# An Evaluation of the Physical Demands of American Football Training in the NFL

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# ABSTRACT

American football is one of the most popular sports in the United States. However, unlike other football codes, little is known about its physical demands. Aside from a limited amount of research conducted on college players during training and matches, no research exists on players at the elite level, in the National Football League (NFL). Therefore, the primary aim of this thesis was to evaluate the physical demands of training in the NFL. This aim was achieved by establishing a systematic approach to training evaluation using three main phases of study: (1) Evaluation of monitoring strategies in American football; (2) Description of American football training demands with an emphasis on periodization; and, (3) Examination of the consequences of training with an emphasis on injury risk.

The first study of this thesis (Chapter 3) showed that three commercially available inertial sensors were able to differentiate between fundamental American football actions (e.g., sprinting, change of direction, and collisions) during movement tasks in a controlled setting and may be useful for quantifying the physical demands of training. During training sessions, Session Rating of Perceived Exertion exhibited a variety of individual responses making sRPE challenging to use when exclusively evaluating the physical demands of training (Chapter 4). Therefore, more objective measures (e.g., GPS and inertial sensors) were evaluated during training (Chapter 5) and indicate that commonly used measures of distance and velocity may not adequately describe the physical demands for some

position groups. As such, inertial sensors offer more flexibility to classify a broad range of activities within the sport. A number of inertial sensor metrics are available to the practitioner in commercially used systems. Chapter 6 utilized a principal components analysis to reduce eleven variables to 3 principal components, explaining 79% of the variance within the data. These findings suggest that a small number of variables (e.g., Player Load and IMA) may be adequate when describing the training demands of the sport. Given the reduction in measures to report, Chapter 7 used Player Load and IMA to describe the periodization strategies across a season and within the training week employed by the coaches of one NFL team. Training load was observed to decreases across the season with no clear periodization structure. Conversely, within the weekly micro-cycle, coaches appear to employ some pattern of periodization whereby training load is seen to systematically decrease as the game nears. The final phase of this thesis (Chapter 8) investigated the consequences of American football training by exploring the relationship between training load measures (Player Load, IMA, and Impacts) and non-contact soft tissue injury. Several logistic regression models were compared using Bayesian Information Criterion (BIC). The best model suggested that sessions with greater volume ($PL_{Total}$) and intensity ($Impacts_{High}$) were associated with non-contact soft tissue injury in American football players and may have implications for practitioners when designing training programs within the sport.

Collectively, this thesis has the potential to not only offer practitioners within American football a way forward in terms of evaluating training demands but also may be influential to the broader scope of sports science given some of the novel statistical approaches taken to understanding training load monitoring.

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# PUBLICATIONS & PRESENTATIONS

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# CONTENTS

# LIST OF ABBREVIATIONS

AIC, Akaike Information Criterion

AFL, Australian Football League

ANOVA, Analysis of Variance

AU, Arbitrary Units

BDS, Backpedal-Decelerate-Sprint

BIC, Bayesian Information Criterion

CI, Confidence Interval

CV, Coefficient of Variation

DB, Defensive Back

DEF, Defense

DL, Defensive Line

dRPE, Differential Rating of Perceived Exertion

GD, Game Day

GPS, Global Position System

HR, Heart Rate

HSD, High-Speed Distance

IMA, Inertial Movement Analysis

KMO, Kaiser-Meyer-Olkin

LB, Linebacker

NCAA, National Athletics Association

NFL, National Football League

OFF, Offense

OL, Offensive Line

OR, Odds Ratio

PCA, Principal Components Analysis

PL, Player Load

QB, Quarterback

RB, Running Back

SD, Standard Deviation

SE, Standard Error

sRPE, Session Rating of Perceived Exertion

TD, Total Distance

TE, Tight End

UEFA, Union of European Football Associations

WR, Wide Receiver

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# THE STRUCTURAL APPROACH TO THE CONSTRUCTION OF THIS THESIS

This thesis adopts an alternative framework in its presentation than that frequently used in PhD's. The formal scientific evaluation of training demands in NFL athletes has yet to be conducted within the scientific literature. This thesis attempts to address a number of pertinent issues to sports science monitoring and data interpretation within the sport firstly from a methodological perspective and then from a theoretical/practical standpoint. As such, the chapters contained in this thesis are not sequentially ordered, as is common within a thesis, but are instead structured more in a manner that is "flat" (i.e. non-hierarchical). This is a consequence of the research questions being located around issues that seem of importance at similar stages of the research process. This would seem to make it difficult to present the projects in a very linear way and to indicate that they need to be read in a particular order. Due to this structure, each introduction in each experimental chapter serves to re-introduce American football and its sporting demands. This is necessary to ensure that the reader is reminded of the fundamental concepts of the sport. This is important, as many may not be familiar with this information given the paucity of research currently available in the area. To help focus the reader, the chapters have been grouped into three phases of research, which attempt to address similar research components:

