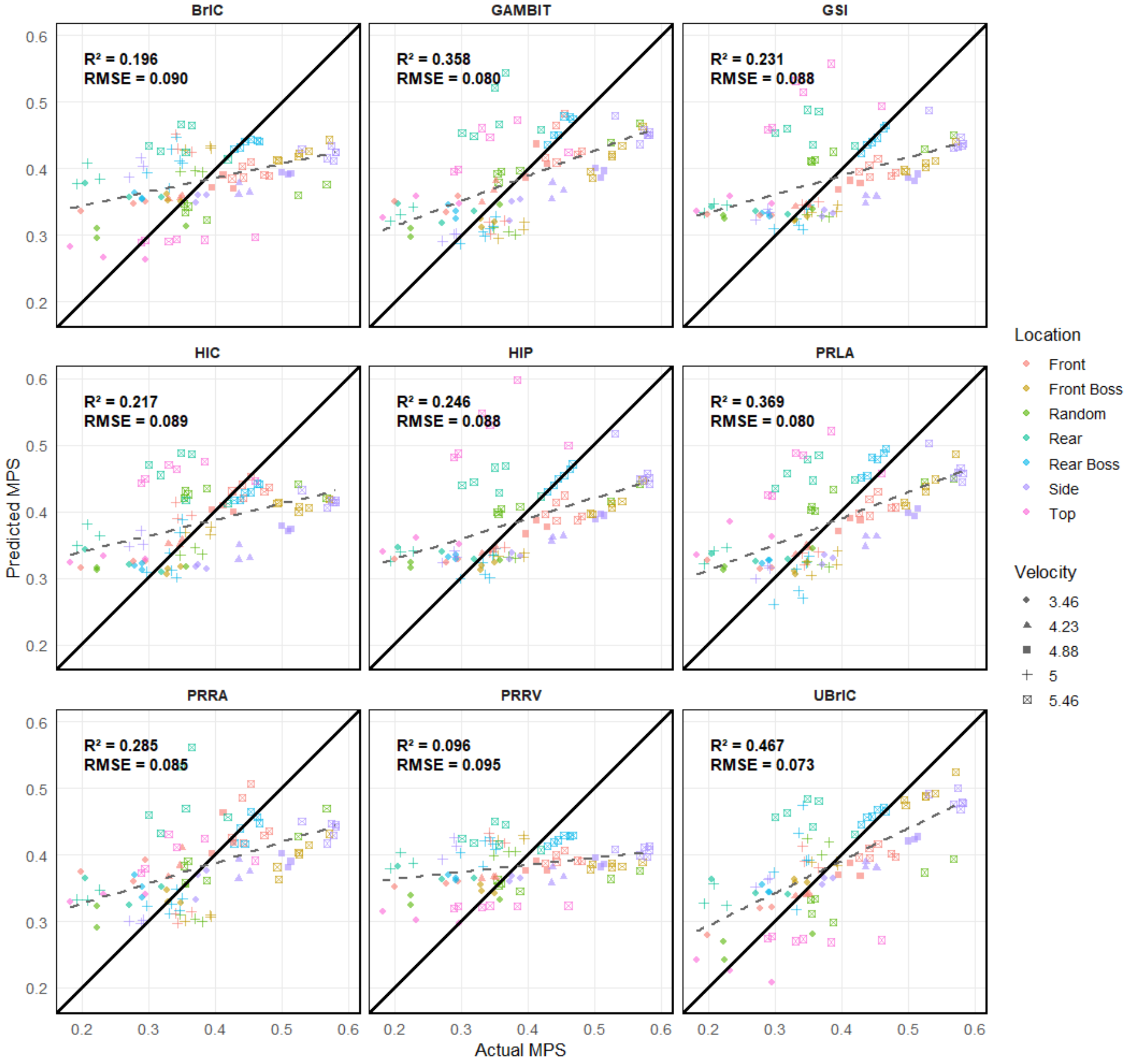
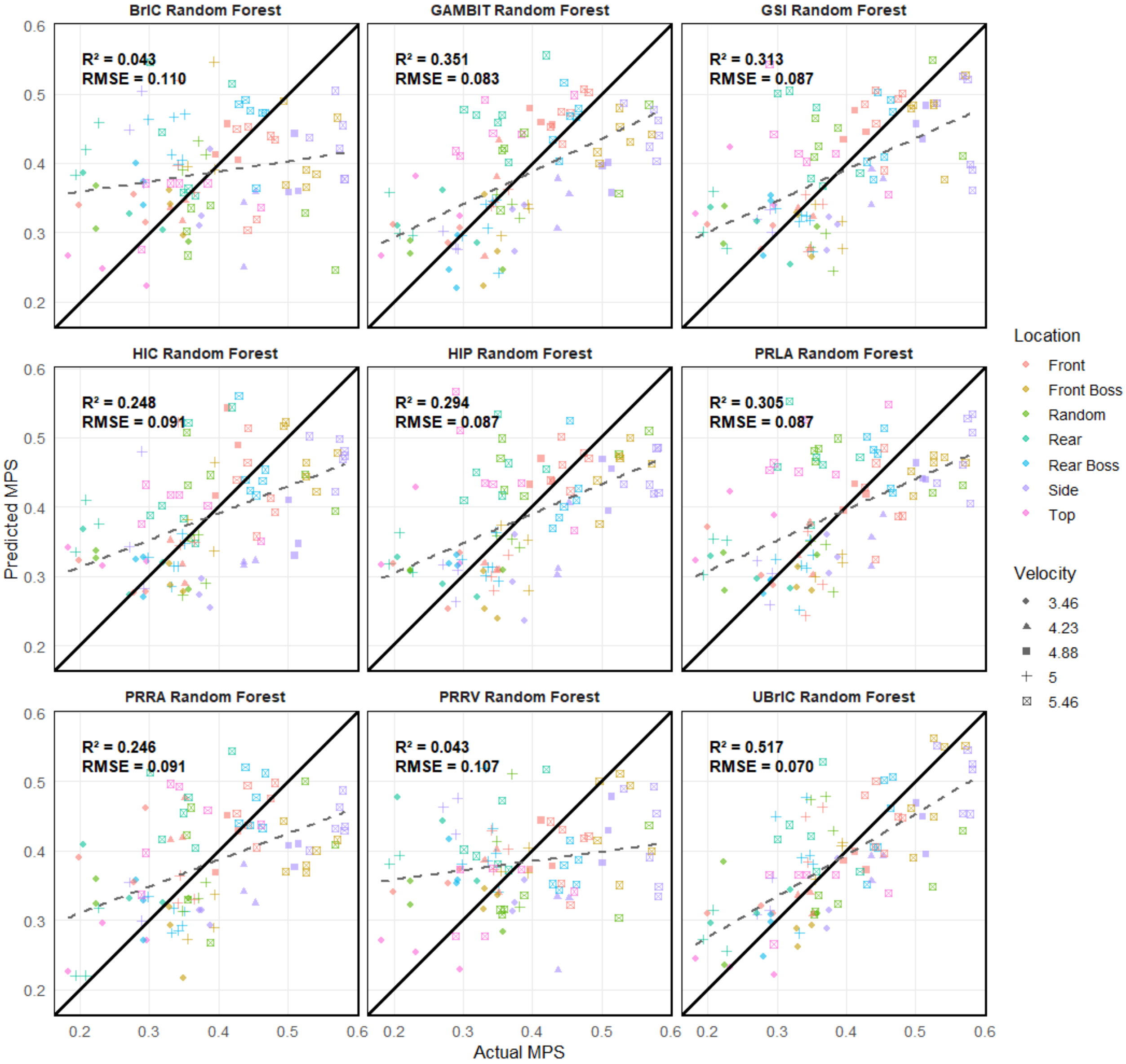


