The Performance of Helmet-Based Kinematic Measurement Systems: Importance for Mild Traumatic Brain Injury Prevention

Mari Angelica Allison
University of Pennsylvania, mariallison1@gmail.com

Follow this and additional works at: http://repository.upenn.edu/edissertations
Part of the Biomedical Commons

Recommended Citation
http://repository.upenn.edu/edissertations/1002

This paper is posted at ScholarlyCommons. http://repository.upenn.edu/edissertations/1002
For more information, please contact libraryrepository@pobox.upenn.edu.
The Performance of Helmet-Based Kinematic Measurement Systems: Importance for Mild Traumatic Brain Injury Prevention

Abstract
It is estimated that millions of mild traumatic brain injuries (mTBIs) occur each year, and studies show that these injuries can have more long-term neurological consequences than previously thought. High impact sports provide a unique real-world opportunity to study the biomechanical inputs that lead to mTBI and helmet-based instrumentation can be used to estimate the kinematics of head impacts in sports. In Chapter 1, we evaluate two helmet-based measurement systems that use different approaches to estimate kinematics by impacting a helmeted anthropometric test device (ATD) in a laboratory setting. The relationships between the helmet sensor system and reference ATD measures are evaluated. In Chapter 3, we explore the effect of real-world impact and usage variations on the relationships between helmet system and ATD-measured head impact kinematics. The factors varied include the interface between the head and the helmet, repeatability of sensor/helmet systems, helmet geometry/construction, effective mass of the torso, and impacting surface. In Chapter 4 we assess the effect of helmet-based sensor performance on brain injury metrics calculated using finite element analysis. This is done by using helmet system and ATD data from the laboratory impacts as inputs into a finite element head model and comparing outcomes. Chapter 5 discusses the implications of the findings on the implementation of helmet-based systems in real-world scenarios.

Degree Type
Dissertation

Degree Name
Doctor of Philosophy (PhD)

Graduate Group
Bioengineering

First Advisor
Kristy B. Arbogast

Keywords
concussion, head acceleration, head impact biomechanics, helmet sensors, impact monitoring, mTBI

Subject Categories
Biomedical

This dissertation is available at ScholarlyCommons: [http://repository.upenn.edu/edissertations/1002](http://repository.upenn.edu/edissertations/1002)
THE PERFORMANCE OF HELMET-BASED KINEMATIC MEASUREMENT SYSTEMS: IMPORTANCE FOR MILD TRAUMATIC BRAIN INJURY PREVENTION

Mari A. Allison

A DISSERTATION

in

Bioengineering

Presented to the Faculties of the University of Pennsylvania

in

Partial Fulfillment of the Requirements for the

Degree of Doctor of Philosophy

2015

Supervisor of Dissertation

_____________________

Kristy B. Arbogast, PhD, Research Associate Professor of Pediatrics

Graduate Group Chairperson

_____________________

Jason A. Burdick, PhD, Professor of Bioengineering

Dissertation Committee

David F. Meaney, PhD, Professor and Chair of Bioengineering
Beth A. Winkelstein, PhD, Professor of Bioengineering
Flaura K. Winston, MD, PhD, Professor of Pediatrics
Jason P. Mihalik, PhD, CAT(C), ATC, Assistant Professor of Exercise and Sport Science
THE PERFORMANCE OF HELMET-BASED KINEMATIC MEASUREMENT SYSTEMS: IMPORTANCE FOR MILD TRAUMATIC BRAIN INJURY PREVENTION

COPYRIGHT

2015

Mari Angelica Allison

This work is licensed under the Creative Commons Attribution-NonCommercial-ShareAlike 3.0 License

To view a copy of this license, visit

http://creativecommons.org/licenses/by-ny-sa/2.0/
ACKNOWLEDGEMENTS

During my time at both The Children’s Hospital of Philadelphia and the University of Pennsylvania I have been blessed with incredible mentors, teachers, and role models. They have given me much to aspire to and the things that I have learned from them I will carry with me throughout my life. Dr. Arbogast, I cannot even begin to explain the number of ways and the magnitude to which you have impacted me. I wish I could put into words how grateful I am. Thank you to those who have contributed to this body of work, as well as to everyone who has helped me grow professionally throughout this process and prepared me for the next steps in my career, including my committee members and those at the Center for Injury Research and Prevention. And finally, thank you to my family, my friends, and those who have become like family to me, not only for your support but also for making this time period in my an life exceptional one.
ABSTRACT

THE PERFORMANCE OF HELMET-BASED KINEMATIC MEASUREMENT SYSTEMS: IMPORTANCE FOR MILD TRAUMATIC BRAIN INJURY PREVENTION

Mari A. Allison
Kristy B. Arbogast, Ph.D.

It is estimated that millions of mild traumatic brain injuries (mTBIs) occur each year, and studies show that these injuries can have more long-term neurological consequences than previously thought. High impact sports provide a unique real-world opportunity to study the biomechanical inputs that lead to mTBI and helmet-based instrumentation can be used to estimate the kinematics of head impacts in sports. In Chapter 1, we evaluate two helmet-based measurement systems that use different approaches to estimate kinematics by impacting a helmeted anthropometric test device (ATD) in a laboratory setting. The relationships between the helmet sensor system and reference ATD measures are evaluated. In Chapter 3, we explore the effect of real-world impact and usage variations on the relationships between helmet system and ATD-measured head impact kinematics. The factors varied include the interface between the head and the helmet, repeatability of sensor/helmet systems, helmet geometry/construction, effective mass of the torso, and impacting surface. In Chapter 4 we assess the effect of helmet-based sensor performance on brain injury metrics calculated using finite element analysis. This is done by using helmet system and ATD data from the laboratory impacts as inputs into a finite element head model and comparing outcomes. Chapter 5 discusses the implications of the findings on the implementation of helmet-based systems in real-world scenarios.
TABLE OF CONTENTS

ACKNOWLEDGEMENTS .................................................................................. III

ABSTRACT ........................................................................................................ IV

TABLE OF CONTENTS .................................................................................... V

LIST OF TABLES ............................................................................................... IX

LIST OF ILLUSTRATIONS ................................................................................. XI

CHAPTER 1 - INTRODUCTION ...................................................................... 1

1.1: Epidemiology of mild traumatic brain injury .................................................. 1

1.2: Potential for long term consequences ............................................................ 2

1.3: Children are particularly vulnerable ............................................................. 5

1.4: Biomechanics of prevention .......................................................................... 6

1.5: Technologies to study impact biomechanics in sports ................................... 8

1.6: Studying impact biomechanics using instrumented helmets in football .......... 9

1.7: Studying impact biomechanics using instrumented helmets in ice hockey ..... 12

1.8: Head injury metrics developed from instrumented helmet data .................. 13

1.9: Helmet instrumentation system accuracy ..................................................... 15

1.10: Research objectives .................................................................................... 17

CHAPTER 2 - TECHNIQUES TO EVALUATE HELMET-BASED MEASUREMENT SYSTEMS IN A LABORATORY SETTING TO QUANTIFY ERRORS IN PEAK KINEMATIC MEASURES ................................................. 19

2.1: Introduction .................................................................................................. 19

2.1.1: Previous helmet-based research ............................................................... 19

2.1.2: HIT System measurement approach and previous validation .................. 20

2.1.3: GFT measurement approach ................................................................. 26

2.1.4: Research objective .................................................................................. 26

2.2: Methods ...................................................................................................... 27

2.2.1: Laboratory test setup .............................................................................. 27
3.4: Discussion ............................................................................................................. 123
3.4.1: Interface between the ATD head and the helmet ............................................. 124
3.4.2: Helmet geometry/construction ....................................................................... 125
3.4.3: Repeatability of the helmet/sensor system ..................................................... 126
3.4.4: Effective mass of the torso .............................................................................. 127
3.4.5: Impacting Surface ............................................................................................ 129
3.4.6: Limitations ...................................................................................................... 130

3.5: Conclusions ........................................................................................................ 131

CHAPTER 4 - THE EFFECT OF HELMET-BASED SYSTEM PERFORMANCE ON
THE CALCULATION OF BRAIN INJURY METRICS USING FINITE ELEMENT
ANALYSIS ......................................................................................................................... 132

4.1: Introduction ........................................................................................................ 132
4.1.1: Biomechanical characteristics apart from peak kinematics influence injury risk 132
4.1.2: Use of real-world kinematic data in finite element analysis ............................. 133
4.1.3: Other FEA findings related to risk of mTBI ...................................................... 134
4.1.4: Research objectives ........................................................................................ 135

4.2: Methods................................................................................................................ 136
4.2.1: Laboratory testing ........................................................................................... 136
4.2.2: Finite element model ....................................................................................... 137
4.2.3: Analysis groups and filtering .......................................................................... 139
4.2.4: Analysis of Outcome Measures ...................................................................... 142

4.3: Results .................................................................................................................. 143
4.3.1: CSDM 0.15 ........................................................................................................ 143
4.3.2: CSDM 0.25 ........................................................................................................ 148
4.3.3: Maximum principal strain ............................................................................... 153
4.3.4: Summary of HIT System and GFT brain injury metric errors across testing conditions .......................................................................................................................... 160

4.4: Discussion .......................................................................................................... 160
4.4.1: General differences in brain injury metrics based on source of input data .... 161
4.4.2: Effect of data calibration before input into SIMon ......................................... 163
4.4.3: Implications of findings ................................................................................... 164
4.4.4: Limitations and Future Work ......................................................................... 166

4.5: Conclusions ....................................................................................................... 168

CHAPTER 5 - OVERVIEW AND IMPLICATIONS FOR REAL-WORLD USE ..... 169

5.1: Overview of findings ........................................................................................... 169
5.2: Importance of absolute error vs. relative error ................................................. 171
5.3: Implications of the influence of other parameters on accuracy ....................... 172
5.4: Magnitude of Significant Differences ................................................................. 175
5.5: Implications of findings for researchers ............................................................ 179
5.6: Performance under conditions most likely to lead to mTBI in ice hockey ........................................ 184
5.7: Implications of findings for consumers ........................................................................................................ 191
5.8: Development of future real-world kinematic measurement systems ....................................................... 192
5.9: Future evaluations of helmet-based systems ............................................................................................... 195
5.10: Implications of findings on the future of mTBI prevention research ......................................................... 197

APPENDIX 1 – SUPPLEMENTARY DATA FOR CHAPTER 2 .................................................. 201
A1.1: Regressions and coefficients of determination for other sensor locations ........................................... 201
A1.2: Estimation of impact direction for other sensor locations ...................................................................... 213

APPENDIX 2 – SUPPLEMENTARY DATA FOR CHAPTER 3 ............................................. 216
A2.1: Repeatability of helmet/sensor system data for other sensor locations ................................................. 216
A2.2: Effective mass of the torso data for other sensor locations ................................................................. 220
A2.3: Impacting surface data for other sensor locations ................................................................................. 227

REFERENCES .................................................................................................................................................... 235
LIST OF TABLES

Table 2.1: Linear and power regression fit equations for HIT System data and their associated $R^2$ values................................................................. 48

Table 2.2a: Linear and power regression fit equations for GFT data from the inside top sensor on the Bauer helmet and their associated $R^2$ values.......................... 51

Table 2.3: Absolute error between the HIT System-measured and reference peak resultant accelerations............................................................................. 53

Table 2.4: Absolute error between the GFT-measured and reference peak resultant kinematics............................................................................................. 56

Table 2.5: Summary of p-values for statistical significance of impact direction and sensor location..................................................................................... 60

Table 2.6: Average absolute errors of GFT estimation of impact azimuth stratified by impact direction and sensor location.................................................. 64

Table 3.1: Linear and power regression fit equations stratified by impact direction for HIT System combined helmet/sensor sets 1 and 2 and their associated $R^2$ values............. 109

Table 3.2: Inside top sensor location power regression fit equations stratified by impact direction for GFT combined helmet/sensor sets 1 and 2 and their associated $R^2$ values.111

Table 3.3: Summary of p-values for statistical significance of combined helmet/sensor set ........................................................................................................ 113

Table 3.4: Inside top sensor location power regression fit equations stratified by impact direction for the two mounting setups (rigid and translational) and their associated $R^2$ values. ........................................................................................................ 116

Table 3.5: Summary of p-values testing for statistically significant effect of the mounting setup .................................................................................................. 118

Table 3.6: Inside top sensor location power regression fit equations stratified by impact direction for the two impacting surfaces (UHMWPE and the hockey elbow pad) and their associated $R^2$ values. ........................................................................................................ 121

Table 3.7: Summary of p-values testing for statistically significant effect of the impacting surface ........................................................................................ 123

Table 4.1: Results for SIMon CSDM 0.15 calculations resulting from ATD data, raw HIT System data, and adjusted HIT System data from laboratory evaluations used as input 145

Table 4.2: Results for SIMon CSDM 0.15 calculations resulting from ATD data, raw GFT data, and adjusted GFT data from laboratory evaluations used as input............ 148

Table 4.3: Results for SIMon CSDM 0.25 calculations resulting from ATD data, raw HIT System data, and adjusted HIT System data from laboratory evaluations used as input 150
Table 4.4: Results for SIMon CSDM 0.25 calculations resulting from ATD data, raw GFT data, and adjusted GFT data from laboratory evaluations used as input................. 153

Table 4.5: Results for SIMon MPS calculations resulting from ATD data, raw HIT System data, and adjusted HIT System data from laboratory evaluations used as input 156

Table 4.6: Results for SIMon MPS calculations resulting from ATD data, raw GFT data, and adjusted GFT data from laboratory evaluations used as input................................................................. 159

Table 4.7: Errors in metric calculations across all impact directions combined .......... 160

Table A2-3.6b: Outside top sensor location power regression fit equations stratified by impact direction for the two impacting surfaces (UHMWPE and the hockey elbow pad) and their associated $R^2$ values...............................Error! Bookmark not defined.

Table A2-3.6c: Outside right sensor location power regression fit equations stratified by impact direction for the two impacting surfaces (UHMWPE and the hockey elbow pad) and their associated $R^2$ values...............................Error! Bookmark not defined.

Table A2-3.6d: Outside back sensor location power regression fit equations stratified by impact direction for the two impacting surfaces (UHMWPE and the hockey elbow pad) and their associated $R^2$ values...............................Error! Bookmark not defined.
LIST OF ILLUSTRATIONS

Figure 2.1: Geometrical differences between Easton S9 and Bauer RE-AKT helmets........ 29
Figure 2.2: GFT sensor locations.................................................................................. 29
Figure 2.3: HIT System accelerometer locations in the helmet................................. 31
Figure 2.4: HIT System test setup for the side, oblique, and back impact directions...... 33
Figure 2.5: GFT test setup for front, side, oblique, and back impact directions.......... 33
Figure 2.6: Test matrix for impacts to HIT System for ice hockey instrumented helmets 34
Figure 2.7: Test matrix for impacts to GFT instrumented helmets............................. 35
Figure 2.8: Example of regression equations used to calculate average absolute error for all impact directions combined or stratified by impact direction ....................... 39
Figure 2.9: Characteristics of the impacts removed from the dataset by a HIT System processing algorithm................................................................................................. 43
Figure 2.10: Time history for valid impacts and impacts determined to be “invalid” by a processing algorithm......................................................................................... 43
Figure 2.11: Data comparing peak resultant linear and rotational acceleration as measured by the ATD and by the HIT System for all impact directions combined and then stratified by impact direction .......................................................................................................................... 47
Figure 2.12: Data comparing peak resultant linear acceleration and peak resultant rotational velocity as measured by the ATD and by GFT for all impact directions combined and then stratified by impact direction .......................................................................................................................... 50
Figure 2.13: Comparison of HIT System-reported and actual impact azimuth for side, back, and oblique back impacts ................................................................. 61
Figure 2.14: Comparison of GFT-reported and actual impact azimuth for side, oblique, back, and front impacts for the inside top sensor ........................................... 63
Figure 2.15: Still frames showing a front impact to the facemask and corresponding helmet system and ATD resultant acceleration time histories. This depicts the difference in accelerations experienced by the helmet and the ATD at different time points for facemask impacts .................................................................................................................. 75
Figure 2.16: Timing of peak resultant linear acceleration for 10 impacts at two impacting speeds and corresponding high speed video at time of peak acceleration ............... 79
Figure 3.1: Rigid and translating mounting setups for the ATD head and neck ............... 92
Figure 3.2: HIT System for ice hockey test conditions for impacts used to assess the effect of the interface between the ATD head and the helmet........................................ 96
Figure 3.3: GFT test conditions highlighting impacts used to assess the effect of helmet geometry/construction on the relationship between peak GFT and corresponding reference ATD measures

Figure 3.4: HIT System for ice hockey test conditions for impacts used to assess combined helmet/sensor system repeatability

Figure 3.5: GFT test conditions highlighting impacts used to assess combined helmet/sensor system repeatability

Figure 3.6: GFT test conditions highlighting impacts used to assess the influence of effective mass of the torso on the relationship between peak GFT and corresponding reference ATD measures

Figure 3.7: GFT test conditions highlighting impacts used to assess the effect of impacting surface on the relationship between peak GFT and corresponding reference ATD measures

Figure 3.8: The UHMWPE and hockey elbow pad impacting surfaces used during testing

Figure 3.9: Differing relationships between peak resultant linear acceleration as measured by the HIT System for ice hockey and ATD for side impacts for three different interfaces between the head and the helmet

Figure 3.10: Data comparing helmet/sensor sets for peak resultant linear and rotational acceleration as measured by the ATD and by the HIT System for ice hockey stratified by impact direction

Figure 3.11: Inside top sensor location data comparing combined helmet/sensor sets for peak resultant linear acceleration and rotational velocity as measured by the ATD and GFT stratified by impact direction

Figure 3.12: Ratios of peak ATD measure to peak respective GFT measure for helmet/sensor sets 1 and 2 versus impact intensity for data from the inside top sensor location. The ratios were used as the outcome measure for the statistical analysis

Figure 3.13: Inside top sensor location data comparing mounting setups (rigid or translating) for peak resultant linear acceleration and rotational velocity as measured by the ATD and GFT stratified by impact direction

Figure 3.14: Ratios of peak ATD measure to peak respective GFT measure for the rigid and translating mounts versus impact intensity for data from the inside top sensor location. The ratios were used as the outcome measure for the statistical analysis

Figure 3.15: Inside top sensor location data comparing impacting surfaces (UHMWPE or hockey elbow pad) for peak resultant linear acceleration and rotational velocity as measured by the ATD and GFT stratified by impact direction

Figure 3.16: Ratios of peak ATD measure to peak respective GFT measure for the UHMWPE and elbow pad impacting surfaces versus impact intensity for data from the
inside top sensor location. The ratios were used as the outcome measure for the statistical analysis.

Figure 3.17: Still frames depicting a front impact to the facemask showing an initial rotation of the helmet in the direction opposite rotation of the ATD head.

Figure 4.1: The improved SIMon finite element head model.

Figure 4.2: SIMon inputs and outcomes for comparison of calculated brain injury metrics based on ATD data to those based on HIT System data.

Figure 4.3: SIMon inputs and outcomes for comparison of calculated brain injury metrics based on ATD data to those based on GFT data.

Figure 4.4: Exemplar SIMon-calculated CSDM 0.15 for side, oblique, and back impacts using an UHMWPE impacting surface.

Figure 4.5: Exemplar SIMon-calculated CSDM 0.15 for a side, oblique, and back impact using an UHMWPE impacting surface.

Figure 4.6: Exemplar SIMon-calculated CSDM 0.15 for a side, oblique, and back impact using a hockey elbow pad impacting surface.

Figure 4.7: Exemplar SIMon-calculated CSDM 0.25 for a side, oblique, and back impact using an UHMWPE impacting surface.

Figure 4.8: Exemplar SIMon-calculated CSDM 0.25 for a side, oblique, and back impact using an UHMWPE impacting surface.

Figure 4.9: Exemplar SIMon-calculated CSDM 0.25 for a side, oblique, and back impact using a hockey elbow pad impacting surface.

Figure 4.10: Exemplar SIMon-calculated maximum principal strain for a side, oblique, and back impact using an UHMWPE impacting surface.

Figure 4.11: Exemplar SIMon-calculated maximum principal strain for a side, oblique, and back impact using an UHMWPE impacting surface.

Figure 4.12: Exemplar SIMon-calculated maximum principal strain for a side, oblique, and back impact using a hockey elbow pad impacting surface.

Figure 5.1: Exemplar data depicting the effect size of impact direction on the difference between the average ATD measure and the average system measure (+SD).

Figure 5.2: Exemplar data depicting the effect size of sensor location on the difference between the average ATD measure and the average system measure.

Figure 5.3: Exemplar data depicting the effect size of interface between the ATD head and the helmet on the difference between the average ATD measure and the average system measure.

Figure 5.4: Exemplar data depicting the effect size of helmet brand (for two impact directions) on the difference between the average ATD measure and the average system measure.
Figure 5.5: Exemplar data depicting the effect size of impacting surface (for two impact directions) on the difference between the average ATD measure and the average system measure .................................................................................................................................................. 178

Figure 5.6: Example of the effect of the 43% average absolute error in rotational acceleration found for the raw HIT System for ice hockey data on prediction of injury risk using the Rowson et al. (2012) rotational injury risk curve ........................................................................................................ 181

Figure 5.7: ATD-measured peak resultant linear acceleration versus the error in HIT System for ice hockey-measured peak resultant linear acceleration after impact direction-specific regression adjustment of the HIT System data ........................................................................ 186

Figure 5.8: ATD-measured peak resultant rotational acceleration versus the error in HIT System for ice hockey-measured peak resultant rotational acceleration after impact direction-specific regression adjustment of the HIT System data ........................................................................ 187

Figure 5.9: ATD-measured peak resultant linear acceleration versus the error in GFT-measured peak resultant linear acceleration after impact direction-specific regression adjustment of the GFT data .................................................................................. 188

Figure 5.10: ATD-measured peak resultant rotational velocity versus the error in GFT-measured peak resultant rotational velocity after impact direction-specific regression adjustment of the GFT data .................................................................................. 189

Figure 5.11: The mTBI pathway from impact to clinical outcome with the tools used to for injury prevention research and some of the factors influencing each aspect of the pathway .................................................................................................................................................. 199

Figure A2-3.11b: Outside top sensor location data comparing combined helmet/sensor sets for peak resultant linear acceleration and rotational velocity as measured by the ATD and GFT stratified by impact direction .......................................................................................... 216

Figure A2-3.11c: Outside right sensor location data comparing combined helmet/sensor sets for peak resultant linear acceleration and rotational velocity as measured by the ATD and GFT stratified by impact direction .......................................................................................... 217

Figure A2-3.11d: Outside back sensor location data comparing combined helmet/sensor sets for peak resultant linear acceleration and rotational velocity as measured by the ATD and GFT stratified by impact direction .......................................................................................... 218

Figure A2-3.13b: Outside top sensor location data comparing mounting setups (rigid or translating) for peak resultant linear acceleration and rotational velocity as measured by the ATD and GFT stratified by impact direction .......................................................................................... 221

Figure A2-3.13c: Outside right sensor location data comparing mounting setups (rigid or translating) for peak resultant linear acceleration and rotational velocity as measured by the ATD and GFT stratified by impact direction .......................................................................................... 223

Figure A2-3.13d: Outside back sensor location data comparing mounting setups (rigid or translating) for peak resultant linear acceleration and rotational velocity as measured by the ATD and GFT stratified by impact direction .......................................................................................... 224
Figure A2-3.15b: Outside top sensor location data comparing impacting surfaces (UHMWPE or hockey elbow pad) for peak resultant linear acceleration and rotational velocity as measured by the ATD and GFT stratified by impact direction .................... 228

Figure A2-3.15c: Outside right sensor location data comparing impacting surfaces (UHMWPE or hockey elbow pad) for peak resultant linear acceleration and rotational velocity as measured by the ATD and GFT stratified by impact direction .................... 230

Figure A2-3.15d: Outside back sensor location data comparing impacting surfaces (UHMWPE or hockey elbow pad) for peak resultant linear acceleration and rotational velocity as measured by the ATD and GFT stratified by impact direction .................... 231
Chapter 1 - Introduction

1.1: Epidemiology of mild traumatic brain injury

Over the past half of a century, research efforts have focused on preventing moderate and severe traumatic brain injury (TBI), leading to a 20 percent reduction in the TBI-associated death rate in the United States from 1980 through 1994, from 24.7 per 100,000 population to 19.8 per 100,000 population (Alverson et al. 1999). However, a recent rise in awareness of the prevalence and potential long term consequences of mild TBI (mTBI) has led the Centers for Disease Control and Prevention to declare these injuries as a research priority (National Center for Injury Prevention and Control (U.S.) 2003). The evolving definition of mTBI has contributed to this awareness, as it was previously thought that loss of consciousness was a primary symptom. However, it is now recognized that the vast majority of these injuries do not involve loss of consciousness and that its presence or absence is not a reliable indicator of injury severity or long-term deficits, thus greatly expanding the numbers of individuals recognized as sustaining mTBI (Collins et al. 2003; Lau et al. 2009; Schulz et al. 2004).

Of the 1.7 million TBIs seen in emergency departments (ED) each year, the majority are considered “mild” (Faul et al. 2010). Furthermore, an estimated 1.6 to 3.8 million sports and recreation-related mTBIs occur each year, and children from the ages of 5-18 account for approximately 65% of all of these presenting to EDs (“Nonfatal Traumatic Brain Injuries from Sports and Recreation Activities--United States, 2001-2005.” 2007). The
number of mTBIs presenting to EDs due to motor vehicle trauma is estimated around
300,000 each year (Bazarian et al. 2005).

For the purposes of this research, mTBI and concussion will be used synonymously and
will be defined as rapidly onset impairments in neurological function as the result of
either a direct or impulsive load to the head (McCrory et al. 2005; “Practice Parameter:
Standards Subcommittee.” 1997).

1.2: Potential for long term consequences

Concern regarding mild TBI is heightened given that an increasing number of studies
show that these injuries can lead to long-term neurological consequences. Some of this
research focuses on measures of cognitive impairment. One study showed that
approximately 30% of those sustaining mTBI suffered from post-concussive symptoms
more than 12 months after the injury and this subset of mTBI patients exhibited deficits
in a battery of neurocognitive tests (Sterr et al. 2006). A later study demonstrated that,
more than a year post-injury, deficits in working memory and information processing
speeds still exist in symptomatic mTBI patients compared to mTBI patients without
symptoms, controls with symptoms similar to those associated with post-concussion
syndrome (i.e. headache and fatigue), and controls without symptoms (Dean and Sterr
2013). A group in New Zealand also found residual deficits in eye and motor function at
12 months post mild closed head injury, even when there was a lack of cognitive
impairment (Heitger et al. 2006). Another study, comparing patients with uncomplicated
mTBI to matched trauma controls, found that the mild TBI patients performed worse on the Visual Memory portion of the Immediate Post-Concussion Assessment and Cognitive Testing battery (ImPACT) at one week and three months post injury (Ponsford et al. 2011). Furthermore, repeated concussions in athletes have been linked to deficits in cognitive performance compared to those who have only suffered a single concussion after a recovery period of at least three months after the most recent concussion (Wall et al. 2006).

Other research has looked at how patients feel they are affected by mTBI. The aforementioned Ponsford et al. study also found that mTBI patients were more likely to report ongoing memory and concentration problems in their daily lives (Ponsford et al. 2011). Stulemeijer et al. showed that at 6 months post-injury, one-third of mTBI patients suffered from severe fatigue compared to one-eighth of control patients who had suffered minor injury (Stulemeijer et al. 2006). Another study found that fatigue can persist years after injury and, furthermore, that it correlates with deficits in information processing (Johansson, Berglund, and Ro 2009).

Studies in animal models support the findings that mild traumatic brain injury can have more serious consequences than previously thought. A study in Wistar rats that utilized a cortical impact injury model found impaired spatial learning abilities that persisted 20-25 days after mild injury (Dawish et al. 2012). In a swine model of mTBI it was demonstrated that, although the animals quickly returned to seemingly normal behavior as measured by their eating, drinking, and recovery from initial slow movement and
sluggish response to stimuli, permanent damage to the brain can still occur in the form of axonal bulbs and swellings throughout the cerebrum, cerebellum, midbrain, and brainstem, with some degenerating neurons in the cortex and hippocampus (Browne et al. 2011). This study supports the premise that mTBI lies on the spectrum of diffuse axonal injury (DAI) as these phenomena are well documented in histopathological studies of DAI (Adams et al. 1989; Blumbergs, Jones, and North 1989; Povlishock et al. 1983; Strich 1956).

Although mTBI does not lead to noticeable changes in computed tomography (CT) or magnetic resonance imaging (MRI) scans, more recent imaging studies using diffusion tensor imaging (DTI) have shown changes in white matter integrity post-injury (Bazarian et al. 2007; Cubon et al. 2011; Inglese et al. 2005). This damage is measured by changes in fractional anisotropy and mean diffusivity and it is particularly apparent in areas of the brain that are frequently effected in DAI (Inglese et al. 2005). The white matter damage seen in DTI further supports the link between mTBI and DAI and provides new evidence that concussion is a more serious than previously thought. Additionally, based on studies of previous contact sport athletes, researchers have suggested a link between repetitive head impacts and a progressive neurodegenerative disease called chronic traumatic encephalopathy (McKee et al. 2009; Stern et al. 2011). Symptoms include memory disturbances, movement abnormalities, and personality and behavioral changes.

Researchers have studied the underlying pathophysiological changes that occur due to concussive injury, causing dysfunction. It has been found that the mechanical disturbance
of neurons leads to depolarization and large changes in ion concentrations, including an exaggerated efflux of potassium and glutamate (Katayama et al. 1990) along with accumulation and influx of calcium (Samii et al. 1999). The disruption in normal ion concentrations requires increased activity of active membrane ion pumps, increasing energy demand and leading to an initial hypermetabolic state and increase in glucose utilization, followed by a metabolic depression (Yoshino et al. 1991). The presence of the hypometabolic state despite an increased need for energy post-injury may be due to mitochondrial dysfunction, caused by the increased intracellular calcium (Xiong et al. 1998). Calcium influx in axons after stretch also correlates to loss of cytoskeletal integrity and development of axonal swellings (Maxwell et al. 1995). Giza and Hovda describe in depth the cellular-level changes associated with mTBI, calling it the neurometabolic cascade of concussion (Giza and Hovda 2001).

1.3: Children are particularly vulnerable

Children and adolescents are particularly vulnerable to mTBI; in addition to accounting for the majority of sports and recreation-related mTBIs presenting to EDs, the time course of their recovery from concussion appears to be extended compared to adults (Field et al. 2003), contrary to the initial belief that children would recover better due to increased plasticity of the brain. The developing brain exhibits differences in cerebral blood flow, brain glucose utilization, and ion concentrations (Bauer and Fritz 2004; Udomphorn, Armstead, and Vavilala 2008). Given that, as described above, these factors are influenced in the pathophysiological changes associated with concussion, they may account for this increased recovery time. Children also have a higher synaptic density,
which peaks within the first couple of years of life and then decreases throughout adolescence (Huttenlocher 1979). Given that neurotransmitter release is a key component of the pathophysiological cascade of concussion, the increased number of synapses may lead to more of this release and consequentially greater ion imbalance, requiring more time to recover to baseline conditions. Since changes are continuously occurring until mid-20s, it is important to study differences in mTBI across the age range of brain development.

It is also particularly important to study the pediatric population as deficits in neurocognitive function can affect performance in school (Sady, Vaughan, and Gioia 2011). This subsequently may influence grades and class placements; hence mTBI has the potential to compromise education. McKinlay et al. studied the long-term effects on the behavior of kids suffering more severe (inpatient) mTBI during pre-school years and, based yearly maternal and teacher ratings from age 7 to 13, found persistent negative effects in the form of attention deficits and defiant conduct (McKinlay et al. 2010).

1.4: Biomechanics of prevention

As leading causes of concussion (Bazarian et al. 2005; Faul et al. 2010; “Nonfatal Traumatic Brain Injuries from Sports and Recreation Activities--United States, 2001-2005.” 2007), sports and motor vehicle crashes are two ideal targets for preventing these injuries. In both of these arenas, head injury prevention has focused on reducing linear acceleration of the head, as evidenced by the current helmet and federal motor vehicle safety standards (FMVSS), which are both based on linear acceleration (Daneshvar et al.
Head Injury Criterion (HIC) (Equation 1.1), used in FMVSS No. 208 (‘ Occupant Protection in Frontal Crashes’), is based on the Wayne State Tolerance Curve, which is in turn derived from direct head impact linear accelerations leading to skull fracture in adult cadavers (Eppinger et al. 1999). However, HIC has been shown to be a poor predictor of TBI (Nirula et al. 2004), which is not surprising as linear acceleration has primarily been tied to changes in pressure gradients within the brain and focal head injuries. Gennarelli et al. demonstrated a lack of concussive injury but presence of focal injuries with pure translation of the head in a primate model (Gennarelli, Thibault, and Ommaya 1972). In contrast, rotational kinematics have shown to be improved predictors of diffuse axonal injury across the spectrum of severity, as they correlate to measures of strain within the brain (Gennarelli, Thibault, and Ommaya 1972; Gennarelli et al. 1982; Meaney and Smith 2011; Ommaya 1995). A finite element model study predicted that rotational kinematics contribute more than 90 percent of strain, whereas translational kinematics produce minimal strain (J. Zhang et al. 2006).

When considering prevention, it is also important to take into account the axis of rotation, as differences in injury susceptibility have been observed in animal models. In a primate model it has been demonstrated that coronal acceleration leads to more severe injury in terms of both neurological disturbances and axonal injury (Gennarelli et al. 1987; Gennarelli et al. 1982). In a swine model, worse outcomes have been observed due to horizontal rotations but, due to differences in anatomy, this is thought to be consistent with coronal rotation in primates (Eucker et al. 2011; Smith et al. 2000). Finite element
analysis has also been used to predict that coronal rotation leads to increased strains in the brain compared to other impact directions (L. Zhang, Yang, and King 2001).

1.5: Technologies to study impact biomechanics in sports

High impact sports provide a unique opportunity to study the inputs that lead to mTBI in real-world settings. Athletes participating in high-impact sports are a defined cohort at increased risk for mTBI on which to take baseline measures and monitor head impacts, neurocognitive function, and clinical symptoms. Given the growing awareness of the potentially serious consequences of mTBI, this is an expanding area of research. While impact reconstructions based on game film have been performed and provide valuable information on injury biomechanics (e.g. Pellman et al. 2003), wearable technologies provide the opportunity to collect direct measurements from athletes that estimate the biomechanics of head impacts by measuring all injurious and subconcussive impacts that athletes sustain during play. New designs of wearable technologies are constantly emerging.