1) Methodological Evaluation of Monitoring Strategies (Chapters 3-6)

2) Description of Training Demands (Chapter 7)

3) Consequences of Training (Chapter 8)

# CHAPTER 1

# GENERAL INTRODUCTION

## 1.1 Background

American football is one of the most watched sports in the United States (Hoffman, 2008). The highest level of the game is played in the NFL where 32 teams compete in 16 games over 17 weeks during the regular season with the objective to win as many games as possible and make the post-season playoffs. Below this elite competition, players play at the collegiate level in the National Collegiate Athletics Association (NCAA). The sport of American football irrespective of level is played on a 100 by 53.3 yard field and consists of four 15 min quarters separated by a halftime of 12 min in the NFL (20 min in the NCAA). Over the course of a game, the offense aims to drive the ball down the field and score either a touchdown (6 points) or field goal (3 points) while the opposition defense attempts to prevent them from doing so. The winning team is the one that accumulates the most points at the end of the match.

From a physical perspective, these game requirements consist of brief high-intensity bouts of activity followed by periods of recovery (which serve to set up the team tactics for the next play) (Iosia & Bishop, 2008). During these rest intervals the offense will substitute players out of the game to set up a play that offers them the best opportunity to gain yards and move closer to the goal line. Conversely, the defense reacts to these substitutions by rotating their players out of the game to provide them with the best possible match up against the offense. While these descriptions provide some detail surrounding the activities completed by players during the game they are limited in their ability to provide any insights specific into the physical loads imposed on the players during competition.

The physical demands of American football have been investigated in the research literature. This research has attempted to understand the physical requirements of the sport by interpreting data from tests of anthropometric and physical qualities (e.g., speed, agility, power output) of players prior to entering the NFL at the NFL Scouting Combine. Although this information may useful for identifying the broad physical fitness requirements for each specific position group, it is limited in its ability to provide detailed information on the actual physical demand of competition. Such insights are only available through attempts to objectively measure actual in-game physical loads. Recently, the physical demands of American football have been evaluated at the Collegiate level for both training and games (DeMartini et al. 2011; Wellman et al. 2016; Wellman et al. 2017). These investigations have quantified both locomotor and collision-based activities, suggesting that some positions are required to perform larger volumes of running (e.g. WR and DB) while others engage in a greater amount of physical contact and collisions (e.g., DL and OL) (Wellman et al. 2017). Collectively, this information has supported observational accounts of the game reported over two decades ago (Pincevero & Bompa, 1997) that would suggest that the game requires aspects of specific muscle function (e.g. strength and flexibility) and aerobic and anaerobic energy provision. While this information provides an understanding of the physical demands of

American football at the collegiate level it fails to provide any detail regarding the requirements in the NFL, the highest level of the sport.

At the present time little is known about the specific physical demands of participating in American football in the NFL. League rules currently prohibit teams from performing any direct quantification of in-game activities, making it impossible to generate objective data that may enable insights into the types and extent of loads players may need to tolerate. Teams are, however, able to employ load-monitoring strategies in their own training sessions. This may provide an opportunity to collect information that provides some insight into the physicality of the sport for scientific purposes. These monitoring strategies have not however been subjected to high levels of methodological critique making their appropriateness as measurement tools uncertain. As such, a systematic approach to evaluating and modeling the physical demands of training may offer scientists a clearer way of understanding the demands of the sport. Such approaches may also provide practitioners with relevant information that can be used for the planning and implementation of training program design.

## 1.2 Aims and Objectives

The overall aim of this thesis is to examine the physical demands of American football training in the NFL. This aim will be achieved through the following objectives:

1. Determine the utility of integrated micro technology units for quantifying commonly performed actions in American football.
2. Evaluate the usefulness of subjective rating of perceived exertion to quantify American football training.
3. Evaluate between position group differences in on field activities during training.
4. Use a parsimonious statistical approach to help reduce the number of integrated micro technology features when reporting training demands in American football.
5. Describe the periodization strategies of coaches during the in-season period for one American football team.
6. Identify the relationship between training load and injury in one American football team.