Figure 6

MPS Predicted by Random Forest Regressions of Kinematic Brain Injury Metrics and Peak Resultant Kinematics, Plotted Against Actual MPS Calculated from NOCSAE Youth Football Helmet Impacts



5.3.2 Peak Kinematic Variables

Predictive performance of multiple regression models based on peak kinematic variables are presented in Figure 7. Multiple regression of peak resultant kinematics demonstrated greater performance in predicting MPS for adult testing protocols when compared to all other models based on kinematic brain injury metrics, achieving $R^2 = 0.362$ and RMSE = 0.089. When peak kinematic components were used as predictor variables for the multiple regression model, predictive performance marginally increased ($R^2 = 0.416$, RMSE = 0.086). Including both peak resultant kinematics and peak kinematic components as predictors led to a substantial increase in multiple regression model performance ($R^2 = 0.862$, RMSE = 0.042). Figure 8 shows that random forest regression outperformed multiple regression models when predicting MPS from peak resultant kinematics ($R^2 = 0.539$, RMSE = 0.076), peak kinematic components ($R^2 = 0.883$, RMSE = 0.041), and all kinematics combined ($R^2 = 0.906$, RMSE = 0.037).

Figure 7

MPS Predicted by Multiple Regression of Peak Resultant Kinematics, Peak Kinematic Components, and All Peak Kinematics, Plotted Against Actual MPS Calculated from NOCSAE Adult Football Helmet Impacts

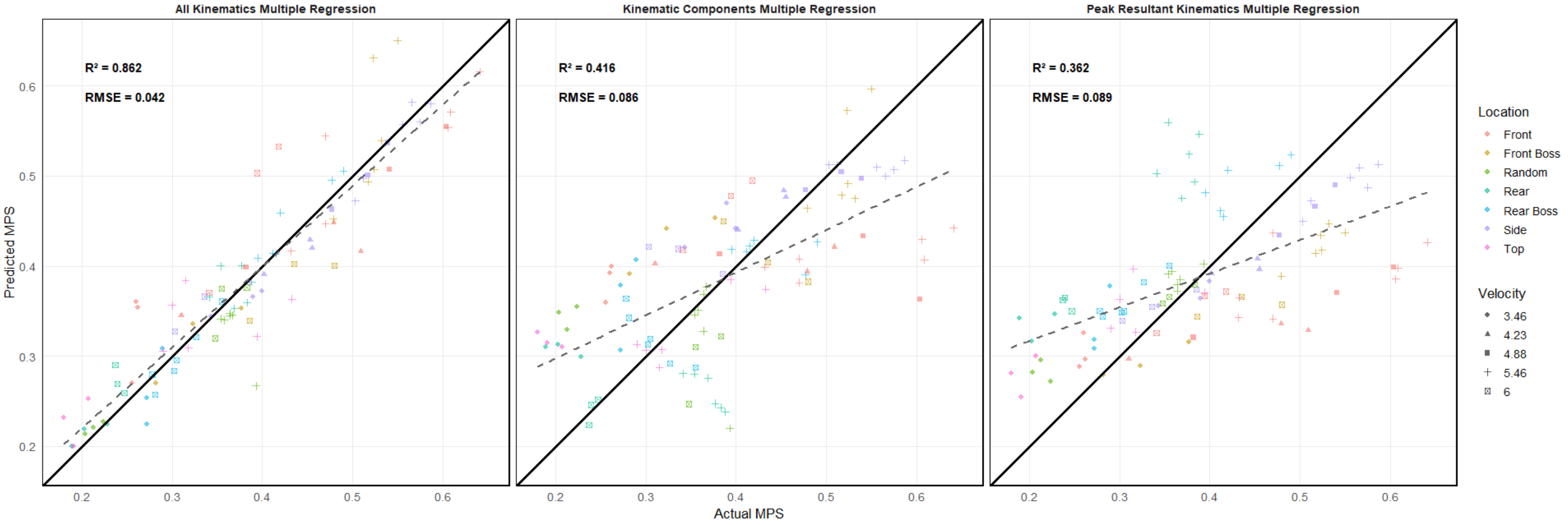
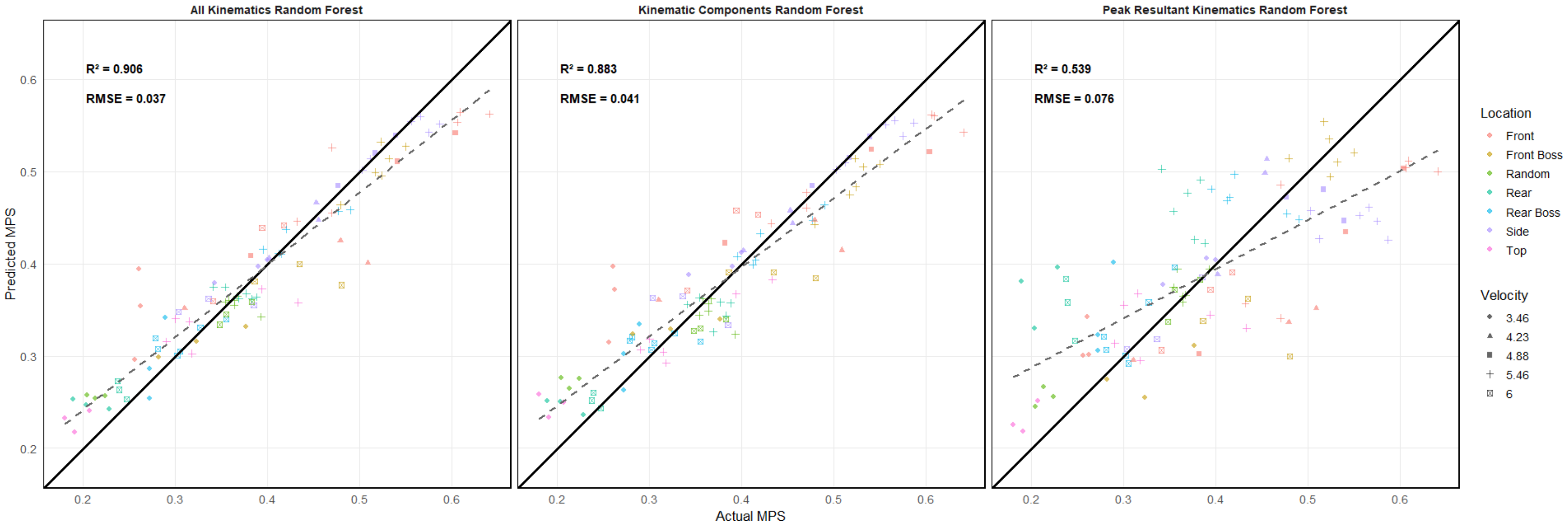


Figure 8

MPS Predicted by Random Forest Regression of Peak Resultant Kinematics, Peak Kinematic Components, and All Peak Kinematics, Plotted Against Actual MPS Calculated from NOCSAE Adult Football Helmet Impacts



Multiple regression of kinematics demonstrated similar predictive performance for youth impacts as for adult (Figure 9). Model prediction performance was greatest when both peak resultant kinematics and peak kinematic components were included as predictor variables (R^2 = 0.831, RMSE = 0.041), followed by peak kinematic components only (R^2 = 0.609, RMSE = 0.063), then peak resultant kinematics only (R^2 = 0.383, RMSE = 0.079). Again, random forest regression improved performance over multiple regression (Figure 10). The random forest regression model based on all kinematics showed a small increase in performance (R^2 = 0.857, RMSE = 0.039), while those using peak kinematic components only (R^2 = 0.860, RMSE = 0.039) and peak resultant kinematics only (R^2 = 0.538, RMSE = 0.068) demonstrated large improvements over multiple regression. Appendix G contains summary tables of the performance measures for each peak kinematics-based prediction model.