Helmet-based instrumentation, particularly the Head Impact Telemetry (HIT) System (Simbex LLC, Lebanon, New Hampshire), is the most established wearable technology, having been tested in laboratory settings and used in football and hockey research over the past decade (see discussion in sections 1.6-1.9) (Brolinson et al. 2006; Crisco et al. 2010; Mihalik et al. 2007, 2012; Rowson et al. 2009). Researchers are also developing, validating, and implementing instrumented mouthguards as a means to study head impacts (Camarillo et al. 2013; King et al. 2014; Siegmund et al. 2014; Wu et al. 2014).
Furthermore, companies are developing other systems that can be employed on helmets, such as the gForce Tracker (GFT) (Gforcetracker Inc., Markham, ON) and the Shockbox (Impakt Protective Inc., Kanata, ON). The GFT can also be used in other capacities, such as in headbands for soccer or on goggle straps for women’s lacrosse. Similarly, other recently developed technologies are integrated into headbands or skull caps, such as the CHECKLIGHT (Reebok International, Ltd., Canton, MA and MC10 Inc., Cambridge, MA) and the SIM-P and SIM-G (Triax Technologies Inc., Norwalk, CT). There is also an adhesive patch that is placed behind the ear to measure head impact biomechanics called the xPatch (X2 Biosystems, Inc., Seattle, WA). These technologies typically have some form of accelerometers and some include gyroscopes to measure rotation. It is important to note that most of these technologies are geared towards consumers (i.e. coaches, parents, and athletic trainers) rather than researchers.

1.6: Studying impact biomechanics using instrumented helmets in football

As mentioned above, using instrumented helmets in contact sports is one method to study brain injury thresholds and mechanisms a real-world setting. To date, head impact biomechanics research using instrumented helmets has mainly focused on adult populations, particularly collegiate athletes, and has been largely American football based. Most of this research has been done using the six-accelerometer, five-degree of freedom HIT System for football.
The real-world data collected in football players by instrumenting their helmets and monitoring them during practices and games has been used in a variety of capacities. Some of the earlier studies focused on describing the incidence, peak acceleration, direction, and duration of impacts that collegiate players experience, paying particular attention to injurious impacts, (Brolinson et al. 2006; Duma et al. 2005; Rowson et al. 2009). This type of data has also been used to look for key differences in head impacts sustained between various teams and playing positions. Differences have been found, including that linemen and linebackers have the most impacts per practice and game (Crisco et al. 2010). These types of studies been extended to high school (Broglio et al. 2009, 2010, 2013; Schnebel et al. 2007) and more recently youth football players (Cobb et al. 2013; Daniel, Rowson, and Duma 2012; Young et al. 2013). Based on the findings in terms of impact magnitude and incidence in these age groups, several researchers have suggested restructuring practices to reduce impact magnitude and frequency in younger athletes (Broglio et al. 2013; Cobb et al. 2013; Daniel, Rowson, and Duma 2012).

Given that a primary goal of this line of research is to determine the biomechanical inputs that lead to mTBI, some studies have attempted to find correlations between peak accelerations and neurocognitive and clinical measures. McCaffrey et al. compared baseline measures in the Automated Neuropsychological Assessment Metrics, NeuroCom Sensory Organization Test, and Graded Symptom Checklist to those after a low-impact session (in which no head impacts above 60g were sustained) and a high-impact session (in which an impact of at least 90g was sustained) as measured by the HIT System for football and found no deficits after either low or high impact sessions (McCaffrey et al.
Guskiewicz et al. attempted to relate the acceleration magnitudes and directions of thirteen concussive impacts measured by the HIT System in college football players to change scores in symptom severity, postural stability, and neurocognitive function but found no substantial correlations between these measures (Guskiewicz et al. 2007). A similar study at the high school level also failed to find a correlation between symptoms, changes in measures of cognitive performance, and biomechanical measures in concussed athletes (Broglio et al. 2011). Subconcussive impacts and concussion history have also not correlated to changes in measures of neurological function (Gysland et al. 2012), nor has cumulative impact burden been shown to relate to concussion threshold (Eckner et al. 2011). However, studies found that athletes receive higher magnitude and a greater number of impacts on days of diagnosed concussion (Beckwith et al. 2013a) and that kinematic measures relate to the timing of concussion diagnosis; immediate diagnosis was associated with higher kinematic measures, whereas delayed diagnosis was associated with a higher number of impacts on the day of injury (Beckwith et al. 2013b).

Others have included the use of imaging to relate exposure as measured by instrumented helmets to outcomes. Urban et al. proposed metrics to quantify risk-weighted cumulative impact exposure throughout a season based on linear acceleration, rotational acceleration, or a combination of the two as measured by the HIT system (Urban et al. 2013) and these metrics were subsequently used in combination with diffusion tensor imaging (DTI) and ImPACT data collected pre- and post season (Davenport et al. 2014). Davenport et al. found significant correlations between the risk-weighted cumulative exposure metrics and the number of abnormal DTI voxels for fractional, linear, planar, and spherical
anisotropy as well as mean diffusivity, which represent changes in white matter integrity. The DTI measures also correlated with the change in Verbal Memory score for ImPACT, and all of these changes occurred in the absence of clinically diagnosed concussion. Using functional magnetic resonance imaging (fMRI) and ImPACT, a group of researchers found abnormalities in both athletes that were and were not clinically diagnosed with concussion and the changes correlated to the number of impacts experienced as measured by the HIT system (E. L. Breedlove et al. 2012; K. M. Breedlove et al. 2014). In concussed athletes, McAllister et al. used pre and post-mTBI DTI along with the Dartmouth Subject-Specific Head FE Model and head acceleration data from the HIT System for ten concussive injuries to quantify a correlation between changes in white matter integrity and model-predicted strain and strain rate (McAllister et al. 2012). As has been described, a large amount of real-world kinematic impact data has been collected using the HIT System for football and it has been used to study a variety of factors related to mTBI.

1.7: Studying impact biomechanics using instrumented helmets in ice hockey

Several researchers have expanded this line of research to ice hockey using the HIT System for ice hockey. Mihalik and colleagues have identified that teenage ice hockey players regularly sustain head impacts as severe as collegiate football players and described the frequency, magnitude, and direction of impacts in different playing positions during practices and games (Mihalik et al. 2008; Mihalik et al. 2012). Other researchers have quantified similar data in collegiate men’s and women’s ice hockey (Wilcox, Beckwith, et al. 2014) and in Canadian youth ice hockey (Reed et al. 2010).
Other studies in youth hockey players have found that head accelerations resulting from infractions are generally higher than those from legal collisions (Mihalik, Greenwald, et al. 2010), isometric cervical muscle strength did not affect head impact accelerations (Mihalik et al. 2011), open-ice collisions result in greater head accelerations than those along the boards, and anticipated collisions tend to result in lower rotational head accelerations than unanticipated collisions (Mihalik, Blackburn, et al. 2010). Brainard et al. reported that women receive fewer and generally lower magnitude impacts despite a higher frequency of concussion diagnoses in collegiate ice hockey (Brainard et al. 2012) and Wilcox et al. found that approximately half of head impacts were caused by contact with another player (a more frequent cause than contact with the ice, contact with the boards, indirect contact, or celebrating) but that contact with the ice tends to result in higher accelerations (Wilcox, Machan, et al. 2014).

1.8: Head injury metrics developed from instrumented helmet data

Researchers studying head impact biomechanics using helmet-based systems have identified limitations associated with applying current head injury metrics such as HIC and peak acceleration to concussion, as they have not been predictive of the probability or severity of injury in real-world scenarios (E. L. Breedlove et al. 2012; Broglio et al. 2011; Guskiewicz and Mihalik 2011; Guskiewicz et al. 2007; McCaffrey et al. 2007). To address this lack of predictive ability, attempts have been made to use on-field data collected through these systems from concussive and subconcussive impacts to establish new measures for injury risk. In developing what has been called the Head Impact Telemetry Severity Profile (HITsp), Greenwald et al. used a weighted principal
component analysis of impact data collected using the HIT System to find the formula that best described risk of concussion based on linear acceleration, rotational acceleration, HIC, GSI, and impact direction (Equation 1.2) (Greenwald et al. 2008). One of the limitations of this injury risk metric is that both GSI and HIC are calculated using linear acceleration, so this measure is accounted for multiple times in the formula. HITsp is also based only on adult data. At this time no models have been developed for the biomechanics of mTBI in the pediatric population using helmet instrumentation.

The development of another metric called Brain Injury Criterion (BrIC) is based on rotational kinematics and was formulated for injury across the spectrum of severity (Tahounts et al. 2011, 2013). BrIC was developed based on animal study data for AIS 4+ injury and then scaled to other injury severities. Part of the development process involved employing data collected using the HIT System for football to evaluate the BrIC prediction of AIS 2+ injury.

Other studies have used Weibull distributions to develop probability density functions and cumulative distribution functions from instrumented helmet data that form the basis of injury risk curves in terms of peak linear head accelerations (Funk et al. 2007), peak rotational head accelerations (Rowson et al. 2012), and a combination of both measures (Rowson and Duma 2013). However, the development of these risk curves employs various assumptions relating to underreporting of head injury and system error discussed in detail throughout this dissertation. These researchers have developed a system for evaluating football helmets based off of the injury risk curves (Rowson and Duma 2011).
The majority of helmet instrumentation studies have been done conducted in football and therefore most of the understanding about the biomechanics of mTBI is based largely on football data. However, there may be various mechanistic subtypes of concussion. For instance, blast-induced mTBI is attributed to rapid, high-pressure waves (Elder and Cristian 2009) and is considered distinctly different from sport-related concussion. Furthermore mTBI occurring from motor vehicle crashes may be due to impacts of different duration from football. It is possible that various types of impacts with different proportions of linear and rotational acceleration cause different subtypes of mTBI, with one being more prevalent than another in a sport based on the nature of that sport. For example, the biomechanics of impacts in boxing have been shown to differ substantially from football impacts, with lower Head Injury Criterion (HIC) and linear acceleration values but proportionally higher rotational acceleration values (Viano et al. 2005). Therefore, there may be limitations in using only one type of impact data to develop a mechanistic understanding about mTBI. Increasing the amount of data on the biomechanics of impacts across a range of sports could add information that is valuable in establishing concussion injury thresholds.

1.9: Helmet instrumentation system accuracy

The findings discussed in the previous sections are highly dependent on accuracy of the helmet-based systems in estimating head impact biomechanics. Validation studies have been done on the HIT Systems for football (Beckwith, Greenwald, and Chu 2012; Manoogian et al. 2006; Rowson et al. 2011), boxing (Beckwith, Chu, and Greenwald
2007), and soccer (Hanlon and Bir 2010). Published validation of the HIT System for ice hockey system is extremely limited in methodological detail, (Gwin, Chu, and Greenwald 2006). Each of these studies will be discussed in detail in Chapter 2, however it is important to note that 1) none of these validation studies report the average absolute error of the peak resultant linear and rotational accelerations in a way that is useful for interpreting individual values that are obtained via helmet instrumentation, 2) they assume that the acceleration value measured from the instrumented helmet corresponds exactly to the acceleration experienced by the head (i.e. there is no systematic sensor bias, the relationship is 1:1), and 3) they have not comprehensively evaluated the accuracy across a range of impact conditions that are similar to on-field impacts.

Calculated average absolute error of the peak resultant linear and rotational accelerations is critical for interpretation of data obtained from injured athletes. When reporting error, average relative error has been used, which involves maintaining the polarity of the error for each impact before calculating an average, therefore averaging negative and positive values together and resulting in an error near zero if the measurement error is random (Rowson et al. 2011). The rationale given was that large datasets would be used in their injury risk analyses and hence when the real-world data were averaged the error should be near zero. However, there are very few injurious data points in many of these data sets, particularly compared to subconcussive impacts, and a number of studies have relied on reporting the measures and circumstances surrounding individual impacts that have caused mTBI (Broglio et al. 2010; Brolinson et al. 2006; Duma et al. 2005; Guskiewicz et al. 2007; McAllister et al. 2012). If the dataset of injuries is further divided by other
factors that are suspected to be important, such as impact direction, this results in an even fewer number of data points in each group. Therefore, it is important to know, and account for in data analysis, the amount of error that can be expected to be associated with the measurement of an individual impact that leads to an injury. Difficulty to date in correlating impact biomechanics to injury and symptoms (Broglio et al. 2011; Duhaime et al. 2012; Guskiewicz and Mihalik 2011) may be in part due to the limited treatment of error, both systematic sensor bias as well as random measurement error, in these studies.

Due to the fact that the helmet is not rigidly attached to the head and the helmet itself is not rigid, it is likely that the relationship between the helmet instrumentation measures and reference head acceleration varies across factors that may be important in real-world scenarios, such as the impacting surface, impact direction, the interface between the head and the helmet (i.e. human hair), and the effective mass of the torso. These characteristics have not been parametrically explored in previous helmet instrumentation validation studies and the magnitude of their effect on accuracy of helmet-based sensor measurements may be crucial for interpreting data obtained from real-world implementation of these systems.

1.10: Research objectives

Quantitatively linking head impact biomechanics measured on actual athletes during competition with the clinical entity of concussion can provide new insight into how to prevent this common and potentially life-changing injury, both in sports and motor vehicle crashes. This is particularly important for youth who are disproportionately
affected by this injury. A number of measurement devices are coming to market to meet this need. However, they lack proper evaluation of their accuracy under various real world impact scenarios. These devices may be used by researchers, teams, athletic trainers, or parents to try to understand the inputs that lead to injury and improve the safety of the athletes that participate in high-impact sports. This study begins to address this need by defining and implementing a method to evaluate the accuracy of helmet-based biomechanical measurement systems, conducting a systematic and comprehensive analysis of the effect of several factors that may vary in the real-world, and exploring the influence of these accuracy measures on brain injury metrics using finite element analysis.
Chapter 2 - Techniques to evaluate helmet-based measurement systems in a laboratory setting to quantify errors in peak kinematic measures

2.1: Introduction

High impact sports provide a unique real-world opportunity to study the biomechanical inputs that lead to mild traumatic brain injury. This is a scenario where the head is regularly loaded and the helmets required to play these sports provide a vehicle by which to estimate kinematic measures of head impacts. Furthermore, the athletes are a defined cohort at increased risk for mTBI, so baseline clinical and neurocognitive measures can be taken on them. Over the past decade, helmet-based accelerometer systems have become a common means to study mTBI biomechanics in these real-world settings.

2.1.1: Previous helmet-based research

The most widely-used helmet-based systems to date have been the Head Impact Telemetry (HIT) Systems for football and ice hockey (Simbex LLC; Lebanon, NH). Data collected using these accelerometer systems have been used to compare head impact magnitudes based on a number of characteristics, including playing position, gender, awareness of impending impact, cervical muscle strength, and sport specific scenarios (Brainard et al. 2012; Crisco et al. 2010; Mihalik et al. 2007, 2011, 2012; Mihalik, Greenwald, et al. 2010; Ocwieja et al. 2011; Reed et al. 2010; Stojsih et al. 2010). Concussion risk curves for football players based on peak resultant linear and rotational head acceleration have been developed using data collected via the HIT System for
football (Funk et al. 2007, 2012; Rowson and Duma 2011; Rowson et al. 2012). HIT Systems have also been developed for use in boxing headgear (Beckwith, Chu, and Greenwald 2007) and soccer headgear (Hanlon and Bir 2010). Details of these previous helmet-based research studies are discussed in detail in Chapter 1, sections 1.6-1.9.

2.1.2: HIT System measurement approach and previous validation

The HIT Systems each use six single-axis linear accelerometers (apart from a specialized six-degree-of-freedom system for football and the HIT System for boxing which employ twelve accelerometers (Beckwith, Chu, and Greenwald 2007; Rowson et al. 2011)) embedded in the padding of the helmet in a spring-loaded manner to encourage engagement of the sensors to the head (Manoogian et al. 2006). Due to accelerometer placement restraints based on helmet design, the six-accelerometer HIT System for football is a 5-degree-of-freedom system (5DOF) that does not allow for estimation of z-axis rotational acceleration. Assuming rigid body dynamics and using iterative optimization, an algorithm is used to calculate the linear and rotational acceleration at the estimated center of gravity (CG) of the head from the individual accelerometer measurements. However, the HIT Systems developed for each sport differ slightly from each other both in construction and processing algorithm. Specifically, the orientation of the accelerometers in the HIT System for ice hockey is tangential to the head, whereas they are oriented normal to the head in the HIT System for football. This variation requires adjusting the algorithm from which the three orthogonal linear and rotational accelerations of the head are calculated. For the normally-oriented accelerometers (football), the position vectors and individual accelerometer measurements are used to
estimate linear acceleration magnitude and impact direction at the center of gravity of the head assuming a sphere of given geometry (Crisco, Chu, and Greenwald 2004). To estimate rotational acceleration, this technique requires assuming rotations about a fixed point in the neck to estimate rotational acceleration and does not allow for estimation of z-axis rotational acceleration (Chu et al. 2006). However, tangential orientation of the accelerometers (hockey) allows for calculation of rotational accelerations using iterative optimization of the formula for acceleration projected along the sensing axis, given that centripetal acceleration can be removed from the equation since the sensing axis is orthogonal to the radial orientation of this component (Equation 2.1) (Chu et al. 2006).

\[ |a_i| = \vec{r}_{ai} \cdot \vec{H} + \vec{r}_{ai} \cdot (\vec{a} \times \vec{r}_i) + [r_{ai} \cdot (\vec{\omega}_i \times (\vec{\omega}_i \times \vec{r}_i))] \]

Equation 2.1 where \( a_i \) is acceleration at ith point, \( H \) is linear acceleration at the head CG, \( r_{ai} \) is accelerometer sensing axis orientation in head CG coordinate system, \( r_i \) is accelerometer location relative to the head CG, \( \alpha_i \) is rotational acceleration about the CG, and \( \omega_i \) is rotational velocity about the CG. The bracketed portion can be ignored with accelerometers tangential to the head.

Critical to the success of efforts to quantify head biomechanics is the ability of the helmet-mounted instrumentation to accurately estimate the kinematics (rotational and linear) of the CG of the head. Validation efforts for the HIT Systems for football (Beckwith, Greenwald, and Chu 2012; Manoogian et al. 2006; Rowson et al. 2011), boxing (Beckwith, Chu, and Greenwald 2007) and soccer (Hanlon and Bir 2010) have been previously published and are reviewed below.
Manoogian et al. simulated helmet-to-helmet impacts, using a helmeted Hybrid II ATD head on neck on a pendulum to impact a helmeted Hybrid III ATD (Manoogian et al. 2006). The Hybrid III was placed in a wheel chair to allow translational motion after impact and its helmet was instrumented with the HIT System for football. Accelerometers were also placed on the inside of the helmet shell at the point of impact. The testing was conducted at 2, 3.5, and 5 m/s with impact locations on the side, back, top, and front (above the facemask). This study analyzed linear accelerations and found the acceleration of the head CG to be less than 10% of that of the helmet shell. They also report HIT System measures were almost identical to those measured at the center of gravity of the Hybrid III ATD head in peak magnitude, time to peak, and waveform shape, but these findings were not quantified.

Subsequently, Beckwith et al. compared head kinematics measured by the HIT System for football to those from a Hybrid III ATD (Beckwith, Greenwald, and Chu 2012). In this study a Hybrid III head and neck was mounted directly to a linearly translating table. No mass was used to account for the effective mass of the torso. Two nylon stockings were put over the Hybrid III head to reduce friction between the head and the helmet and a medium sized helmet instrumented with the HIT System for football was fit to the ATD head. A pneumatic linear impactor was used to impact the helmeted Hybrid III with a curved impacting face with a layer of vinyl nitrile foam (used in many football helmets) beneath it, and this configuration was designed to replicate helmet-to-helmet impacts. The impact sites were chosen based on locations most frequently resulting in injury according to video analysis of NFL players. In comparing peak HIT System measures to
peak ATD measures for the same impacts, regression analysis resulted in coefficients of
determination of 0.903 for peak resultant linear acceleration and 0.528 for peak resultant
rotational acceleration. Errors in peak measures were not quantified but the slopes of the
linear regression equations were used to state that this system overestimates linear
acceleration by 0.9% (m=1.009) and underestimates rotational acceleration by 6.1%
(m=0.939).

Jadischke et al. employed a similar method to evaluate the HIT System for football, but
tested the system using both a size medium and size large helmet (Jadischke et al. 2013).
Using the medium-sized helmet they found that, for both peak resultant linear and
rotational acceleration, more than half of the impacts exhibited average absolute errors
greater than 15%. Using the large-sized helmet, they found similar results for peak
resultant linear acceleration, but around three quarters of the impacts exhibited average
absolute errors greater than 15% in peak resultant rotational acceleration. They also
compared the fits of helmets on high school football players to those of the medium and
large helmets on the Hybrid III head and found the large helmet on ATD to be more
representative of the volunteers. This helmet fit assessment is described in more detail in
Chapter 3, section 3.1.2.

The 6DOF HIT System for football, which consists of 12 accelerometers rather than 6
and allows for estimation of z-axis rotational acceleration, was also evaluated (Rowson et
al. 2011). This system was developed for research purposes only and has received limited
use on-field. The methods for this study were similar to those described above for the
Beckwith study (Beckwith, Greenwald, and Chu 2012). However, rather than two nylon stockings, a skullcap made of nylon and spandex was used as the interface between the ATD head and the helmet. Different impact locations were used but they were also chosen based on video analysis of NFL impacts. This study utilized power regressions rather than linear regressions to assess the relationships between peak 6DOF HIT System and peak ATD measures, resulting in coefficients of determination of 0.88 for linear acceleration and 0.85 for rotational acceleration. They did not calculate average absolute error, instead calculating average relative error which maintains the polarity of the error for each impact before calculating an average, therefore averaging negative and positive values together and resulting in an error near zero if the system error is random. For peak resultant linear acceleration, average relative error was 1% ± 18%, whereas for peak resultant rotational acceleration it was 3% ± 24%. The study also reported a root mean square error of 12.5 ± 8.32 g for resultant linear acceleration and 907 ± 685 rad/s² for resultant rotational acceleration.

The HIT System for boxing has been integrated into boxing headgear and consists of 12 single-axis linear accelerometers. Beckwith et al. assessed this system by laboratory comparison with a Hybrid III head (Beckwith, Chu, and Greenwald 2007). The head and neck were mounted to an adjustable platform and the head was impacted with a weighted pendulum in locations typically hit during boxing matches. Linear regression analysis found correlation coefficients and slopes of 0.91 and m=0.98 for peak resultant linear acceleration and 0.91 and m=1.08 for peak resultant rotational acceleration. Root mean
square errors were $5.9 \pm 2.6$ g for resultant linear acceleration and $595 \pm 405$ rad/s$^2$ for resultant rotational acceleration. Average absolute error was not reported in this study.

The validation of the HIT System for soccer (consisting of six single-axis linear accelerometers) performed by Hanlon and Bir simulated both head-to-head and ball-to-head impacts (Hanlon and Bir 2010). Ball-to-head impacts were emulated using an air cannon to shoot the ball at a Hybrid III head fit with the instrumented soccer headgear at 3 speeds (8, 10, and 12 m/s) and at 3 locations chosen to represent a range of on-field impacts. Head-to-head impacts were performed by mounting one Hybrid III head and neck to a linear impactor and using it to impact another Hybrid III head, which was fit with the HIT System for soccer and mounted to a trolley. This was done at three speeds (2.5, 3.5, and 4.75 m/s) and two locations. Ball-to-head impacts resulted in weak coefficients of determination for linear regressions of 0.3403 for peak resultant linear acceleration and 0.5716 for peak resultant rotational acceleration, but strong correlations for head-to-head impacts of 0.8940 and 0.8998 for peak resultant linear and rotational acceleration respectively. Average absolute error was not reported.

Published data on the validation of the HIT System for ice hockey is extremely limited, and does not include details on test methodology or data analysis as it only exists in abstract form (Gwin, Chu, and Greenwald 2006). This abstract reports mean linear and rotational acceleration errors of 9% and 11% respectively, with coefficients of determination of values of 0.93 and 0.86 (Gwin, Chu, and Greenwald 2006). It is unclear how these errors were calculated. Due to the differences in the accelerometer orientation,
processing algorithm, and helmet shape for ice hockey compared to the other HIT Systems, a comprehensive validation on the HIT System for ice hockey is needed.

2.1.3: GFT measurement approach

Recently, a number of other helmet-based systems have become available to measure the kinematics associated with head impacts, some of them integrating use of gyroscopes so that rotational velocity can be directly measured rather than estimated via calculations. The gForce Tracker (GFT) (Markham, ON) is one such system that employs triaxial accelerometers and gyroscopes. Accurate measurement of rotational kinematics is particularly important when studying thresholds of traumatic brain injury since rotational movement is correlated to measures of strain within the brain, which are predictive of diffuse axonal injury across the spectrum of severity (Browne et al. 2011; Gennarelli, Thibault, and Ommaya 1972; Meaney et al. 1993; Takhounts et al. 2008). It is likely more accurate to measure rotational kinematics than calculate them, as is done in the HIT System. No published data exists on the accuracy of the GFT or other systems that use gyroscopes.

2.1.4: Research objective

The objective of this study was to compare the head kinematics measured by these two helmet-based measurement systems, one that relies solely on accelerometers (the HIT System for ice hockey) and one that incorporates gyroscopes as well (GFT), with true head kinematics. We accomplished this objective by subjecting a hockey-helmeted ATD
head and neck equipped with these systems to repeated head impacts of multiple intensities and directions, and then comparing the system-reported peak head kinematics with those measured at the CG of the ATD head. The quantitative comparison between the helmet-based system data and the ATD reference data employed more comprehensive methods than had been used in previous studies. This allowed for evaluation of two systems that use different approaches for estimating head impact kinematics.

2.2: Methods

2.2.1: Laboratory test setup

A Hybrid III (HIII) 50th percentile male ATD head and neck with the 3-2-2-2 accelerometer array (Padgaonkar, Krieger, and King 1975) and three angular rate sensors was rigidly mounted at T1. Rigid mounting of the ATD head and neck was chosen to reach the desired range of resultant accelerations within the limits of impact velocities able to be generated by the linear impactor and to simulate a large effective mass of the torso. Resultant accelerations from this approach were similar to those test setups that used a linear slide table without incorporation of torso mass for the fixation of T1 (Rowson et al. 2011), however they were achieved with lower impact velocities. For comprehensiveness, a comparison between results from a rigid mount and a sliding mount that accounts for the mass of the torso is included in Chapter 3, but this does not address any differences that may exist between translating tables that do and do not account for torso mass.
2.2.2: Helmets and measurement systems

An Easton S9 hockey helmet (Easton-Bell Sports Inc., Van Nuys, CA) instrumented with the HIT System for ice hockey, along with both an Easton S9 hockey helmet and a Bauer RE-AKT hockey helmet (Bauer Hockey, Inc., Exeter, NH) (Figure 2.1) each instrumented with GFT sensors in four different locations (outside top, outside back, outside right, and inside top) (Figure 2.2), were fit to the ATD head. Differences in helmet construction and sizing recommendations based on head circumference led to the use of a large-sized adult Easton helmet and a medium-sized adult Bauer helmet. USA Hockey guidelines were used to fit the helmets by marking the ATD head with approximate eyebrow locations and then centering the helmet on the head with the “rim” one finger width above the eyebrows, tight enough to prevent axial rotation of the helmet about the head (USA Hockey). Based upon observation of youth hockey teams in play and practice, player hair is wet during play. Thus, a human hair wig was adhered to the ATD head using double-sided tape that kept the wig from displacing on the ATD head and the wig was sprayed with water to simulate perspiration before fitting the helmets to the head. The alignment of the helmet on the ATD head was checked before each impact to confirm repeatability of the testing conditions. Both helmets had their corresponding facemasks attached, as hockey players under the age of 18 are required by USA Hockey rules to wear such a facemask.
The HIT System for ice hockey consists of six linear single-axis accelerometers, oriented tangentially to the head (Figure 2.3). A spring between the helmet shell and each accelerometer’s housing is designed to enhance contact between the accelerometer and the head (Manoogian et al. 2006). When one of the accelerometers detects an acceleration of at least 10 g, the system is triggered to collect 40 ms of data, 8 ms before the threshold.
is reached and 32 ms after, at 1000 Hz (Mihalik, Greenwald, et al. 2010). Data from the six accelerometers are passed through a 0.5 Hz AC hardware filter and a 400 Hz low-pass filter and then automatically and wirelessly transferred to a sideline data storage system. The data are uploaded to a Simbex server and, based on the individual accelerometer measurements, an algorithm proprietary to Simbex is used to calculate linear and rotational acceleration at an estimated center of gravity of the head based upon rigid body dynamics and iterative optimization (Chu et al. 2006). The processed impact data are then sent back to the end users. The general theory and equations used to calculate linear acceleration based on data from 6 single axis accelerometers oriented normal to the head (as used in the football application of this system) on a hemispherical object were published in 2004 (Crisco, Chu, and Greenwald 2004). The theoretical approach was subsequently updated to calculate linear and rotational acceleration based on data from 6 accelerometers oriented tangential to the head, as is the case for the HIT System for ice hockey, and published in abstract form (Chu et al. 2006). However the raw accelerometer data and the processing algorithm itself are unavailable to end users of the HIT System for ice hockey.
Figure 2.3: HIT System accelerometer locations in the helmet indicated by white oval markings. The front of the helmet is facing the left side. The two accelerometer locations shown on the top of the photo are mirrored by the two accelerometer locations on the bottom.

The GFT consists of triaxial accelerometers and gyroscopes housed in a casing that is attached to a helmet via adhesive or Dual Lock Reclosable Fasteners (3M, St. Paul, MN). This allows integration into a helmet of choice, and implementation across a range of helmeted sports. Impact data are stored on-board and uploaded via USB connection. The data obtained by the end-user is the raw acceleration and velocity data, and has not been processed apart from use of a simple first-order hardware low pass filter on the accelerometers with a cut-off frequency of 300 Hz, so it has not been transformed to an approximate center of gravity of the head or adjusted to account for the helmet’s dissipation of energy. Impact data are recorded over a 40 ms timespan at 3000 Hz for linear acceleration data and 760 Hz for rotational velocity data. However, if the acceleration remains above the user-set threshold beyond this timepoint, the system
continues recording 40 ms timespans of data until the acceleration falls below the threshold. For this study, that threshold was set to 8 g.

2.2.3: Impactor

A pneumatic linear impactor, weighing 23.9 kg, was used to contact the helmets at various speeds and in different directions (Figure 2.4, Figure 2.5). Reported impacting speeds were measured immediately before impact with the impactor in free-flight. One of two ultra-high molecular weight polyethylene (UHMWPE) impacting surfaces were used in each test, both of which were cylindrical with the flat end of the cylinder contacting the helmet. Both cylinders were two inches thick from the impacting surface to the site of attachment on the impactor. One impacting surface had a 8.26 cm in diameter and weighed 0.4 kg, while the other was 10.16 cm in diameter and weighed 0.6 kg. For both impacting surfaces, the flat surface of the cylinder had rounded edges. For HIT System testing, the 8.26 cm impactor was used for side and oblique back impacts and the 10.16 cm impactor was used for back, front, and oblique front impacts. For GFT testing, the 10.16 cm impactor was used for all impact. While high speed video of HIT System testing suggests that the helmet was not conforming beyond the ends of the smaller impactor, use of the larger impactor in subsequent tests made this even less likely.
2.2.4: Directions and speeds

Four or five repeat tests were conducted at one of five impact directions (front, back, side, oblique back-side, or oblique front-side) and one of four speeds (1.5, 2.5, 3.75 or 5 m/s) (Figures 2.6, 2.7). These speeds were chosen to achieve the range of accelerations...
that may be experienced during on-ice play. For HIT System testing, oblique impacts were measured at 30 degrees from the sagittal plane (Figure 2.4). For GFT testing, due to use of the larger impacting face for all impact directions and its possible interactions with geometrical features of the helmets, oblique impacts were measured at 45 degrees from the sagittal plane (Figure 2.5).

<table>
<thead>
<tr>
<th>Helmet/Sensor Set</th>
<th>Impacting Speed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1.5 m/s</td>
</tr>
<tr>
<td>Side</td>
<td>5</td>
</tr>
<tr>
<td>Oblique Back</td>
<td>5</td>
</tr>
<tr>
<td>Back</td>
<td>5</td>
</tr>
<tr>
<td>Oblique Front</td>
<td>5</td>
</tr>
<tr>
<td>Front</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Helmet/Sensor Set</td>
<td>Impacting Speed</td>
</tr>
<tr>
<td></td>
<td>1.5 m/s</td>
</tr>
<tr>
<td>Side</td>
<td>5</td>
</tr>
<tr>
<td>Oblique Back</td>
<td>5</td>
</tr>
<tr>
<td>Back</td>
<td>5</td>
</tr>
<tr>
<td>Oblique Front</td>
<td>5</td>
</tr>
<tr>
<td>Front</td>
<td>5</td>
</tr>
</tbody>
</table>

Figure 2.6: Test matrix for impacts to HIT System for ice hockey instrumented helmets
<table>
<thead>
<tr>
<th></th>
<th>Impacting Speed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1.5 m/s</td>
</tr>
<tr>
<td>Bauer</td>
<td>Side</td>
</tr>
<tr>
<td></td>
<td>Oblique Back</td>
</tr>
<tr>
<td></td>
<td>Back</td>
</tr>
<tr>
<td></td>
<td>Front</td>
</tr>
<tr>
<td>Easton</td>
<td>Side</td>
</tr>
<tr>
<td></td>
<td>Oblique Back</td>
</tr>
<tr>
<td></td>
<td>Back</td>
</tr>
<tr>
<td></td>
<td>Front</td>
</tr>
</tbody>
</table>

**Figure 2.7: Test matrix for impacts to GFT instrumented helmets**

### 2.2.5: Data analysis

ATD-collected acceleration time histories were processed with a CFC 1000 filter and rotational accelerations were calculated from the nine accelerometer array via the process outlined by Padgaonkar et al. (Padgaonkar, Krieger, and King 1975). Similarly, rotational velocities measured via angular rate sensors were processed using a CFC 60 filter. In addition to calculating the head acceleration and impact direction, the HIT System for ice hockey algorithm determines whether an impact is considered “valid”. There are two reasons that an impact may not be considered valid: 1) the resultant linear acceleration is less than 10 g even though a single acceleration registered greater than 10 g or, 2) based on rigid body dynamics, the acceleration pulse does not have characteristics of an impact to a helmeted head. The purpose of the latter is to remove data resulting from occurrences such as a player throwing his or her helmet down on the bench. Impacts that, based on the
algorithm, fall into one of these categories are removed from the processed data set and are not normally sent back to the end user. In this test series, we recorded the time of each impact performed and were able to confirm that raw data were collected for all impacts by viewing the data before it was wirelessly uploaded to the server for processing. Through cooperation with the HIT System manufacturer, we were able to obtain those data that were removed from processing per the reasons outlined above and compare them to data from similar impacts (having the same speed and direction) that were not removed from the dataset. The GFT system does not employ a similar processing step.