# CHAPTER 2

# LITERATURE REVIEW

*This section attempts to appraise pertinent literature that underpins the aims and objectives of the thesis. This chapter has been modeled on the systematic review approach commonly observed in peer-reviewed publications such as Sports Medicine. This strategy has been chosen to support the demonstration of the skills related to critical analysis and the concise presentation of ideas required by publications for this style of scientific communication.*

## 2.1 Introduction

The physiological demands in a variety of football codes have been well described by researchers (Reilly & Gilbourne, 2003; Duthie et al., 2003; Drust et al., 2007; Johnston et al., 2012; Sanctuary et al., 2012). This research has allowed for a greater understanding of training (Moreira et al., 2015; Malone et al., 2015) and match demands (Gregson et al., 2010; Kempton et al., 2013) and has also led to the development of injury prediction models to improve player health and well being (Gabbett, 2010; Gabett & Jenkins, 2011). While the scientific body of research in these sports is well established, less is known about the requirements of American football. At the present time, the scientific literature that has focused on the physical demands of American football is small (Hoffman, 2008). A pubmed search using the term, "AMERICAN FOOTBALL", returned 619 papers (search conducted May 12, 2018). The majority of these 619 papers that are identified are epidemiological studies whose function is primarily to describe injury rates (Dick et al. 2007; Lievers et al., 2015) or the occurrence of brain trauma (Baugh et al., 2016; Clark et al. 2017). Such a number can be compared to the 2797 and 9134 papers that are returned if a pubmed search for either "RUGBY" or "SOCCER" is completed, respectively.

This review will attempt to summarize the current scientific literature specific to the physical demands of American football. This critical analysis of the literature will be completed to provide an overview of the sport and to identify important areas that have the potential for scientific investigation. Literature from other team sports will be discussed where appropriate in an attempt to provide context for some of the concepts and ideas that are relevant to the research themes that are proposed for American football and this thesis in particular.

## 2.2 Conceptual and Theoretical Approaches to Evaluating the Demands of Sport

The physical demands of a sport can be understood through the application of one, or all, of three main methodological approaches: (1) understanding the physical characteristics (e.g., anthropometry, strength, power) of the individuals who participate in the sport; (2) the observation of matches and training; and (3) the monitoring of players during competition or training. These approaches have provided an opportunity for scientists to identify key physical attributes that are specific to the sport (Gabbett et al., 2008) and to quantify the demands associated with both competition (Gregson et al., 2010; Kempton et al., 2013) and preparation (Impellizieri et al., 2005; Moreira et al., 2015; Malone et al., 2015) in a variety of different team sports.  These theoretical approaches may therefore represent a useful starting point with which to investigate the physical demands of American football.

A small amount of research has attempted to use these approaches to describe the sport of American Football.  The majority of these papers have focused on analyzing the physical characteristics of the players (Fry et al., 1991; Secora et al., 2004; Garstecki et al., 2004; Kraemer et al., 2005; Kuzmits et al., 2008; et al., 2003; Teramoto et al., 2016; Pryor et al., 2014). While this type of data, on initial inspection, seems reasonably well reported very little of this data has actually been completed on players at the highest level of play, i.e. those in the NFL. This is an important consideration as the sport at an elite level is different to that observed at sub-elite levels of play. For example, the offensive play at the collegiate level relies more heavily on an up tempo “air raid” type offensive play style, which is not typically performed in the NFL. Such an offensive approach is a consequence of teams employing strategies that have more likelihood of being successful with less skilled players. The lack of research on the game within the NFL therefore would seem to limit the understanding of the sport and its requirements at the highest level of competition. Nevertheless, the available data does provide a broad description of the physical attributes that appear to be important for American football and as such may serve as a useful initial framework with which to understand the physical demands of the sport.