Figure 9

MPS Predicted by Multiple Regression of Peak Resultant Kinematics, Peak Kinematic Components, and All Peak Kinematics, Plotted Against Actual MPS Calculated from NOCSAE Youth Football Helmet Impacts

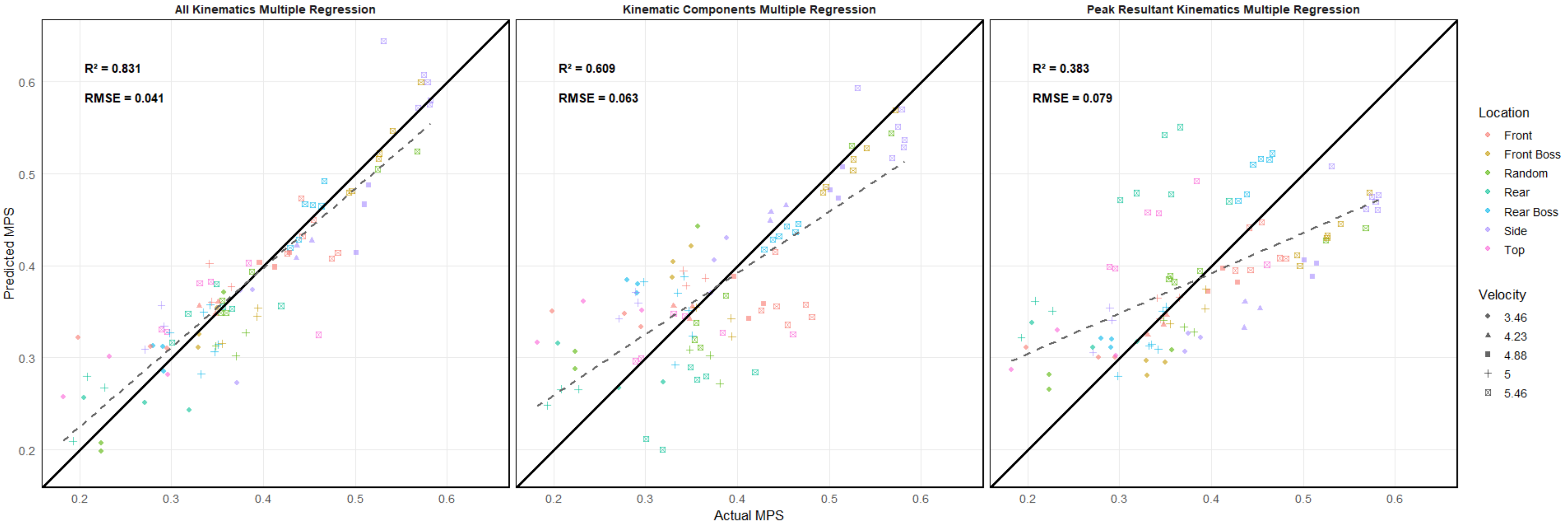
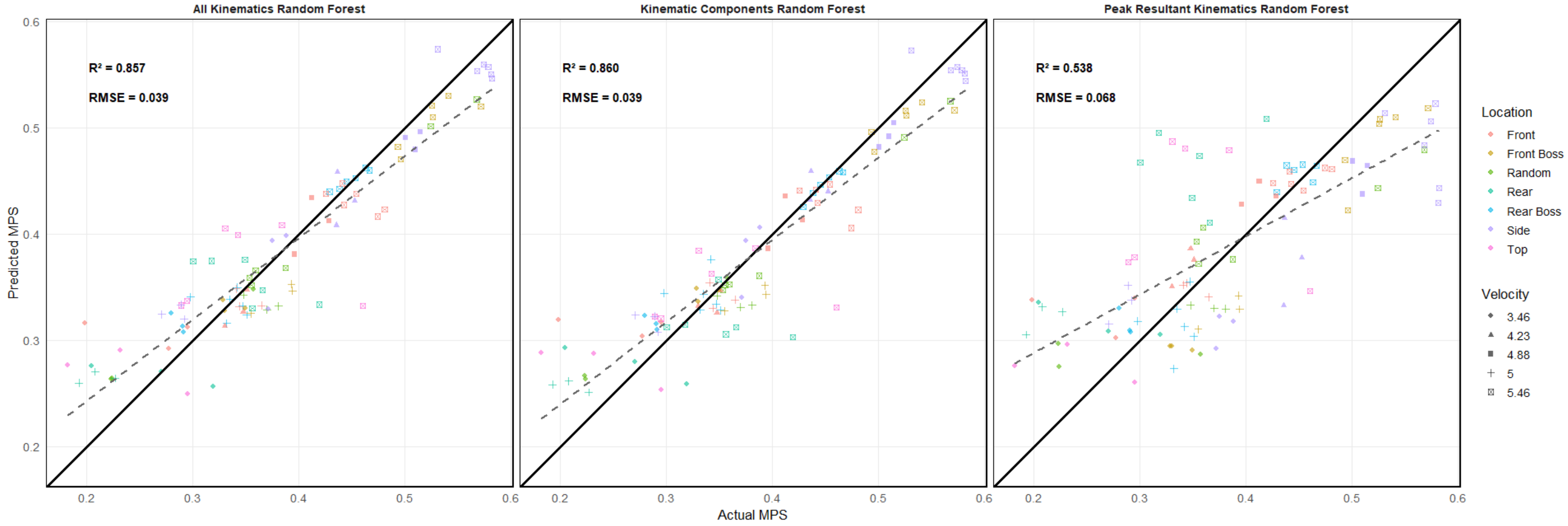


Figure 10

MPS Predicted by Random Forest Regression of Peak Resultant Kinematics, Peak Kinematic Components, and All Peak Kinematics, Plotted Against Actual MPS Calculated from NOCSAE Youth Football Helmet Impacts



6. Discussion

The results of this study reveal a clear progression in predictive performance across the different modeling approaches. First, kinematic brain injury metrics demonstrated weak correlations and predictions of MPS under NOCSAE impact conditions. Second, models based on individual peak resultant kinematic variables also showed limited predictive capability, indicating that single measures of head motion do not adequately represent the biomechanical factors influencing brain tissue strain. Finally, prediction accuracy improved substantially when multiple peak kinematic variables and their directional components were incorporated into multivariable regression and random forest models. This progression suggests that brain tissue deformation during NOCSAE standard impacts is greatly influenced by complex interactions between multiple aspects of head kinematics that cannot be fully represented using single metrics. The following section discusses potential explanations and implications of these findings in the context of the existing literature.