Peak values of the ATD and HIT-System resultant linear and angular head acceleration for the same impact were compared. Similarly maximum values of resultant linear acceleration and resultant rotational velocity were compared between the ATD and GFT measurement systems for the same impact. The correlations between helmet system-estimated and ATD-measured peak kinematics were quantified using two regression techniques: a linear fit and a power fit. Regressions were found for data from all impact directions combined and then for data stratified by impact direction. The quality of the regression was assessed using coefficients of determination ($R^2$ values). Power regression was chosen in addition to linear regression due to the deformable nature of the helmet. Given that the helmet is meant to dissipate forces imparted to the head, the mechanical response of the helmet can differ based on impact severity, leading to more deformation and force dissipation at higher speeds. If the helmet’s dissipation of energy is not linearly related to impacting speed for all impact directions, this would influence system
measures leading to non-linear relationships between system and ATD-measured kinematics.

While $R^2$ values describe the strength of the correlations between ATD and helmet-based system data that can be achieved using equations to relate the sets of measures, the absolute differences between the measures are also important for understanding accuracy. Therefore, absolute errors were also calculated to assess system accuracy. Three types of average absolute error were calculated to compare the HIT System peak resultant acceleration to the ATD peak resultant acceleration. The first was total percent error (Equation 2.2) – i.e. the absolute difference between the two measures, expressed as a percentage of the Hybrid III measure. This is also referred to as the absolute error of the “raw” HIT System values; for this system the “raw” values are those provided to the end user after processing by the Simbex proprietary algorithm. The second was the percent error of the data after it was corrected using the regression relationships found for the peak kinematic measures when impacts from all directions were included (Figure 2.8, left); in other words, the error was re-calculated after the aforementioned linear (Equation 2.3a) and power (Equation 2.3b) regression equations were applied to the HIT System measures. The last approach was to use the regression equations for individual impact directions (Figure 2.8, right) to calculate direction-specific absolute errors. The averages and standard deviations of these errors were calculated.

$$\text{Percent Error} = \frac{|\text{HIT}_{\text{max}} - \text{ATD}_{\text{max}}|}{\text{ATD}_{\text{max}}} \times 100$$

Equation 2.2
Percent Error of Linear Regression Adjusted Data

\[
\frac{\left| (a \times \text{HIT}_{\text{max}} + b) - \text{ATD}_{\text{max}} \right|}{\text{ATD}_{\text{max}}} \times 100
\]

Equation 2.3a where \(a\) and \(b\) are coefficients of the linear regression equation

Percent Error of Power Regression Adjusted Data

\[
\frac{\left| (a \times \text{HIT}_{\text{max}}^b) - \text{ATD}_{\text{max}} \right|}{\text{ATD}_{\text{max}}} \times 100
\]

Equation 2.3b where \(a\) and \(b\) are coefficients of the power regression equation

For the GFT system, all error calculations were separated by helmet brand and sensor location and three types of absolute error were calculated. First, the average absolute error of the raw data for all impacts to each helmet was calculated. Then two additional absolute errors were calculated using data calibrated by regression equations. Since the GFT data are filtered but otherwise unprocessed, the linear acceleration and rotational velocity measures have not been adjusted to estimate values at the center of gravity. Given that the sensors are attached to the helmet, and the purpose of the helmet is to dissipate forces imparted to it, this cannot be done using a direct rigid body transformation. For this reason, an empirical method was used to calibrate the data, applying the power regressions mentioned above to the peak resultant measures of linear acceleration and rotational velocity (Equation 2.4). First, the regression equation developed from using data from all impact directions combined was applied to the peak values before calculating absolute error (Figure 2.8, top). As a second approach, the
regression equations developed from data stratified by impact direction were applied to peak values for that impact direction and then absolute error was calculated (Figure 2.8, bottom).

Percent Error of Power Regression Adjusted Data

\[ \frac{\left| (a \times \text{GFT}_{\text{max}}^b) - \text{ATD}_{\text{max}} \right|}{\text{ATD}_{\text{max}}} \times 100 \]

Equation 2.4 where \(a\) and \(b\) are coefficients of the power regression equation

Figure 2.8: Example of regression equations used in Equation 2.4 to calculate average absolute error for all impact directions combined (top) or stratified by impact direction (bottom). The data shown is for impacts to the Bauer helmet.
All statistical analyses were performed using the mixed models procedure in SAS 9.3 (SAS Institute Inc.; Cary, NC). For the HIT System data, the relationship between the primary outcome measure (ATD peak resultant acceleration) and the HIT System peak resultant acceleration was assessed with impact direction included in the model as a categorical variable. The effect of this variable on the interaction between peak HIT System-calculated and ATD-measured peak resultant acceleration was assessed; in other words, we determined whether there was a significant interaction between peak HIT measure and impact direction (side, back, or oblique back) in the model (Model 2.1). This analysis was done for both linear and rotational acceleration. The statistical analysis for peak GFT kinematic measures was done with both impact direction (front, side, back, or oblique back) and sensor location (outside top, outside right, outside back, or inside top) included in the model as categorical variables. Because another variable was introduced into the model, the ratio of peak ATD measure to peak GFT measure was used as the primary outcome measure in order to facilitate interpretation of the results. The effect of these categorical variables on the ratio between ATD and GFT peak resultant measures was assessed (Model 2.2). In cases of statistically significant interactions between impact direction and sensor location, data were stratified to test for specific effects (Models 2.3a and 2.3b), using Bonferroni corrections to adjust for multiple tests. Again, statistical analyses were performed for both peak linear accelerations and peak rotational velocities.
Model 2.1: Statistical model for data stratified by helmet brand. \( V1 = \text{impact direction} \).

\[
ATD_{peak} = \beta_0 + \beta_1 \times HIT_{peak} + \beta_2 \times V1 + \beta_3 \times HIT_{peak} \times V1 + \epsilon
\]

Model 2.2: Statistical model for data stratified by helmet brand. \( V1 = \text{impact direction} \) and \( V2 = \text{sensor location} \).

\[
\frac{ATD_{peak}}{GFT_{raw\ peak}} = \beta_0 + \beta_1 \times V1 + \beta_2 \times V2 + \beta_3 \times V1 \times V2 + \epsilon
\]

Model 2.3a: Statistical model for data stratified by helmet brand and sensor location. \( V1 = \text{impact direction} \).

\[
\frac{ATD_{peak}}{GFT_{raw\ peak}} = \beta_0 + \beta_1 \times V1 + \epsilon
\]

Model 2.3b: Statistical model for data stratified by helmet brand and impact direction. \( V2 = \text{sensor location} \).

\[
\frac{ATD_{peak}}{GFT_{raw\ peak}} = \beta_0 + \beta_1 \times V2 + \epsilon
\]

The impact direction calculated by the HIT System, which includes a categorical description of direction (side, front, top, back) and the estimated azimuth and elevation angles of each impact, was compared to the actual impact direction for each of those tests. Similarly, the impact direction calculated by the GFT, which includes the estimated azimuth and elevation angles of each impact, was compared to the actual impact direction for each of those tests. As the attachment of T1 was fixed relative to the impactor and the line of action of the impactor was known, the actual impact direction was initially measured upon set-up and reconfirmed before each test.
2.3: Results

2.3.1: Impacts removed from the dataset

48 of the 218 impacts in the HIT System test matrix were removed from the dataset by the processing algorithm for impact “validity” (Figure 2.9). ATD-measured peak resultant acceleration showed that 8 of these 48 impacts were below the 10g threshold and therefore accurately removed according to the lower threshold defined in the algorithm. Of the 40 impacts remaining, 28 (70%) of these were front and oblique front impacts, representing 53% of the data for these impact directions. Thus, with more than half of data in the frontal and frontal oblique impact directions removed by the algorithm, the remainder of the HIT System results will focus exclusively on the 139 impacts in the side, back, and oblique back directions. Graphs of the acceleration time histories of front impacts for each axis did not reveal any noticeable differences between the data for impacts that were retained and those that were removed from the dataset (Figure 2.10). Analyzable data were obtained for all GFT impacts given that the system does not utilize a validity algorithm.
Figure 2.9: Characteristics of the impacts removed from the dataset by a HIT System processing algorithm.

Figure 2.10a: X-axis linear acceleration time history for valid (dashed gray) impacts and impacts determined to be “invalid” by a processing algorithm (solid black).
Figure 2.10b: Y-axis linear acceleration time history for valid (dashed gray) impacts and impacts determined to be “invalid” by a processing algorithm (solid black).

Figure 2.10c: Z-axis linear acceleration time history for valid (dashed gray) impacts and impacts determined to be “invalid” by a processing algorithm (solid black).

Figure 2.10d: X-axis rotational acceleration time history for valid (dashed gray) impacts and impacts determined to be “invalid” by a processing algorithm (solid black).
2.3.2: Regressions and coefficients of determination

In general, the intercepts associated with the linear regression equations were not equal to zero and, as a result, a power fit was the focus of analysis. The power fit through zero improved the correlation between the reference acceleration and the HIT System-measured acceleration for all impact directions for peak linear acceleration, and for all impact directions except side for peak rotational acceleration (Table 2.1). Power regression analysis of peak HIT System kinematics compared to peak reference HIII
kinematics showed strong relationships between these measures. For the data from all impact directions combined, the coefficient of determination was 0.88 for peak resultant linear acceleration and 0.60 for peak resultant rotational acceleration (Figure 2.11, Table 2.1). Coefficients of determination for data stratified by individual impact directions ranged from .89-.98 for peak linear acceleration and from .84-.92 for peak rotational acceleration (Figure 2.11, Table 2.1).
Figure 2.11: Data comparing peak resultant linear (left) and rotational (right) acceleration as measured by the ATD and by the HIT System for all impact directions combined and then stratified by impact direction. Each data point represents a single impact, with HIT System measure on the abscissa and ATD measure on the ordinate. The line corresponds to the power regression relationship.
<table>
<thead>
<tr>
<th>Direction</th>
<th>Regression Equation: Linear Fit</th>
<th>Linear Fit $R^2$</th>
<th>Regression Equation: Power Fit</th>
<th>Power Fit $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Data  (n=140)</td>
<td>$y = 1.47x - 3.71$</td>
<td>0.73</td>
<td>$y = 0.88x^{1.11}$</td>
<td>0.88</td>
</tr>
<tr>
<td>Side (n=66)</td>
<td>$y = 1.21x + 3.14$</td>
<td>0.97</td>
<td>$y = 1.80x^{0.91}$</td>
<td>0.98</td>
</tr>
<tr>
<td>Back (n=36)</td>
<td>$y = 1.37x - 6.70$</td>
<td>0.81</td>
<td>$y = 0.53x^{1.21}$</td>
<td>0.89</td>
</tr>
<tr>
<td>Oblique (n=38)</td>
<td>$y = 2.33x - 25.19$</td>
<td>0.81</td>
<td>$y = 0.25x^{1.49}$</td>
<td>0.92</td>
</tr>
<tr>
<td>All Data  (n=140)</td>
<td>$y = 1.51x - 971.57$</td>
<td>0.64</td>
<td>$y = 0.40x^{1.12}$</td>
<td>0.60</td>
</tr>
<tr>
<td>Side (n=66)</td>
<td>$y = 1.92x - 860.57$</td>
<td>0.94</td>
<td>$y = 0.53x^{1.14}$</td>
<td>0.92</td>
</tr>
<tr>
<td>Back (n=36)</td>
<td>$y = 0.81x - 141.02$</td>
<td>0.85</td>
<td>$y = 0.30x^{1.11}$</td>
<td>0.90</td>
</tr>
<tr>
<td>Oblique (n=38)</td>
<td>$y = 1.76x - 3123.39$</td>
<td>0.71</td>
<td>$y = 0.0002x^{1.99}$</td>
<td>0.84</td>
</tr>
</tbody>
</table>

Table 2.1: Linear and power regression fit equations for HIT System data and their associated $R^2$ values.

Power regression analysis of peak GFT kinematics compared to peak reference HIII kinematics also showed strong relationships between these measures. For the data from all impact directions combined, coefficients of determination ranged from 0.60-0.80 for peak resultant linear acceleration and 0.83-0.91 for peak resultant rotational velocity (Figure 2.8 top, Figure 2.12, Table 2.2, Appendix 1). Coefficients of determination for data stratified by individual impact directions ranged from .77-.99 for peak linear
acceleration and from .78-1.0 for peak rotational velocity (Figure 2.8 bottom, Figure 2.12, Table 2.2, Appendix 1).
Figure 2.12: Data comparing peak resultant linear acceleration (left) and peak resultant rotational velocity (right) as measured by the ATD and by GFT for all impact directions combined and then stratified by impact direction. The graphs show both the data collected from impacts to the Easton helmet and data collected from impacts to the Bauer helmet. Each data point represents a single impact, with GFT measure on the abscissa and ATD measure on the ordinate. The solid lines correspond to the power regression relationships for impacts to the Easton helmet, while the dashed lines correspond to power regression relationships for impacts to the Bauer helmet. This is all data for the inside top sensor location.
<table>
<thead>
<tr>
<th>Direction</th>
<th>Regression Equation: Linear Fit</th>
<th>Linear Fit R²</th>
<th>Regression Equation: Power Fit</th>
<th>Power Fit R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Data</td>
<td>$y = 0.67x - 8.31$</td>
<td>0.65</td>
<td>$y = 0.37x^{1.08}$</td>
<td>0.74</td>
</tr>
<tr>
<td>Side</td>
<td>$y = 1.02x - 16.22$</td>
<td>0.95</td>
<td>$y = 0.33x^{1.20}$</td>
<td>0.96</td>
</tr>
<tr>
<td>Oblique</td>
<td>$y = 0.61x - 8.03$</td>
<td>0.92</td>
<td>$y = 0.14x^{1.28}$</td>
<td>0.93</td>
</tr>
<tr>
<td>Back</td>
<td>$y = 0.58x - 3.23$</td>
<td>0.87</td>
<td>$y = 0.52x^{1.01}$</td>
<td>0.92</td>
</tr>
<tr>
<td>Front</td>
<td>$y = 0.26x + 5.73$</td>
<td>0.91</td>
<td>$y = 1.20x^{0.71}$</td>
<td>0.91</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Direction</th>
<th>Regression Equation: Linear Fit</th>
<th>Linear Fit R²</th>
<th>Regression Equation: Power Fit</th>
<th>Power Fit R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Data</td>
<td>$y = 0.88x + 203.52$</td>
<td>0.77</td>
<td>$y = 2.86x^{0.86}$</td>
<td>0.84</td>
</tr>
<tr>
<td>Side</td>
<td>$y = 0.95x + 1.26$</td>
<td>0.95</td>
<td>$y = 0.72x^{1.04}$</td>
<td>0.96</td>
</tr>
<tr>
<td>Oblique</td>
<td>$y = 1.09x + 26.13$</td>
<td>0.93</td>
<td>$y = 1.15x^{0.99}$</td>
<td>0.96</td>
</tr>
<tr>
<td>Back</td>
<td>$y = 1.17x + 69.45$</td>
<td>0.90</td>
<td>$y = 1.94x^{0.94}$</td>
<td>0.94</td>
</tr>
<tr>
<td>Front</td>
<td>$y = 0.65x + 326.38$</td>
<td>0.93</td>
<td>$y = 14.0x^{0.62}$</td>
<td>0.92</td>
</tr>
</tbody>
</table>

Table 2.2a: Linear and power regression fit equations for GFT data from the inside top sensor on the Bauer helmet and their associated R² values.
Direction Regression Equation: Linear Fit Regression Equation: Power Fit Power Fit

<table>
<thead>
<tr>
<th>Direction</th>
<th>All Data</th>
<th>Linear Fit</th>
<th>Power Fit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear Acceleration</td>
<td>$y = 0.52x - 4.95$</td>
<td>$0.75$</td>
<td>$y = 0.41x^{1.02}$</td>
</tr>
<tr>
<td>Side</td>
<td>$y = 0.56x + 4.74$</td>
<td>$0.98$</td>
<td>$y = 1.14x^{0.87}$</td>
</tr>
<tr>
<td>Oblique</td>
<td>$y = 0.72x - 28.91$</td>
<td>$0.86$</td>
<td>$y = 0.03x^{1.98}$</td>
</tr>
<tr>
<td>Back</td>
<td>$y = 0.43x - 6.07$</td>
<td>$0.65$</td>
<td>$y = 0.42x^{0.98}$</td>
</tr>
<tr>
<td>Front</td>
<td>$y = 0.45x - 3.07$</td>
<td>$0.87$</td>
<td>$y = 0.41x^{0.99}$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Direction</th>
<th>All Data</th>
<th>Linear Fit</th>
<th>Power Fit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rotational Velocity</td>
<td>$y = 0.96x + 69.90$</td>
<td>$0.82$</td>
<td>$y = 1.67x^{0.93}$</td>
</tr>
<tr>
<td>Side</td>
<td>$y = 0.81x + 64.41$</td>
<td>$0.96$</td>
<td>$y = 1.28x^{0.94}$</td>
</tr>
<tr>
<td>Oblique</td>
<td>$y = 1.24x - 95.57$</td>
<td>$1.00$</td>
<td>$y = 0.60x^{1.09}$</td>
</tr>
<tr>
<td>Back</td>
<td>$y = 1.19x - 145.22$</td>
<td>$0.79$</td>
<td>$y = 0.93x^{1.02}$</td>
</tr>
<tr>
<td>Front</td>
<td>$y = 0.83x + 192.58$</td>
<td>$0.97$</td>
<td>$y = 5.46x^{0.76}$</td>
</tr>
</tbody>
</table>

Table 2.2b: Linear and power regression fit equations for GFT data from the inside top sensor on the Easton helmet and their associated $R^2$ values.

2.3.3: Average absolute errors in peak kinematics

Average absolute error in HIT System-measured peak resultant linear acceleration was 24% for the data from all impact directions combined, ranging from 18-31% for individual impact directions. Applying the power regression equations (Table 2.1) to the HIT System measures reduced these errors to 18% for the data from all impact directions combined and 7-18% for individual impact directions. The smallest average absolute
errors were for the side and back impact directions (Table 2.3). For peak resultant rotational acceleration, average error was 43% for data from all impact directions combined and ranged from 35-64% for individual impact directions. Applying the power regression equation for the data from all impact directions combined to the HIT System measures kept the average absolute error approximately the same at 45%, but impact direction-specific regressions reduced the errors in peak rotational acceleration to 12-27% for individual impact directions (Table 2.3). Average absolute errors did not vary by impact severity for the HIT System, which is discussed further in Chapter 5 (section 5.5).

<table>
<thead>
<tr>
<th>Direction</th>
<th>Average Error (Eq 3)</th>
<th>Adjusted Error: Linear Fit (Eq 4a)</th>
<th>Adjusted Error: Power Fit (Eq 4b)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All Data</td>
<td>Direction Specific Data</td>
<td>Adjusted with ‘All Data’ regression</td>
</tr>
<tr>
<td>Linear Acceleration</td>
<td>Side (n=66)</td>
<td>24% (+15%)</td>
<td>23% (+8%)</td>
</tr>
<tr>
<td></td>
<td>Back (n=36)</td>
<td>18% (+13%)</td>
<td>7% (+5%)</td>
</tr>
<tr>
<td></td>
<td>Oblique Back (n=38)</td>
<td>31% (+22%)</td>
<td>19% (+15%)</td>
</tr>
<tr>
<td>Rotational Acceleration</td>
<td>Side (n=66)</td>
<td>43% (+35%)</td>
<td>35% (+12%)</td>
</tr>
<tr>
<td></td>
<td>Back (n=36)</td>
<td>37% (+22%)</td>
<td>50% (+48%)</td>
</tr>
<tr>
<td></td>
<td>Oblique Back (n=38)</td>
<td>64% (+58%)</td>
<td>38% (+41%)</td>
</tr>
</tbody>
</table>

Table 2.3: Absolute error (+ standard deviation) between the HIT System-measured and reference peak resultant accelerations as calculated by equations 3, 4a, and 4b.
Comparison between the raw GFT peak linear acceleration and the reference acceleration at the ATD CG showed expected large differences (100-150%, Table 2.4a). These differences can be attributed to several reasons: no in-built algorithm to transform the data to the CG of the ATD, the role of the helmet in dissipating forces imparted to the head, and sensor error. After applying the regression equations developed using data stratified by specific impact directions, these differences were substantially reduced.

Average absolute errors for peak linear acceleration ranged from 5-22% for the Bauer helmet and from 4-23% for the Easton helmet (Table 2.4a). The average absolute errors for data adjusted using direction-specific regressions were generally larger for the Easton helmet than for the Bauer helmet, particularly for back and front impacts, and were generally smaller for side impacts than other impact directions for both helmet brands (Table 2.4a). After applying the regression equations developed using data from all impact directions combined, average absolute errors for peak linear acceleration ranged from 25-35% for the Bauer Re-Akt helmet and from 25-40% for the Easton S9 helmet (Table 2.4a). The outside back sensor location generally had the largest error. Average absolute errors did not vary by impact severity for the GFT, which is discussed further in Chapter 5 (section 5.5).

The differences between GFT-measured peak resultant rotational velocities and the corresponding ATD measures were lower for than those for linear acceleration (Table 2.4b). Raw data average percent differences ranged from 9-17%. After applying the regression equations developed using data stratified by specific impact directions,
average absolute errors in peak rotational velocity ranged from 3-11% for the Bauer helmet and from 2-19% for the Easton helmet. After applying the regression equations developed using data from all impact directions combined, average absolute errors in peak rotational velocity ranged from 13-14% for the Bauer Re-Akt helmet and from 11-15% for the Easton S9 helmet. The average absolute errors in peak resultant rotational velocity did not vary substantially by sensor location, helmet brand, or impact direction. Again, average absolute errors did not vary by impact severity for the GFT (see Chapter 5, section 5.5).
<table>
<thead>
<tr>
<th></th>
<th>Inside Top Sensor</th>
<th>Outside Top Sensor</th>
<th>Outside Right Sensor</th>
<th>Outside Back Sensor</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Raw Data</td>
<td>Adjusted with ‘All Data’ regression</td>
<td>Adjusted with ‘Direction-specific’ regression</td>
<td>Raw Data</td>
</tr>
<tr>
<td>Bauer Side Impacts</td>
<td>97% (±66%)</td>
<td>11% (±8%)</td>
<td>12% (±8%)</td>
<td>112% (±76%)</td>
</tr>
<tr>
<td>Oblique Impacts</td>
<td>27% (±23%)</td>
<td>121% (±66%)</td>
<td>25% (±17%)</td>
<td>28% (±31%)</td>
</tr>
<tr>
<td>Front Impacts</td>
<td>12% (±7%)</td>
<td>12% (±8%)</td>
<td>11% (±83%)</td>
<td>22% (±12%)</td>
</tr>
<tr>
<td>Back Impacts</td>
<td>10% (±8%)</td>
<td>10% (±7%)</td>
<td>10% (±7%)</td>
<td>8.1% (±6.0%)</td>
</tr>
<tr>
<td>Easton Side Impacts</td>
<td>134% (±72%)</td>
<td>5% (±3%)</td>
<td>13% (±9%)</td>
<td>4% (±3%)</td>
</tr>
<tr>
<td>Oblique Impacts</td>
<td>28% (±16%)</td>
<td>154% (±87%)</td>
<td>25% (±22%)</td>
<td>152% (±110%)</td>
</tr>
<tr>
<td>Front Impacts</td>
<td>18% (±15%)</td>
<td>154% (±87%)</td>
<td>25% (±22%)</td>
<td>152% (±110%)</td>
</tr>
<tr>
<td>Back Impacts</td>
<td>22% (±14%)</td>
<td>154% (±87%)</td>
<td>25% (±22%)</td>
<td>152% (±110%)</td>
</tr>
</tbody>
</table>

Table 2.4a: Absolute error (± standard deviation) between the GFT-measured and reference peak resultant linear accelerations as calculated by equations 3 and 4b.
<table>
<thead>
<tr>
<th></th>
<th>Inside Top Sensor</th>
<th>Outside Top Sensor</th>
<th>Outside Right Sensor</th>
<th>Outside Back Sensor</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Raw Data</td>
<td>Adjusted with ‘All Data’ regression</td>
<td>Adjusted with ‘Direction-specific’ regression</td>
<td>Adjusted with ‘All Data’ regression</td>
</tr>
<tr>
<td>Bauer</td>
<td>Side Impacts</td>
<td>15% (±10%)</td>
<td>14% (±11%)</td>
<td>7% (±4%)</td>
</tr>
<tr>
<td></td>
<td>Oblique Impacts</td>
<td>14% (±12%)</td>
<td>14% (±10%)</td>
<td>6% (±6%)</td>
</tr>
<tr>
<td></td>
<td>Front Impacts</td>
<td>9% (±5%)</td>
<td>10% (±6%)</td>
<td>15% (±9%)</td>
</tr>
<tr>
<td></td>
<td>Back Impacts</td>
<td>10% (±6%)</td>
<td>8% (±5%)</td>
<td>9% (±7%)</td>
</tr>
<tr>
<td>Easton</td>
<td>Side Impacts</td>
<td>13% (±8%)</td>
<td>13% (±8%)</td>
<td>6% (±4%)</td>
</tr>
<tr>
<td></td>
<td>Oblique Impacts</td>
<td>11% (±9%)</td>
<td>11% (±7%)</td>
<td>2% (±1%)</td>
</tr>
<tr>
<td></td>
<td>Front Impacts</td>
<td>7% (±5%)</td>
<td>8% (±3%)</td>
<td>17% (±14%)</td>
</tr>
<tr>
<td></td>
<td>Back Impacts</td>
<td>14% (±7%)</td>
<td>5% (±4%)</td>
<td>5% (±4%)</td>
</tr>
</tbody>
</table>

Table 2.4b: Absolute error (+ standard deviation) between the GFT-measured and reference peak resultant rotational velocities as calculated by equations 3 and 4b.
2.3.4: Statistical findings

Statistical analysis showed that the relationship between peak HIT System-measured and reference head acceleration of the ATD varied by impact direction (Figure 2.11, Table 2.1). Specifically, the relationship between peak reference acceleration and HIT System-measured acceleration significantly differed for back and oblique impacts (p<0.001) and side and oblique back impacts (p<0.001). The relationship between peak reference acceleration and HIT System-measured acceleration was not statistically different for side and back impacts (p=0.08).

In the statistical analysis of the relationship between peak GFT-measures and reference head kinematics, for both the Easton and Bauer peak linear acceleration data there were significant two-way interactions between sensor location and impact direction (p<0.0001). When the data were stratified by impact direction to test for significance of sensor location, adjusted p-values were significant for all directions (Table 2.5). The outside top sensor location was the reference sensor location. For some impact directions, such as side, the outside top sensor data were significantly different than all other sensor locations. For other impact directions the outside top sensor data were only significantly different than some of the other sensor locations. For example, for front impacts to the Easton helmet, the outside top sensor data were significantly different than the outside back and inside top, but not significantly different from the outside right sensor data. Similarly, when the peak linear acceleration data were stratified by sensor location to test for significance of impact direction, adjusted p-values were all significant (Table 2.5).
For all sensor locations, the side impact data (designated as the reference) was significantly different from all other impact directions. Statistical analysis of the peak rotational velocity data had similar results for significance of impact direction, but some differences in significance of sensor location. While sensor location remained significant in the majority of impact directions, for front impacts to the Bauer helmet and for front and back impacts to the Easton helmet sensor location was not statistically significant (Table 2.5).
<table>
<thead>
<tr>
<th>Significance of Impact Direction</th>
<th>Bauer Peak Linear</th>
<th>Easton Peak Linear</th>
<th>Bauer Peak Rotational</th>
<th>Easton Peak Rotational</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inside Top Sensor</td>
<td>0.0004*</td>
<td>0.0004*</td>
<td>0.0004*</td>
<td>0.0004*</td>
</tr>
<tr>
<td>Outside Top Sensor</td>
<td>0.0004*</td>
<td>0.0004*</td>
<td>0.0004*</td>
<td>0.0012*</td>
</tr>
<tr>
<td>Outside Back Sensor</td>
<td>0.0004*</td>
<td>0.0004*</td>
<td>0.0004*</td>
<td>0.0024*</td>
</tr>
<tr>
<td>Outside Right Sensor</td>
<td>0.0004*</td>
<td>0.0004*</td>
<td>0.0004*</td>
<td>0.0004*</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Significance of Sensor Location</th>
<th>Side Impact</th>
<th>Front Impact</th>
<th>Back Impact</th>
<th>Oblique Impact</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.0004*</td>
<td>0.0016*</td>
<td>0.0004*</td>
<td>0.0004*</td>
</tr>
<tr>
<td></td>
<td>0.0004*</td>
<td>0.0004*</td>
<td>0.4604</td>
<td>0.0512</td>
</tr>
<tr>
<td></td>
<td>0.0004*</td>
<td>0.0268*</td>
<td>0.0004*</td>
<td>0.8636</td>
</tr>
<tr>
<td></td>
<td>0.0004*</td>
<td>0.0004*</td>
<td>0.0116*</td>
<td>0.0004*</td>
</tr>
</tbody>
</table>

*Statistically significant

Table 2.5: Summary of p-values after Bonferroni adjustment for statistical significance of impact direction and sensor location on the ratio of peak GFT measure to peak corresponding ATD measure.

2.3.5: Estimation of impact direction

The HIT System accurately determined the general categorical impact direction (front, back, or side) for 100% of side and back impacts and for 79% of oblique back impacts. Comparing the HIT System-reported impact azimuth with the actual impact direction, the average errors (+standard deviation) were 4±3%, 10±5%, and 31±15% for side, back, and
oblique back impacts, respectively. For oblique back impacts, the HIT System-measured azimuth has systematic error with reported azimuth biased towards the back impact direction (Figure 2.13).

Comparing the GFT-reported impact azimuth with the actual impact direction, the average absolute errors for the inside top sensor ranged from 3-30% (Figure 2.14, Table 2.6). For the outside top sensor, the average absolute errors ranged from 3-47% (see
Appendix 1, Figure A1-2.14b, Table 2.6). For the outside right sensor, the average absolute errors ranged from 5-28% (see Appendix 1, Figure A1-2.14c, Table 2.6). For the outside back sensor, the average absolute errors ranged from 1-13% (see Appendix 1, Figure A1-2.14d, Table 2.6). Side impacts had large systematic error in azimuth estimation for the inside top and outside top sensors. Systematic error was also evident for other impact direction-sensor location combinations, such as outside right sensor estimation of azimuth for back and front impacts (see Appendix 1, Figure A1-2.14c).
Figure 2.14: Comparison of GFT-reported and actual impact azimuth for side, oblique, back, and front impacts for the inside top sensor. Actual impact azimuth is indicated by the arrow, while system-reported azimuths for each impact are indicated by the markers.
<table>
<thead>
<tr>
<th>Sensor Location</th>
<th>Inside Top</th>
<th>Outside Top</th>
<th>Outside Right</th>
<th>Outside Back</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bauer Side</td>
<td>21% (+6%)</td>
<td>47% (+36%)</td>
<td>5% (+3%)</td>
<td>1% (+1%)</td>
</tr>
<tr>
<td>Oblique (45° from back)</td>
<td>9% (+4%)</td>
<td>8% (+3%)</td>
<td>11% (+2%)</td>
<td>8% (+6%)</td>
</tr>
<tr>
<td>Back</td>
<td>11% (+4%)</td>
<td>19% (+12%)</td>
<td>28% (+4%)</td>
<td>--</td>
</tr>
<tr>
<td>Front</td>
<td>4% (+2%)</td>
<td>2% (+1%)</td>
<td>7% (+3%)</td>
<td>9% (+7%)</td>
</tr>
<tr>
<td>Easton Side</td>
<td>30% (+4%)</td>
<td>31% (+8%)</td>
<td>9% (+2%)</td>
<td>1% (+1%)</td>
</tr>
<tr>
<td>Oblique (45° from back)</td>
<td>7% (+1%)</td>
<td>5% (+2%)</td>
<td>10% (+5%)</td>
<td>6% (+6%)</td>
</tr>
<tr>
<td>Back</td>
<td>5% (+3%)</td>
<td>13% (+9%)</td>
<td>24% (+37%)</td>
<td>12% (+14%)</td>
</tr>
<tr>
<td>Front</td>
<td>3% (+3%)</td>
<td>3% (+2%)</td>
<td>8% (+9%)</td>
<td>13% (+10%)</td>
</tr>
</tbody>
</table>

Table 2.6: Average absolute errors (+ standard deviation) of GFT estimation of impact azimuth stratified by impact direction and sensor location.

2.4: Discussion

2.4.1: System designs

This study evaluated two major types of helmet-based sensors that have been developed and used in a research capacity to study the biomechanics that lead to mild traumatic
brain injury. The first, and most widely used over the past decade, consists of spring-loaded linear accelerometers integrated into the padding throughout the helmet and designed to maintain contact with the head. The data from those accelerometers is then processed by an algorithm to approximate linear and rotational acceleration at an estimated center of gravity of the head. This is the approach that the HIT System uses, and it requires using linear measures to estimate rotational kinematics. The most common alternate approach has been to develop small sensors that enclose components to measure both linear and rotational kinematics in a single housing, as is the case for GFT. The sensor is then adhered to the shell of the helmet in a single location.