### 2.3.1 Physical Characteristics of American Football Players

Detailed evaluations of the characteristics of different playing positions have primarily come from the completion of various test batteries that have attempted to measure individual players anthropometric and athletic qualities (Fry et al., 1991; Secora et al., 2004; Garstecki et al., 2004; Kraemer et al., 2005; Pryor et al., 2014; Anzell et al., 2011). This data is available largely as a consequence of systematic testing programs completed by the professional league as part of the process to identify talent. The NFL Scouting Combine represents the most common testing battery of anthropometric and physical tests as it serves a practical purpose of profiling players entering the NFL draft (Kuzmits et al., 2008; Robbins, 2011; Terramoto et al., 2016). Testing at the NFL Combine consists of medical evaluations, anthropometric measurements (e.g., height, bodyweight, wing span, hand size), physical performance testing (e.g., Vertical and Broad Jump, 36.6m Sprint, Bench Press, and Change of Direction Tests), position specific drills (e.g., drills designed by coaches that are specific to what they believe players within a given position might perform during a game), and a psychological test called the Wonderlic Test (Kuzmits, et al 2008). While limited evidence exists regarding the ability of such test batteries to predict on field physical performance (Kuzmits et al., 2008; Wolfson et al., 2011; Mulholland & Jensen, 2014; Teramoto et al., 2016; Robbins, 2010; Lyons et al., 2011; see below for detailed discussion) coaches, scouts, and managers use this information to profile players they might be interested in drafting for certain position groups in their player rosters (McGee & Burkett, 2003; Sierer et al., 2008; Robbins, 2010; Mullholand & Jensen, 2014). This approach is in keeping with the theoretical position that understanding the requirements of certain position groups, through measurable physical qualities such as speed, size, or power output, may give a useful insight into the characteristics required to fulfill the demands of the sport.

Physical testing conducted on players at the NFL Combine has revealed that anthropometric and athletic characteristics can vary considerably between positional groups, regardless of the level of play (Garstecki et al., 2004; Kraemer et al., 2005; Anzell et al., 2011; Robbins, 2011) (**Figure 2.1 & Table 2.1**). These differences may therefore highlight physical attributes that are specific to each positional group and hence may reflect subtle differences in the demands associated with each position (Robbins, 2011). It has been suggested that players in position groups that oppose each other on offense and defense share similar physical characteristics, reflecting a potential mirroring of their physical demands (Kraemer et al., 2005; Robbins, 2011; Bosch et al., 2014; Dengel et al., 2014). For example, compared to Backs [Offensive and Defensive Backs], Linemen [Offensive and Defensive Linemen] are heavier in terms of body mass (Garstecki et al., 2004), perform worse in tests of speed, vertical jump, and change of direction abilities (Robbins, 2011), but have greater absolute strength (Mayhew et al, 1987; Fry & Kraemer, 1991; Black & Roundy, 1994; Pryor et al., 2014). Conversely, wide receivers, running backs, and defensive backs tend to be leaner, and possess greater speed, vertical jump, and change of direction abilities (Robbins, 2011). Linebackers and tight ends possess a blend of size, speed, change of direction ability, and strength thereby placing their physical abilities between those of linemen and backs (Garstecki et al., 2004). Broadly speaking, these physical attributes offer a general understanding of the athletic qualities necessary to play the game at the highest level but provide no direct link to how these qualities manifest themselves on field play in match-play.