6.1 Maximum Principal Strain

MPS represents the deformation experienced by brain tissue during head impacts and has been associated with injury mechanisms relevant to concussion. Excessive strain can produce deformation of neuronal axons and surrounding cellular structures, potentially disrupting neural signaling and leading to the transient neurological symptoms characteristic of concussive injury (Blumbergs et al., 1994; Povlishock, 1992; Smith et al., 1999; Tang-Schomer et al., 2010; Wilde et al., 2008; Wright & Ramesh, 2012). Because of this relationship, MPS derived using FE brain models is used as a biomechanical surrogate for concussion risk in impact studies (Cournoyer & Hoshizaki, 2021; Ghazi et al., 2021; Kleiven, 2007; McAllister et al., 2012; Patton et al., 2013; Post et al., 2018; Taylor et al., 2019, 2020; Zhang et al., 2004).

FE analysis of NOCSAE standard impacts found that adult and youth protocols resulted in mean MPS values of 0.386 and 0.383, respectively. A large range of MPS values was produced, from 0.180 to 0.641. These values are within the concussive range proposed in the literature (Kimpara & Iwamoto, 2012; Kleiven, 2007; Patton et al., 2013; Zhang et al., 2004), with the higher MPS values observed in this study representing a greater risk of loss of consciousness and persistent post-concussion symptoms (Cournoyer & Hoshizaki, 2021; Koncan, 2018; Post et al., 2015). Despite strain measurements reflecting concussive injury risk, no impact surpassed the NOCSAE certification threshold values for GSI or PRRA, suggesting these thresholds are not intended to represent the risk of concussion. These findings present an opportunity for the improvement of helmet performance criteria to better represent the mechanisms of concussive injury.

6.2 Linear Regression Correlations

Correlations with MPS were compared between various kinematic brain injury metrics and peak resultant kinematic variables to provide insight into the relationship between these measures and concussive injury risk represented by MPS under NOCSAE standard impact conditions. Linear regression of kinematic brain injury metrics revealed poor correlations with MPS ($R^2 < 0.4$). The sole exception was UBrIC under youth impact conditions, which demonstrated moderate correlation ($0.4 < R^2 < 0.7$). For both adult and youth data, GAMBIT and UBrIC demonstrated the highest correlation, while GSI and HIC achieved among the lowest correlations. Certain kinematic brain injury metrics, particularly those including multiple kinematic variables, may capture more of the variance in MPS produced during NOCSAE standard impact testing than those currently used as evaluation criteria; however, differences are marginal and even the best-performing metric demonstrated poor correlation with MPS. This is likely due to the presence of multiple factors influencing MPS that are not reflected in these metrics, such as impact location, temporal characteristics of the kinematic curve, and brain tissue properties. In addition, the complex interactions between these factors and linear and rotational kinematics likely creates a non-linear relationship with strain. Although many of these metric equations are non-linear, the functions remain simple, inflexible curves that do not adapt to the conditional interactions that influence MPS. Assessing correlations using linear regression assumes that metrics scale linearly with MPS; however, non-linear methods may represent the relationship between these variables more accurately.

These findings are consistent with previous research showing UBrIC to correlate better with FE measures of brain tissue strain than other kinematic brain injury metrics for car accident and hockey-relevant head impact characteristics (Levy et al., 2021; Osth et al., 2023). In contrast, although Gabler et al. (2016) also found HIC, HIP, and GSI to correlate poorly with MPS for car accident impact characteristics, correlations of GAMBIT ($R^2 = 0.032$) and BrIC ($R^2 = 0.778$) differed greatly from the present study. This would suggest that metric performance varies depending on the characteristics of a given impact. Kinematic brain injury metrics were developed using datasets containing impacts with specific characteristics and injury outcomes; therefore, their predictive performance depends on how closely new impact conditions and injury mechanisms align with those represented in the original development dataset. For example, a metric developed using impacts dominated by linear accelerations to predict risk of skull fracture will likely correlate poorly with brain tissue strain measured from rotationally dominant impacts. This may also play a role in the observed differences in PRRV performance between studies (Gabler et al., 2016; Levy et al., 2021). Differences in hockey and automotive impact characteristics may have resulted in greater rotational kinematics than observed in NOCSAE testing, resulting in strain measurements largely driven by rotational velocity. This would result in PRRV and BrIC having a higher correlation with MPS than they would for NOCASE standard impacts, in which linear accelerations have a greater influence on MPS. Furthermore, each study employed a different FE model to calculate strain measures, thereby introducing another source of variance. Although results varied slightly, the current research is consistent with the existing literature, finding kinematic brain injury metrics to correlate poorly with measures of brain tissue strain (Gabler et al., 2016; Levy et al., 2021; Osth et al., 2023). While alternative metrics such as GAMBIT and UBrIC may be more associated with MPS than GSI and PRRA under NOCSAE standard test protocols, kinematic brain injury metrics do not capture the variance in MPS produced by these impact characteristics. Therefore, the development of MPS prediction models specific to NOCSAE standard impact conditions may allow for more accurate assessment of the risk of concussive injury during standardized helmet testing.

6.3 Prediction of MPS

Linear regression models of kinematic brain injury metrics and individual peak resultant kinematic variables demonstrated poor capacity to predict MPS from unseen NOCSAE impact data. For both adult and youth data, R^2 values mirrored the full-dataset linear model correlation trends, with only UBrIC achieving moderate correlation ($R^2 = 0.467$) for youth impacts. UBrIC also achieved the lowest MPS prediction error for both adult and youth data (RMSE = 0.092 and 0.073, respectively); however, when considering the standard deviation of MPS within the adult and youth datasets were 0.112 and 0.100, respectively, prediction error for all linear regression models can be interpreted as high (RMSE > 70% SD of MPS). These findings demonstrate that linear regressions of kinematic brain injury metrics and peak resultant kinematics are poor predictors of MPS under NOCSAE football helmet test conditions. This was to be expected given the poor associations with MPS. Because metrics and peak resultant kinematics are unable to capture much of the variance in MPS during NOCSAE impact testing, they provide little benefit for predicting MPS from new data when used as single predictors.

Random forest regression of each kinematic metric and peak resultant kinematic variable resulted in no meaningful change from linear regression models. While some metrics saw an increase in performance and others saw a decrease, differences were marginal and performance remained poor for all models. RMSE of all models remained high in comparison to the standard deviation of MPS for the respective datasets, and all correlations were low ($R^2 < 0.4$; RMSE > 80% SD of MPS). The only exception was UBrIC with youth data, which had moderate correlation ($R^2 = 0.517$); however, prediction error remained high (RMSE = 0.070; 70% SD of MPS). Negligible differences between random forest and linear regression models can be attributed to the fact that these two methods result in similar functions when there is only one predictor variable. The benefit of a random forest model is that it is able to learn non-linear interactions between variables that a linear regression model cannot. When there is only one predictor variable, this is not possible. Instead, when only a single predictor is used, random forest regression reduces to a collection of one-dimensional trees that partition the predictor into intervals and assign the mean response within each interval. Because the predictor variables examined in this research generally increase with greater MPS, this piecewise-constant approximation resembles a linear fit, resulting in little meaningful difference in predictive performance compared to linear regression. Therefore, this research shows that kinematic brain injury metrics and peak resultant kinematics are poor predictors of MPS during NOCSAE standard testing, regardless of whether linear or random forest regression is employed. These findings generally align with pre-experimental expectations based on the original purposes of each kinematic brain injury metric. Most of the examined metrics were developed to predict TBIs using datasets of head impacts with characteristics different from those produced under NOCSAE standard test conditions, and they reflect injury mechanisms and anatomical structures that differ from those associated with strain-based injuries (Gadd, 1966; Newman, 1986; Newman & Shewchenko, 2000; Takhounts et al., 2013). As a result, these metrics are not expected to associate with MPS under NOCSAE standard impact conditions. Although HIP and UBrIC were developed specifically for sport-related brain injuries predominantly driven by rotation-induced brain tissue strain (Gabler et al., 2018; Versace, 1971), the current research found these metrics to be poor predictors of MPS. This further demonstrates the need for strain-based head injury criteria specific to the impact characteristics generated during NOCSAE standard testing.