2.4.2: Errors in peak kinematic measures

The evaluation showed that both the HIT System for ice hockey and GFT had strong relationships between helmet system-measured and reference ATD-measured kinematics. However, the systems exhibited differences in kinematic measurement accuracy. The HIT System, having linear accelerometers integrated throughout the padding and processed using a system algorithm, had smaller average absolute errors in measuring of peak resultant linear acceleration. For raw HIT System measures, errors in peak linear acceleration ranged from 18-31%, whereas raw GFT measures had expectedly large average percent differences, upwards of 100%. For the version of GFT hardware and software evaluated in this study, the raw data are not processed through an in-built algorithm to transform the data to the center of gravity of the head. As mentioned above, this leads to large differences in sensor measures compared to those measured at the CG.
of the ATD for three primary reasons: the data has not been transformed from the location on the helmet to the center of gravity of the head, the energy dissipation of the helmet has not been accounted for, and there is some amount of sensor error. This study was not designed to calculate the independent effects of these three contributions to the differences observed, but demonstrates that it is important to develop regression equations that describe the relationships between peak GFT measures and peak linear acceleration ATD measures so that these can be used to empirically adjust the data and improve linear acceleration accuracy. After adjustment using direction-specific regressions there were much smaller differences in average absolute error for peak resultant linear acceleration, at approximately 5-40% for the GFT versus 5-30% for the HIT System for ice hockey.

Conversely, GFT, using gyroscopes to directly measure rotational velocity, had much lower errors in peak resultant rotational kinematics. The HIT System had significant errors in raw peak resultant rotational acceleration, ranging from 35-64%, while GFT had relatively small average absolute error in raw peak resultant rotational velocity, ranging from 10-15%. After correction using direction-specific regressions, average absolute error in peak resultant rotational kinematics was approximately 2-20% for the GFT versus 10-60% for the HIT System for ice hockey.
2.4.3: Importance of rotational kinematics

Although systems used to study mTBI in real-world scenarios should be as accurate as possible in estimating both linear and rotational kinematics, given the evidence that rotational measures are better predictors of diffuse brain injury across the spectrum of severity (Browne et al. 2011; Gennarelli, Thibault, and Ommaya 1972; Meaney et al. 1993; Takhounts et al. 2008), rotational accuracy is likely a higher priority. The GFT’s use of gyroscopes addresses this need for accurate prediction of rotational kinematics. However, the version of the GFT evaluated herein requires use of a correction factor for peak linear accelerations measures, as the raw data does not estimate this measure at the center of gravity of the head and therefore has very large errors. For the GFT peak rotational velocity measures, on the other hand, this processing step is not necessary as the raw data are quite accurate.

The errors in rotational kinematic measures for the HIT System for ice hockey versus GFT is not a direct comparison as the HIT System estimates rotational acceleration and GFT measures rotational velocity. Measurement of rotational acceleration is inherently noisier than rotational velocity, which likely contributes to the lower rotational measurement errors exhibited by GFT. The other factor that likely contributes to this difference is that the use of gyroscopes allows the rotational velocity to be directly measured rather than estimated using linear measures. Studies have shown that rotational velocity accurately predicts strains within the brain and is thus a good metric for quantifying traumatic brain injury risk across the spectrum of severity (Takhounts et al. 2008).
2013). These elements combined suggest that rotational velocity, rather than acceleration, is likely a better measurement choice for helmet-based systems.

2.4.4: Systematic error

Both the HIT System for ice hockey and GFT exhibited systematic error based on impact direction, evident in the statistical significance of impact direction on the relationship between peak system and peak reference measure. This suggests that the biomechanics of the helmet are influencing the system measure, which would be expected for GFT as this system is adhered to the shell of the helmet. However, the HIT System design is intended to measure head rather than helmet acceleration, with the accelerometer housings spring loaded to keep them in contact with the head. Despite these differences, the average absolute errors in peak linear acceleration for data from all impact directions combined, while lower for the HIT System (20-25%) than GFT (25-35%), are not as much lower as would be expected if the accelerometers truly measured head acceleration rather than helmet acceleration. It is likely that they are losing contact with the head during the impact, translating along the head as the kinematic pulse from the helmet transfers through the spring, or both. It is interesting to note that Manoogian et al. found head acceleration to be less than 10 percent of helmet acceleration (Manoogian et al. 2006), but the raw GFT measure of peak linear acceleration with its placement on the shell of the helmet did not exhibit measures this much larger than head acceleration. For some impact direction-sensor location combinations, the linear acceleration of the center of gravity of the head was as low as 50% of GFT-measured linear acceleration. Other
combinations demonstrated smaller differences (Figure 2.11). This disparity may be due to accelerometer placement. In the Manoogian study, the accelerometer measuring helmet shell acceleration was placed at the point of impact, whereas in this study no direct impacts to GFT were performed. The energy may dissipate very quickly as it moves through the shell of the helmet, leading to much lower linear accelerations at small distances from the point of impact.

There were also differences in system accuracy based on impact direction. Generally, the average absolute errors were the smallest for side impacts, likely due to the tightness of the helmets on the ATD head along this plane and less helmet deformation in this direction. In contrast, there was likely more relative motion between the ATD head and the helmet and more helmet deformation during back and oblique impacts. For the HIT System, oblique impacts generally had the largest error, whereas for the GFT the specific direction with the largest error varied between back or oblique impacts and was dependent on the helmet brand, the sensor location, and whether we were examining linear or rotational kinematics. For oblique impacts, there was the greatest opportunity for helmet deformation due to the construction and fit of the helmets. These impacts were also likely the least centric, allowing for more relative motion between the head and the helmet. For the back impacts, the helmets consist of two parts that can slide along each other in the plane of this impact, with screws that tighten to help hold the two pieces in place. However the lack of rigid attachment of the two pieces of the helmet likely contributed to increased helmet deformation and relative movement with back impacts.
Most of the GFT sensor locations were on the anterior component of the helmet, while this impact location was on the posterior component.

2.4.5: Accounting for the variability

One method to account for the variability of relationship between peak system and peak reference kinematic measures is to calculate regression equations to be used as adjustment factors for the on-ice data. This method has the potential to appreciably reduce measurement errors for both the HIT System for ice hockey and GFT when applied on an impact direction-specific basis, removing the systematic error associated with the effect of impact direction on helmet biomechanics. However, this method requires researchers to accurately determine the impact direction, which adds a level of complexity to the data analysis. The evaluation showed that neither system consistently estimated impact azimuth to the level of accuracy necessary to distinguish between, for example, back and oblique back impacts. This means that system-estimated impact azimuth cannot be relied on to determine which direction-specific regression should be applied to the data, and another means of determining direction would be necessary to use this approach. Many researchers collect game film in order to confirm that the data are associated with true impacts and to gather information about the circumstances surrounding each impact (i.e. player awareness of impending impact) (Crisco et al. 2010; Mihalik, Greenwald, et al. 2010; Ocwieja et al. 2011). This video may help confirm the impact direction, providing more information to help determine which calibration factor should be applied to the data. However, it is logistically difficult for use more widely if
determining impact direction is reliant on filming all practices and games from multiple viewpoints. Chapter 5 will discuss practical implementation of these sensors in more detail. It is important to note that disparities between system-estimated and experimentally-implemented impact azimuths may be related to the centricity of the impacts and the system algorithms used to estimate impact azimuth. For impacts that do not go through the center of gravity of the head, the direction of linear acceleration that is produced at the center of gravity of the head may differ from azimuth of the impact location. Therefore, if the system algorithms that are used to calculate impact azimuth rely only on linear acceleration, not accounting for rotational kinematics, differences would be expected between the impact azimuth of the testing setup and the calculated azimuth for those non-centric impacts.

A more feasible approach for many researchers would be to accept a larger error and account for it in data analysis. For the HIT System for ice hockey this could mean either directly using the algorithm-processed data or combining data from all impact directions and applying a single regression equation to the data. For GFT, it is appropriate to use the raw rotational velocity data as its error was relatively small, but for linear acceleration it would be necessary to combine impact data from all impact directions and apply a single regression equation to the data to make the absolute error acceptable. The combined direction approach may be further improved by developing a combined direction regression that weights the data from the individual directions (front, back, side, top) corresponding to the percentage of impacts in each direction seen on ice (Mihalik et al. 2008, 2012).
As mentioned above, for this version of GFT hardware and software, the raw data has not been transformed to the center of gravity of the head, leading to large average absolute errors in raw peak resultant linear acceleration. This means that, even if direction-specific regressions will not be used to reduce the average absolute error as much as possible, it is important to develop regression equations that describe the relationships between peak GFT measure and peak linear acceleration at the center of gravity of the head so that these can be used to correct the data and improve linear acceleration accuracy. This would require impact testing, accounting for controllable parameters that significantly affect the relationship between peak head kinematics and peak GFT measure such as the sensor location. Those specific parameters should then be used for all players on a given team to collect real-world data that will be adjusted using the experimentally-derived regressions. Given that average absolute errors in peak linear acceleration were larger for certain sensor locations, even after correction using the all-impact location regression equations, such testing would ideally include multiple sensor location options. The best location could then be determined by comparing average absolute errors after data are corrected using the regression method of choice (all impact directions combined or direction-specific). An ideal choice for sensor location would also be one that is less likely to be directly impacted, such as the top of the helmet (Mihalik et al. 2008, 2012).
2.4.6: Impacts removed from the dataset

As stated in the methods, the HIT System’s processing algorithm removes impacts from the dataset if 1) the resultant linear acceleration is less than 10 g or, 2) based on rigid body dynamics, the acceleration pulse does not have characteristics of an impact to a helmeted head. The purpose of the latter is to remove data resulting from occurrences such as a player throwing his or her helmet down on the bench. In this analysis, 19% of the impacts were removed from the dataset. Through cooperation with the HIT System’s manufacturer, we were able to obtain those removed data by matching the time stamp of impact. Many of these removed impacts were to the facemask, likely due to the irregular shape of the facemask as well as its non-rigid attachment to the helmet itself, causing the acceleration pulses recorded by the helmet instrumentation system to be atypical compared to impacts to the shell of the helmet (Figure 2.15). Inspection of the acceleration time histories of the removed impacts from impact directions other than the front and comparison to impacts performed at the same speed and direction that were not removed from the dataset did not identify any key characteristics of the pulse that were different: the magnitude, shape, and duration were similar (Figure 2.10). The details of the algorithm used to filter the data, as well as the theory behind it, are proprietary and unavailable to the authors making it difficult to identify the specific reason these impacts may have been removed. However, in a real-world situation, unless each impact is being uploaded, tracked, and verified as an on-ice occurrence while it is happening, if an impact was removed from the dataset the researchers would be unaware that it occurred. Given that this study evaluated a single impact scenario across a range of speeds and directions,
an on-ice analysis is necessary to understand how often impacts occur during play but are removed from the dataset during processing. This will aid in understanding whether this finding affects the interpretation of on-ice data. The reverse has been done, using film to validate that impacts recorded by the HIT System were actual on-ice impacts to the head (Brainard et al. 2012; Wilcox, Machan, et al. 2014), but this does not aid in understanding whether all on-ice impacts to the head are included in the processed data set.
Figure 2.15: Still frames showing a front impact to the facemask and corresponding helmet system and ATD resultant acceleration time histories. This depicts the difference in accelerations experienced by the helmet and the ATD at different time points for facemask impacts.

GFT does not have a processing algorithm to determine whether or not an impact was likely to be a “real” on-ice impact. In this case, the researcher needs to determine a method to try to filter out those impacts that occurred when the helmet was not on the head, such as noting when players take off their helmets on the bench and keeping track of practice and game start and end times. However, this also ensures that the researcher
has access to the full data set. Whereas for the HIT System most facemask impacts were removed from the data set, for GFT front impacts peak kinematic measures had very small average absolute errors after correction using a direction-specific regression equation.

2.4.7: Comparison to previous validation studies

Comparison of peak linear and angular acceleration as calculated by the HIT System for ice hockey and the ATD highlighted that the error between the two measures reported herein is greater than that previously reported for the specialized version of the HIT System for football that includes twelve single-axis accelerometers organized into six orthogonal pairs (6DOF system). This can largely be attributed to differences in how error was calculated. In a validation study of the 6DOF HIT System for football, Rowson et al. included the polarity of the difference between the HIT System and reference acceleration measures in their average error calculations, thus averaging values that were both positive and negative, resulting in a small overall error (Rowson et al. 2011). Given that the error associated with this type of system appears to be random, it is not surprising that this approach led to an average error close to zero. In contrast, in the current study the absolute value of the difference between the measures was included in the error calculations, calculating absolute error rather than relative error. As a result, the errors reported herein for the ice hockey HIT system are larger than reported for the 6DOF football system but the method of error calculation is more appropriate, particularly when assessing the possible error associated with a single on-field measurement from the HIT
System. Other validation studies on HIT System instrumentation for football, boxing, and soccer did not report the average error between the instrumentation-measured peak acceleration and reference peak head acceleration as measured via the ATD (Beckwith, Chu, and Greenwald 2007; Beckwith, Greenwald, and Chu 2012; Hanlon and Bir 2010; Manoogian et al. 2006). These include validations of the most widely used system, which is the HIT System for football that consists of six single-axis accelerometers (five degree of freedom system). However, coefficients of determination reported herein are comparable to those reported, by impact location, in a validation study of the five degree of freedom system for football (Beckwith, Greenwald, and Chu 2012). In the future, the errors associated with this helmet instrumentation system for ice hockey must be accounted for in analysis of real word data, particularly when working with a small sample size or analyzing individual impacts.

As mentioned previously, the HIT System for football is different from that for ice hockey, so this study’s findings are not directly transferrable to the football instrumentation. However, given the growing use of the football system for research purposes, a validation study on the football instrumentation system calculating the absolute error as outlined herein and quantifying any differences in system performance with impact direction is critically important for researchers using this system, particularly for those studies which analyze data from small sample sizes, individual impacts, or a small numbers of injuries. It is important to note that a recent study by Jadischke et al. on the HIT System for football had similar findings for both magnitude of error (10-20% for peak resultant linear acceleration) and percentage of impacts removed from the dataset.
(25%) due to the algorithm determining the “validity” of an impact (Jadischke et al. 2013). If the study presented herein were repeated on the HIT System for football, slightly smaller errors in peak linear acceleration may be expected due to football helmets being smoother, with fewer geometrical irregularities than hockey helmets. However, slightly higher errors in peak rotational acceleration could be expected as the configuration of accelerometers in the HIT System for football does not allow for estimation of z-axis rotational acceleration, while the accelerometer placement in the HIT System for ice hockey allows estimation of rotational acceleration for all axes. The coefficients of determination found in a validation study by Beckwith et al. for the HIT System for football were 0.90 and 0.53 for peak resultant linear and rotational acceleration respectively, compared to the 0.88 and 0.60 for linear and rotational acceleration found in this study on the HIT System for ice hockey (Beckwith, Greenwald, and Chu 2012).

2.4.8: Limitations

This examination was limited in that it does not incorporate the full range of impact scenarios that players may experience on-ice. First, rigidly mounting the ATD head and neck at the level of T1 is unlike on-ice conditions in which the torso can move. The rigid mounting simulates a torso with an infinite effective mass. Given the relatively large mass of the torso compared to the head, and the coupling of the two via the neck, the real-world scenario is likely more similar to an infinite effective mass, particularly in the initial milliseconds of the impact when the acceleration reaches its peak. Additionally, ice
hockey impacts frequently occur against the boards and this coupling of the torso to the boards would further increase the effective mass of the torso. Furthermore, the peak acceleration occurs early in the time history. The high speed video of the impact at the time of peak acceleration shows that the neck has flexed very little if at all, and is not near the end of its range of motion, which is in line with previous studies (Figure 2.16) (Viano, Casson, and Pellman 2007). Thus, the contribution of torso inertia on the peak head acceleration is likely negligible. This factor was explored in Chapter 3.

Figure 2.16: Timing of peak resultant linear acceleration for 10 impacts at two impacting speeds and corresponding high speed video at time of peak acceleration.

Second, helmet fit varies among individuals as athletes may or may not wear their helmets with an ideal fit; some may find the helmet uncomfortable if it is too tight. The design of the HIT System is based on spring-loaded accelerometers, which are intended to maintain better contact between the head and the helmet so that head acceleration is
measured rather than helmet acceleration (Manoogian et al. 2006). Similarly, the gForce Tracker is adhered to the helmet, so the more strongly coupled the helmet is to the head the more accurate it can be expected to perform. In this analysis the HIT System and GFT were each evaluated under one fit condition – i.e. with a wet human hair wig, a Hybrid III 50th percentile male head, and a single size helmet. Through pilot observations of how adolescent hockey players wear their helmets, we felt this scenario most closely mimicked the on-ice situation. In this study, we opted to employ a helmet fit that we felt was realistic, using helmet sizes that allowed some movement between the ATD head and the helmet rather than using smaller helmets that would be extremely tight on the ATD head. USA Hockey guidelines specify that the helmet should be snug enough to prevent rotation (USA Hockey) and our test setup ensured this criterion was met. As noted in the methods, the helmet was aligned to the neutral position before each impact; however, little displacement of the helmet relative to the ATD head occurred, particularly for side, back, and oblique back impacts.

Two aspects of helmet fit around the chin area in our tests must be noted. First, due to a lack of structure on the underside of the ATD chin, the chin strap could not be tightened against an anatomical structure to further couple the helmet to the head. Second, the chin pad on the facemask did not come in contact with the ATD chin (approximately a finger width apart) when the helmet was in the neutral position (as defined in the methods). In sum, the fit of the helmet on the cranium of the ATD appeared to mimic resistance to rotation prescribed by guidelines and observed in actual players, however the lack of coupling of the helmet to the ATD in the chin region may have led to an increased ability
of the helmet to translate upward if force was applied in that direction. Impacts to the facemask were likely those impacts that were most affected by this chin coupling, but impacts in this study were not in an upwards direction. Furthermore, there were small errors in GFT peak rotational velocity for front impacts after correction using direction-specific regressions. Observation of helmet fit on youth players revealed that they, too, often have gaps between their chins and the chin pads, as well as somewhat loose chin straps. Therefore, although this aspect of fit likely represents a worst case scenario, it is still realistic and did not appear to affect the testing substantially.

A study by Jadischke et al. looked specifically at the fit of football helmets in the real world compared to those on an ATD head and how fit affected errors in peak accelerations as measured by the HIT System for football (Jadischke et al. 2013). In this study they used a skull cap instrumented with pressure sensors to measure the maximum, average, and distribution of pressures between the helmet and the head in high school football players (n=68) using helmets that had previously been fitted on the players by team staff. They compared the real-world pressures to pressures generated by medium (used in previous HIT System for football validation studies (Beckwith, Greenwald, and Chu 2012; Rowson et al. 2011)) and large Riddell (Rosemont, IL) helmets on an ATD head. The large helmet resulted in pressures more similar to high school football players, with the average pressure at 39th percentile rather than 99th percentile for the medium helmet. During impact testing, they found similar errors in peak linear acceleration for the two helmets, but larger errors in peak rotational acceleration with size large helmet.
The outer shape of the hockey helmet also has more protuberances than a football helmet and can deform upon impact. These characteristics likely influence how well the helmets are coupled to the head during an impact. The ability of the helmet-based systems to accurately measure head acceleration may vary by these geometric and deformation parameters, but evaluation of this variability was not the focus of the current analysis.

Third, we chose a flat impacting surface (with rounded edges) to mimic surfaces such as the boards or the ice which are common surfaces of head impact during ice hockey. We note that the size of the impacting surface is infinitely smaller than the flat surface of the boards or ice. While in our testing we did not observe the helmet-to-impactor contact area extending beyond the edges of the impactor surface, and thus our impact conditions appear to be applicable to impacts to large flat surfaces, a larger impacting surface would more accurately mimic the real world. In hockey, players may also contact other objects such as another player’s elbow or hockey stick that may differ in compliance or impactor size. The impacting surface was not varied in this evaluation, but was explored in a subsequent study (Chapter 3). In previous validations of the HIT System for football (Beckwith, Greenwald, and Chu 2012; Rowson et al. 2011), a layer of foam was interposed between the UHMWPE impacting surface and the impactor because helmet-to-helmet impacts are common in football. Helmet-to-helmet impacts have not been shown to be a primary cause of concussion in ice hockey (Scott Delaney, Puni, and Rouah 2006). Instead, the UHMWPE impacting surface without foam backing is more in line with head contact to the boards or ice.
Lastly, it is important to note that we only evaluated the peak values of linear and angular kinematics in the current study. Peak resultant measures were chosen as the focus for this evaluation because the majority of real-world studies done using helmet-based system data have concentrated on these measures. However, linear acceleration brain injury metrics such as HIC consider the acceleration time-history, not just the peak value (Versace 1971). Similarly, rotational kinematic metrics for injury also have been shown to be dependent upon the shape of the acceleration pulse, not just the peak value (Post, Hoshizaki, and Gilchrist 2012; Yoganandan et al. 2008). Differences between the time histories measured by the ATD and helmet-based systems are explored tangentially in a subsequent study by using the time histories as input into a finite element head model (Chapter 4). However, future studies evaluating the accuracy of measurement systems could benefit from a more direct comparison between ATD and helmet-based system time histories, comparing impact characteristics such as duration, time-to-peak, and area under the curve for both resultant and axis-specific data.

2.4.9: Implications

Before analyzing data collected using these systems to study the biomechanics of head impacts that lead to mTBI, more work should be done to translate the findings from this study into practical strategies for implementation. Chapter 5 will comment on this topic. It would be beneficial for future work to include direct impacts to the GFT sensor, as well as a sensitivity analysis to determine how small changes in impact direction may affect
the relationship between peak GFT or peak HIT measures and reference kinematic measures.

2.5: Conclusions

This study evaluated two major types of helmet-based sensors that have been developed and used to study the biomechanics that lead to mild traumatic brain injury, one that consists of spring-loaded linear accelerometers integrated into the padding throughout the helmet (HIT System) and another that uses accelerometers and gyroscopes in a single location adhered to the shell of the helmet (GFT). This evaluation showed that both systems exhibited strong relationships between helmet system-measured and reference ATD-measured kinematics. GFT values exhibited large errors in raw peak resultant linear acceleration (>100%), so data processing is necessary for these measures, likely using regression equations that describe the relationship between GFT measures and reference head kinematics. Application of these regressions to the data reduced error substantially. The HIT System, having linear accelerometers integrated throughout the padding, had smaller average absolute errors in raw measurement of peak resultant linear acceleration, and these errors got somewhat smaller after direction specific data adjustment. At 5-30%, they were still smaller than the GFT errors of 5-40% after direction-specific correction. Conversely, GFT, using gyroscopes to directly measure rotational velocity, had low raw average absolute errors in peak resultant rotational kinematics while the HIT System had
higher raw errors. At 2-20%, they were still smaller than the HIT System errors of 10-60% after direction-specific correction.

Both the HIT System for ice hockey and GFT exhibited systematic error based on impact direction, evident in the statistical significance of impact direction on the relationship between peak system and peak reference measure. Given that neither system estimated impact direction to the degree of accuracy necessary to employ direction-specific correction factors, this means that end users should either accept larger error and account for it in data analysis or go through the resource-intensive process of collecting on-ice film from multiple viewpoints to determine impact direction for each impact. Sensor location was also a statistically significant factor affecting the relationships between peak GFT and reference measures, indicating that a particular sensor location should be chosen for testing to determine the necessary correction factors and then used for all players on-ice. More work should be done to translate the findings from this study into practical strategies for implementation.
Note: The data presented in this chapter has been published in the following peer-reviewed journal articles


Chapter 3 - The effect of key real world impact and usage variations on the relationships between helmet system and ATD-measured head impact kinematics

3.1: Introduction

For the past decade, helmet-based systems have been used in high impact sports to measure the kinematics of head impacts in real-world settings (Brolinson et al. 2006; Crisco et al. 2010; Mihalik et al. 2007, 2012; Rowson et al. 2009). The kinematics can then be correlated to clinical and neurocognitive measures to study the inputs that lead to mild traumatic brain injury (mTBI). However, the success of using helmet-based measurement systems to study the biomechanical thresholds for mTBI in a real-world setting is highly dependent on the accuracy of the system. For this reason, laboratory studies comparing helmet-system measures to standardized laboratory measures of kinematics at the center of gravity of the head are necessary to evaluate the error associated with the systems. The accuracy of two of these systems across a range of impact speeds and directions was quantified in Chapter 2. In this chapter, the effects of real-world variations in impact conditions are studied.

3.1.1: Importance of real-world variations

In sports, there are many ways in which impacts can vary. Researchers have studied the various characteristics of impacts that lead to concussion in ice hockey (Agel and Harvey
2010; Delaney, Al-Kashmiri, and Correa 2014; Hutchison et al. 2013a, 2013b; Rishiraj et al. 2009). For example, one factor that can vary widely in ice hockey is the surface the player’s head comes in contact with, such as the boards, the ice, or an opponent’s shoulder, elbow, glove, or hockey stick. Whether an athlete’s torso is in free motion or constrained (i.e. a player is pinned against the boards) during impact may also vary. Additionally, players vary in their hair styles, prefer to wear particular brands and models of helmets, and wear their helmets tighter or looser than a teammate, influencing the fit of the helmet on the head. Some of these factors may be controllable across a given team, such as the helmet model, but others are inherent to the sport, such as the surface that the player’s head contacts. Laboratory evaluation of the influence of these factors on helmet-based system measures is important to determine if system performance varies largely by the circumstances surrounding the impact. System errors that are unknown or unaccounted for in analyses can lead to unreliable study conclusions, or if the system is being used for monitoring purposes, the errors could cause users to overlook injurious impacts. Therefore, it is important to evaluate a range of impact conditions that may occur in the real-world in order to understand system performance in those scenarios.

3.1.2: Real-world variations previously assessed

In Chapter 2, an evaluation of the accuracy of two helmet-based systems with different measurement approaches was presented. Unlike most evaluations to date which have used sliding tables, this testing involved rigidly mounting the ATD head and neck at the level of T1. Rigid mounting simulates an infinite effective mass of the torso, while the
sliding tables used in previous studies simulate zero effective mass of the torso. The real-world scenario is somewhere in between these two, but given the large effective mass of the torso compared to the head, rigid mounting is likely the more realistic scenario. However, to date no studies have explored the influence of effective mass on the torso on the relationship between helmet-based system and reference ATD measures.

Jadischke et al. assessed the influence of helmet fit on the performance of the HIT System for football (Jadischke et al. 2013). To address the influence of this important real-world variation on system performance they first measured helmet fit on volunteers, using the football helmets that had previously been fit on them by team staff. To do this they used a pressure sensing skull cap on the players’ heads and then asked the players to put on and secure their helmets, recording the pressures associated with the helmet’s fit. They then did the same thing on the Hybrid III head, but used both a medium helmet and a large helmet on the ATD head for comparison to the data from football players. Impact testing was done in the laboratory to both the medium and large HIT System instrumented helmets to compare system performance. They found that fitting a large helmet on the ATD head resulted in pressures comparable to the average pressures associated with the football players’ helmets, but the medium helmet caused pressures greater than the 99th percentile volunteer data. Impacting testing revealed that using the large-sized helmet compared to the medium helmet resulted in similar errors for peak resultant linear acceleration, but larger errors in peak resultant rotational acceleration.
Another influence on the interaction between the head and the helmet is the player’s hair and any caps utilized by the player underneath the helmet. In the testing in Chapter 2, a human hair wig was adhered to the ATD head and wet with water to simulate perspiration. Previous studies have used a nylon cap between the ATD head and the helmet, an interface that may be more common in certain sports and levels of competition than others. In hockey, for example, player use of nylon caps is uncommon. No studies have explored the influence of the interface between the ATD head and the helmet on the relationship between helmet-based system and reference ATD measures.

Validation studies that have been done on the HIT Systems developed for football, boxing, and soccer are described in Chapter 2, section 2.1.2. As discussed, these studies simulated certain real-world impact characteristics specific to those sports. For instance, studies on the HIT Systems for football used impacting surfaces with the curvature and layer of foam that exists in a football helmet in order to imitate helmet-to-helmet impacts (Beckwith, Greenwald, and Chu 2012; Rowson et al. 2011). The study on the HIT System for soccer was designed to imitate two head impact scenarios that would be likely in soccer: head-to-head and ball-to-head (Hanlon and Bir 2010). In this chapter, the use of a hockey elbow pad was explored as this is an impact surface relevant to ice hockey.

While the HIT System is only integrated into specific brands of helmets and head gear, GFT provides the opportunity to choose a helmet in which to implement it. This addresses a logistical challenge in that it allows players to use helmets they prefer for comfort and design reasons. Various helmets, however, have different construction and
may respond differently to impacts. Hence, while the effect of helmet
geometry/construction of sensor accuracy did not apply to previous HIT System
validation studies, now that newer technologies can be used in any helmet it is important
to assess the effect of helmet geometry and construction on the performance of helmet-
based systems.

3.1.3: Research objectives

The objective of this chapter was to perform a laboratory evaluation across a range of
impact characteristics that vary in real-world usage of helmet-based kinematic
measurement systems in order to assess their influence on the performance of these
systems. Filling this gap in knowledge will provide researchers and consumers more
insight into how the accuracy of helmet-based systems differs across a range of impact
conditions experienced in sports, increasing understanding of how measures can be
interpreted. The elements studied herein include 1) the interface between the head and the
helmet, 2) repeatability of sensor/helmet systems, 3) helmet geometry/construction, 4)
effective mass of the torso, and 5) impacting surface.
3.2: Methods

3.2.1: Mounting setup

A Hybrid III 50\textsuperscript{th} percentile male anthropometric test device (ATD) head and neck with a 3-2-2-2 accelerometer array (Padgaonkar, Krieger, and King 1975) and three angular rate sensors was mounted at the level of T1 in two fashions. First it was rigidly mounted, as in Chapter 2, and then it was mounted to a table attached to two rails that gave it the ability to translate linearly (Figure 3.1). The translating portion of this setup, to which the ATD head and neck was attached, was built to weigh within 1 kg of the mass of the Hybrid III 50\textsuperscript{th} percentile male torso.

![Figure 3.1: Rigid (left) and translating (right) mounting setups for the ATD head and neck.](image-url)
3.2.2: Helmets and sensor systems

Two Easton S9 hockey helmets (Easton-Bell Sports Inc., Van Nuys, CA) instrumented with the HIT System for ice hockey, along with an Easton S9 hockey helmet and two Bauer RE-AKT hockey helmets (Bauer Hockey, Inc., Exeter, NH) (see Chapter 2, Figure 2.1) each instrumented with GFT sensors in four different locations (outside top, outside back, outside right, and inside top) (see Chapter 2, Figure 2.2), were fit to the ATD head. Differences in helmet construction and sizing recommendations based on head circumference led to the use of a large-sized adult Easton helmet and a medium-sized adult Bauer helmet. USA Hockey guidelines were used to fit the helmets by marking the ATD head with approximate eyebrow locations and then centering the helmet on the head with the “rim” one finger width above the eyebrows, tight enough to prevent axial rotation of the helmet about the head (USA Hockey). The alignment of the helmet on the ATD head was checked before each impact to confirm repeatability of the testing conditions. Both helmets had their corresponding facemasks attached, as hockey players under the age of 18 are required by USA Hockey rules to wear such a facemask.

The HIT System for ice hockey consists of six linear single-axis accelerometers embedded in the padding of the helmet and oriented tangentially to the head (see Chapter 2, Figure 2.3), which are spring-loaded to enhance contact between the accelerometer and the head (Manoogian et al. 2006). When one of the accelerometers detects an acceleration of at least 10 g, the system is collects 40 ms of data at 1000 Hz (Mihalik, Greenwald, et al. 2010). Accelerometer data are passed through a 0.5 Hz AC hardware filter and a 400
Hz low-pass filter and wirelessly transferred to a sideline data storage system. The data are uploaded to a Simbex server and an algorithm proprietary to Simbex is used to calculate linear and rotational acceleration at an estimated center of gravity of the head based upon rigid body dynamics and iterative optimization (Chu et al. 2006). The processed impact data are then sent back to the end users.

The GFT consists of triaxial accelerometers and gyroscopes housed in a casing that is attached to a helmet via adhesive or Dual Lock Reclosable Fasteners (3M, St. Paul, MN), allowing integration into a helmet of choice. Acceleration thresholds for collecting data were set to 8g, and impact data were uploaded via USB connection. For these versions of hardware and software the data obtained by the end-user is the raw data, processed only with a simple first-order hardware low pass filter on the accelerometers with a cut-off frequency of 300 Hz. Impact data are recorded over a 40 ms timespan at 3000 Hz for linear acceleration data and 760 Hz for rotational velocity data. However, if the acceleration remains above the user-set threshold beyond this timepoint, the system continues recording 40 ms timespans of data until the acceleration falls below the threshold.

3.2.3: Impactor

A pneumatic linear impactor, weighing 23.9 kg, was used to contact the helmets at various speeds and in different directions (see Chapter 2, Figures 2.4 and 2.5). For the majority of impact testing, one of two impacting surfaces was used. Both of these were
made of ultra-high molecular weight polyethylene (UHMWPE) and were cylindrical with rounded edges and the flat end of the cylinder contacting the helmet. One impacting surface had a 8.26 cm in diameter and weighed 0.4 kg, while the other was 10.16 cm in diameter and weighed 0.6 kg. For HIT System testing, the 8.26 cm impactor was used for side and oblique back impacts and the 10.16 cm impactor was used for back, front, and oblique front impacts. For GFT testing, the 10.16 cm impactor was used for all impact directions. While high speed video of HIT System testing suggests that the helmet was not conforming beyond the ends of the smaller impactor, use of the larger impactor in subsequent tests made this even less likely. These hard impacting surfaces were meant to simulate contact between a player’s head and one of the hard surfaces present in the ice hockey rink, such as the boards or the ice.

3.2.4: Interface between the ATD head and the helmet

A subset of impacts to a HIT System instrumented Easton S9 hockey helmet were conducted at 2, 3.5, and 5 m/s in the front, back and side impact directions (Figure 3.2). The impacting speeds were chosen to produce accelerations across the range of measures observed during on-ice play (Mihalik et al. 2012). To analyze the effect of the interface between the ATD head and the helmet, three different head surfaces were tested: a nylon skull cap to mimic previous validation efforts for the football HIT System (Beckwith, Greenwald, and Chu 2012; Rowson et al. 2011), a dry human hair wig adhered to the ATD head using a strong double-sided tape that kept the wig from displacing relative to
the ATD head, and the same wig sprayed with water to simulate perspiration. Three to five impacts were performed per speed–direction–head surface combination.

Figure 3.2: HIT System for ice hockey test conditions for impacts used to assess the effect of the interface between the ATD head and the helmet.