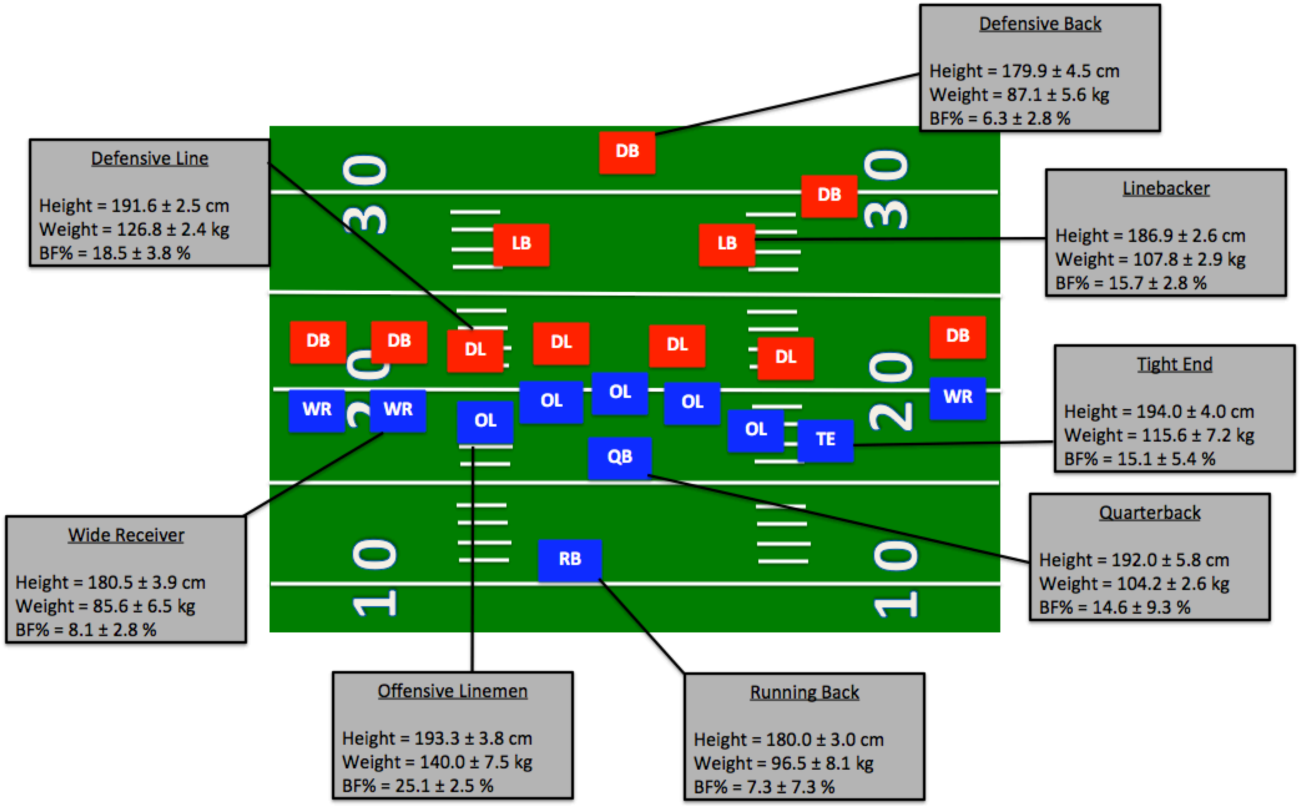


**Figure 2.1.** Anthropometric qualities of NFL players in specific positional groups according to Pryor et al (2014). Differences among positional groups highlight attributes that may be relevant for the tactical demands of each group. (BF% = Body fat percentage).

**Table 2.1.** Athletic qualities tested on players at the NFL Combine (2011 – 2015). (Data from: http://nflcombineresults.com/nflcombinedata.php)

| Position | 36.6 m (40 yard) Sprint (s) | Vertical Jump (cm) | Broad Jump (cm) | 18.3 m (5-10-5) Shuttle (s) | 3 Cone Drill (s) | 102 kg (225 lb) Bench Press (reps) |
|---|---|---|---|---|---|---|
| Defensive Backs | 4.53 ± 0.09 | 89.8 ± 6.18 | 307.0 ± 14.4 | 4.16 ± 0.13 | 6.91 ± 0.19 | 16 ± 4 |
| Defensive Line | 4.95 ± 0.22 | 78.6 ± 9.2 | 279.0 ± 20.3 | 4.53 ± 0.20 | 7.42 ± 0.32 | 27 ± 6 |
| Linebackers | 4.71 ± 0.14 | 86.2 ± 7.81 | 297.0 ± 16.0 | 4.30 ± 0.14 | 7.13 ± 0.22 | 23 ± 5 |
| Offensive Line | 5.25 ± 0.17 | 70.6 ± 7.12 | 258.5 ± 16.8 | 4.73 ± 0.18 | 7.80 ± 0.28 | 26 ± 5 |
| Quarterbacks | 4.79 ± 0.19 | 81.4 ± 8.31 | 286.6 ± 18.8 | 4.29 ± 0.17 | 7.04 ± 0.21 | NA |
| Running Backs | 4.56 ± 0.12 | 89.0 ± 7.31 | 301.1 ± 13.6 | 4.25 ± 0.14 | 7.02 ± 0.19 | 21 ± 4 |
| Tight Ends | 4.76 ± 0.17 | 84.6 ± 7.81 | 291.9 ± 14.6 | 4.40 ± 0.14 | 7.15 ± 0.20 | 21 ± 4 |
| Wide Receivers | 4.50 ± 0.09 | 90.3 ± 7.95 | 306.0 ± 13.9 | 4.20 ± 0.15 | 6.91 ± 0.20 | 15 ± 5 |