With the aim of improving predictive performance over single-predictor models, multiple regression models were developed using various combinations of peak kinematic variables. The baseline model consisted of peak resultant kinematic predictors (PRLA, PRRA, and PRRV). Given the known influence of impact location and loading direction on measures of brain tissue strain (Gennarelli et al., 1987; Kleiven, 2003, 2005; Post et al., 2014, 2018; Prange & Margulies, 2002; Prange & Meaney, 2000; Taylor et al., 2020; Zhang et al., 2001), it was hypothesized that directional kinematic variables may improve model performance. Therefore, a second model was developed using the peak components (x, y, and z) of linear acceleration, rotational acceleration, and rotational velocity as predictors. A third model was then created, combining the predictor variables from the previous two models to determine whether including both the peak resultant kinematics and their peak components improved predictive performance. Multiple regression of only peak resultant kinematics demonstrated similar performance to linear and random forest regression of kinematic metrics for the adult and youth datasets, while using peak kinematic components marginally improved MPS predictions for both age groups. Including all peak kinematic variables (resultants and components) as predictors greatly improved model performance, demonstrating high correlation and relatively low error ($R^2 > 0.83$, RMSE < 0. 04). These findings suggest that both peak resultant kinematics and their peak components are influential in the calculation of MPS and should be considered in combination for improved predictive performance when using a multiple regression model structure. A potential explanation for the difference in performance between the two simpler models and the model including all kinematics is that both peak resultant kinematics and peak kinematic components provide unique information. Peak kinematic components provide information regarding loading direction and axis dominance; however, the magnitude of each component reflects peak magnitude along only one axis, thereby underestimating the overall magnitude of the impact. While peak resultant kinematics do not provide directional information, they better represent the overall loading magnitude as the vector sum of the three components. Furthermore, peak magnitudes of each component and resultant may occur at different times within the kinematic response curve. As a result, including all of these variables may provide information regarding the temporal structure of the impact. Differences between component and resultant peak relationships may reflect curve shape and duration characteristics, which are known to influence MPS (Hoshizaki et al., 2013; Post et al., 2012; Post, Hoshizaki, Gilchrist, & Cusimano, 2017; Yoganandan et al., 2008). Since MPS depends on impact magnitude, loading direction, and the shape and duration of the kinematic response curve (Hoshizaki et al., 2013; Hoshizaki, Post, et al., 2017; Post et al., 2012; Post, Hoshizaki, Gilchrist, & Cusimano, 2017; Taylor et al., 2020; Yoganandan et al., 2008), combining these features provides a more complete representation of the mechanical drivers of brain deformation; however, this information allows for only weak encoding of temporal information and does not provide a true time-series representation.

Three random forest models were developed to predict MPS using the same combinations of kinematic predictor variables as the previous multiple regression models. This was conducted with the aim of determining whether non-linear machine learning models could improve predictive performance over linear equations. Increased prediction correlation and decreased prediction error were observed in all random forest models compared to their multiple regression equivalents for both adult and youth datasets. Random forest regression likely outperformed multiple linear regression because it can capture non-linear and interaction effects among correlated kinematic predictors. Multiple regression assumes that the effects of each variable on MPS are linear, independent, and additive. In contrast, random forests model the response through recursive threshold-based splits, which naturally capture the non-linear relationships and conditional interactions that are present among kinematic predictors (Post et al., 2013b; Post, Hoshizaki, Gilchrist, & Cusimano, 2017; Post & Blaine Hoshizaki, 2015). Furthermore, differences between peak component and resultant magnitudes may encode implicit information about kinematic response curve shape and duration characteristics, which are unlikely to influence MPS in a purely linear or additive manner. Random forests can flexibly model these complex relationships without requiring explicit interaction terms, whereas linear regressions do not. Although employing random forest regression greatly improved performance in the models using only peak resultant kinematics or only peak kinematic components compared to their multiple regression equivalents, the random forest models including all kinematic variables only marginally outperformed multiple regression. This is likely due to a “ceiling effect”, with multiple regression model performance already high, leaving little room for improvement without including additional variables. When all kinematic variables are included as predictors, the multiple regression model already captures most of the explainable variance, leaving limited structured signal for the more flexible random forest to exploit. The remaining unexplained variance likely arises from noise in experimental measurements, FE model variability, or other biomechanical factors influencing MPS that are not encoded by kinematics, such as brain tissue properties and temporal curve features. In contrast, when using peak kinematic components or resultants alone, non-linear interactions between predictors were not fully represented within a linear additive framework, allowing the random forest to provide larger gains. Interestingly, random forest regression of peak kinematic components resulted in very similar predictive performance to the random forest model using all kinematic variables. This suggests that, although the additional information provided by peak resultant kinematics is beneficial for the performance of multiple regression models, random forests are able to extract the majority of this information from peak kinematic components alone. As a result, including peak resultant kinematic variables as predictors in the random forest model does not meaningfully affect performance compared to using peak kinematics alone.

Overall, results demonstrated single peak resultant kinematic variables and kinematic brain injury metrics to be poor predictors of MPS under adult and youth NOCSAE standard impact conditions, whether linear or random forest regression model structures were employed. Multiple regression of both peak resultant kinematics and peak kinematic components greatly improved predictions, while random forest regression of peak kinematic components further (albeit marginally) improved performance beyond multiple regression. Including both peak resultant kinematics and peak kinematic components as predictors did not meaningfully affect random forest model predictive performance compared to peak kinematic components alone.

Findings suggest that the current NOCSAE football helmet evaluation criteria (GSI and PRRA) do not reflect strain-based brain injury risk during standard helmet impacts. Random forest regression models demonstrate high capacity to predict MPS from kinematic data obtained during standard impacts, providing a biologically meaningful measure for predicting concussive injury risk. This research supports the notion of incorporating multiple kinematic variables into football helmet performance criteria to better represent the risk of concussion during testing. Multivariable models can easily be integrated into certification protocols, without requiring additional equipment or data collection, to predict brain tissue strain. In doing so, test standards may provide a more accurate measure of concussive injury risk to guide helmet manufacturers in developing safer equipment.