3.2.5: Speeds and directions

Based upon observation of youth hockey teams in play and practice, player hair is wet during play. Thus, the remaining impact tests were conducted with the wet human hair wig. Four or five repeat tests were conducted at one of four impact directions (front, back, side, oblique back-side, or oblique front-side) and one of four speeds (1.5, 2.5, 3.75 or 5 m/s). Again, these speeds were chosen to achieve the range of accelerations that may be experienced during on-ice play (Mihalik et al. 2012). For HIT System testing, oblique impacts were measured at 30 degrees from the sagittal plane (see Chapter 2, Figure 2.4). For GFT testing, due to use of the larger impacting face for all impact directions and its
possible interactions with geometrical features of the helmets, oblique impacts were measured at 45 degrees from the sagittal plane (see Chapter 2, Figure 2.5).

3.2.6: Helmet geometry/construction

To test whether the differences in construction and geometry between two different helmets influenced the relationship between peak GFT and reference measures, the rigid mounting setup and UHMWPE surface were used to impact an Easton S9 and a Bauer helmet, both equipped with GFT (Figure 3.3). First, the Easton helmet was impacted with GFT sensors in the inside top, outside top, outside right, and outside back locations. Those sensors were then moved to the corresponding locations on the Bauer helmet and the same set of impacts was repeated for this helmet. These helmets have geometrical differences, with the Easton S9 having larger ridges in the back of the helmet (see Chapter 2, Figure 2.1), and they have different padding inside of the helmet.
Figure 3.3: GFT test conditions highlighting impacts used to assess the effect of helmet geometry/construction on the relationship between peak GFT and corresponding reference ATD measures.

3.2.7: Repeatability of helmet/sensor systems

In order to assess repeatability of the combined helmet/sensor system, two Easton S9 hockey helmets, each instrumented with the HIT System for ice hockey, were tested (Figure 3.4). These impacts used the UHMWPE impacting surface and rigid mounting of the ATD head and neck at the level of T1. Similarly, to assess the repeatability of the combined helmet/sensor system for GFT, two Bauer RE-AKT helmets instrumented with sensors in the same four aforementioned locations underwent impacts for side and
oblique-back impact directions (Figure 3.5). These impacts were done with the UHMWPE impacting surface and the ATD head and neck mounted to the translating table at the level of T1.

Figure 3.4: HIT System for ice hockey test conditions for impacts used to assess combined helmet/sensor system repeatability.

Figure 3.5: GFT test conditions highlighting impacts used to assess combined helmet/sensor system repeatability.
3.2.8: Effective mass of the torso

Impacts to GFT-instrumented helmets were used to assess the remaining the real-world factors, and the same sensor set was used for all of these tests. To assess whether simulating the actual effective mass of the torso, rather than an infinite effective mass of the torso, affected the relationship between peak GFT and reference ATD measures, the same set of impacts was repeated for the rigid and translating mount setups (Figure 3.6). These impact tests were both done using the UHMWPE impacting surface.

Figure 3.6: GFT test conditions highlighting impacts used to assess the influence of effective mass of the torso on the relationship between peak GFT and corresponding reference ATD measures.
3.2.9: Impacting surface

In order to test the effect of impacting surface on the relationship between helmet-based system reference peak measures, a softer surface was used for a subset of impacts to the Bauer helmet so that the relationships between peak GFT and reference measure could be compared to those for the more rigid UHMWPE surface impacts (Figure 3.7). This surface was an Easton Mako M5 elbow pad (Easton-Bell Sports Inc., Van Nuys, CA), which was attached to the impacting ram (Figure 3.8) and simulated one player’s elbow hitting another player in the head. Both of these sets of tests, employing the different impacting surfaces, were done with the ATD head and neck mounted to the translating table.

![Diagram showing test conditions and setups]

Figure 3.7: GFT test conditions highlighting impacts used to assess the effect of impacting surface on the relationship between peak GFT and corresponding reference ATD measures.
Figure 3.8: The UHMWPE (left) and hockey elbow pad (right) impacting surfaces used during testing.

3.2.10: Data processing and analysis

ATD-collected acceleration time histories were processed with a CFC 1000 filter and rotational accelerations were calculated from the nine accelerometer array via the process outlined by Padgaonkar et al. (Padgaonkar, Krieger, and King 1975). Rotational velocities measured via angular rate sensors were processed using a CFC 60 filter. Peak values of the ATD and HIT-System resultant linear and rotational head acceleration for the same impact were compared. Similarly maximum values of resultant linear acceleration and resultant rotational velocity were compared between the ATD and GFT measurement systems for the same impact. The correlations between helmet system-estimated and ATD-measured peak kinematics were quantified using power regression fits. Given the significant effects of impact direction and, for GFT, sensor location on the relationship
between peak helmet-based system and reference ATD measures (see Chapter 2) regressions were found for data stratified by these two factors. The quality of the regression was assessed using coefficients of determination ($R^2$ values).

Statistical analyses were performed using the mixed models procedure in SAS 9.3 (SAS Institute Inc.; Cary, NC). To test for significance of the interface between the ATD head and the helmet, the ATD peak resultant acceleration was used as the primary outcome measure and the interaction between HIT System peak resultant acceleration and the categorical variable of interface was assessed (Model 3.1). Similarly, to test for repeatability of the relationship between peak HIT System and reference measures for two different helmet/sensor sets, the ATD peak resultant acceleration was again used as the primary outcome measure and the interaction between HIT System peak resultant acceleration and the categorical variable of helmet/sensor system was assessed (Model 3.2).

$$ATD_{peak} = \beta_0 + \beta_1 \times HIT_{peak} + \beta_2 \times V1 + \beta_3 \times HIT_{peak} \times V1 + \varepsilon$$

Model 3.1: Statistical model for HIT System data to test significance of the interface between the ATD head and the helmet. $V1 = \text{interface (nylon cap, dry human hair wig, or wet human hair wig)}$.

$$ATD_{peak} = \beta_0 + \beta_1 \times HIT_{peak} + \beta_2 \times V2 + \beta_3 \times HIT_{peak} \times V2 + \varepsilon$$

Model 3.2: Statistical model for HIT System data to test inter-helmet/sensor system reproducibility. $V2 = \text{helmet/sensor set (1 or 2)}$. 

103
For statistical analyses involving GFT measures, given the statistical significance of both impact direction and sensor location (Chapter 2) data were stratified by these factors. In line with the initial analyses of the effects of impact direction and sensor location for GFT measures, the ratio of peak ATD measure to peak GFT measure was used as the primary outcome measure in order to facilitate interpretation of the results and the effect of the categorical variables on these ratios was assessed (Models 3.3-3.6). Bonferroni corrections were used to adjust for multiple tests. Statistical analyses were performed for both peak linear accelerations and peak rotational velocities.

\[
\frac{ATD_{\text{peak}}}{GFT_{\text{raw peak}}} = \beta_0 + \beta_1 \times V2 + \epsilon
\]

Model 3.3: Statistical model for GFT data (stratified by helmet brand and sensor location) to test inter-helmet/sensor system reproducibility. \(V2 = \) helmet/sensor set (1 or 2).

\[
\frac{ATD_{\text{peak}}}{GFT_{\text{raw peak}}} = \beta_0 + \beta_1 \times V3 + \epsilon
\]

Model 3.4: Statistical model for GFT data (stratified by helmet brand and sensor location) to test significance of helmet geometry and construction. \(V3 = \) helmet brand (Easton or Bauer).

\[
\frac{ATD_{\text{peak}}}{GFT_{\text{raw peak}}} = \beta_0 + \beta_1 \times V4 + \epsilon
\]

Model 3.5: Statistical model for GFT data (stratified by helmet brand and sensor location) to test significance of impacting surface. \(V4 = \) impacting surface (UHMWPE or elbow pad).
Model 3.6: Statistical model for GFT data (stratified by helmet brand and sensor location) to test significance of effective mass of the torso. V5 = mounting setup (rigid or translating).

\[
\frac{ATD_{\text{peak}}}{GFT_{\text{raw \ peak}}} = \beta_0 + \beta_1 \times V5 + \varepsilon
\]

3.3: Results

3.3.1: Interface between the ATD head and the helmet

In testing the effect of the interface between the ATD and the helmet, side impacts provided the primary data set for analysis of this factor as, due to a HIT System processing algorithm meant to remove impacts from the data set that are suspected not to be impacts to a helmeted head, the side impact direction was the only one that resulted in full sets of data for all three interfaces. The different interfaces between the ATD head and the helmet resulted in varying power regression relationships between peak HIT System for ice hockey-measured and reference ATD resultant linear acceleration (Figure 3.9). Statistical analysis indicated a significant effect of interface between the ATD head and the helmet on the relationship (Model 3.1) between peak HIT System and reference measure (p<0.001). The wet wig (designated as the reference) was significantly different from the nylon cap (p=0.002), but was not significantly different from the dry wig (p=0.147).
Figure 3.9: Differing relationships between peak resultant linear acceleration as measured by the HIT System for ice hockey and ATD for side impacts for three different interfaces between the head and the helmet.

3.3.2: Helmet geometry/construction

For assessing the effect of helmet geometry and construction on peak GFT and corresponding peak ATD measures, the data and regression relationships for the Easton and Bauer helmets are presented in Chapter 2. Initial statistical analysis evaluated the relationship between GFT peak kinematic measures and reference kinematic measures for all of the impact directions combined and showed a significant three-way interaction between helmet brand, sensor location, and impact direction. However, helmet brand alone had a statistically significant effect (p=0.04) and this is a controllable parameter in on-field implementation, so the data were stratified by helmet brand for all other analyses.
3.3.3: Repeatability of helmet/sensor systems

For the subsequent testing of the HIT System for ice hockey, 48 of the 218 impacts in the test matrix were removed from the dataset by the aforementioned processing algorithm for impact “validity” described in Chapter 2. Thus, analysis of the HIT System results focused on the 139 impacts in the side, back, and oblique back directions.

Evaluation of the repeatability of the combined helmet/sensor system for the HIT System for ice hockey showed that the two combined helmet/sensor system sets did not result in largely different power regression relationships (Figure 3.10, Table 3.1). Statistical analysis on the ratios of the peak measures showed that the effect of the combined helmet/sensor set on the relationship between peak HIT System and reference measure was not significant (p=0.49).
Figure 3.10: Data comparing helmet/sensor sets for peak resultant linear (left) and rotational (right) acceleration as measured by the ATD and by the HIT System for ice hockey stratified by impact direction. Each data point represents a single impact, with HIT System measure on the abscissa and ATD measure on the ordinate. The lines correspond to the power regression relationships.
Table 3.1: Linear and power regression fit equations stratified by impact direction for HIT System combined helmet/sensor sets 1 and 2 and their associated $R^2$ values.

For the evaluation of the repeatability of the combined helmet/sensor system for GFT, most of the impact direction-sensor location combinations resulted in good agreement between data for the two sensors (Figures 3.11, Table 3.2, Appendix 2 section A2.1). Others resulted in some differences in the power regression relationships between the two helmet/sensor sets.

Statistical analysis of the effect of the combined helmet/sensor set on the ratios of the peak measures (Figure 3.12) showed that, for most sensor location-impact direction combinations, it was not significant (Table 3.3). For the outside back sensor, there was a significant effect of helmet/sensor set on peak resultant linear acceleration measures for
oblique impacts. For the outside top sensor, there was a significant effect of helmet/sensor set on peak resultant rotational velocity measures for side impacts.

![Graphs showing peak resultant linear acceleration and rotational velocity](image)

**Figure 3.11**: Inside top sensor location data comparing combined helmet/sensor sets for peak resultant linear acceleration (left) and rotational velocity (right) as measured by the ATD and GFT stratified by impact direction. Each data point represents a single impact, with GFT measure on the abscissa and ATD measure on the ordinate. The lines correspond to the power regression relationships.
<table>
<thead>
<tr>
<th>Direction</th>
<th>Linear Acceleration</th>
<th>Regression Equation: Sensor Set 1</th>
<th>Set 1 $R^2$</th>
<th>Regression Equation: Sensor Set 2</th>
<th>Set 2 $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Side</td>
<td>$y = 0.67x^{1.04}$</td>
<td>.99</td>
<td>$y = 0.53x^{1.06}$</td>
<td>.94</td>
<td></td>
</tr>
<tr>
<td>Oblique</td>
<td>$y = 0.21x^{1.28}$</td>
<td>.94</td>
<td>$y = 0.23x^{1.27}$</td>
<td>.90</td>
<td></td>
</tr>
<tr>
<td>Rotational Acceleration</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Side</td>
<td>$y = 1.10x^{0.95}$</td>
<td>.98</td>
<td>$y = 0.64x^{1.13}$</td>
<td>.99</td>
<td></td>
</tr>
<tr>
<td>Oblique</td>
<td>$y = 1.06x^{1.04}$</td>
<td>.99</td>
<td>$y = 0.69x^{1.19}$</td>
<td>.97</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.2: Inside top sensor location power regression fit equations stratified by impact direction for GFT combined helmet/sensor sets 1 and 2 and their associated $R^2$ values.
Figure 3.12: Ratios of peak ATD measure to peak respective GFT measure for helmet/sensor sets 1 and 2 versus impact intensity for data from the inside top sensor location. The ratios were used as the outcome measure for the statistical analysis.
### Significance of Sensor/Helmet Set

<table>
<thead>
<tr>
<th>Sensor Location</th>
<th>Peak Linear Acceleration</th>
<th>Peak Rotational Velocity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Impact Direction</td>
<td>Impact Direction</td>
</tr>
<tr>
<td></td>
<td>Side</td>
<td>Oblique</td>
</tr>
<tr>
<td>Inside Top</td>
<td>0.8016</td>
<td>1.0000</td>
</tr>
<tr>
<td>Outside Top</td>
<td>1.0000</td>
<td>0.4104</td>
</tr>
<tr>
<td>Outside Back</td>
<td>0.5368</td>
<td>0.0224</td>
</tr>
<tr>
<td>Outside Right</td>
<td>1.0000</td>
<td>0.0544</td>
</tr>
</tbody>
</table>

Table 3.3: Summary of p-values after Bonferroni adjustment for statistical significance of combined helmet/sensor set (1 or 2) on the ratio of peak GFT measure to corresponding peak ATD measure. Shading indicates statistical significance.

### 3.3.4: Effective mass of the torso

The evaluation of the influence of effective mass of the torso on the relationship between peak GFT and corresponding peak ATD measure generally showed good agreement between data collected using the rigid mounting setup and the translating mounting setup (Figures 3.13, Table 3.4, Appendix 2 section A2.2). For certain sensor location-impact direction combinations, there were some differences in the power regression relationships between the two mounting setups, particularly for peak rotational velocity for front impacts.
Statistical analysis of the influence of the effective mass of the torso on the ratios of the peak measures (Figure 3.14) showed that, for most sensor location-impact direction combinations, it was not significant (Table 3.5). A consistent exception was the statistical significance of the mounting setup on the ratio of peak resultant rotational velocity for front impacts. For oblique impacts, mounting setup significantly affected the peak resultant rotational velocity ratio for the inside top and outside top sensors, as well as the peak resultant linear acceleration ratio for the inside top sensor.
Figure 3.13: Inside top sensor location data comparing mounting setups (rigid or translating) for peak resultant linear acceleration (left) and rotational velocity (right) as measured by the ATD and GFT stratified by impact direction. Each data point represents a single impact, with GFT measure on the abscissa and ATD measure on the ordinate. The lines correspond to the power regression relationships.
Table 3.4: Inside top sensor location power regression fit equations stratified by impact direction for the two mounting setups (rigid and translational) and their associated $R^2$ values.
Figure 3.14: Ratios of peak ATD measure to peak respective GFT measure for the rigid and translating mounts versus impact intensity for data from the inside top sensor location. The ratios were used as the outcome measure for the statistical analysis.
Table 3.5: Summary of p-values after Bonferroni adjustment testing for statistically significant effect of the mounting setup (rigid or translating) on the ratio of peak GFT measure to corresponding peak ATD measure. Shading indicates statistical significance.

3.3.5: Impacting surface

The evaluation of the influence of impacting surface on the relationship between peak GFT and corresponding peak ATD measure showed a mix of good agreement between data collected using the UHMWPE impacting surface and the elbow pad and differences between the data for the two surfaces (Figure 3.15, Tables 3.6, Appendix 2 section A2.3). The most significant differences in the relationships between peak resultant GFT and ATD measures were for front and back impacts.
Statistical analysis of the influence of the impacting surface on the ratios of the peak measures (Figure 3.16) resulted in a combination of results for significance of particular sensor location-impact direction combinations (Table 3.7). For peak resultant linear acceleration ratios, impacting surface had a significant effect for multiple sensor locations for side, back, and front impacts. For peak resultant rotational velocity ratios, impacting surface had a significant effect for multiple sensor locations for front impacts.
Figure 3.15: Inside top sensor location data comparing impacting surfaces (UHMWPE or hockey elbow pad) for peak resultant linear acceleration (left) and rotational velocity (right) as measured by the ATD and GFT stratified by impact direction. Each data point represents a single impact, with GFT measure on the abscissa and ATD measure on the ordinate. The lines correspond to the power regression relationships.
Table 3.6: Inside top sensor location power regression fit equations stratified by impact direction for the two impacting surfaces (UHMWPE and the hockey elbow pad) and their associated $R^2$ values.
Figure 3.16: Ratios of peak ATD measure to peak respective GFT measure for the UHMWPE and elbow pad impacting surfaces versus impact intensity for data from the inside top sensor location. The ratios were used as the outcome measure for the statistical analysis.
### Significance of Mounting Setup

<table>
<thead>
<tr>
<th>Sensor Location</th>
<th>Peak Linear Acceleration</th>
<th>Peak Rotational Velocity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Impact Direction</td>
<td>Impact Direction</td>
</tr>
<tr>
<td></td>
<td>Side Oblique Back Front</td>
<td>Side Oblique Back Front</td>
</tr>
<tr>
<td>Inside Top</td>
<td>0.0015 0.3750 0.0015 0.0015 0.6540 1.0000 1.0000 0.0015</td>
<td></td>
</tr>
<tr>
<td>Outside Top</td>
<td>0.0015 0.0945 0.0015 0.0105 0.0150 1.0000 1.0000 0.0015</td>
<td></td>
</tr>
<tr>
<td>Outside Back</td>
<td>0.9495 1.0000 N/A 0.0240 1.0000 0.0015 N/A 0.5070</td>
<td></td>
</tr>
<tr>
<td>Outside Right</td>
<td>0.0015 1.0000 0.0015 0.7005 1.0000 1.0000 1.0000 0.0015</td>
<td></td>
</tr>
</tbody>
</table>

**Table 3.7:** Summary of p-values after Bonferroni adjustment testing for statistically significant effect of the impacting surface (UHMWPE or elbow pad) on the ratio of peak GFT measure to corresponding peak ATD measure. Shading indicates statistical significance.

### 3.4: Discussion

This study was the first to assess a number of factors that may vary in real-world collection of head impact biomechanics data and that may influence the performance of helmet-based measurement systems. The results reveal ways to improve laboratory testing of these helmet-based systems, as well as factors to consider in collecting and analyzing real-world impact data using such systems.
3.4.1: Interface between the ATD head and the helmet

Previous laboratory testing of helmet-based systems has typically involved either direct contact between the ATD head and the helmet (or headgear) or use of a nylon cap between the two surfaces (Beckwith, Chu, and Greenwald 2007; Beckwith, Greenwald, and Chu 2012; Hanlon and Bir 2010; Manoogian et al. 2006; Rowson et al. 2011). In this chapter, the effect of the interface between the ATD head and the helmet on the accuracy of the HIT system for ice hockey was evaluated. Results demonstrated that the relationships between system and reference peak resultant measures varied significantly with head/helmet interface.

Due to the poor biofidelity of the surface texture of the ATD, direct contact between the ATD head and the helmet was not used herein, but for comparison with previous validation studies of the HIT System for football (Beckwith, Greenwald, and Chu 2012; Rowson et al. 2011) a nylon cap was used as one of the interfaces. However, use of these types of nylon caps may be more common in some scenarios than others; for example, they may be used more often in football than ice hockey. To most closely mimic the hockey environment a human hair wig was used, specifically a wig wet with water to simulate the perspiration that occurs during play.

It is interesting to note that the nylon cap resulted in the largest HIT System peak measures for a given ATD peak measure, while the dry human hair wig resulted in the
smallest, and the wet wig was generally in between. This suggests that hair may have a
damping effect on the accelerometers measures, which may or may not be due to the
spring loading of the accelerometers in this system’s design that attempts to keep them in
contact with the head.

The significant effect of head-helmet interface suggests that, in the laboratory evaluation
of a helmet-based biomechanical measurement system, it is important to simulate as
closely as possible the interface between the head and the helmet for the real-world
setting in which it will be used in. Furthermore, the accuracy of the system may vary
across players with different hair or who use various caps that change the interface
between the head and the helmet. Future study should evaluate whether there is a
significant effect of the interface between the ATD head and the helmet on the
relationships between peak system and reference measures for helmet-based systems
adhered to the shell rather than integrated into the padding.

3.4.2: Helmet geometry/construction

While the HIT System for ice hockey was only integrated into a single helmet brand and
model, other helmet-based sensor systems, such as GFT, allow integration into a range of
helmets for different sports. However, the significant effect of helmet brand on the ratio
between peak ATD and GFT measure suggests that it is important to define the
relationships between these measures for each helmet model in which it will be used. The
helmet model is a controllable parameter, and therefore can be kept consistent for a
research study on the biomechanics of head impacts, but this would require laboratory impact evaluation of the sensor on the particular helmet model that is to be used for that study. Notably, differences based on helmet model may not be significant in cases where the helmet construction and geometry are more similar than the two models evaluated here. The Easton S9 helmet geometry has more distinct ridges than the Bauer RE-AKT (see Chapter 2, Figure 2.1). Furthermore, the two helmet models consist of very different padding; the Easton S9 employs a dual-density Vinyl Nitrile liner, while the Bauer RE-AKT uses a light Vertex foam liner, memory foam pads, and a free-floating suspension liner that moves independently from the rest of the padding in an attempt to reduce the rotational kinematics of the head. The significant difference in the relationships between GFT and ATD peak kinematic measures based on helmet model suggest that GFT kinematic measures are influenced by the helmet’s mechanical response to an impact. This significance would be expected, as it is adhered to the helmet shell.

3.4.3: Repeatability of the helmet/sensor system

For both the HIT System for ice hockey and GFT, there was generally no significant effect of the combined helmet/sensor set on the relationship between peak system and peak reference measure. The repeatability between two combined helmet/sensor systems is important because it suggests that two helmets of the same brand and model that are instrumented with one of these helmet-based sensors in the same location should perform similarly. This is crucial in studying the biomechanical inputs that lead to mTBI because
most often a number of players from a given team are monitored at the same time using these helmet-based sensor systems.

3.4.4: Effective mass of the torso

The majority of previous laboratory studies involving evaluation of helmet (or headgear)-based measurement systems have used translating table mounting setups during the impacts (Beckwith, Greenwald, and Chu 2012; Hanlon and Bir 2010; Rowson et al. 2011). However, this setup does not simulate the effective mass of the torso, essentially emulating a head and neck moving linearly in space with zero effective mass of the torso. We hypothesized that, given the large effective mass of the torso in comparison to the head, the real-world scenario is more similar to infinite than zero effective mass of the torso (Chapter 2). In this chapter the original rigid mounting setup, simulating infinite effective mass of the torso, was compared to a translating table designed to mimic the effective mass of the Hybrid III 50th male torso. For most impact direction-sensor location combinations these two configurations did not lead to significant differences in the ratios of peak ATD and GFT measures. The notable exception was consistent significantly different peak rotational velocity ratios for front impacts. This is likely due to the non-rigid attachment of the facemask to the helmet, which causes the helmet to initially rotate in the direction opposite the rotation of the head (Figure 3.17). The timing of this rotation in comparison to the head affects the peak rotational velocity measure, and the translating table allows the heck and neck to move, affecting the movement of the ATD head in comparison to the base of the neck. This testing does not address whether
an effective torso mass close to zero, used in previous testing of the HIT System (Beckwith, Greenwald, and Chu 2012; Rowson et al. 2011), versus simulating the effective mass of the torso in a translating table setup affects the relationships between peak GFT and reference measures.

Figure 3.17: Still frames depicting a front impact to the facemask showing an initial rotation of the helmet in the direction opposite rotation of the ATD head. The position of the top left corner of the facemask in comparison to the facemask clip shows the relative movement.
3.4.5: Impacting Surface

The significance of impacting surface on the relationship between helmet-based and reference measure for a number of impact direction-sensor location combinations complicates analysis of real-world data as there are a number of surfaces that players may come in contact with. Based on the data shown in Figure 3.15 (and Appendix 2, section A2.3) for side impacts, although the differences are statistically significant they may not be meaningful in implementation, especially considering that other factors cause more variability in the data. The statistical differences in the peak linear resultant acceleration relationships between impacting surfaces for front and back impacts may relate to helmet structure and fit on the ATD head along the sagittal plane. The shells of these hockey helmets consist of two parts that slide along each other (they are not rigidly attached to each other but screws help tighten them in place) in that plane for fitment purposes. Furthermore, the shape of the ATD head results in a looser fit along the sagittal plane than the coronal plane. It is possible that in the initial moments of the impact, while the foam of the softer impacting surface is compressing, the helmet has not yet fully coupled to the head. If this is the case, by the time the helmet is fully coupled with the head, the foam may already be compressed so the head does not experience the effect of the deformation, causing it to experience higher accelerations relative to the helmet. The ratio of peak rotational measures for front impacts showed consistent influence of impacting surface, likely due to the non-rigid attachment of the facemask resulting in rotation of the helmet in the direction opposite of the head (Figure 3.17).
There are a number of ways to account for the effect of impacting surface. One would be to collect game film for the purpose of determining impact surface (along with other impact conditions) to apply the proper relationships to the data. Another would be to analyze the most commonly impacted surfaces in various sports and use the results to decide what surface to use during impact testing. A third approach would be to use the relationships for the harder surfaces that players may come in contact with, as these are more likely to cause higher magnitude peak kinematics.

3.4.6: Limitations

This chapter explored a subset of the factors and impact conditions that may be encountered in real-world scenarios of collecting head impact biomechanical data from helmet-based instrumentation. However, there are a range of other head surfaces, impacting surfaces, impact directions, and helmet geometries and constructions that exist in the real world that were not evaluated herein. Furthermore, a number of the limitations outlined in Chapter 2 also apply to this chapter, including use of only one helmet fit, the challenges of fitting a helmet to the Hybrid III head, the analysis of only peak measures, and the lack of a sensitivity analysis to examine the influence of small differences in impact direction.

This evaluation involved completing all of the impacts (at various speeds and in different directions) for a specific set of testing conditions encompassing impacting surface, helmet brand, sensor set, and mounting setup, then changing the conditions and...
performing the next set of impacts. Given this methodology it is possible that some of the differences seen could be due to changes in sensor performance over time. However, a subset of impacts with the same characteristics were performed at the beginning of testing and repeated after other testing was complete. There were no significant differences in the data for these sets of impacts, suggesting that there was no significant change in sensor performance over time.

3.5: Conclusions

Impact conditions that led to statistically significant effects on the relationships between peak helmet-based system and peak reference ATD measures include the interface between the ATD head and the helmet, the differences in helmet geometry and construction of two different brands, and the impacting surface. Factors that led to largely similar relationships between peak measures include the effective mass of the torso and the repeatability between helmet/sensor systems. These findings have implications for both laboratory evaluation of current and future helmet-based biomechanical measurement systems and the analysis of real-world data collected using these systems.
Chapter 4 - The effect of helmet-based system performance on the calculation of brain injury metrics using finite element analysis

4.1: Introduction

4.1.1: Biomechanical characteristics apart from peak kinematics influence injury risk
The majority of previous helmet instrumentation studies have focused on using peak linear and rotational acceleration as the primary biomechanical measures, the accuracy of which has been evaluated under various conditions and is described in Chapters 2 and 3. However, other factors have been identified as potentially key in understanding the inputs that lead to mTBI and researchers are increasingly using finite element head models to understand how head impacts affect various regions of the brain. One study in this line of work used acceleration profiles from the reconstruction of sixty-one real-world football, motorcycle, and pedestrian accidents to show that data on the mechanical response of the brain obtained from finite element analysis (FEA) can lead to more accurate head injury prediction than global head acceleration-based metrics such as the traditional HIC injury metric and a recently proposed criterion called Head Impact Power (Marjoux et al. 2008). Furthermore, using theoretical acceleration profiles, researchers have found that the shape of the pulse and the separation interval between acceleration and deceleration influence FEA outcome measures such stress, strain, and pressure in the brain, indicating that characteristics of the acceleration-time history curve apart from the peak magnitude
likely influence injury risk (Post, Hoshizaki, and Gilchrist 2012; Post et al. 2014; Yoganandan et al. 2008).

4.1.2: Use of real-world kinematic data in finite element analysis

The authors of one study commented on the importance of being able to use real-life injury acceleration pulses for future research in finite element analysis (Post, Hoshizaki, and Gilchrist 2012). Some researchers have attempted to do this using helmet-based system data, particularly data collected from the HIT Systems for football and ice hockey, in finite element models to study mTBI. Takhounts et al. explored the use of data collected from the six-degree-of-freedom HIT System for football in finite element analysis using the improved version of the Simulated Injury Monitor (SIMon) (Takhounts et al. 2008). The SIMon finite element head and brain model was developed by the National Highway Traffic Safety Administration (NHTSA) and has an intentionally simplified version, in the interest of computation time, along with an improved, more complex version that accounts for the major anatomical structures. The portion of the Takhounts et al. study analyzing helmet-based data resulted in two main findings. First, none of the biomechanical injury metrics calculated using SIMon, including maximum principal stress, correlated with linear acceleration. Second, there were some impacts that resulted in levels of maximum principal strain that many researchers would expect to result in severe injury, although there were no known injuries associated with those impacts. There are several possible reasons for this discrepancy, including errors in the acceleration-time histories of the on-field data that were used as input into the model.
McAllister et al. used data from ten diagnosed concussions in the Dartmouth Subject-Specific FE Head Model to correlate outcome measures to changes in white-matter integrity as measured by diffusion tensor imaging DTI (McAllister et al. 2012). They found that the FE measures of model-predicted strain and strain rate had statically significant correlations with DTI changes in fractional anisotropy (FA) and mean diffusivity (MD). It is important to note that the majority of impact data from the HIT System for football has been collected using the version of the system that only calculates data for two axes of rotational acceleration, lacking an estimation of axial rotation. Therefore this data would likely lead to larger errors in brain injury metrics calculated via FEA, particularly if, as was found by Weaver at al. (discussed below), axial rotation leads to higher global CSDM (Weaver, Danelson, and Stitzel 2012).

4.1.3: Other FEA findings related to risk of mTBI

Other FEA studies have looked at the influence of impact direction and linear versus rotational acceleration on strains in the brain. An evaluation by Weaver et al. on the influence of direction used cumulative strain damage measure (CSDM), a measure of the volume percentage of the brain exceeding a predetermined strain threshold ranging from 5 to 25 percent, as the outcome measure. This study found differences in both global and regional CSDM values based on the direction of input even when controlling the input magnitude, with the largest global CSDM values occurring during impacts with a component of axial rotation (Weaver, Danelson, and Stitzel 2012). Similarly, in a comparison between frontal and lateral impacts, Zhang et al. found much higher shear
stress in lateral impacts than in frontal impacts of the same severity (L. Zhang, Yang, and King 2001). This corresponds to findings in previous animal studies. The large variations in the mechanical response of the brain due to directions of movement are not captured in injury risk functions that rely on peak resultant acceleration or velocity. Another finite element analysis study found that rotational acceleration contributes more than 90 percent of strain in the brain while translational acceleration produces very little strain, which is again in line with findings in animal models (J. Zhang et al. 2006).

4.1.4: Research objectives

While finite element analysis has been used to analyze data from helmet-based systems in a limited number of impacts (McAllister et al. 2012; Takhounts et al. 2008), no studies exist that evaluate the effect of helmet-based system performance, as highlighted in previous chapters, on brain injury metrics calculated from FEA. This is critical given that, as discussed, previous studies have found that injury metric outcomes in finite element models are influenced by more than peak resultant kinematic measures. This chapter begins to address this need by using laboratory data as FEA input and comparing brain injury metrics calculated using reference ATD data to brain injury metrics calculated using helmet-based system data for the same impacts.
4.2: Methods

4.2.1: Laboratory testing

The laboratory testing is fully described in Chapter 2 and Chapter 3 (see sections 2.2 and 3.2). It is briefly reviewed here. A Hybrid III 50\textsuperscript{th} percentile male anthropometric test device (ATD) head and neck with a 3-2-2-2 accelerometer array (Padgaonkar, Krieger, and King 1975) and three angular rate sensors was mounted at the level of T1 in two fashions: rigidly and then to a translating table (see Chapter 3, Figure 3.1). The translating portion of the second setup was built to account for the effective mass of the Hybrid III 50\textsuperscript{th} percentile male torso. Two Easton S9 hockey helmets instrumented with the HIT System for ice hockey, along with two Bauer RE-AKT hockey helmets instrumented with GFT sensors in four different locations, were fit to the ATD head. The HIT System for ice hockey consists of six single-axis linear accelerometers embedded in the padding of the helmet and oriented tangentially to the head (see Chapter 2, Figure 2.3), while the GFT consists of a triaxial accelerometer and a triaxial gyroscope housed in a casing that is attached to a helmet. Details on these two systems are described in Chapter 2 (see section 2.2.2).

In order to most closely mimic a real-world scenario of the interface between the head and the helmet, a human-hair wig was adhered to the ATD head and wet with water to simulate perspiration. The helmets were fit to the ATD head following USA Hockey guidelines (USA Hockey) and the alignment of the helmet on the ATD head was checked before each impact to confirm repeatability of the testing conditions. Both helmets had
their corresponding facemasks attached, as hockey players under the age of 18 are required by USA Hockey rules to wear such a facemask.

A pneumatic linear impactor, weighing 23.9 kg, was used to contact the helmets at various speeds and in different directions (see Chapter 2, Figures 2.4 and 2.5). Two ultra-high molecular weight polyethylene (UHMWPE) cylinders with rounded edges and a hockey elbow pad were used as the impacting surfaces to contact the helmets.