Despite NFL Combine data being collected since 1982, debate still remains regarding the ability of these tests to predict future NFL success (Kuzmits et al., 2008; Wolfson et al., 2011; Mulholland & Jensen, 2014; Teramoto et al., 2016; Robbins, 2010; Lyons et al., 2011). For example, Teramoto and colleagues (2016) found faster 9.1 m sprint times to be predictive of greater rushing yards per attempt and vertical jump performance to be associated with greater receiving yards per reception in NFL running backs and wide receivers, respectively. However, these results have not been consistent across studies. Kuzmitis and colleagues (2008) found the 36.6 m sprint to be the only test of predictive of future success in one positional group (average yards per carry in running backs) while Sawyer and colleagues (2002) found vertical jump to be predictive of coaches' subjective rankings of the player's performance (football playing ability). These inconsistent findings suggest that the relationship between physical qualities, as evaluated using generic tests of function, and performance is complex. This may be a consequence of a number of factors related to the tests such as non-sport-specific testing batteries and a lack of understanding regarding the specific type of assessment that may evaluate the specific physical qualities that make up successful position players. It may also be related to the incorrect assumption that such measured physical traits would have a large correlation with team sport success given the multitude of interactions between the athlete, their teammates, and their opponent (Lames, 2007). This represents an inherent limitation in this conceptual approach towards understanding the demands of the game.

### 2.3.2 Observational Analysis of American Football

Research that is predominantly observational in nature has provided useful descriptions of the movement activities that take place during American football. It has also provided detail on other aspects of the activity profile relevant to the demands of the sport such as the exercise-to-rest ratio during competition (Pincevero & Bompa, 1997; Rhea et al., 2006; Iosia & Bishop, 2008). If this data is examined closely it can be seen that American football is a collision-based sport that at a fundamental activity level consists of brief bouts of high-intensity actions separated by periods of rest (used predominantly to set up the next play) (Iosia & Bishop, 2008; Hoffman et al., 2008). These within-play actions include a variety of locomotor and collision-based tasks (e.g., accelerations, decelerations, maximal sprinting, backpedaling, cutting, jumping, explosive muscle actions to evade, and blocking and tackling of opposing players) (Pincevero & Bompa, 1997). From an ergonomics standpoint, there seems to be some position specificity to the movement patterns performed as observations of the game have indicated that linemen collide with each other in movements to block and tackle during each play while Running Backs, Wide Receivers, and Defensive Backs perform greater amounts of sprinting, change of direction, and agility type movements (Pincevero & Bompa, 1997). Linebackers and Tight Ends are versatile players and perform a variety of game demands reflected in both collision and locomotor activities (Pincevero & Bompa, 1997). This type of information would seem to provide a useful initial starting point for the understanding of the positional demands within the game.

Unfortunately, such subjective descriptions provide little information to improve our understanding of the physiological aspects of training and competition. These findings may also be limited by the fact that they are relatively old (were made 20 years ago) and thus may not adequately reflect the contemporary requirements of the game (Elferink-Gemser et al., 2012).

Evaluating the exercise-to-rest ratio of game activities provides a way of understanding the energetic demands of sport. Observations of exercise-to-rest ratio in American football have been made by scientists watching game film and using a stopwatch to quantify play duration and time between plays (Iosia & Bishop, 2008). The average play duration in NCAA games was found to be 5.2 ± 1.7 s with run plays [a play where the quarterback hands the ball off to the running back or runs the ball himself] observed to be shorter than pass plays [a play consisting of a pass from the quarterback to a wide receiver, tight end, or running back] (4.86 ± 1.4 s compared to 5.6 ± 1.7 s respectively). The average rest between plays is approximately 6 times longer (i.e., 36.1 ± 6.7 s) (Iosia and Bishop 2008). This exercise-to-rest ratio seems to be relatively consistent across levels of the sport as Rhea et al. (2006) noted play and rest durations of 5.7 s and 35.2 s in NFL games. While these data provide context around the exercise-to-rest requirements of the sport, which may provide some information on the dominant energy systems used to support the activity, they lack clear descriptions of the physical actions of players within their respective positional groups. For example, these exercise and rest ratios will be composed of different actions for different players with some players performing a greater amount of running (DeMartini, et al., 2011; Wellman et al., 2016) compared to others who engage in more collisions and impacts (Wellman et al., 2017). They also lack direct physiological measurements that may measure the body's responses to these exercise bouts. As such the evaluation of exercise-to-rest ratio alone may lack any real ability to clearly reflect the energetic demands and different metabolic requirements during training.