6.4 Limitations

As described, a 6.88 kg linear impactor arm was not available for use during youth helmet testing, and a 14.0 kg arm was used instead, likely resulting in greater impact magnitudes than those produced in exact NOCSAE youth protocols (Karton et al., 2013). Furthermore, an adult FE model of the brain was scaled to the 95th percentile to represent youth, as opposed to using a youth-specific FE model. While scaling addresses size differences, it does not account for potential differences in material properties (Lenroot & Giedd, 2006; Prange & Margulies, 2002). As a result, strains measured by the UCD2 may not accurately represent the brain tissue response of a youth. Moreover, the UCD2 model is one of many FE models that can be used to measure brain tissue strain, and there exists variability between models with different mesh resolutions, represented tissues, and material models (Dixit & Liu, 2017; Madhukar & Ostoja-Starzewski, 2019). Despite having outputs validated against cadaveric data (Hardy et al., 2001; Nahum et al., 1977), MPS values measured by the UCD2 may vary from other models. MPS is a mathematical estimate of the brain tissue's response to impact and should not be considered ground-truth data as it is unable to capture the influence of strain direction and region on neurological injury. Furthermore, despite research demonstrating high correlation between MPS and concussion (Kleiven, 2007; Patton et al., 2013; Viano et al., 2005; Willinger & Baumgartner, 2003; Zhang et al., 2004), the exact relationship between brain tissue strain and injury is not fully described. As a result, specific MPS values cannot be interpreted as being causative of concussion. These results must be interpreted in terms of injury likelihood. Additionally, the present analysis focused on peak linear and rotational kinematic variables, which describe the magnitude of head motion but do not capture the complete time history of the impact event. Previous studies have demonstrated that brain deformation can be sensitive to the duration and shape of the head acceleration curve (Hoshizaki et al., 2013; Post et al., 2012; Post, Hoshizaki, Gilchrist, & Cusimano, 2017; Yoganandan et al., 2008). As a result, models incorporating full acceleration curves may further improve strain prediction compared to models based solely on peak values. Future work could explore the inclusion of temporal descriptors or complete kinematic time histories. Finally, the analyses performed in this study were conducted using kinematic data from NOCSAE standard football helmet impacts with controlled environments and impact conditions. Therefore, results may not be generalizable to impacts outside of NOCSAE test conditions.

7. Conclusion

This study investigated the relationship between kinematic-based brain injury metrics and FE measures of brain tissue strain under NOCSAE football helmet test conditions. Results found commonly used kinematic brain injury metrics to demonstrate weak associations with MPS, with GSI and HIC exhibiting the lowest associations. Although UBrIC and GAMBIT performed better than other metrics, correlations remained limited. When employed to predict MPS from unseen NOCSAE impact data, linear and random forest regression models using individual kinematic metrics or peak resultant kinematic variables were poor predictors of MPS for both youth and adult testing conditions, with all models producing low correlations and high prediction errors. These findings indicate that the ability of kinematic brain injury metrics to reflect the biomechanical factors associated with brain tissue strain under NOCSAE test conditions is limited, highlighting the potential value of more comprehensive kinematic-based approaches for assessing concussion risk. Furthermore, despite impacts producing brain tissue strains within ranges associated with concussive injury risk, none exceeded the existing NOCSAE certification thresholds. This suggests that current helmet performance criteria primarily reflect mechanisms associated with traumatic brain injury rather than strain-based injury risk.

In contrast to single-metric models, predictive performance improved substantially when multiple kinematic variables were incorporated simultaneously. Multiple regression models using both peak resultant kinematics and their directional components captured a greater proportion of the variance in MPS, while random forest models provided additional, though modest, improvements. These results suggest that combining multiple kinematic measures allows models to better represent the complex interactions between impact magnitude, direction, and temporal characteristics that influence brain tissue strain.

Overall, this research highlights important limitations in existing helmet evaluation criteria and demonstrates the potential for multivariable modeling approaches to more accurately estimate brain tissue strain during standardized helmet testing. Incorporating such approaches into NOCSAE football helmet evaluation standards may provide a more biologically relevant assessment of concussion risk and support the continued development of protective equipment that more effectively mitigates the risk of brain injury in football.

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Appendix A

Figure A1

Adult football helmet models

Left to right: Riddell Axiom, Riddell Speedflex, Riddell Speed Classic Icon

Figure A2

Youth football helmet models

Left to right: Riddell Speedflex, Riddell Speed Classic, Riddell Victor

Appendix B

Figure B1

Wire-guided drop carriage, helmeted headform, and MEP anvil used for NOCSAE football helmet drop impact test protocol.

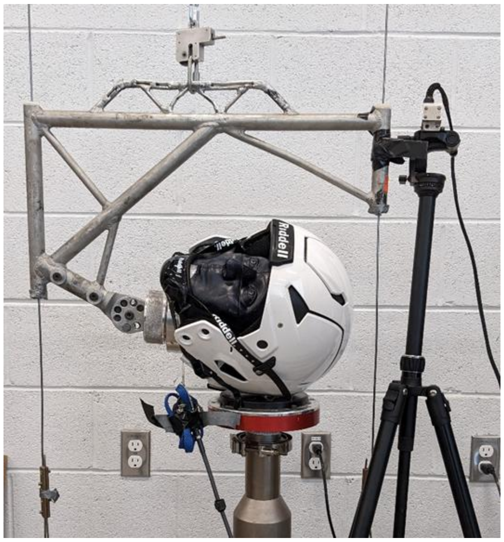
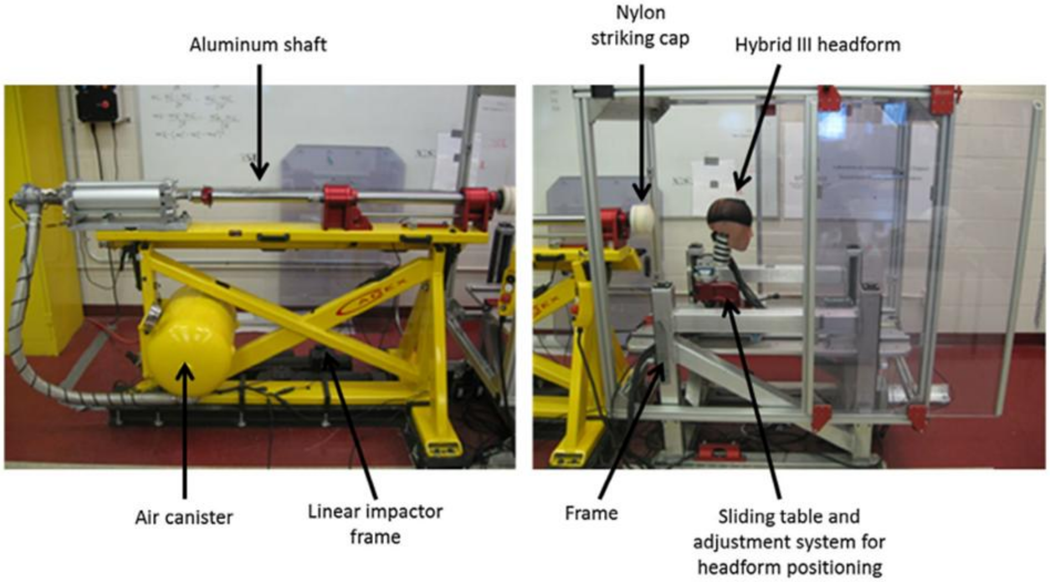


Figure B2

Linear impactor and sliding table rig (Post et al., 2018)