4.2.2: Finite element model

The improved SIMon finite element head model was chosen for this analysis. SIMon was developed by NHTSA and was intentionally simplified compared to other FE brain models for the purpose of decreased computation time, allowing for a relatively large number of impacts to be analyzed in a time-efficient manner (Takhounts et al. 2003). An improved version has since been developed that has more elements and accounts for more anatomical structures, but it requires increased computation time. The improved SIMon consists of 42,500 nodes and 45,875 elements, including 5153 shell elements, 14 beam elements, and 40,708 solid elements (Takhounts et al. 2008). It accounts for major anatomical structures including the cerebrum, cerebellum, brainstem, ventricles, falk cerebri, tentorium cerebelli, parasagittal blood vessels, formen magnum, and a combined cerebrospinal fluid and pia arachnoid complex layer (Figure 4.1). A study was done that included simulating animal experiments to compare CSDM and maximum principal strain (MPS) calculations between SIMon and the Global Human Body Models.
Consortium (GHBMC) head model (Takhounts et al. 2013). The GHBMC head model consists of 270,787 elements, more than 5 times the number of those in SIMon, yet this study found no significant differences in CSDM and MPS calculations between the SIMon and GHBMC models. Takhounts et al. describes in detail the development and validation of the SIMon finite element head model (Takhounts et al. 2008).

SIMon requires six inputs for simulations: time histories for x, y, and z linear acceleration, along with time histories for x, y, and z rotational velocities. The results for the improved SIMon model include two main outcomes measures. One is CSDM which, as previously discussed, is a measure of the volume percentage of the brain exceeding a predetermined strain and relates to risk of diffuse axonal injury. SIMon calculates CSDM values for 0.05, 0.10, 0.15, and 0.25 levels of strain. The other injury metric output by this version of SIMon is the maximum principal strain that is calculated within the brain.

Figure 4.1: The improved SIMon finite element head model
Given that researchers suggest strain-based measures are most appropriate to study mTBI in finite element analysis (McAllister et al. 2012; Takhounts et al. 2008), but no consensus on the specific metric or threshold has been reached, this study explores the effect of the performance of helmet-based systems on three SIMon output measures: CSDM 0.15, CSDM, 0.25, and maximum principal strain. For the impacts simulated, the CSDM 0.05 and CSDM 0.10 measures regularly reached or came close to the maximum level of 1, meaning 100% of the finite element model brain experienced those levels of strain, so these results are not reported. A CSDM 0.25 of 0.54 has been associated with a 50% probability of DAI (Takhounts et al. 2008).

4.2.3: Analysis groups and filtering

Only 5 m/s impacts, the highest velocity used in the laboratory testing, were analyzed via finite element analysis. These impacts tended to have accelerations above 90g and consequently were more likely to be in the range of impacts of interest in studying mTBI (Pellman et al. 2003), allowing injury metrics that are possibly more applicable to injury to be analyzed (i.e. CSDM 0.25). Lower velocity impacts were excluded as they led to values near zero for some outcome measures, particularly CSDM 0.25. This, in combination with the aforementioned exclusion of CSDM 0.05 and 0.10, ensured that the focus of this exploration was neither at the upper or lower limits of the injury metrics, but rather in the range where we would expect variability with the impact conditions studied.
Four groups of helmet-based system data were defined for analysis in comparison to outcomes based on ATD data from the corresponding impacts. For the purposes of this study, within analysis groups the impacts were further separated by test conditions such as impact direction and impacting surface as these were shown to influence helmet-based system measures in Chapters 2 and 3. Group 1 consisted of raw HIT System time series data for all six inputs into SIMon. However, given that the HIT System estimates rotational acceleration and SIMon requires rotational velocity as the input, the rotational data were integrated to calculate an estimated rotational velocity time history. Group 2 consisted of the same HIT System data, but before being input into SIMon it was adjusted using average peak value ratios developed for each axis (Equation 4.1). These ratios were derived from the lab data presented in Chapter 2 section 2.3.2. The time series data for each axis was multiplied by its axis-specific adjustment factor. Since the impacts were separated by test conditions, the average ratios for each axis were also calculated specific to these conditions. The inputs and outputs for Group 1 and Group 2 comparisons are depicted in Figure 4.2.

\[
\text{Adjustment Factor} = \frac{\sum_{i=1}^{n} \frac{\text{Peak ATD}_i}{\text{Peak HIT}_i}}{n}
\]

**Equation 4.1: Equation used to calculate adjustment factors for each axis**
Figure 4.2: SIMon inputs and outcomes for comparison of calculated brain injury metrics based on ATD data to those based on HIT System data

Group 3 consisted of raw GFT time series data for all six inputs into SIMon. Given that GFT measures rotational velocity rather than rotational acceleration, no integration was necessary to use this data as input into SIMon. However, for this system linear acceleration is collected at 3000 Hz whereas rotational velocity is collected at 760 Hz, so the rotational velocity data were interpolated so that the linear and rotational time histories would have the same number of data points. Similar to Group 2, Group 4 consisted of GFT data that was adjusted before being used as input into SIMon via average peak value ratios developed for each axis. Data from Chapter 3, section 3.3 was used to do this. The inputs and outputs for Group 3 and Group 4 comparisons are depicted in Figure 4.3.
Before being used as input, the ATD-measured linear acceleration time histories were filtered using CFC 1000 and the rotational velocity time histories, as measured by the angular rate sensors, were filtered using CFC 60. No further filtering was done on the HIT System or GFT data beyond what is built into each system. As described in Chapter 2, for the HIT System the data from the six accelerometers are passed through a 0.5 Hz AC hardware filter and a 400 Hz low-pass filter, whereas GFT uses a simple first-order hardware low pass filter on the accelerometers with a cut-off frequency of 300 Hz.

4.2.4: Analysis of Outcome Measures

The three resulting CSDM 0.15, CSDM 0.25, and maximum principal strain calculations (reference CSDM, system CSDM, and adjusted system CSDM, along with reference
MPS, system MPS, and adjusted system MPS) were plotted for each impact. The CSDM and maximum principal strain values resulting from helmet-based system data were compared to those resulting from ATD data for the same impact by calculating the absolute difference of the metrics at the end of the simulation and expressing it as percent error (Equation 4.2). The averages and standard deviations for these absolute errors were found for each group, stratified by testing conditions. To assess overall patterns, the averages and standard deviations of absolute differences across testing conditions were found for each of the four groups: the raw HIT System data, adjusted HIT System data, raw GFT data, and adjusted GFT data.

\[
\text{Metric Absolute Percent Error} = \left| \frac{\text{Metric}_{\text{ATD}} - \text{Metric}_{\text{helmet system}}}{\text{Metric}_{\text{ATD}}} \right| \times 100\%
\]

Equation 4.2 where metric is CSDM 0.15, CSDM 0.25, or MPS

4.3: Results

4.3.1: CSDM 0.15

In the HIT System analysis, average ATD-based calculations of CSDM 0.15 ranged from 0.45 to 0.60 across test conditions. Average HIT System-based calculations for the same impacts ranged from 0.40 to 0.76, whereas average adjusted HIT System-based calculations ranged from 0.38 to 0.77. Exemplar graphs of CSDM 0.15 outputs based on ATD and HIT System inputs are shown below, one for each impact direction (Figure 4.4). Average absolute errors in estimated CSDM 0.15 values for raw HIT System input
ranged from 21% to 66%, while errors for adjusted HIT System input were generally lower, particularly for side impacts, ranging from 15% to 36% across all impact directions (Table 4.1).

Figure 4.4: Exemplar SIMon-calculated CSDM 0.15 for side (top left), oblique (top right), and back (bottom) impacts using an UHMWPE impacting surface. The y-axis measure is the volume fraction of the brain that has exceeded 15% strain by that time point.
<table>
<thead>
<tr>
<th>Conditions</th>
<th>n</th>
<th>ATD CSDM Avg (SD)</th>
<th>HIT CSDM Avg (SD)</th>
<th>Adjusted HIT CSDM Avg (SD)</th>
<th>Error (HIT vs ATD) Avg (SD)</th>
<th>Error (Adjusted HIT vs ATD) Avg (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Side, UHMWPE, sensor/helmet 1</td>
<td>10</td>
<td>0.45 (0.03)</td>
<td>0.69 (0.05)</td>
<td>0.38 (0.05)</td>
<td>54% (11%)</td>
<td>15% (9%)</td>
</tr>
<tr>
<td>Side, UHMWPE, sensor/helmet 2</td>
<td>4</td>
<td>0.46 (0.02)</td>
<td>0.76 (0.08)</td>
<td>0.49 (0.08)</td>
<td>66% (19%)</td>
<td>15% (7%)</td>
</tr>
<tr>
<td>Back, UHMWPE, sensor/helmet 1</td>
<td>3</td>
<td>0.56 (0.01)</td>
<td>0.40 (0.11)</td>
<td>0.73 (0.05)</td>
<td>27% (18%)</td>
<td>30% (8%)</td>
</tr>
<tr>
<td>Back, UHMWPE, sensor/helmet 2</td>
<td>7</td>
<td>0.56 (0.03)</td>
<td>0.40 (0.04)</td>
<td>0.71 (0.05)</td>
<td>28% (11%)</td>
<td>26% (14%)</td>
</tr>
<tr>
<td>Oblique, UHMWPE, sensor/helmet 1</td>
<td>5</td>
<td>0.57 (0.02)</td>
<td>0.76 (0.08)</td>
<td>0.77 (0.06)</td>
<td>35% (17%)</td>
<td>36% (14%)</td>
</tr>
<tr>
<td>Oblique, UHMWPE, sensor/helmet 2</td>
<td>6</td>
<td>0.60 (0.02)</td>
<td>0.56 (0.16)</td>
<td>0.60 (0.15)</td>
<td>21% (12%)</td>
<td>19% (8%)</td>
</tr>
</tbody>
</table>

Table 4.1: Results for SIMon CSDM 0.15 calculations resulting from ATD data, raw HIT System data, and adjusted HIT System data from laboratory evaluations used as input

In the GFT analysis, average ATD-based calculations of CSDM 0.15 ranged from 0.46 to 0.67 across test conditions. Average GFT-based calculations for the same impacts ranged from 0.34 to 0.50, whereas average adjusted GFT-based calculations ranged from 0.33 to 0.81. Exemplar graphs of CSDM 0.15 outputs based on ATD and GFT inputs are shown below, one for each impact direction/impacting surface combination (Figures 4.5, 4.6).

Average absolute errors in estimated CSDM 0.15 values for raw GFT input ranged from 11% to 44%, while average errors for adjusted GFT ranged from 5% to 30% across
impact directions (Table 4.2). For impacts using the UHMWPE surface, adjusting the GFT data had a mixed effect, but for impacts with the elbow pad adjusting the GFT data led to decreases in average error.

Figure 4.5: Exemplar SIMon-calculated CSDM 0.15 for a side (top left), oblique (top right), and back (bottom) impact using an UHMWPE impacting surface. The y-axis measure is the volume fraction of the brain that has exceeded 15% strain by that time point.
Figure 4.6: Exemplar SIMon-calculated CSDM 0.15 for a side (top left), oblique (top right), and back (bottom) impact using a hockey elbow pad impacting surface. The y-axis measure is the volume fraction of the brain that has exceeded 15% strain by that time point.
<table>
<thead>
<tr>
<th>Conditions</th>
<th>n</th>
<th>ATD CSDM Avg (SD)</th>
<th>GFT CSDM Avg (SD)</th>
<th>Adjusted GFT CSDM Avg (SD)</th>
<th>Error (GFT vs ATD) Avg (SD)</th>
<th>Error (Adjusted GFT vs ATD) Avg (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Side, UHMWPE, sensor/helmet 1</td>
<td>5</td>
<td>0.46 (0.03)</td>
<td>0.50 (0.04)</td>
<td>0.33 (0.04)</td>
<td>11% (4%)</td>
<td>30% (5%)</td>
</tr>
<tr>
<td>Side, UHMWPE, sensor/helmet 2</td>
<td>5</td>
<td>0.49 (0.02)</td>
<td>0.42 (0.02)</td>
<td>0.41 (0.02)</td>
<td>14% (2%)</td>
<td>16% (3%)</td>
</tr>
<tr>
<td>Back, UHMWPE, sensor/helmet 1</td>
<td>5</td>
<td>0.64 (0.03)</td>
<td>0.36 (0.04)</td>
<td>0.63 (0.06)</td>
<td>44% (6%)</td>
<td>5% (4%)</td>
</tr>
<tr>
<td>Oblique, UHMWPE, sensor/helmet 1</td>
<td>5</td>
<td>0.62 (0.02)</td>
<td>0.47 (0.03)</td>
<td>0.78 (0.03)</td>
<td>24% (4%)</td>
<td>25% (5%)</td>
</tr>
<tr>
<td>Oblique, UHMWPE, sensor/helmet 2</td>
<td>5</td>
<td>0.67 (0.01)</td>
<td>0.42 (0.04)</td>
<td>0.81 (0.03)</td>
<td>38% (5%)</td>
<td>21% (3%)</td>
</tr>
<tr>
<td>Side, elbow pad, sensor/helmet 1</td>
<td>4</td>
<td>0.48 (0.06)</td>
<td>0.38 (0.11)</td>
<td>0.39 (0.12)</td>
<td>23% (15%)</td>
<td>20% (18%)</td>
</tr>
<tr>
<td>Back, elbow pad, sensor/helmet 1</td>
<td>5</td>
<td>0.57 (0.04)</td>
<td>0.34 (0.03)</td>
<td>0.64 (0.02)</td>
<td>41% (5%)</td>
<td>13% (7%)</td>
</tr>
<tr>
<td>Oblique, elbow pad, sensor/helmet 1</td>
<td>4</td>
<td>0.55 (0.02)</td>
<td>0.40 (0.02)</td>
<td>0.65 (0.02)</td>
<td>27% (3%)</td>
<td>19% (4%)</td>
</tr>
</tbody>
</table>

Table 4.2: Results for SIMon CSDM 0.15 calculations resulting from ATD data, raw GFT data, and adjusted GFT data from laboratory evaluations used as input

4.3.2: CSDM 0.25

In the HIT System analysis, average ATD-based calculations of CSDM 0.25 ranged from 0.09 to 0.19 across test conditions. Average HIT System-based calculations for the same
impacts ranged from 0.06 to 0.31, whereas average adjusted HIT System-based calculations ranged from 0.06 to 0.33. Exemplar graphs of CSDM 0.25 outputs based on ATD and HIT System inputs are shown below, one for each impact direction (Figure 4.7). Average absolute errors in estimated CSDM 0.25 values for raw HIT System input ranged from 35% to 200%, while errors for adjusted HIT System ranged from 26% to 101% (Table 4.3). Errors in calculations based on adjusted HIT System data were much smaller than the raw data for side impacts, but larger for both back and oblique impacts.

Figure 4.7: Exemplar SIMon-calculated CSDM 0.25 for a side (top left), oblique (top right), and back (bottom) impact using an UHMWPE impacting surface. The y-axis measure is the volume fraction of the brain that has exceeded 25% strain by that time point.
### Table 4.3: Results for SIMon CSDM 0.25 calculations resulting from ATD data, raw HIT System data, and adjusted HIT System data from laboratory evaluations used as input

In the GFT analysis, average ATD-based calculations of CSDM 0.25 ranged from 0.08 to 0.21 across test conditions. Average GFT-based calculations for the same impacts ranged from 0.03 to 0.11, whereas average adjusted GFT-based calculations ranged from 0.03 to 0.29. Exemplar graphs of CSDM 0.25 outputs based on ATD and GFT inputs are shown below, one for each impact direction/impacting surface combination (Figures 4.8, 4.9).

Average absolute errors in estimated CSDM 0.25 values for raw GFT input ranged from 21% to 77%, while average errors for adjusted GFT ranged from 15% to 71% (Table
4.4). For impacts using the UHMWPE surface was an increase in average error for side impacts and a decrease in average error for back and oblique impacts associated with adjusting the GFT data, but for impacts with the elbow pad adjusting the GFT data led to decreases in average error for all impact directions.

Figure 4.8: Exemplar SIMon-calculated CSDM 0.25 for a side (top left), oblique (top right), and back (bottom) impact using an UHMWPE impacting surface. The y-axis measure is the volume fraction of the brain that has exceeded 25% strain by that time point.
Figure 4.9: Exemplar SIMon-calculated CSDM 0.25 for a side (top left), oblique (top right), and back (bottom) impact using a hockey elbow pad impacting surface. The y-axis measure is the volume fraction of the brain that has exceeded 25% strain by that time point.
<table>
<thead>
<tr>
<th>Conditions</th>
<th>n</th>
<th>ATD CSDM Avg (SD)</th>
<th>GFT CSDM Avg (SD)</th>
<th>Adjusted GFT CSDM Avg (SD)</th>
<th>Error (GFT vs ATD) Avg (SD)</th>
<th>Error (Adjusted GFT vs ATD) Avg (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Side, UHMWPE, sensor/helmet 1</td>
<td>5</td>
<td>0.10 (0.01)</td>
<td>0.11 (0.02)</td>
<td>0.03 (0.01)</td>
<td>21% (7%)</td>
<td>71% (5%)</td>
</tr>
<tr>
<td>Side, UHMWPE, sensor/helmet 2</td>
<td>5</td>
<td>0.11 (0.01)</td>
<td>0.06 (0.01)</td>
<td>0.06 (0.01)</td>
<td>43% (6%)</td>
<td>49% (7%)</td>
</tr>
<tr>
<td>Back, UHMWPE, sensor/helmet 1</td>
<td>5</td>
<td>0.12 (0.02)</td>
<td>0.04 (0.01)</td>
<td>0.12 (0.03)</td>
<td>66% (8%)</td>
<td>15% (11%)</td>
</tr>
<tr>
<td>Oblique, UHMWPE, sensor/helmet 1</td>
<td>5</td>
<td>0.18 (0.01)</td>
<td>0.07 (0.02)</td>
<td>0.25 (0.02)</td>
<td>61% (8%)</td>
<td>37% (11%)</td>
</tr>
<tr>
<td>Oblique, UHMWPE, sensor/helmet 2</td>
<td>5</td>
<td>0.21 (0.01)</td>
<td>0.05 (0.01)</td>
<td>0.29 (0.03)</td>
<td>77% (5%)</td>
<td>34% (9%)</td>
</tr>
<tr>
<td>Side, elbow pad, sensor/helmet 1</td>
<td>4</td>
<td>0.11 (0.04)</td>
<td>0.06 (0.04)</td>
<td>0.07 (0.05)</td>
<td>53% (26%)</td>
<td>43% (32%)</td>
</tr>
<tr>
<td>Back, elbow pad, sensor/helmet 1</td>
<td>5</td>
<td>0.08 (0.02)</td>
<td>0.03 (0.01)</td>
<td>0.12 (0.02)</td>
<td>67% (6%)</td>
<td>56% (28%)</td>
</tr>
<tr>
<td>Oblique, elbow pad, sensor/helmet 1</td>
<td>4</td>
<td>0.14 (0.01)</td>
<td>0.05 (0.01)</td>
<td>0.18 (0.01)</td>
<td>66% (3%)</td>
<td>22% (8%)</td>
</tr>
</tbody>
</table>

Table 4.4: Results for SIMon CSDM 0.25 calculations resulting from ATD data, raw GFT data, and adjusted GFT data from laboratory evaluations used as input

4.3.3: Maximum principal strain

In the HIT System analysis, average ATD-based calculations of maximum principal strain ranged from 0.50 to 0.62 for different test conditions. Average HIT System-based
calculations for the same impacts ranged from 0.57 to 0.83, whereas average adjusted HIT System-based calculations ranged from 0.45 to 0.80. Exemplar graphs of maximum principal strain outputs based on ATD and HIT System inputs are shown below, one for each impact direction (Figure 4.10). Average absolute errors in estimated MPS values for raw HIT System input ranged from 7% to 52%, while errors for adjusted HIT System ranged from 5% to 47% (Table 4.5). Errors in calculations based on adjusted HIT System data were smaller than the raw data for side and oblique impacts, but larger for back impacts.
Figure 4.10: Exemplar SIMon-calculated maximum principal strain for a side (top left), oblique (top right), and back (bottom) impact using an UHMWPE impacting surface. The y-axis measure is the maximum strain that has been measured anywhere in the finite element head model by that time point.
<table>
<thead>
<tr>
<th>Conditions</th>
<th>n</th>
<th>ATD MPS Avg (SD)</th>
<th>HIT MPS Avg (SD)</th>
<th>Adjusted HIT MPS Avg (SD)</th>
<th>Error (HIT vs ATD) Avg (SD)</th>
<th>Error (Adjusted HIT vs ATD) Avg (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Side, UHMWPE, sensor/helmet 1</td>
<td>10</td>
<td>0.50 (0.02)</td>
<td>0.64 (0.04)</td>
<td>0.45 (0.02)</td>
<td>29% (8%)</td>
<td>10% (4%)</td>
</tr>
<tr>
<td>Side, UHMWPE, sensor/helmet 2</td>
<td>4</td>
<td>0.51 (0.01)</td>
<td>0.68 (0.09)</td>
<td>0.48 (0.02)</td>
<td>34% (19%)</td>
<td>5% (3%)</td>
</tr>
<tr>
<td>Back, UHMWPE, sensor/helmet 1</td>
<td>3</td>
<td>0.62 (0.01)</td>
<td>0.57 (0.06)</td>
<td>0.78 (0.03)</td>
<td>7% (8%)</td>
<td>25% (4%)</td>
</tr>
<tr>
<td>Back, UHMWPE, sensor/helmet 2</td>
<td>7</td>
<td>0.62 (0.03)</td>
<td>0.57 (0.02)</td>
<td>0.75 (0.05)</td>
<td>8% (5%)</td>
<td>22% (10%)</td>
</tr>
<tr>
<td>Oblique, UHMWPE, sensor/helmet 1</td>
<td>5</td>
<td>0.54 (0.01)</td>
<td>0.83 (0.08)</td>
<td>0.80 (0.07)</td>
<td>52% (17%)</td>
<td>47% (15%)</td>
</tr>
<tr>
<td>Oblique, UHMWPE, sensor/helmet 2</td>
<td>6</td>
<td>0.58 (0.01)</td>
<td>0.72 (0.07)</td>
<td>0.69 (0.06)</td>
<td>25% (11%)</td>
<td>20% (11%)</td>
</tr>
</tbody>
</table>

Table 4.5: Results for SIMon MPS calculations resulting from ATD data, raw HIT System data, and adjusted HIT System data from laboratory evaluations used as input

In the GFT analysis, average ATD-based calculations of maximum principal strain ranged from 0.49 to 0.62 for different test conditions. Average GFT-based calculations for the same impacts ranged from 0.42 to 0.65, whereas average adjusted GFT-based calculations ranged from 0.46 to 0.66. Exemplar graphs of maximum principal strain outputs based on ATD and GFT inputs are shown below, one for each impact direction/impacting surface combination (Figures 4.11, 4.12). Average absolute errors in estimated MPS values for raw GFT input ranged from 6% to 28%, while average errors
for adjusted GFT ranged from 4% to 21% (Table 4.6). For impacts using both surfaces adjusting the GFT data had a mixed effect on error in MPS calculation.

![Graphs showing maximum principal strain over time for different impact scenarios.](image)

**Figure 4.11:** Exemplar SIMon-calculated maximum principal strain for a side (top left), oblique (top right), and back (bottom) impact using an UHMWPE impacting surface. The y-axis measure is the maximum strain that has been measured anywhere in the finite element head model by that time point.
Figure 4.12: Exemplar SIMon-calculated maximum principal strain for a side (top left), oblique (top right), and back (bottom) impact using a hockey elbow pad impacting surface. The y-axis measure is the maximum strain that has been measured anywhere in the finite element head model by that time point.
<table>
<thead>
<tr>
<th>Conditions</th>
<th>n</th>
<th>ATD MPS Avg (SD)</th>
<th>GFT MPS Avg (SD)</th>
<th>Adjusted GFT MPS Avg (SD)</th>
<th>Error (GFT vs ATD) Avg (SD)</th>
<th>Error (Adjusted GFT vs ATD) Avg (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Side, UHMWPE, sensor/helmet 1</td>
<td>5</td>
<td>0.50 (0.02)</td>
<td>0.65 (0.02)</td>
<td>0.56 (0.03)</td>
<td>28% (6%)</td>
<td>11% (4%)</td>
</tr>
<tr>
<td>Side, UHMWPE, sensor/helmet 2</td>
<td>5</td>
<td>0.52 (0.01)</td>
<td>0.48 (0.01)</td>
<td>0.46 (0.01)</td>
<td>8% (1%)</td>
<td>13% (2%)</td>
</tr>
<tr>
<td>Back, UHMWPE, sensor/helmet 1</td>
<td>5</td>
<td>0.52 (0.02)</td>
<td>0.49 (0.03)</td>
<td>0.59 (0.01)</td>
<td>6% (5%)</td>
<td>14% (3%)</td>
</tr>
<tr>
<td>Oblique, UHMWPE, sensor/helmet 1</td>
<td>5</td>
<td>0.59 (0.02)</td>
<td>0.46 (0.02)</td>
<td>0.60 (0.03)</td>
<td>23% (3%)</td>
<td>4% (2%)</td>
</tr>
<tr>
<td>Oblique, UHMWPE, sensor/helmet 2</td>
<td>5</td>
<td>0.62 (0.02)</td>
<td>0.48 (0.02)</td>
<td>0.66 (0.04)</td>
<td>23% (2%)</td>
<td>8% (4%)</td>
</tr>
<tr>
<td>Side, elbow pad, sensor/helmet 1</td>
<td>4</td>
<td>0.51 (0.04)</td>
<td>0.45 (0.03)</td>
<td>0.46 (0.05)</td>
<td>12% (1%)</td>
<td>11% (3%)</td>
</tr>
<tr>
<td>Back, elbow pad, sensor/helmet 1</td>
<td>5</td>
<td>0.49 (0.01)</td>
<td>0.45 (0.02)</td>
<td>0.59 (0.01)</td>
<td>7% (3%)</td>
<td>21% (3%)</td>
</tr>
<tr>
<td>Oblique, elbow pad, sensor/helmet 1</td>
<td>4</td>
<td>0.56 (0.01)</td>
<td>0.42 (0.01)</td>
<td>0.54 (0.01)</td>
<td>25% (1%)</td>
<td>3% (1%)</td>
</tr>
</tbody>
</table>

Table 4.6: Results for SIMon MPS calculations resulting from ATD data, raw GFT data, and adjusted GFT data from laboratory evaluations used as input
4.3.4: Summary of HIT System and GFT brain injury metric errors across testing conditions

Average absolute errors of all testing conditions combined for the raw HIT System data ranged from 27% to 107% for the different injury metrics. For the adjusted HIT System data, they ranged from 20% to 56%. For the raw GFT data, these errors ranged from 16% to 56%, whereas for the adjusted GFT data they ranged from 11% to 41% (Table 4.7).

<table>
<thead>
<tr>
<th></th>
<th>Error (HIT vs ATD) Avg (SD)</th>
<th>Error (Adjusted HIT vs ATD) Avg (SD)</th>
<th>Error (GFT vs ATD) Avg (SD)</th>
<th>Error (Adjusted GFT vs ATD) Avg (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CSDM 0.15</td>
<td>40% (21%)</td>
<td>22% (12%)</td>
<td>28% (13%)</td>
<td>19% (10%)</td>
</tr>
<tr>
<td>CSDM 0.25</td>
<td>107% (78%)</td>
<td>56% (37%)</td>
<td>56% (19%)</td>
<td>41% (23%)</td>
</tr>
<tr>
<td>MPS</td>
<td>27% (18%)</td>
<td>20% (16%)</td>
<td>16% (9%)</td>
<td>11% (6%)</td>
</tr>
</tbody>
</table>

Table 4.7: Errors in metric calculations across all impact directions combined

4.4: Discussion

Although data collected in real-world scenarios via helmet-based kinematic measurement systems has previously been used as input into finite element models that assess the risk of brain injury, this is the first study to evaluate the effect of sensor performance on this type of analysis. Analyzing laboratory-derived data allowed us to compare finite element analysis brain injury outcome measures based on data from a standard measurement
system, an ATD head and neck instrumented with accelerometers and angular rate sensors, to those based on data from helmet-based measurement systems. This is an important first step in determining whether the range of sensor performance quantified in Chapters 2 and 3 limits the value of using real-world data collected using these systems as input for FEA to calculate injury risk metrics.

4.4.1: General differences in brain injury metrics based on source of input data

For all three of the injury risk metrics (CSDM 0.15, CSDM 0.25, and MPS), using helmet-based system data as the input resulted in substantial differences compared to the ATD reference data as input, particularly when using the raw helmet-based system data. For both the HIT System and GFT data, estimations of maximum principal strain had the smallest errors.

For all injury metrics, GFT-collected data led to smaller errors averaged across test conditions (Table 4.7) than HIT System-collected data, both before and after axis-specific adjustment. This is despite the large errors in peak linear acceleration present in the raw GFT data that were discussed in Chapter 2, likely because the calculation of strain-based measures is highly dependent on rotational kinematics. The GFT directly measures rotational velocity using gyroscopes, improving the accuracy of the rotational kinematic estimations, while the HIT System has two major sources of error in the calculation of rotational kinematics. First, the rotational acceleration is estimated by an algorithm that uses linear acceleration measures. Second, SIMon requires rotational velocity inputs so
the rotational acceleration time histories obtained from the HIT system must be integrated
to estimate the rotational velocity time histories. If errors were to be calculated for other
injury metrics that rely more on linear kinematics, such as pressure within the brain, they
would likely be smaller for HIT System data input than GFT data input.

It is important to note that, for the unadjusted HIT System data, average absolute errors in
peak resultant rotational acceleration were the smallest for side impacts (see Chapter 2,
Table 2.3), yet for the unadjusted HIT System data finite element simulations, side
impacts resulted in the largest average absolute errors in the calculation of injury risk
metrics (Tables 4.1, 4.3, and 4.5). This suggests that, while side impact peak acceleration
measures are similar for the ATD and HIT System, there are substantial differences in the
time histories of those impacts compared to other impact directions. Those differences
should be explored to understand which time history characteristics most strongly
influence the calculation of strain-related measures in the finite element simulation of
head impacts.

Although they are very similar measures, differing only in amount of strain, the
calculation of CSDM 0.15 resulting from helmet-based system data had approximately
half as much error as the calculation of CSDM 0.25. One possible reason for this
observation is that it is possible that the chosen impact magnitudes (i.e. those from 5 m/s
impacts in the laboratory) result in areas of the brain reaching strains near the threshold
of 25% during SIMon simulations. If, for example, ATD data predicted strains just above
25% while helmet-based system data predicted strains just below 25% in those areas, this
could cause large disparities in CSDM 0.25 measures despite relatively small differences in strain calculation.

4.4.2: Effect of data calibration before input into SIMon

Using the mathematical relationships developed in Chapters 2 and 3, the raw HIT system and GFT data were calibrated or adjusted prior to input into SIMon. The data adjustments were designed to represent the best-case scenarios of data correction based on peak kinematic measures. They were axis specific, as there was an adjustment factor for each input into SIMon (x, y, and z linear acceleration as well as x, y, and z rotational velocity), and impact scenario-specific, as each group of impacts with a certain set of test conditions had its own set of six adjustment factors. Additionally, they were impacting speed specific, since only the peak measures of the 5 m/s impacts were used to develop them. Despite the specificity of these correction factors, there was not a consistent effect of adjustment on the resulting brain injury metrics. In certain subsets of impacts the brain injury metric was higher than that calculated from the raw data and, for others, it was lower. Adjustment of HIT System-measured side impacts consistently led to substantially lower errors in all three injury metrics. This can possibly be attributed to the tighter fit of the Easton S9 helmet (only used with the HIT system in the set of data analyzed in the chapter) on the ATD head along that axis, resulting in adjustment factors that are more accurate transfer functions between the helmet-based measure and true reference acceleration. Beyond this observation, the lack of consistent effect of data adjustment suggests that other characteristic differences, besides peak measure, between
the input time histories are contributing to differences in the calculated injury metrics. Difference in calculated strain based on loading curve characteristics has been found in other FEA studies; for instance, as the separation interval between acceleration and deceleration increases the strain calculated in the brain increase (Yoganandan et al. 2008) and a longer time to peak resulted in higher strains than the same shaped loading curve mirrored, with an earlier time to peak (Post et al. 2014). However, averaging the errors across impact scenarios (Table 4.7) shows that, overall, the data adjustment did lead to smaller errors in all three injury metric calculations for both the HIT System and GFT input into SIMon. However it is important to note that although the percentages of error are large, the clinical significance of the absolute error is unknown. For example, although a reference (ATD-based) CSDM 0.25 of 0.15 and a HIT System-based one of 0.20 represents a 33% error, the significance of the 0.05 difference in CSDM 0.25 calculation is unknown.

4.4.3: Implications of findings

This analysis demonstrated that using helmet-based systems as input into a finite element head model to calculate brain injury metrics can lead to large differences from the brain injury metrics calculated using a true (reference) measure of head kinematics. In this study, the errors in peak kinematics described in Chapters 2 and 3 were in many cases magnified, resulting in greater errors in calculated injury metrics than were seen in the peak biomechanical measures. The findings of this study emphasize the need to either 1) improve the sensor technology and implementation such that they can more accurately
measure head kinematics or 2) use laboratory analyses to calculate transfer functions (and their associated variability) between the helmet-based measure and truth before using real-world data as input in FEA simulations. Taking this step will help researchers account for the errors in their analyses and quantify the effect of sensor performance on the outcome metrics of interest. This approach may illustrate scenarios in which sensor performance is too variable such that conclusions regarding brain injury risk based on such data cannot be made.

As discussed in Section 4.1, Takhounts et al. explored the use of data collected on-field (via the HIT System for football) in SIMon finite element analyses (Takhounts et al. 2008). The authors commented that two of the impact simulations resulted in maximum principal strains of 0.96 which, based on previous research, would be expected to result in diffuse axonal injury. However, no known injuries were sustained during these impacts. It is likely that part of this discrepancy is due to the error that results from using helmet-based system data as input into finite element models. If, for example, the HIT System for football resulted in a similar amount of error as was demonstrated in the HIT System for ice hockey, taking the average error for raw data across all impact scenarios (27%), the maximum principal strain could easily be closer to 0.76 or even lower, as average errors for specific impact conditions were higher than 27%. While this level of strain is still high, it does not necessarily mean that widespread areas are experiencing such high levels and, under these global loading conditions, a lower MPS likely correlates to lower strain values throughout the brain. Because MPS does not describe
strains experienced by the brain as a whole, CSDM may be a better metric for assessing risk of mTBI as it incorporates a volumetric measure of brain strain.