### 2.3.3 Physiological Measurements Associated with the Demands of American Football

Research has described the physiological responses during both training and competition in a variety of team sports (Gregson et al., 2010; Johnston et al., 2012; Austin et al., 2013; Kempton et al., 2014). Because this type of research takes place during the actual sporting activity, it allows for a highly ecological evaluation of the physical demands of the activities. This permits a more detailed understanding of the physiological requirements that underpin performance in the sport. This may enable the broader application of these demands to considerations such as the design of training sessions (Torres-Ronda et al., 2016). Much of the available data relating to physiological measures in American football have been aimed at evaluating markers of muscle damage as a means of understanding the consequences of game (Hoffman et al., 2002; Hoffman et al., 2005; Kraemer et al., 2009; Sterczala et al., 2014). While these data suggests that a combination of locomotor and collision activities can lead to a substantial amount of muscle damage following competition in collision-based sports (Smart et al., 2008;

McLellan et al., 2010) it does not in itself provide any detail on more relevant physiological markers of the demands of the sport such as the contributions of different energy systems. Measurements of blood and salivary markers, amongst other physiological indicators may provide additional information regarding the physical consequences of the game but such markers have not been evaluated in any detail with respect to either positional and/or individual differences within American football. This is probably a consequence of the practical difficulties in obtaining such measurements in the sport. Detailed investigations of the relationship between on-field actions and a range of physiological measurements have therefore yet to be explored within American football. Such research may prove useful in helping to quantify the requirements of the sport both in general terms and in relation to specific playing positions.

### 2.4.1 Training and Physical Preparation for Sport

The previous section of the literature review has outlined the major physical characteristics required by individual players to fulfill the demands of the sport. While it is acknowledged that an individual's genetic predisposition may play a role in determining the physical characteristics of an individual athlete (Heffernan et al., 2016) systematic training is a fundamental process that allows the athlete to tolerate competition demands (Morgans et al., 2014). Despite the availability of specialists in the area of physical preparation in team sport organizations this type of preparation is still often dictated by the head coach as part of the overall training strategy required for them to prepare the team for upcoming competition (Malone et al., 2015; Weston, 2018) as such training programs in team sport can often be based on a holistic performance model. Irrespective of this generalized view such programs do still require a balance between the training that is completed to improve the physical fitness for the sport, periods of regeneration for adaptation, and that which prepares the athlete for the technical and tactical requirements of the game. A carefully considered training plan should attempt to balance these requirements across important time periods related to competition (e.g. the time between games) (Anderson, 2016).

### 2.4.2 Conceptual Models for the Organization of Structured Training Plans: Periodization

The theoretical basis for planning training is fundamentally centered on the athlete's exposure and tolerance (adaptation) to a given training stress. This theoretical model of training was originally adapted from Han's Selye's General Adaptation Syndrome, which describes the body's general response to any type of stressor (Selye, 1956). Newer research, however, has indicated that the way in which such training stressors lead to fitness improvements is complex, highly individualized, and not as "general" as Selye once believed (Kiley, 2017). This newer approach to conceptualizing the training process accounts for the role that factors such as genetics, training history, nutritional status, and psycho-emotional outputs play in the inter-individual responses to adaptation (Kiley, 2017). The relationship between an athlete's cycle of stress and adaptation in theory enables a specific time course of stress and recovery to be planned. The implementation of this plan in a systematic approach within sport has been termed “periodization” (Wathen et al., 2008).

Periodization represents the formal process of altering training variables (e.g., intensity, duration, volume) to create long-term adaptations in strength and fitness (Wathen et al., 2008). Structured periodization establishes discrete phases of training across the competitive year with specific physiological goals to be planned (Gamble, 2006). These phases are built in sequence to establish periods of increased training demand (via the manipulation of factors such as intensity or volume) and periods of unloading (to remove stress and dissipate fatigue). Periodisation around long-term cycles (e.g. a calendar year) is referred to as macro-cycle periodization. Smaller planning units, known as meso-cycles, represent shorter discrete blocks of time (e.g., 4-6 weeks). These meso-cycles when combined will collectively make up the macro-cycle. Within the team sport environment, common meso-cycles are the off-season, pre-season, and in-season phases (Gamble, 2006; Wathen et al., 2008). These meso-cycles can be further subdivided into smaller sections, each with a specific focus (Malone et al., 2015). A meso-cycle is typically comprised of micro-cycles, which represent the shortest period of time within the training plan (e.g., one-week). The micro-cycle is of critical importance in team sports as it reflects a team’s preparation leading into the next match (Malone, et al., 2015). While this information reflects the broadly held beliefs about planning training in sports such as American football there is currently little research data that has evaluated the application of this model to real world settings.