Appendix C

Figure C1

Impact areas described by NOCSAE (2025b)

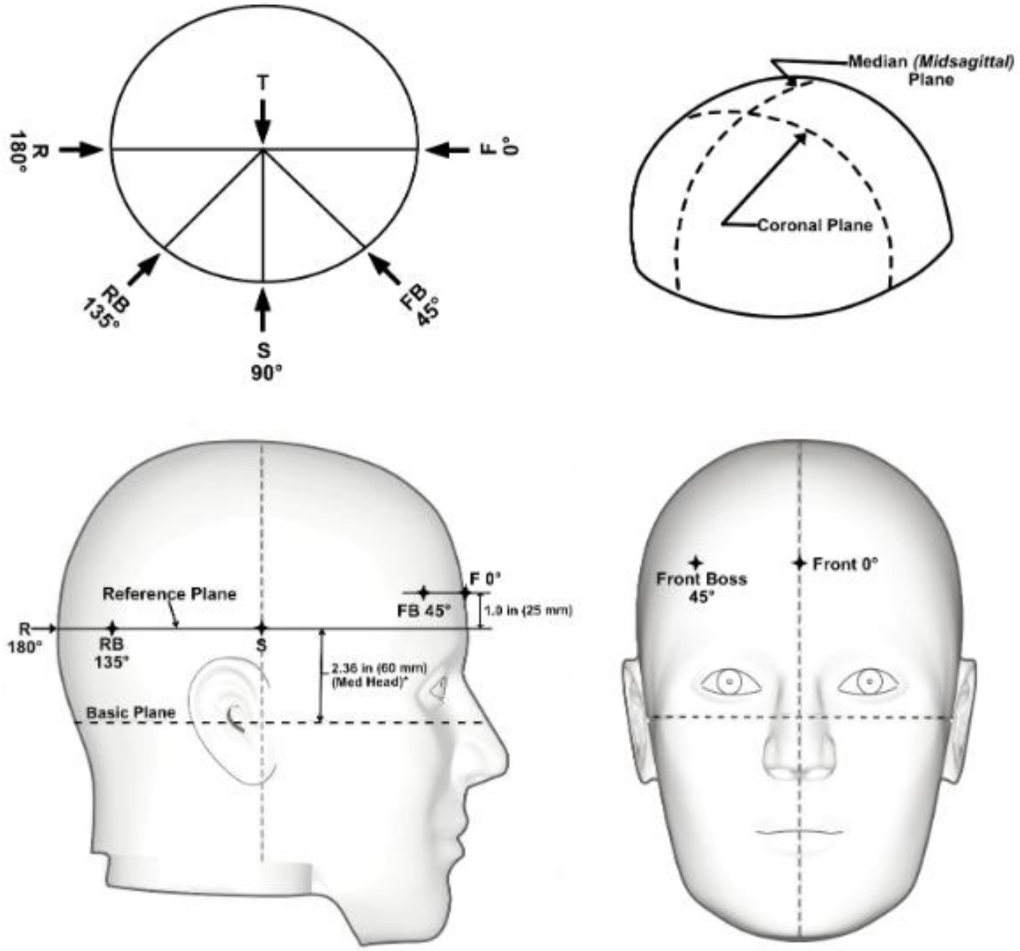


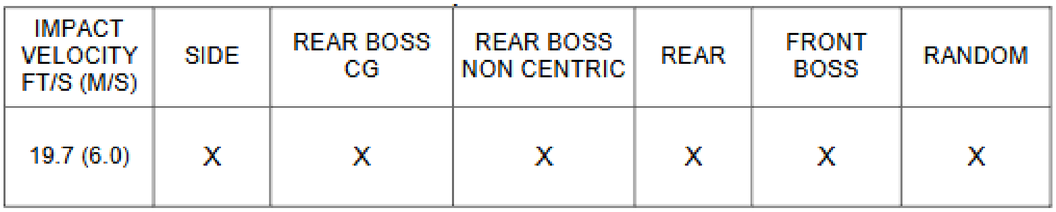
Table C1

Drop impact locations and velocities described by NOCSAE (2025b)

IMPACT VELOCITY FT/S (M/S)	FRONT	SIDE	F. BOSS	R. BOSS	REAR	TOP	RANDOM
11.34 (3.46)	X	X	X	X	X	X	X
13.89 (4.23)	X	X					
16.04 (4.88)	X	X					
17.94 (5.46)	X	X	X	X	X	X	X
17.94 (5.46)	X	X	X	X	X	X	X

Table C2

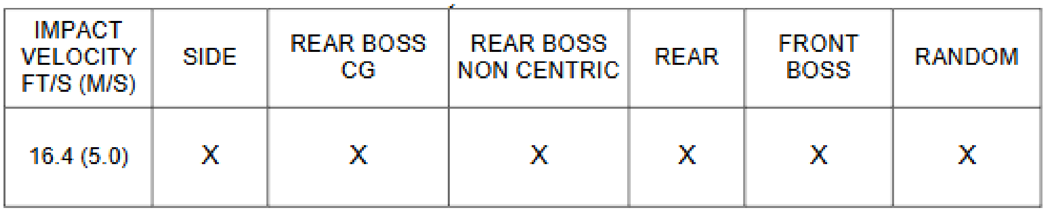
Adult pneumatic ram impact locations and velocities described by NOCSAE (2025b)



IMPACT VELOCITY FT/S (M/S)	SIDE	REAR BOSS CG	REAR BOSS NON CENTRIC	REAR	FRONT BOSS	RANDOM
19.7 (6.0)	X	X	X	X	X	X

Table C3

Youth pneumatic ram impact locations and velocities described by NOCSAE (2025a)



IMPACT VELOCITY FT/S (M/S)	SIDE	REAR BOSS CG	REAR BOSS NON CENTRIC	REAR	FRONT BOSS	RANDOM
16.4 (5.0)	X	X	X	X	X	X

Appendix D

Table D1

Constraints and critical values used in kinematic metric equations

Metric	***Constraints & Critical Values***	***Reference***
GAMBIT	$a_c = 250g$; $\alpha_c = 25 \text{krad/s}^2$; $m, n, s = 2$	Newman (1986)
HIP	$m = 4.5\text{kg}$; $I_x = 0.016\text{kg}\cdot\text{m}^2$; $I_y = 0.024\text{kg}\cdot\text{m}^2$; $I_z = 0.022\ \text{kg}\cdot\text{m}^2$	Newman & Shewchenko (2000)
BrIC	$\omega_{xc} = 66.3\text{rad/s}$; $\omega_{yc} = 53.8\text{rad/s}$; $\omega_{zc} = 41.5\text{rad/s}$	Takhounts et al. (2013)
UBrIC	$\omega_{xcr} = 211\text{rad/s}$; $\omega_{ycr} = 171\text{rad/s}$; $\omega_{zcr} = 115\text{rad/s}$; $\alpha_{xcr} = 20\text{krad/s}^2$; $\alpha_{ycr} = 10.3\text{krad/s}^2$; $\alpha_{zcr} = 7.76\text{krad/s}^2$	Gabler et al. (2018)

Appendix E

Table E1

Coefficient of determination values and correlation strength classifications of linear regression of kinematic metrics against MPS for adult NOCSAE test data