McAllister et al. used HIT System data from concussed athletes in the Dartmouth Subject Specific Head FE Model and was able to find correlations between predicted strain (and strain rate) in the corpus callosum and changes in white matter integrity seen in diffusion tensor imaging (McAllister et al. 2012). However, this was a preliminary study that did not use control subjects so exploration of false positives as in the Takhounts study – i.e. subjects with high strain measure but no injury – could not be conducted. Nevertheless, it suggests that it is feasible to use helmet-based data in finite element analysis to establish general correlations, although specific injury metric numbers are likely to have sizable error. With the current state of helmet-based measurement technology it is likely premature to use the data in conjunction with finite element models to develop injury thresholds.

4.4.4: Limitations and Future Work

This study has only looked at data from two helmet-based systems and all of the outcome measures that were analyzed are strain-based. Future studies should assess errors resulting from a range of real-world head impact measurement systems. Measurement systems that are directly attached to the head (not on a helmet) may have more accurate measures of actual head kinematics. Additionally, other brain injury metrics should be
explored such as strain rate, pressure, and Von Mises stress (Marjoux et al. 2008; McAllister et al. 2012).

This study also only utilized a single finite element brain model. SIMon is intentionally simplified for the sake of decreased computation time, allowing a relatively large number of simulations to be performed. The use of other models should be more detailed than SIMon should be explored as they may result in different findings. However, as discussed previously, SIMon does account for major anatomical structures and a study comparing SIMon to the GHBMC head model, which consists of more than five times the number of elements, found no significant differences in CSDM and MPS calculations (Takhounts et al. 2013). Furthermore, this study was not done to calculate injury risk, but to compare results from two different sets of inputs. Therefore, the number of laboratory impacts simulated is likely more important than the particular model chosen in this instance.

Future studies should also evaluate not only global injury metrics, but also those calculated for specific brain structures. It is possible that particular areas of the brain either contribute more to the injury metric errors or are of particular interest in studying the inputs that lead to mTBI (i.e. the corpus callosum (Adams et al. 1989; Henry et al. 2011; Margulies, Thibault, and Gennarelli 1990; McAllister et al. 2012)). This is one area in which a more detailed model may be particularly helpful.

Finally, future research should explore other means to adjust the helmet-based system data. In this study the correction factors that were used to try to reduce error were all
based on peak kinematic measures. However, as mentioned previously, this did not lead to reductions in error for all impact scenarios. Other means of data adjustment, such as using the area under the curve, the time to peak, or the impact duration, should be explored.

4.5: Conclusions

This study is a first look at the effect of helmet-based sensor performance on brain injury metrics calculated using finite element analysis. Estimates of maximum principal strain generally had the smallest average absolute errors (defined as the percentage difference in injury metrics resulting from inputs using the helmet-based sensor data compared to reference input data from the ATD), ranging from 7% to 52% for raw data. Conversely, estimates of CSDM 0.25 had the largest average absolute errors, ranging from 21% to 200% for the raw input data. HIT System data resulted in larger errors than GFT data, likely because of the improved way in which GFT measures rotational kinematics. Adjustment of the data based on axis and impact scenario-specific peak kinematic measures lead to an overall decrease in error, but the reductions were not consistent and errors were still substantial, particularly for estimates of CSDM 0.25. Given that the error is considerable, caution should be taken in employing helmet-based system data in this manner as the outcome measures of interest demonstrate considerable variation. Further analysis should be done to better understand how helmet-based system performance influences injury metric calculations in finite element analysis.
Chapter 5 - Overview and implications for real-world use

5.1: Overview of findings

The studies described herein focus on laboratory evaluations of helmet-based systems that can be used in the real-world to estimate the biomechanics of head impacts during play in high-impact sports. These systems have the potential to help develop injury thresholds and metrics in human populations. The laboratory evaluation findings support that these systems can be used to estimate peak head kinematics during impacts in helmeted sports. However, to date, the data collected using these systems have been used as if the measures are equal to the actual kinematics at the center of gravity of the head, not accounting for system error or variation in sensor performance/accuracy based on impact characteristics. Helmet-based system measures and their absolute errors need to be better characterized over a range of real-world conditions before interpreting data collected in sports to discern injury thresholds.

Chapter 2 evaluated two helmet-based systems that use different approaches to estimate the kinematic measurements of head impacts. One uses spring-loaded single-axis linear accelerometers integrated throughout the padding and employs an algorithm to calculate triaxial linear and rotational acceleration based on those measures. The other uses triaxial linear accelerometers and gyroscopes in a casing adhered to the helmet shell to measure head kinematics. It was found that both had substantial average absolute errors, but there were ways to potentially reduce those errors. The HIT System for ice hockey, had
somewhat smaller errors in linear acceleration, while the GFT had much smaller errors in measuring rotational kinematics. Both systems exhibited systematic error based on impact direction, and the GFT, which allows for the sensor to be placed anywhere on the helmet, also exhibited systematic error based on sensor location.

Chapter 3 explored factors that may vary in real-world impact scenarios and varied them in a laboratory setting to evaluate how they may influence helmet-based system measures. The interface between the ATD head and the helmet, differences in helmet geometry and construction, and impacting surface all significantly influenced the relationship between helmet-based system measures and ATD reference measures. Changing the effective mass of the torso in the laboratory led to relatively small differences in helmet-based system measures.

Chapter 4 took the comparison one step further; rather than evaluating measures directly from the systems, the head kinematic data were used in finite element analysis to calculate the effect of helmet-based system performance evaluated in previous chapters on head injury metrics. This analysis found that employing helmet-based system data in SIMon generally led to larger errors than those seen in peak kinematic measures. Adjustment of the data based on axis and impact scenario-specific peak kinematic measures led to an overall decrease in error, but the reductions were not consistent and errors were still substantial.
5.2: Importance of absolute error vs. relative error

As was discussed in Chapter 1, previous studies evaluating the accuracy of helmet-based systems have not calculated the average absolute errors of peak kinematic measures (Beckwith, Chu, and Greenwald 2007; Beckwith, Greenwald, and Chu 2012; Hanlon and Bir 2010; Manoogian et al. 2006; Rowson et al. 2011). One of these studies calculated average relative error instead (Rowson et al. 2011), while another assessed the slope of the linear regression equation relating peak HIT System measures to ATD measures (Beckwith, Greenwald, and Chu 2012). The rationale for this was that only large data sets of impacts averaged together would be used for analysis and interpretation. However, there are relatively few injurious impacts and data from these has been used in many different capacities, including presenting the kinematic measures and the circumstances surrounding the impacts in a case-study format, as well as using the data to calculate injury risk curves.

Chapters 2 and 3 calculate average absolute errors of kinematic measures and the results show that these errors are considerable. This finding indicates that future evaluations of technologies meant to estimate the kinematic measures of head impacts should include calculation of average absolute error, as the findings have implications for how data should be analyzed and interpreted.
5.3: Implications of the influence of other parameters on accuracy

As shown in Chapters 2 and 3, there are strong relationships between peak helmet-based system measures and peak measures at the center of gravity of the ATD head. This indicates that the systems can be valuable tools to estimate peak kinematics at the center of gravity of the head in real-world scenarios. However, these relationships may not be one-to-one and different factors can cause variability, so it cannot be assumed that a system measure is equal to truth. Applying the relationships for certain conditions to system measures can reduce the error of the system estimations of impact kinematics.

As an example, for the version of GFT software evaluated herein, it is crucial to adjust the linear acceleration data as the output is raw acceleration measured at the helmet shell which differs substantially from linear acceleration of the center of gravity of the head. There are two reasons for this. First, the helmet is designed to dissipate energy imparted to the head. Second, assuming rigid body dynamics, the linear acceleration at one point on a rigid body is dependent not only on the linear acceleration at another point on the body, but also the angular velocity and angular acceleration of that body. Given that a rigid body transformation alone would not account for both of these factors, an empirical adjustment of the data using laboratory comparisons between GFT and ATD measures may be more appropriate. The empirical method used to transform the data (i.e. all impact directions combined or direction-specific adjustment) could vary based on how the data are being used and therefore the precision necessary for those circumstances. This highlights the importance of understanding the conditions under which a system will
be used and evaluating it under similar conditions to understand what the relationships between system measures and references measures are in those scenarios.

Some of the parameters that can contribute to variability in helmet-based sensor measures are easily controlled. For the GFT, the sensor location and helmet brand/model are parameters that influenced the performance of the system. These can be chosen and standardized for a given team or research study. Once these are chosen, the sensor system can be evaluated using those parameters and the resulting relationships between system and reference measures can be used in the analysis of real-world data. To potentially further reduce variability, several options for helmet model and sensor location can be tested to determine whether there are any significant or meaningful differences in the average absolute error, therefore assessing if any set of conditions is preferable to another.

Looking at our data in this context, errors were generally larger for sensors on the Easton helmet than on the Bauer helmet for direction-specific calibrated data and the outside back sensor location had slightly larger errors than the other sensor locations for data calibrated using all directions combined. This poorer performance of the outside back sensor location could be related to the two-piece design of the hockey helmet shell (a front part and a back part that slide along each other for size adjustment), as the other three sensor locations were on the front half of the shell. Furthermore, based on unpublished data by the sensor manufacturer, it would be best to avoid directly impacting the sensor. Therefore, a sensor location in which the system is less likely to be directly
contacted would be beneficial. According to on-ice data collected using the HIT System for ice hockey, researchers have found that impacts to the top of the helmet are the least common (Mihalik et al. 2012; Wilcox, Beckwith, et al. 2014), making a sensor location on the top of the helmet a practical choice. There were no distinct differences seen between the inside top and outside top sensor locations, but for the Bauer Re-Akt helmet the inside top sensor location required modifying the helmet padding, which is not preferable and would require recertification testing in order to be implementable on-ice. Having the sensor on the outside of the helmet could have other consequences. If it is obvious that a player (or team) is wearing a sensor to monitor impacts, it could influence on-ice play. It is possible that the opposing team could try to hit the player(s) harder in order to get a high measurement. Conversations with parents of youth hockey players have revealed that this is of concern to them in deciding whether or not they would be willing to use helmet-based sensors on their child’s helmet. One solution may be to choose a helmet model in which the padding allows for inside top placement of the sensor without modification or further recertification.

The significant effects of helmet brand, impact direction, and the interface between the head and the helmet on the relationship between peak helmet-based system and peak reference kinematics imply that the system measures are influenced by the helmet’s mechanical response to the impact. This would be expected for the GFT, as it is adhered to the shell of the helmet. However, the HIT System also exhibited directional dependence, which suggests that the accelerometers are influenced by helmet mechanics despite the spring-loading meant to couple them to the head. While the helmet brand is a
controllable parameter, the interface between the head and the helmet will vary between players, as they have different hair styles. While it is not practical to formulate and implement data adjustment factors based on all hair styles and types, this does indicate it is best to use the most realistic interface between the head and the helmet possible in evaluating head impact measurement systems. Impact direction is also not controllable, and adds complexity to data analysis and interpretation. This is discussed in section 5.5.

5.4: Magnitude of Significant Differences

In Chapters 2 and 3 it was shown that impact direction, sensor location, interface between the head and the helmet, helmet brand, and impacting surface all had statistically significant effects on the relationships between helmet-based system and ATD measures of head impact kinematics. However, it is also important to consider the magnitude of these differences (in other words the absolute difference in measures caused by the specific parameter). Figures 5.1-5.5 graphically depict the magnitudes of these differences showing that the effects of these statistically significant parameters vary in magnitude across parameters and, within a parameter, the effects vary by specific test condition. For instance, when looking at the effect of impacting surface, there is no effect of this parameter on the difference between the ATD measure and the GFT measure for side impacts (Figure 5.5 left) but an effect of more than 70 g on the difference between the ATD measure and the GFT measure for back impacts (Figure 5.5 right).
Figure 5.1: Exemplar data depicting the effect size of impact direction on the difference between the average ATD measure (dashed line) and the average system measure (±SD) [solid line (±shaded box)].

Figure 5.2: Exemplar data depicting the effect size of sensor location on the difference between the average ATD measure (dashed line) and the average system measure (±SD) [solid line (±shaded box)].
Figure 5.3: Exemplar data depicting the effect size of interface between the ATD head and the helmet on the difference between the average ATD measure (dashed line) and the average system measure (+SD) [solid line (+shaded box)].

Figure 5.4: Exemplar data depicting the effect size of helmet brand (for two impact directions) on the difference between the average ATD measure (dashed line) and the average system measure (+SD) [solid line (+shaded box)].
Figure 5.5: Exemplar data depicting the effect size of impacting surface (for two impact directions) on the difference between the average ATD measure (dashed line) and the average system measure ($\pm$SD) [solid line ($\pm$shaded box)].

As discussed previously, some of these parameters that contribute to variability in helmet-based sensor measures are easily controlled such as helmet brand and sensor location. The exemplar data shows that both sensor location and helmet brand can cause differences of at least 40 g, which is a substantial effect as an impact measuring 90 g at one location or on one helmet could be measured as 130 g at another location or on a different helmet brand. Controlling these parameters removes these two sources of variability, making them inconsequential as long as, for the helmet brand and sensor location that are used, the performance of the system is properly characterized in the laboratory.

Of the remaining parameters, for the exemplar data that was chosen, the impacting surface had the largest effect size, with differences up to 70 g between the elbow pad and the UHMWPE surface. Direction had a similarly large effect size, with differences up to
60 g across impact directions. Interface between the ATD head and the helmet had the smallest effect size, with differences up to 20 g. It is important to note that these are not direct comparisons as interface comparisons were done using the HIT System data, which has undergone processing via a system algorithm that the GFT data has not undergone. However, it suggests that the addressing the effects of impact direction and impacting surface may be higher priorities.

5.5: Implications of findings for researchers

Knowing the magnitude of the average absolute error associated with these helmet-based systems can help guide researchers in developing studies and analyzing data. The substantial error suggests that use of this data for certain analyses, such as development of injury risk curves, may not be appropriate, particularly without taking steps to reduce the error in the data by applying impact scenario-specific corrections to the data. In attempting to identify a biomechanical threshold for concussion, there are already a number of confounding factors that make this task difficult. Some of the factors that are thought to influence mTBI threshold include impact direction (Gennarelli et al. 1987), concussion history (Yuen et al. 2009), gender (Dick 2009), age (Field et al. 2003), and genetics (Teasdale et al. 1997). Adding substantial error of the biomechanical metric (which is the independent variable) in with the confounding factors further complicates the development of an injury risk curve, making it even more difficult to discern which biomechanical inputs are or are not likely to lead to concussion. The error also influences the interpretation of injury risk based on a proposed injury risk curve. If, for example,
data from an impact was collected using the HIT System for ice hockey, the average absolute error in raw rotational acceleration data are expected to be approximately 43% (see Chapter 2, section 2.3.3). If that impact has a peak rotational acceleration that, according to the Rowson et al. rotational injury risk function (Rowson et al. 2012), should result in approximately 50% chance of injury, taking into account the average error in peak rotational acceleration there may actually be anywhere from 0.5% or 99.5% chance of injury (Figure 5.6). Further studies evaluating the effects of the levels of absolute error associated with helmet-based systems on resulting injury risk curves or functions should be carried out before using the data in this manner. Furthermore, individual impact magnitudes should be reported in terms of ranges, taking into consideration the average peak acceleration and standard deviation based on the absolute error. It is important to note that there are many differences between developing and mature brains, some of which are outlined in Chapter 1, section 1.3. For this reason, separate injury risk curves for different stages of development are needed. Injury risk curves intended for kids should be developed based on kid-specific data.
Figure 5.6: Example of the effect of the 43% average absolute error in rotational acceleration found for the raw HIT System for ice hockey data (see Chapter 2) on prediction of injury risk using the Rowson et al. (2012) rotational injury risk curve.

Some research studies have more broadly categorized impacts and averaged kinematic measures from a number of impacts together. Therefore, they may be less influenced by the system measurement error. For instance, in football, Ocwieja et al. compared the estimated kinematic measures of head impacts resulting from collisions with a long closing distance (greater than or equal to 10 yards) to those with a closing distance of less than 10 yards and found that longer closing distances tend to lead to higher head accelerations (Ocwieja et al. 2011). Another study evaluated how the offensive scheme may affect head impact biomechanics, and found that run-first plays tend to lead to more head impacts, but past-first plays generally lead to higher impact magnitudes in high school football players (Martini et al. 2013). Schmidt et al. grouped HIT System measures into levels of impact magnitude to study the influence of cervical muscle characteristics on linear head acceleration and found that greater cervical stiffness, but
not stronger or larger cervical muscles, decreased the odds of sustaining moderate
(greater than 66g and less than 106g) and severe (greater than or equal to 106g) head
impacts (Schmidt et al. 2014). In an ice hockey study, McPherson et al. used the HIT
System to determine the five players on the team who sustained the most head impacts
and then used video data to analyze their on-ice behaviors, finding that they consistently
exhibited aggressive and at-risk behaviors that could be changed to potentially reduce
risk (McPherson et al. 2009). These are examples of studies that either use the helmet-
based system to determine the number of impacts sustained or that categorize and
average broad groups of impact events together. Therefore, studies along these lines are
likely to be less sensitive to the peak kinematic measurement error of the system.

Chapter 2 also established that both systems exhibited inaccuracy in estimating the
direction of impact, which is an important metric for researchers for two reasons. First,
the significance of impact direction on the threshold for traumatic brain injury has been
well established in the animal model research literature (Gennarelli et al. 1987;
Gennarelli et al. 1982). Given its importance, having a reliable measure of impact
direction from these systems would be beneficial to determine injury thresholds in
humans and how they vary with direction. Second, Chapter 2 also established that the
relationships between system-estimated kinematics and kinematics at the center of
gravity of the ATD head vary by impact direction. Therefore reliably knowing the impact
direction could help researchers apply direction-specific adjustment factors to the data to
reduce the error as much as possible. While one feasible means to verify impact direction
would be to film all practices and games in which data are collected, this is resource
intensive in filming and reviewing hours of video, requires multiple angles of view, and may still lead to an inability to determine impact direction in some cases.

Some researchers use helmet-based systems to count the number head impacts sustained by athletes, as it is believed that an accumulation of subconcussive hits may have neurological consequences and reduce threshold for mTBI (Beckwith et al. 2013b; Eckner et al. 2011; Urban et al. 2013; Wong, Wong, and Bailes 2014). In Chapter 2 (section 2.3.1), we found that approximately 20% of the impacts to the helmented ATD head and neck were removed from the dataset by a system processing algorithm that classified the impacts as unrealistic. This algorithm is meant to remove impacts to the helmet that occur when it is not on a player’s head. Jadischke et al. had a similar finding in the HIT System for football (Jadischke et al. 2013). As discussed in Chapter 2, section 2.4.6, an on-ice analysis is necessary to understand how often impacts occur during play but are removed from the dataset during processing. If a similar proportion of on-ice impacts are removed from the dataset during play then, in assessing the cumulative burden of head impacts, researchers may be missing a fifth of the data. On the other hand, the GFT does not employ such an algorithm so the number of impacts may be overestimated. One way to address this problem is to film practices and games and use the video to determine whether the data for each impact is from an on-ice hit or, for example, from the player taking the helmet off and dropping it on the bench. However, this is both time and resource intensive.
The use of real-world kinematic time histories collected with helmet-based systems in finite element models should be approached with caution. Chapter 4 demonstrated that helmet-based system performance can cause substantial differences in the calculation of head injury risk metrics compared to those calculated using a standard measurement system (an instrumented Hybrid III head) for the same impacts. Variations not only in peak kinematic measures, but also in characteristics of the time histories likely led to these differences, as scaling the input data to the same magnitude as the ATD did not always reduce the differences. This indicates that, even for a system that has small average absolute errors in peak kinematics, it is necessary to carry out a laboratory evaluation of the influence of system performance on the calculation of brain injury metrics in FEA. In other words, before employing real-world helmet-based system data in finite element models, researchers should use a method similar to that employed in Chapter 4 to analyze the calculation of chosen injury risk metrics compared to a standard measurement system.

5.6: Performance under conditions most likely to lead to mTBI in ice hockey

Given the relatively small number of injurious impacts that occur compared to subconcussive impacts, the performance of helmet-based systems under conditions most likely to lead to injury are particularly important. As discussed previously, animal studies suggest that there is increased vulnerability to injury with coronal rotation of the head as opposed to sagittal (Eucker et al. 2011; Gennarelli et al. 1987; Smith et al. 2000). Both
the HIT System for ice hockey and the GFT had particularly strong coefficients of
determination for the peak resultant kinematics of side impacts, as well as low average
absolute errors after direction-specific correction of the data using regression
relationships. This suggests that if an impact can be properly characterized as a side
impact and the respective adjustments are made to the data, a sound estimate of the peak
kinematics of that impact can be made.

Impacts with higher magnitude kinematic measures would also be expected to be more
likely to lead to mTBI. Plots of the reference linear and rotational kinematics versus
absolute errors of the helmet-based system corresponding measures (after direction-
specific adjustment) show that error does not increase with increased magnitude of head
kinematic measures (Figures 5.7-5.10). Therefore, overall average system error can be
expected to be relatively consistent across the range of severity of impacts.
Figure 5.7: ATD-measured peak resultant linear acceleration versus the error in HIT System for ice hockey-measured peak resultant linear acceleration after impact direction-specific regression adjustment of the HIT System data.
Figure 5.8: ATD-measured peak resultant rotational acceleration versus the error in HIT System for ice hockey-measured peak resultant rotational acceleration after impact direction-specific regression adjustment of the HIT System data.
Figure 5.9: ATD-measured peak resultant linear acceleration versus the error in GFT-measured peak resultant linear acceleration after impact direction-specific regression adjustment of the GFT data. The data are for the rigid mounting setup and inside top sensor location for both the Easton and Bauer helmets combined.
Figure 5.10: ATD-measured peak resultant rotational velocity versus the error in GFT-measured peak resultant rotational velocity after impact direction-specific regression adjustment of the GFT data. The data are for the rigid mounting setup and inside top sensor location for both the Easton and Bauer helmets combined.

Studies have assessed the circumstances surrounding concussive impacts in ice hockey. Delaney et al. evaluated concussive impacts in both men’s and women’s ice hockey at McGill University and found that, overall, there was approximately an even distribution between concussions due to contact with an opponent and those due to contact with another object such as the boards or ice (Delaney, Al-Kashmiri, and Correa 2014). However, likely due to differences in rules of play, for females there were more injuries from contact with other objects whereas for males there were more injuries from contact
with opponents. Of the concussions due to contact with an opponent, for males there was almost an even distribution between shoulder and elbow contact but for females the majority were due to shoulder contact. Agel and Harvey found similar distributions of overall, men’s, and women’s concussions due to contact with an opponent versus contact with another object in National College Athletic Association hockey players (Agel and Harvey 2010). Similarly, a study in the National Hockey League found that the majority of concussions were due to contact with an opponent, with 62% being directly attributed to contact with shoulders, elbows, or gloves and 37% involving the player’s head contacting the boards or glass (Hutchison et al. 2013a, 2013b). In these studies the majority were attributed to shoulder contact. One study at the University of British Columbia based on a smaller number of injuries (n=23) had different results, with 90% of concussions resulting from players being checked from behind and their heads contacting the boards (Rishiraj et al. 2009).

Given the prevalence of mTBI due to contact with both the hard surfaces of the rink and the hockey pads of opposing players, performance under both of these conditions is important. The HIT System for ice hockey was only evaluated using a hard impacting surface, but the GFT was assessed using both a hard surface and a hockey elbow pad. The coefficients of determination were strong for both surfaces, with no substantial differences in these measures between the two surfaces (see Chapter 3, Section 3.3.5). However, the relationships between peak ATD references measures and peak system measures vary significantly between these two surfaces, particularly for front and pack
impacts. Therefore, it is important to know the impacting surface that caused the injury in order to properly adjust the data.

5.7: Implications of findings for consumers

The majority of helmet-based systems are available to consumers as aftermarket products that can be added to helmets. This makes them available for athletic trainers, coaches, and parents to use to monitor athletes in high-impact sports. However, given the current state of the technology and uncertainty of what these helmet-based system measures mean clinically, especially when other factors are considered (i.e. impact direction, concussion history, gender, age, and genetics), these systems cannot be used diagnostically. Injury should not be ruled out based on the estimated kinematic measures and all of the standard means of screening for and diagnosing mTBI should remain in place. A false negative based on helmet-system measure would be harmful to a player and put them at higher risk of repeated injury.

However, helmet-based systems may be beneficial as an additional monitoring tool to identify players that may have sustained a high-magnitude impact, adding another means to determine whether that player should be assessed clinically. In this case, a false positive would lead only to screening additional players for injury and may help catch injuries that would otherwise go unnoticed or be masked by a player who does not want to be removed from play. This may help reduce the burden of the underreporting of mTBI. Helmet-based systems could also be used to monitor the number of head impacts.
that a player sustains which, if unusually high, could point towards a need to coach the player to modify their playing techniques to reduce risk of injury.

Given the variability of the performance of helmet-based systems, as well as the current lack of understanding on what their real-world measures mean in terms of injury risk, at this time it would not be advantageous to implement a policy requiring contact sport athletes to use these sensor systems during play. With the current state of knowledge, it is unknown how to interpret and use the specific values that are provided by the systems to reduce the risk of concussion. The systems may be adequate to serve as a monitoring tool for clinical side line personnel to direct them to players that may benefit from closer clinical examination. Before encouraging wide-spread use of head impact measurement systems, how they perform under various circumstances must be better understood and data analysis techniques should be improved. Advances in the technology of these systems would also improve the accuracy of data collected. A better understanding of how to implement the measures for improvement of player safety must be developed before using them on a large scale.

5.8: Development of future real-world kinematic measurement systems

Evaluation of two systems using different approaches to estimate the kinematic measures associated with head impacts has shown that the methods have different strengths. The HIT System for ice hockey, using spring-loaded single-axis accelerometers embedded throughout the padding of the helmet in an attempt to maintain contact with the head, had
smaller absolute errors in estimating linear acceleration measures than the GFT. The GFT, on the other hand, employing gyroscopes to estimate rotational velocity, had smaller absolute errors in estimating rotational kinematics than the HIT System, which uses an algorithm to estimate rotational acceleration based off of the linear acceleration measures. While this is not a direct comparison as the two systems calculate different rotational metrics, measuring rotational acceleration data are inherently noisier than measuring rotational velocity data. Furthermore, studies show that rotational velocity accurately predicts strains within the brain and thus is a good metric for quantifying diffuse brain injury risk across the spectrum of severity (Takhounts et al. 2013). Therefore, rotational velocity rather than acceleration is likely a better measurement choice for helmet-based systems.

Given the above findings, a future measurement system combining the two approaches would be preferable, particularly for research purposes. Using both dispersed linear accelerometers throughout the padding to estimate linear acceleration and gyroscopes to estimate rotational velocity would combine the strengths of the two systems and reduce the overall absolute error in kinematic estimates. Another possible improvement to further reduce linear acceleration errors would be to integrate into the system a means to determine which accelerometers lost contact with the head during an impact, so that the data from the remaining accelerometers that maintained contact could be used for that impact. Integration of force sensing pads into the design may also be beneficial in determining the location of an impact, helping researchers better estimate the impact direction.
The studies herein have looked specifically at the performance of helmet-based systems used to collect real-world data in sports. As discussed in Chapter 1, section 1.5, other technologies exist that instead are implemented in caps or headbands to measure head kinematics across a range of sports. Assuming that these systems are coupled relatively well to the head, tight enough to prevent them from coming off or moving excessively, it is possible that they would have smaller errors in peak kinematic errors than helmet-based systems. This is because the function of the helmet is to dissipate forces imparted to the head. Therefore, a system attached to the helmet can experience different kinematics based on the mechanics of the helmet’s energy dissipation, which is likely a reason that the relationships between ATD and helmet-based system measures described in Chapter 2 differ based on impact direction. Section 1.5 also mentions that mouthguard instrumentation exists. The largest sources of error for this technology likely come from jaw movement and slack. Researchers have worked on integrating infrared proximity sensing into the mouthguards to determine whether they are on the teeth at the time of impact, which would address this problem. However, data still would not be collected for impacts where the jaw is too loose. Evaluations similar to those in this study could be done on non-helmet systems. Researchers have made modifications to the Hybrid III headform to allow for simultaneous testing of instrumented mouthguards and helmets (Siegmund et al. 2014).
5.9: Future evaluations of helmet-based systems

Chapters 2, 3, and 4 have outlined ways to evaluate helmet-based systems designed to measure head impact kinematics in a laboratory setting and exhibited the importance of extensive evaluations of these measurement tools. However, future evaluations should include additional analyses that have not been included herein. First, we have retrospectively demonstrated that knowing regression relationships between peak helmet-based system and reference measures has the potential to reduce errors in system measures. In other words, we have developed regression relationships between ATD and helmet-based systems measures and shown the effect of applying those relationships back to the same set of data. However, this should be repeated prospectively, seeing whether these relationships can predict and reduce errors in a new set of data collected under similar laboratory conditions.

Second, sensitivity analyses should be performed in laboratory evaluations, using small changes in impact direction to determine how much the relationships between peak measures vary due to these small changes. This will help determine feasibility of implementing direction-specific correction factors to reduce error. If the regression relationships cannot be employed over a range of directions and each small change in direction requires its own correction factor, it would not be feasible to employ this method in real-world scenarios, particularly considering the helmet-based system inaccuracies in determining impact direction.
Third, it is important to study sport-specific impact scenarios that lead to concussion and employ these conditions in the laboratory in order to learn more about how the system performs under these circumstances. For instance, as described earlier, one research study on injury mechanisms in the National Hockey League attributed the majority of concussions to a direct hit from another player’s shoulder, elbow, or glove, with the majority due to contact with the shoulder followed by contact with the elbow (Hutchison et al. 2013b). Chapter 3 did explore use of an elbow pad and found significant differences in peak measure relationships for this impacting surface as opposed to the hard impacting surface. Therefore, for example, direct contact to the shoulder (including the angles at which these impacts typically occur) should be explored in laboratory evaluations involving helmet-based kinematic measurement systems used on ice hockey helmets.

After determining the influence of various impact conditions in a laboratory setting, in collecting real-world data, video could be used to verify the circumstances surrounding an injurious impact so that the proper data adjustments could be applied. This would result in more accurate estimates of injurious head kinematics.

We acknowledge that there is ongoing discussion about the appropriateness of using the Hybrid III headform to assess helmeted impacts due to the shape and properties of the head. This was not the focus of the current study. We chose to use the Hybrid III head and neck because, at the time of this study, it was most accepted standard kinematic measurement system to evaluate helmeted impacts.
5.10: Implications of findings on the future of mTBI prevention research

These data provide for the first time a comprehensive analysis of the performance of two types of helmet-based head impact measurement systems over a range of real world impact conditions. Despite the level of uncertainty associated with helmet-based measurement systems in their current state, they are still valuable resources for researchers to gain information that can be used to decrease the burden of mTBI. Researchers have shown that the data can be broadly categorized and kinematic measures from a number of impacts can be averaged together to determine sport-specific scenarios that lead to higher acceleration impacts and likely bear higher injury risk. This knowledge can be used to improve safety in sports through countermeasures such as changes in policies, rules, and coaching.

These systems also have the potential to be used by researchers to gain knowledge on the fundamental biomechanics of mTBI. They provide a unique opportunity to study these injuries in human populations, collecting data that cannot be obtained in a traditional laboratory setting. However, this requires improvement of the accuracy of head impact kinematic measurement systems through advances in the technology, the data analysis, or both. This is a worthwhile investment of resources given the tremendous potential that these systems have to allow researchers to develop injury criteria and thresholds for mTBI, which has implications reaching beyond sports injury. A fundamental biomechanical understanding of mTBI can allow for countermeasures to be developed for other injury mechanisms, such as motor vehicle crashes, in addition to sports.
The pathway from head impact to clinical outcome is influenced by a range of factors of which more detailed understanding is needed in order to prevent or mitigate the occurrence of mTBI and any associated long-term outcomes (Figure 5.1). Specific categories of these factors include impact variability, variability associated with the biomechanical assessment of impact severity via head impact measurement systems, injury tolerance and its variability by age or gender, clinical assessment variability, and other individual factors that influence the clinical outcome. At this time, it appears that the largest advancements in understanding the kinematic inputs that cause mTBI can be made by focusing on two of these categories: clinical assessment variability and head impact measurement system variability. In terms of clinical assessment, the major factor that needs to be addressed is the underreporting of mTBI. Underreporting of sports-related mTBI has been recognized as an extensive problem (McCrea et al. 2004; Williamson and Goodman 2006) and with large numbers of injuries going undetected, in addition to these athletes not receiving proper clinical treatment and being at risk for further injury, data from injurious impact scenarios will be misclassified as non-injurious. There is currently no method to assess which impacts have been misclassified, thus negatively influencing the development of injury risk curves and metrics.
Figure 5.11: The mTBI pathway from impact to clinical outcome with the tools used to for injury prevention research and some of the factors influencing each aspect of the pathway.

The evaluations herein have shown the large variability that exists in the accuracy of helmet-based kinematic measurement systems. In combination with being able to more accurately assess the clinical outcome, the development of more accurate sensors (and/or more accurate kinematic measures due to improvements in data analysis) is the first step to quantifying the biomechanical inputs leading to mTBI in human populations. If, for example, an impact occurs with a helmet-based system linear acceleration estimate of 100 g, which, on average, could correspond to anywhere between 75 and 125 g, this makes it difficult to interpret the data. In an area of injury prevention with so many influencing factors, some well characterized and some unknown, if researchers have confidence in the accuracy of the biomechanical measures associated with injurious impacts, they can begin to clarify the effect of more ambiguous factors, such as biological variability. There are clear steps that can be taken to advance our knowledge by reducing
underreporting and improving measurement systems, whereas understanding the influence of impact and biological variability may be more elusive.