Metric	R^2	*Correlation Strength*
GSI	0.127	Poor
HIC	0.112	Poor
HIP	0.159	Poor
GAMBIT	0.342	Poor
BrIC	0.179	Poor
UBrIC	0.333	Poor
PRLA	0.246	Poor
PRRA	0.307	Poor
PRRV	0.150	Poor

Table E2

Coefficient of determination values and correlation strength classifications of linear regression of kinematic metrics against MPS for youth NOCSAE test data

Metric	R^2	*Correlation Strength*
GSI	0.289	Poor
HIC	0.251	Poor
HIP	0.322	Poor
GAMBIT	0.383	Poor
BrIC	0.213	Poor
UBrIC	0.489	Moderate
PRLA	0.398	Poor
PRRA	0.315	Poor
PRRV	0.111	Poor

Appendix F

Table F1

Performance measures and correlation strength classifications of each linear regression model to predict MPS from kinematic metrics obtained during adult NOCSAE standard testing

Metric	***RMSE***	***NRMSE***	R^2	***Correlation Strength***
GSI	0.105	93.8%	0.118	Poor
HIC	0.106	94.6%	0.102	Poor
HIP	0.103	92.0%	0.150	Poor
GAMBIT	0.092	82.1%	0.332	Poor
BrIC	0.102	91.1%	0.166	Poor
UBrIC	0.092	82.1%	0.319	Poor
PRLA	0.098	87.5%	0.234	Poor
PRRA	0.094	83.9%	0.297	Poor
PRRV	0.104	92.9%	0.137	Poor

Note: Normalized Root Mean Squared Error (NRMSE) is reported as a percentage of the standard deviation of MPS within the test dataset

Table F2

Performance measures and correlation strength classifications of each random forest regression model to predict MPS from kinematic metrics obtained during adult NOCSAE standard testing

Metric	***RMSE***	***NRMSE***	***R^2***	***Correlation Strength***
GSI	0.097	86.6%	0.292	Poor
HIC	0.103	92.0%	0.244	Poor
HIP	0.108	96.4%	0.189	Poor
GAMBIT	0.104	92.9%	0.232	Poor
BrIC	0.098	87.5%	0.269	Poor
UBrIC	0.099	88.4%	0.263	Poor
PRLA	0.107	95.5%	0.170	Poor
PRRA	0.103	92.0%	0.233	Poor
PRRV	0.105	93.8%	0.193	Poor

Note: Normalized Root Mean Squared Error (NRMSE) is reported as a percentage of the standard deviation of MPS within the test dataset

Table F3

Performance measures and correlation strength classifications of each linear regression model to predict MPS from kinematic metrics obtained during youth NOCSAE standard testing

Metric	***RMSE***	***NRMSE***	***R^2***	***Correlation Strength***
GSI	0.088	88.0%	0.231	Poor
HIC	0.089	89.0%	0.217	Poor
HIP	0.088	88.0%	0.246	Poor
GAMBIT	0.080	80.0%	0.358	Poor
BrIC	0.090	90.0%	0.196	Poor
UBrIC	0.073	73.0%	0.467	Moderate
PRLA	0.080	80.0%	0.369	Poor
PRRA	0.085	85.0%	0.285	Poor
PRRV	0.095	95.0%	0.096	Poor

Note: Normalized Root Mean Squared Error (NRMSE) is reported as a percentage of the standard deviation of MPS within the test dataset

Table F4

Performance measures and correlation strength classifications of each random forest regression model to predict MPS from kinematic metrics obtained during youth NOCSAE standard testing

Metric	***RMSE***	***NRMSE***	***R^2***	***Correlation Strength***
GSI	0.087	87.0%	0.313	Poor
HIC	0.091	91.0%	0.248	Poor
HIP	0.087	87.0%	0.294	Poor
GAMBIT	0.083	83.0%	0.351	Poor
BrIC	0.110	110.0%	0.043	Poor
UBrIC	0.070	70.0%	0.517	Moderate
PRLA	0.087	87.0%	0.305	Poor
PRRA	0.091	91.0%	0.246	Poor
PRRV	0.107	107.0%	0.043	Poor

Note: Normalized Root Mean Squared Error (NRMSE) is reported as a percentage of the standard deviation of MPS within the test dataset

Appendix G

Table G1

Performance measures and correlation strength classifications of each multiple regression model to predict MPS from peak kinematic variables obtained during adult NOCSAE standard testing

Model	***RMSE***	***NRMSE***	***R^2***	***Correlation Strength***
Peak Resultants	0.089	79.5%	0.362	Poor
Peak Components	0.086	76.8%	0.416	Moderate
All Kinematics	0.042	37.5%	0.862	High

Note: "Peak Resultants" refers to peak resultant linear acceleration, rotational acceleration, and rotational velocity. "Peak Components" refers to the peak x, y, and z components of linear acceleration, rotational acceleration, and rotational velocity. "All Kinematics" refers to all of the previously mentioned kinematic variables. Normalized Root Mean Squared Error (NRMSE) is reported as a percentage of the standard deviation of MPS within the test dataset

Table G2

Performance measures and correlation strength classifications of each random forest regression model to predict MPS from peak kinematic variables obtained during adult NOCSAE standard testing

Model	***RMSE***	***NRMSE***	***R^2***	***Correlation Strength***
Peak Resultants	0.076	67.9%	0.539	Moderate
Peak Components	0.041	36.6%	0.883	High
All Kinematics	0.037	33.0%	0.906	High

Note: "Peak Resultants" refers to peak resultant linear acceleration, rotational acceleration, and rotational velocity. "Peak Components" refers to the peak x, y, and z components of linear acceleration, rotational acceleration, and rotational velocity. "All Kinematics" refers to all of the previously mentioned kinematic variables. Normalized Root Mean Squared Error (NRMSE) is reported as a percentage of the standard deviation of MPS within the test dataset

Table G3

Performance measures and correlation strength classifications of each multiple regression model to predict MPS from peak kinematic variables obtained during youth NOCSAE standard testing

Model	***RMSE***	***NRMSE***	***R^2***	***Correlation Strength***
Peak Resultants	0.079	79.0%	0.383	Poor
Peak Components	0.063	63.0%	0.609	Moderate
All Kinematics	0.041	41.0%	0.831	High

Note: "Peak Resultants" refers to peak resultant linear acceleration, rotational acceleration, and rotational velocity. "Peak Components" refers to the peak x, y, and z components of linear acceleration, rotational acceleration, and rotational velocity. "All Kinematics" refers to all of the previously mentioned kinematic variables. Normalized Root Mean Squared Error (NRMSE) is reported as a percentage of the standard deviation of MPS within the test dataset

Table G4

Performance measures and correlation strength classifications of each random forest regression model to predict MPS from peak kinematic variables obtained during youth NOCSAE standard testing

Model	***RMSE***	***NRMSE***	***R^2***	***Correlation Strength***
Peak Resultants	0.068	68.0%	0.538	Moderate
Peak Components	0.039	39.0%	0.860	High
All Kinematics	0.039	39.0%	0.857	High

Note: "Peak Resultants" refers to peak resultant linear acceleration, rotational acceleration, and rotational velocity. "Peak Components" refers to the peak x, y, and z components of linear acceleration, rotational acceleration, and rotational velocity. "All Kinematics" refers to all of the previously mentioned kinematic variables. Normalized Root Mean Squared Error (NRMSE) is reported as a percentage of the standard deviation of MPS within the test dataset