Despite the errors and variations associated with helmet-based kinematic measurement systems, they provide tremendous potential to help researchers better understand mild traumatic brain injury. Knowing the mechanism of these injuries is the first step in preventing these injuries from occurring. Given the large number of mTBI s occurring each year and the associated neurological consequences, it is worthwhile to invest the resources into further developing head impact measurement technology to take advantage of the unique opportunity to study mTBI in high-impact sports.
Appendix 1 – Supplementary data for Chapter 2

A1.1: Regressions and coefficients of determination for other sensor locations
Figure A1-2.12b: Data comparing peak resultant linear acceleration (left) and peak resultant rotational velocity (right) as measured by the ATD and by GFT for all impact directions combined and then stratified by impact direction. The graphs show both the data collected from impacts to the Easton helmet and data collected from impacts to the Bauer helmet. Each data point represents a single impact, with GFT measure on the abscissa and ATD measure on the ordinate. The solid lines correspond to the power regression relationships for impacts to the Easton helmet, while the dashed lines correspond to power regression relationships for impacts to the Bauer helmet. This is all data for the outside top sensor location.
Figure A1-2.12c: Data comparing peak resultant linear acceleration (left) and peak resultant rotational velocity (right) as measured by the ATD and by GFT for all impact directions combined and then stratified by impact direction. The graphs show both the data collected from impacts to the Easton helmet and data collected from impacts to the Bauer helmet. Each data point represents a single impact, with GFT measure on the abscissa and ATD measure on the ordinate. The solid lines correspond to the power regression relationships for impacts to the Easton helmet, while the dashed lines correspond to power regression relationships for impacts to the Bauer helmet. This is all data for the outside right sensor location.
Figure A1-2.12d: Data comparing peak resultant linear acceleration (left) and peak resultant rotational velocity (right) as measured by the ATD and by GFT for all impact directions combined and then stratified by impact direction. The graphs show both the data collected from impacts to the Easton helmet and data collected from impacts to the Bauer helmet. Each data point represents a single impact, with GFT measure on the abscissa and ATD measure on the ordinate. The solid lines correspond to the power regression relationships for impacts to the Easton helmet, while the dashed lines correspond to power regression relationships for impacts to the Bauer helmet. This is all data for the outside back sensor location.
<table>
<thead>
<tr>
<th>Direction</th>
<th>Regression Equation: Linear Fit</th>
<th>Linear Fit $R^2$</th>
<th>Regression Equation: Power Fit</th>
<th>Power Fit $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Linear Acceleration</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All Data</td>
<td>$y = 0.58x - 8.01$</td>
<td>0.76</td>
<td>$y = 0.37x^{1.05}$</td>
<td>0.77</td>
</tr>
<tr>
<td>Side</td>
<td>$y = 0.74x - 1.77$</td>
<td>0.99</td>
<td>$y = 0.57x^{1.05}$</td>
<td>0.99</td>
</tr>
<tr>
<td>Oblique</td>
<td>$y = 0.72x - 30.77$</td>
<td>0.88</td>
<td>$y = 0.02x^{1.68}$</td>
<td>0.95</td>
</tr>
<tr>
<td>Back</td>
<td>$y = 0.43x + 1.72$</td>
<td>0.93</td>
<td>$y = 0.57x^{0.95}$</td>
<td>0.94</td>
</tr>
<tr>
<td>Front</td>
<td>$y = 0.32x + 4.09$</td>
<td>0.81</td>
<td>$y = 0.70x^{0.85}$</td>
<td>0.88</td>
</tr>
<tr>
<td><strong>Rotational Velocity</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All Data</td>
<td>$y = 0.89x + 128.67$</td>
<td>0.81</td>
<td>$y = 2.28x^{0.88}$</td>
<td>0.85</td>
</tr>
<tr>
<td>Side</td>
<td>$y = 1.12x - 249.04$</td>
<td>0.97</td>
<td>$y = 0.18x^{1.22}$</td>
<td>0.98</td>
</tr>
<tr>
<td>Oblique</td>
<td>$y = 1.11x - 11.07$</td>
<td>0.92</td>
<td>$y = 0.84x^{1.04}$</td>
<td>0.96</td>
</tr>
<tr>
<td>Back</td>
<td>$y = 1.04x + 70.38$</td>
<td>0.93</td>
<td>$y = 2.78x^{0.87}$</td>
<td>0.95</td>
</tr>
<tr>
<td>Front</td>
<td>$y = 0.63x + 314.37$</td>
<td>0.90</td>
<td>$y = 12.7x^{0.63}$</td>
<td>0.90</td>
</tr>
</tbody>
</table>

Table A1-2.2c: Linear and power regression fit equations for GFT data from the outside top sensor on the Bauer helmet and their associated $R^2$ values.
<table>
<thead>
<tr>
<th>Direction</th>
<th>Regression Equation: Linear Fit</th>
<th>Linear Fit $R^2$</th>
<th>Regression Equation: Power Fit</th>
<th>Power Fit $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Data</td>
<td>$y = 0.64x - 9.53$</td>
<td>0.80</td>
<td>$y = 0.37x^{1.07}$</td>
<td>0.72</td>
</tr>
<tr>
<td>Side</td>
<td>$y = 0.71x - 7.22$</td>
<td>0.99</td>
<td>$y = 0.50x^{1.05}$</td>
<td>0.99</td>
</tr>
<tr>
<td>Oblique</td>
<td>$y = 0.85x - 15.56$</td>
<td>0.89</td>
<td>$y = 0.11x^{1.40}$</td>
<td>0.95</td>
</tr>
<tr>
<td>Back</td>
<td>$y = 0.50x + 2.38$</td>
<td>0.97</td>
<td>$y = 1.06x^{0.85}$</td>
<td>0.94</td>
</tr>
<tr>
<td>Front</td>
<td>$y = 0.33x - 3.41$</td>
<td>0.88</td>
<td>$y = 0.12x^{1.19}$</td>
<td>0.90</td>
</tr>
<tr>
<td>All Data</td>
<td>$y = 0.97x + 59.92$</td>
<td>0.78</td>
<td>$y = 1.39x^{0.95}$</td>
<td>0.83</td>
</tr>
<tr>
<td>Side</td>
<td>$y = 0.96x - 53.54$</td>
<td>0.99</td>
<td>$y = 0.55x^{1.07}$</td>
<td>0.99</td>
</tr>
<tr>
<td>Oblique</td>
<td>$y = 1.22x - 155.43$</td>
<td>0.97</td>
<td>$y = 0.35x^{1.16}$</td>
<td>0.98</td>
</tr>
<tr>
<td>Back</td>
<td>$y = 1.16x + 75.11$</td>
<td>0.89</td>
<td>$y = 2.14x^{0.92}$</td>
<td>0.92</td>
</tr>
<tr>
<td>Front</td>
<td>$y = 0.86x - 52.15$</td>
<td>0.94</td>
<td>$y = 2.14x^{0.92}$</td>
<td>0.91</td>
</tr>
</tbody>
</table>

Table A1-2.2d: Linear and power regression fit equations for GFT data from the outside right sensor on the Bauer helmet and their associated $R^2$ values.
<table>
<thead>
<tr>
<th></th>
<th>Direction</th>
<th>Regression Equation: Linear Fit</th>
<th>Linear Fit $R^2$</th>
<th>Regression Equation: Power Fit</th>
<th>Power Fit $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Linear Acceleration</strong></td>
<td>All Data</td>
<td>$y = 0.68x - 12.52$</td>
<td>0.75</td>
<td>$y = 0.50x^{1.00}$</td>
<td>0.69</td>
</tr>
<tr>
<td></td>
<td>Side</td>
<td>$y = 0.78x - 0.16$</td>
<td>0.99</td>
<td>$y = 1.10x^{0.92}$</td>
<td>0.99</td>
</tr>
<tr>
<td></td>
<td>Oblique</td>
<td>$y = 0.63x - 21.16$</td>
<td>0.83</td>
<td>$y = 0.04x^{1.48}$</td>
<td>0.92</td>
</tr>
<tr>
<td></td>
<td>Back</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>Front</td>
<td>$y = 0.39x - 1.06$</td>
<td>0.98</td>
<td>$y = 0.28x^{1.07}$</td>
<td>0.98</td>
</tr>
<tr>
<td><strong>Rotational Velocity</strong></td>
<td>All Data</td>
<td>$y = 0.87x + 81.51$</td>
<td>0.83</td>
<td>$y = 1.23x^{0.96}$</td>
<td>0.86</td>
</tr>
<tr>
<td></td>
<td>Side</td>
<td>$y = 1.12x - 282.26$</td>
<td>0.97</td>
<td>$y = 0.15x^{1.25}$</td>
<td>0.97</td>
</tr>
<tr>
<td></td>
<td>Oblique</td>
<td>$y = 1.05x + 11.75$</td>
<td>0.93</td>
<td>$y = 0.85x^{1.03}$</td>
<td>0.96</td>
</tr>
<tr>
<td></td>
<td>Back</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>Front</td>
<td>$y = 0.71x + 163.47$</td>
<td>0.92</td>
<td>$y = 5.09x^{0.75}$</td>
<td>0.90</td>
</tr>
</tbody>
</table>

Table A1-2.2e: Linear and power regression fit equations for GFT data from the outside back sensor on the Bauer helmet and their associated $R^2$ values.
<table>
<thead>
<tr>
<th>Direction</th>
<th>Linear Acceleration</th>
<th>Rotational Velocity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Regression Equation: Linear Fit</td>
<td>Linear Fit R²</td>
</tr>
<tr>
<td>All Data</td>
<td>$y = 0.57x - 12.75$</td>
<td>0.78</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Side</td>
<td>$y = 0.64x - 7.20$</td>
<td>0.91</td>
</tr>
<tr>
<td>Oblique</td>
<td>$y = 0.72x - 24.06$</td>
<td>0.94</td>
</tr>
<tr>
<td>Back</td>
<td>$y = 0.50x - 16.62$</td>
<td>0.85</td>
</tr>
<tr>
<td>Front</td>
<td>$y = 0.43x - 8.40$</td>
<td>0.84</td>
</tr>
<tr>
<td>All Data</td>
<td>$y = 0.91x + 132.70$</td>
<td>0.92</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Side</td>
<td>$y = 0.83x + 93.02$</td>
<td>0.97</td>
</tr>
<tr>
<td>Oblique</td>
<td>$y = 1.22x - 170.25$</td>
<td>0.99</td>
</tr>
<tr>
<td>Back</td>
<td>$y = 0.94x + 177.51$</td>
<td>0.97</td>
</tr>
<tr>
<td>Front</td>
<td>$y = 0.76x + 302.05$</td>
<td>0.97</td>
</tr>
</tbody>
</table>

Table A1-2.2f: Linear and power regression fit equations for GFT data from the outside top sensor on the Easton helmet and their associated $R^2$ values.
<table>
<thead>
<tr>
<th>Direction</th>
<th>Linear Acceleration</th>
<th>Regression Equation: Linear Fit</th>
<th>Linear Fit $R^2$</th>
<th>Regression Equation: Power Fit</th>
<th>Power Fit $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Data</td>
<td>y = 0.54x - 6.76</td>
<td>0.65</td>
<td>y = 0.25$x^{1.12}$</td>
<td>0.66</td>
<td></td>
</tr>
<tr>
<td>Side</td>
<td>y = 0.78x - 6.22</td>
<td>0.99</td>
<td>y = 0.46$x^{1.09}$</td>
<td>0.99</td>
<td></td>
</tr>
<tr>
<td>Oblique</td>
<td>y = 0.56x - 13.53</td>
<td>0.91</td>
<td>y = 0.05$x^{1.46}$</td>
<td>0.90</td>
<td></td>
</tr>
<tr>
<td>Back</td>
<td>y = 0.55x - 15.08</td>
<td>0.74</td>
<td>y = 0.29$x^{1.07}$</td>
<td>0.79</td>
<td></td>
</tr>
<tr>
<td>Front</td>
<td>y = 0.33x - 4.21</td>
<td>0.83</td>
<td>y = 0.17$x^{1.11}$</td>
<td>0.84</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Direction</th>
<th>Rotational Velocity</th>
<th>Regression Equation: Linear Fit</th>
<th>Linear Fit $R^2$</th>
<th>Regression Equation: Power Fit</th>
<th>Power Fit $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Data</td>
<td>y = 0.90x + 41.03</td>
<td>0.82</td>
<td>y = 0.95$x^{1.00}$</td>
<td>0.85</td>
<td></td>
</tr>
<tr>
<td>Side</td>
<td>y = 0.78x + 53.00</td>
<td>0.98</td>
<td>y = 1.09$x^{0.96}$</td>
<td>0.98</td>
<td></td>
</tr>
<tr>
<td>Oblique</td>
<td>y = 0.86x + 33.46</td>
<td>0.78</td>
<td>y = 0.25$x^{1.17}$</td>
<td>0.78</td>
<td></td>
</tr>
<tr>
<td>Back</td>
<td>y = 1.23x - 230.03</td>
<td>0.92</td>
<td>y = 0.39$x^{1.14}$</td>
<td>0.91</td>
<td></td>
</tr>
<tr>
<td>Front</td>
<td>y = 1.00x + 24.82</td>
<td>0.97</td>
<td>y = 1.56$x^{0.94}$</td>
<td>0.97</td>
<td></td>
</tr>
</tbody>
</table>

Table A1-2.2g: Linear and power regression fit equations for GFT data from the outside right sensor on the Easton helmet and their associated $R^2$ values.
<table>
<thead>
<tr>
<th>Direction</th>
<th>Regression Equation: Linear Fit</th>
<th>Linear Fit R²</th>
<th>Regression Equation: Power Fit</th>
<th>Power Fit R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Data</td>
<td>$y = 0.38x + 6.29$</td>
<td>0.57</td>
<td>$y = 1.23x^{0.77}$</td>
<td>0.60</td>
</tr>
<tr>
<td>Side</td>
<td>$y = 0.61x + 5.71$</td>
<td>0.99</td>
<td>$y = 1.24x^{0.87}$</td>
<td>0.99</td>
</tr>
<tr>
<td>Oblique</td>
<td>$y = 0.61x - 42.89$</td>
<td>0.85</td>
<td>$y = 0.004x^{1.87}$</td>
<td>0.93</td>
</tr>
<tr>
<td>Back</td>
<td>$y = 0.34x - 4.60$</td>
<td>0.83</td>
<td>$y = 0.16x^{1.13}$</td>
<td>0.77</td>
</tr>
<tr>
<td>Front</td>
<td>$y = 0.65x - 3.34$</td>
<td>0.89</td>
<td>$y = 0.25x^{1.21}$</td>
<td>0.96</td>
</tr>
<tr>
<td>All Data</td>
<td>$y = 0.96x + 120.81$</td>
<td>0.93</td>
<td>$y = 2.96x^{0.86}$</td>
<td>0.91</td>
</tr>
<tr>
<td>Side</td>
<td>$y = 1.06x - 64.38$</td>
<td>0.99</td>
<td>$y = 0.55x^{1.09}$</td>
<td>0.99</td>
</tr>
<tr>
<td>Oblique</td>
<td>$y = 1.22x - 80.25$</td>
<td>0.99</td>
<td>$y = 0.59x^{1.09}$</td>
<td>0.99</td>
</tr>
<tr>
<td>Back</td>
<td>$y = 0.85x + 169.44$</td>
<td>0.97</td>
<td>$y = 2.83x^{0.85}$</td>
<td>0.98</td>
</tr>
<tr>
<td>Front</td>
<td>$y = 0.80x + 328.71$</td>
<td>0.99</td>
<td>$y = 14.13x^{0.64}$</td>
<td>0.98</td>
</tr>
</tbody>
</table>

Table A1.2.2h: Linear and power regression fit equations for GFT data from the outside back sensor on the Easton helmet and their associated R² values.
A1.2: Estimation of impact direction for other sensor locations

Figure A1-2.14b: Comparison of GFT-reported and actual impact azimuth for side, oblique, back, and front impacts for the outside top sensor. Actual impact azimuth is indicated by the arrow, while system-reported azimuths for each impact are indicated by the markers.
Figure A1-2.14c: Comparison of GFT-reported and actual impact azimuth for side, oblique, back, and front impacts for the outside right sensor. Actual impact azimuth is indicated by the arrow, while system-reported azimuths for each impact are indicated by the markers.
Figure A1-2.14d: Comparison of GFT-reported and actual impact azimuth for side, oblique, back, and front impacts for the outside back sensor. Actual impact azimuth is indicated by the arrow, while system-reported azimuths for each impact are indicated by the markers.
Appendix 2 – Supplementary data for Chapter 3

A2.1: Repeatability of helmet/sensor system data for other sensor locations

Figure A2-0.1b: Outside top sensor location data comparing combined helmet/sensor sets for peak resultant linear acceleration (left) and rotational velocity (right) as measured by the ATD and GFT stratified by impact direction. Each data point represents a single impact, with GFT measure on the abscissa and ATD measure on the ordinate. The lines correspond to the power regression relationships.
Figure A2-0.2: Outside right sensor location data comparing combined helmet/sensor sets for peak resultant linear acceleration (left) and rotational velocity (right) as measured by the ATD and GFT stratified by impact direction. Each data point represents a single impact, with GFT measure on the abscissa and ATD measure on the ordinate. The lines correspond to the power regression relationships.
Figure A2-0.3: Outside back sensor location data comparing combined helmet/sensor sets for peak resultant linear acceleration (left) and rotational velocity (right) as measured by the ATD and GFT stratified by impact direction. Each data point represents a single impact, with GFT measure on the abscissa and ATD measure on the ordinate. The lines correspond to the power regression relationships.
### Table A2-0.2b: Outside top sensor location power regression fit equations stratified by impact direction for GFT combined helmet/sensor sets 1 and 2 and their associated $R^2$ values.

<table>
<thead>
<tr>
<th>Impact Direction</th>
<th>Regression Equation: Sensor Set 1</th>
<th>Set 1 $R^2$</th>
<th>Regression Equation: Sensor Set 2</th>
<th>Set 2 $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear Acceleration</td>
<td>Side $y = 0.49x^{1.08}$</td>
<td>1.0</td>
<td>$y = 0.22x^{1.24}$</td>
<td>.99</td>
</tr>
<tr>
<td></td>
<td>Oblique $y = 0.05x^{1.52}$</td>
<td>.88</td>
<td>$y = 0.04x^{1.48}$</td>
<td>.84</td>
</tr>
<tr>
<td>Rotational Acceleration</td>
<td>Side $y = 1.10x^{0.94}$</td>
<td>.98</td>
<td>$y = 0.73x^{1.06}$</td>
<td>.99</td>
</tr>
<tr>
<td></td>
<td>Oblique $y = 0.87x^{1.11}$</td>
<td>.99</td>
<td>$y = 0.63x^{1.20}$</td>
<td>.98</td>
</tr>
</tbody>
</table>

### Table A2-0.2c: Outside right sensor location power regression fit equations stratified by impact direction for GFT combined helmet/sensor sets 1 and 2 and their associated $R^2$ values.

<table>
<thead>
<tr>
<th>Impact Direction</th>
<th>Regression Equation: Sensor Set 1</th>
<th>Set 1 $R^2$</th>
<th>Regression Equation: Sensor Set 2</th>
<th>Set 2 $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear Acceleration</td>
<td>Side $y = 0.70x^{0.99}$</td>
<td>.99</td>
<td>$y = 0.38x^{1.14}$</td>
<td>1.0</td>
</tr>
<tr>
<td></td>
<td>Oblique $y = 0.06x^{1.55}$</td>
<td>.99</td>
<td>$y = 0.07x^{1.44}$</td>
<td>.96</td>
</tr>
<tr>
<td>Rotational Acceleration</td>
<td>Side $y = 0.80x^{1.02}$</td>
<td>.98</td>
<td>$y = 0.72x^{1.07}$</td>
<td>1.0</td>
</tr>
<tr>
<td></td>
<td>Oblique $y = 1.17x^{0.99}$</td>
<td>.98</td>
<td>$y = 0.47x^{1.28}$</td>
<td>.98</td>
</tr>
<tr>
<td>Linear Acceleration</td>
<td>Direction</td>
<td>Regression Equation: Sensor Set 1</td>
<td>Set 1 $R^2$</td>
<td>Regression Equation: Sensor Set 2</td>
</tr>
<tr>
<td>---------------------</td>
<td>-----------</td>
<td>-----------------------------------</td>
<td>-------------</td>
<td>-----------------------------------</td>
</tr>
<tr>
<td></td>
<td>Side</td>
<td>$y = 0.81x^{0.99}$</td>
<td>.99</td>
<td>$y = 0.32x^{1.18}$</td>
</tr>
<tr>
<td></td>
<td>Oblique</td>
<td>$y = 0.06x^{1.47}$</td>
<td>.87</td>
<td>$y = 0.03x^{1.54}$</td>
</tr>
<tr>
<td>Rotational Acceleration</td>
<td>Side</td>
<td>$y = 0.91x^{1.00}$</td>
<td>.98</td>
<td>$y = 0.62x^{1.11}$</td>
</tr>
<tr>
<td></td>
<td>Oblique</td>
<td>$y = 0.50x^{1.27}$</td>
<td>.99</td>
<td>$y = 0.51x^{1.26}$</td>
</tr>
</tbody>
</table>

Table A2-0.2d: Outside back sensor location power regression fit equations stratified by impact direction for GFT combined helmet/sensor sets 1 and 2 and their associated $R^2$ values.

A2.2: Effective mass of the torso data for other sensor locations
Figure A2-0.4: Outside top sensor location data comparing mounting setups (rigid or translating) for peak resultant linear acceleration (left) and rotational velocity (right) as measured by the ATD and GFT stratified by impact direction. Each data point represents a single impact, with GFT measure on the abscissa and ATD measure on the ordinate. The lines correspond to the power regression relationships.
Figure A2-0.5: Outside right sensor location data comparing mounting setups (rigid or translating) for peak resultant linear acceleration (left) and rotational velocity (right) as measured by the ATD and GFT stratified by impact direction. Each data point represents a single impact, with GFT measure on the abscissa and ATD measure on the ordinate. The lines correspond to the power regression relationships.
Figure A2-0.6: Outside back sensor location data comparing mounting setups (rigid or translating) for peak resultant linear acceleration (left) and rotational velocity (right) as measured by the ATD and GFT stratified by impact direction. Each data point represents a single impact, with GFT measure on the abscissa and ATD measure on the ordinate. The lines correspond to the power regression relationships.
<table>
<thead>
<tr>
<th>Linear Acceleration</th>
<th>Direction</th>
<th>Regression Equation: Rigid Mount</th>
<th>Rigid R²</th>
<th>Regression Equation: Translating Mount</th>
<th>Translating R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Side</td>
<td>( y = 0.57x^{1.05} )</td>
<td>.99</td>
<td>( y = 0.49x^{1.08} )</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Oblique</td>
<td>( y = 0.02x^{1.68} )</td>
<td>.95</td>
<td>( y = 0.05x^{1.52} )</td>
<td>.88</td>
<td></td>
</tr>
<tr>
<td>Back</td>
<td>( y = 0.57x^{0.95} )</td>
<td>.94</td>
<td>( y = 0.12x^{1.24} )</td>
<td>.90</td>
<td></td>
</tr>
<tr>
<td>Front</td>
<td>( y = 0.70x^{0.85} )</td>
<td>.88</td>
<td>( y = 0.39x^{0.97} )</td>
<td>.91</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Rotational Acceleration</th>
<th>Direction</th>
<th>Regression Equation: Rigid Mount</th>
<th>Rigid R²</th>
<th>Regression Equation: Translating Mount</th>
<th>Translating R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Side</td>
<td>( y = 0.45x^{1.22} )</td>
<td>.98</td>
<td>( y = 1.10x^{0.94} )</td>
<td>.98</td>
<td></td>
</tr>
<tr>
<td>Oblique</td>
<td>( y = 0.97x^{1.04} )</td>
<td>.96</td>
<td>( y = 0.87x^{1.11} )</td>
<td>.99</td>
<td></td>
</tr>
<tr>
<td>Back</td>
<td>( y = 1.65x^{0.87} )</td>
<td>.95</td>
<td>( y = 0.41x^{1.31} )</td>
<td>.93</td>
<td></td>
</tr>
<tr>
<td>Front</td>
<td>( y = 2.86x^{0.63} )</td>
<td>.90</td>
<td>( y = 0.91x^{1.10} )</td>
<td>.89</td>
<td></td>
</tr>
</tbody>
</table>

Table A2-0.4b: Outside top sensor location power regression fit equations stratified by impact direction for the two mounting setups (rigid and translational) and their associated \( R^2 \) values.
<table>
<thead>
<tr>
<th>Direction</th>
<th>Linear Acceleration</th>
<th>Regression Equation: Rigid Mount</th>
<th>Rigid R²</th>
<th>Regression Equation: Translating Mount</th>
<th>Translating R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Side</td>
<td>y = 0.50x^{1.05}</td>
<td>.99</td>
<td></td>
<td>y = 0.70x^{0.99}</td>
<td>.99</td>
</tr>
<tr>
<td>Oblique</td>
<td>y = 0.11x^{1.40}</td>
<td>.95</td>
<td></td>
<td>y = 0.06x^{1.55}</td>
<td>.99</td>
</tr>
<tr>
<td>Back</td>
<td>y = 1.06x^{0.85}</td>
<td>.94</td>
<td></td>
<td>y = 1.22x^{0.84}</td>
<td>.97</td>
</tr>
<tr>
<td>Front</td>
<td>y = 0.12x^{1.19}</td>
<td>.90</td>
<td></td>
<td>y = 0.42x^{0.90}</td>
<td>.88</td>
</tr>
<tr>
<td>Side</td>
<td>y = 0.73x^{1.07}</td>
<td>.99</td>
<td></td>
<td>y = 0.80x^{1.02}</td>
<td>.98</td>
</tr>
<tr>
<td>Oblique</td>
<td>y = 0.67x^{1.16}</td>
<td>.98</td>
<td></td>
<td>y = 1.17x^{0.99}</td>
<td>.98</td>
</tr>
<tr>
<td>Back</td>
<td>y = 1.56x^{0.92}</td>
<td>.92</td>
<td></td>
<td>y = 0.27x^{1.47}</td>
<td>.90</td>
</tr>
<tr>
<td>Front</td>
<td>y = 1.06x^{0.92}</td>
<td>.91</td>
<td></td>
<td>y = 1.49x^{0.91}</td>
<td>.95</td>
</tr>
</tbody>
</table>

Table A2-0.4c: Outside right sensor location power regression fit equations stratified by impact direction for the two mounting setups (rigid and translational) and their associated R² values.
### Table A2-0.4d: Outside back sensor location power regression fit equations stratified by impact direction for the two mounting setups (rigid and translational) and their associated $R^2$ values.

#### Linear Acceleration

<table>
<thead>
<tr>
<th>Direction</th>
<th>Regression Equation: Rigid Mount</th>
<th>Rigid $R^2$</th>
<th>Regression Equation: Translating Mount</th>
<th>Translating $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Side</td>
<td>$y = 1.10x^{0.92}$</td>
<td>.99</td>
<td>$y = 0.81x^{0.99}$</td>
<td>.99</td>
</tr>
<tr>
<td>Oblique</td>
<td>$y = 0.04x^{1.48}$</td>
<td>.92</td>
<td>$y = 0.06x^{1.47}$</td>
<td>.87</td>
</tr>
<tr>
<td>Back</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Front</td>
<td>$y = 0.28x^{1.07}$</td>
<td>.98</td>
<td>$y = 0.22x^{1.09}$</td>
<td>.91</td>
</tr>
</tbody>
</table>

#### Rotational Acceleration

<table>
<thead>
<tr>
<th>Direction</th>
<th>Regression Equation: Rigid Mount</th>
<th>Rigid $R^2$</th>
<th>Regression Equation: Translating Mount</th>
<th>Translating $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Side</td>
<td>$y = 0.41x^{1.25}$</td>
<td>.97</td>
<td>$y = 0.91x^{1.00}$</td>
<td>.98</td>
</tr>
<tr>
<td>Oblique</td>
<td>$y = 0.96x^{1.03}$</td>
<td>.96</td>
<td>$y = 0.50x^{1.27}$</td>
<td>.99</td>
</tr>
<tr>
<td>Back</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Front</td>
<td>$y = 1.87x^{0.75}$</td>
<td>.90</td>
<td>$y = 0.41x^{1.40}$</td>
<td>.95</td>
</tr>
</tbody>
</table>

**A2.3: Impacting surface data for other sensor locations**

![Graphs showing peak resultant linear acceleration and rotational velocity](image-url)
Figure A2-0.7: Outside top sensor location data comparing impacting surfaces (UHMWPE or hockey elbow pad) for peak resultant linear acceleration (left) and rotational velocity (right) as measured by the ATD and GFT stratified by impact direction. Each data point represents a single impact, with GFT measure on the abscissa and ATD measure on the ordinate. The lines correspond to the power regression relationships.
Figure A2.8: Outside right sensor location data comparing impacting surfaces (UHMWPE or hockey elbow pad) for peak resultant linear acceleration (left) and rotational velocity (right) as measured by the ATD and GFT stratified by impact direction. Each data point represents a single impact, with GFT measure on the abscissa and ATD measure on the ordinate. The lines correspond to the power regression relationships.
Figure A2-0.9: Outside back sensor location data comparing impacting surfaces (UHMWPE or hockey elbow pad) for peak resultant linear acceleration (left) and rotational velocity (right) as measured by the ATD and GFT stratified by impact direction. Each data point represents a single impact, with GFT measure on the abscissa and ATD measure on the ordinate. The lines correspond to the power regression relationships.
<table>
<thead>
<tr>
<th>Direction</th>
<th>Linear Acceleration</th>
<th>Regression Equation: UHMWPE</th>
<th>UHMWPE $R^2$</th>
<th>Regression Equation: Elbow Pad</th>
<th>Elbow Pad $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$y = 0.49x^{1.08}$</td>
<td>1.0</td>
<td>$y = 0.15x^{1.33}$</td>
<td>.98</td>
</tr>
<tr>
<td>Side</td>
<td></td>
<td>$y = 0.05x^{1.52}$</td>
<td>.88</td>
<td>$y = 0.03x^{1.57}$</td>
<td>.92</td>
</tr>
<tr>
<td>Oblique</td>
<td></td>
<td>$y = 0.12x^{1.24}$</td>
<td>.90</td>
<td>$y = 0.86x^{0.98}$</td>
<td>.95</td>
</tr>
<tr>
<td>Back</td>
<td></td>
<td>$y = 0.39x^{0.97}$</td>
<td>.91</td>
<td>$y = 0.42x^{1.02}$</td>
<td>.90</td>
</tr>
<tr>
<td>Front</td>
<td></td>
<td>$y = 1.10x^{0.94}$</td>
<td>.98</td>
<td>$y = 0.99x^{1.01}$</td>
<td>.99</td>
</tr>
<tr>
<td>Oblique</td>
<td></td>
<td>$y = 0.87x^{1.11}$</td>
<td>.99</td>
<td>$y = 0.86x^{1.11}$</td>
<td>.98</td>
</tr>
<tr>
<td>Back</td>
<td></td>
<td>$y = 0.41x^{1.31}$</td>
<td>.93</td>
<td>$y = 1.49x^{0.89}$</td>
<td>.89</td>
</tr>
<tr>
<td>Front</td>
<td></td>
<td>$y = 0.91x^{1.10}$</td>
<td>.89</td>
<td>$y = 0.40x^{1.16}$</td>
<td>.98</td>
</tr>
</tbody>
</table>

Table A2-0.1: Outside top sensor location power regression fit equations stratified by impact direction for the two impacting surfaces (UHMWPE and the hockey elbow pad) and their associated $R^2$ values.
<table>
<thead>
<tr>
<th>Direction</th>
<th>Linear Acceleration</th>
<th>Regression Equation: UHMWPE</th>
<th>UHMWPE $R^2$</th>
<th>Regression Equation: Elbow Pad</th>
<th>Elbow Pad $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Side</td>
<td>$y = 0.70x^{0.99}$</td>
<td>.99</td>
<td>$y = 1.01x^{0.92}$</td>
<td>.99</td>
<td></td>
</tr>
<tr>
<td>Oblique</td>
<td>$y = 0.06x^{1.55}$</td>
<td>.99</td>
<td>$y = 0.04x^{1.78}$</td>
<td>.96</td>
<td></td>
</tr>
<tr>
<td>Back</td>
<td>$y = 1.22x^{0.84}$</td>
<td>.97</td>
<td>$y = 0.83x^{1.08}$</td>
<td>.99</td>
<td></td>
</tr>
<tr>
<td>Front</td>
<td>$y = 0.42x^{0.90}$</td>
<td>.88</td>
<td>$y = 0.71x^{0.82}$</td>
<td>.93</td>
<td></td>
</tr>
<tr>
<td>Rotational Acceleration</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Side</td>
<td>$y = 0.80x^{1.02}$</td>
<td>.98</td>
<td>$y = 1.07x^{0.94}$</td>
<td>.99</td>
<td></td>
</tr>
<tr>
<td>Oblique</td>
<td>$y = 1.17x^{0.99}$</td>
<td>.98</td>
<td>$y = 0.77x^{1.09}$</td>
<td>.99</td>
<td></td>
</tr>
<tr>
<td>Back</td>
<td>$y = 0.27x^{1.47}$</td>
<td>.90</td>
<td>$y = 0.92x^{1.07}$</td>
<td>.90</td>
<td></td>
</tr>
<tr>
<td>Front</td>
<td>$y = 1.49x^{0.91}$</td>
<td>.95</td>
<td>$y = 2.06x^{0.71}$</td>
<td>.87</td>
<td></td>
</tr>
</tbody>
</table>

Table A2-0.2: Outside right sensor location power regression fit equations stratified by impact direction for the two impacting surfaces (UHMWPE and the hockey elbow pad) and their associated $R^2$ values.
<table>
<thead>
<tr>
<th>Impact Direction</th>
<th>Linear Acceleration</th>
<th>Rotational Acceleration</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Regression Equation: UHMWPE</td>
<td>UHMWPE R²</td>
</tr>
<tr>
<td>Side</td>
<td>$y = 0.81x^{0.99}$</td>
<td>.99</td>
</tr>
<tr>
<td>Oblique</td>
<td>$y = 0.06x^{1.47}$</td>
<td>.87</td>
</tr>
<tr>
<td>Back</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Front</td>
<td>$y = 0.22x^{1.09}$</td>
<td>.91</td>
</tr>
</tbody>
</table>

|                  | Regression Equation: UHMWPE | UHMWPE R² | Regression Equation: Elbow Pad | Elbow Pad R² |
| Side             | $y = 0.91x^{1.00}$ | .98 | $y = 0.83x^{1.04}$ | .99 |
| Oblique          | $y = 0.50x^{1.27}$ | .99 | $y = 0.80x^{1.13}$ | .99 |
| Back             | N/A                 | N/A | N/A                 | N/A |
| Front            | $y = 0.41x^{1.40}$ | .95 | $y = 0.37x^{1.24}$ | .99 |

Table A2-0.3: Outside back sensor location power regression fit equations stratified by impact direction for the two impacting surfaces (UHMWPE and the hockey elbow pad) and their associated $R^2$ values.
References


237


108x709

239


243