The existence of real world season long periodization models have been evaluated within several team sports (Manzi et al., 2010; Moreira et al., 2015; Malone et al., 2015; Ritchie et al., 2016). Generally, the pre-season period is comprised of greater training load and volume than the in-season period (Jeong et al., 2011; Moreira et al.; 2015, Ritchie et al., 2016). Such differences observed in training load between the pre- and in-season periods are thought to be due to the increased emphasis coaches' place on the physiological conditioning that can support the athletes' performance through the in-season phase (Jeong et al., 2011). Within the competitive season much of the intensity component of the physical load seems to be contained within each weeks competitive performance (Manzi et al., 2010; Moreira et al., 2015; Anderson et al., 2015). These weekly matches therefore seem crucial in shaping the structure of weekly micro-cycle periodization during the in-season phase (Impellizzeri et al., 2004; Manzi et al., 2010; Malone et al., 2014; Anderson et al., 2015). This importance of match-play is also supported by the modification of training loads on the days that immediately precede and follow the competition. For example, days leading up to the match were observed to have significantly lower training load than the days furthest from the match for one elite Premier League Football Club (Malone et al., 2014; Anderson et al., 2016). This data would therefore appear to suggest that there is some systematic adjustment of training load across time periods though the use of comprehensively structured periodization models in the truest sense in team sport have been questioned (Morgans et al., 2014). This may particularly be the case within the sport of American football where no data currently exists at the highest level of play that describes approaches to training preparation strategies.

The only research available that currently describes periodization within American football relates to the strength and conditioning practices used within the sport (Ebben & Blackard, 2001; Hoffman et al., 2003; Kraemer et al., 2015). Results from a 2001 survey of strength coaches in the NFL revealed that 69% of the 26 strength coaches who responded to the survey indicated that they followed some form of periodization model (Ebben & Blackard, 2001). The typical periodization structure reported for both resistance training and running programs was one whereby the off-season phase consisted of a high volume of training at a lower intensity (e.g., 2-3 sets x 15-20 reps) (Ebben & Blackard, 2001). As the training progressed closer to the competitive season, the intensity of exercises and running increased while the total volume decreased (Ebben & Blackard, 2001). These findings indicate that like other team sports some form of meso-cycle periodization structure seems to be used within the sport. This data is however, limited by its description and its limited focus (i.e. only described for resistance training and conditioning based sessions). The importance of this data is also further restricted by the lack of objective quantification. This absence of such of information regarding the periodization strategies of on-field training makes it challenging to fully understand the physical demands of the training week and the implications it may have on match performance.

### 2.4.3 Analytical Approaches to Evaluating Periodization

The understanding of periodization in team sports from the available research studies is partly determined by the analytical approaches used to describe and interpret the data. Analytical procedures are typically focused on making discrete comparisons between specific time periods of the training cycle. For example a comparison of pre- and in-season phases of training or between different meso- (e.g., 4-week blocks of training) or micro-cycle (e.g., 1 week blocks of training) phases (Jeong et al., 2011; Moreira et a., 2015; Ritchie et al., 2015; Malone et al., 2015). While such analysis reflects the differences that are observed in training demands between these phases it neglects to take into account the reality that such data is generated in time series (e.g., repeated measures taken on athletes over time). Given the fact that periodization and planning are fundamentally centered on the inter-play between stress and adaptation, it may be more appropriate to analyze such data using approaches that are more relevant for serial measurements and that may better reflect the athletes' physical changes overtime (Matthews et al., 1990; Weston et al., 2011). Such an approach may not just have more relevance from a scientific perspective but be useful for practitioners by providing a basis to better understand the rate at which adaptations are taking place in the athlete, potentially aiding to influence training program development. This analytical approach may provide a more flexible approach to the application of the basic components of periodization. This would provide the athlete with the training dose that is most appropriate based on how they have responded to previous training loads (Kiely, 2012).

## 2.5 Physical Consequences of Competing in Elite Sport

Better understanding the individual adaptive response to any training stimulus would in theory increase the likelihood of a positive training outcome (i.e. an increase in capability) and negate the potential for process to be maladaptive. The interaction between training stimulus and outcome has previously been investigated by quantifying the dose-response relationship in training repetitions using models of fitness and fatigue. Originally, such fitness-fatigue models were designed for endurance athletes (Calvert et al., 1976). These models were then applied to other sports, specifically training and competition in team sports (Reilly, 1997; Deutsch et al., 1998). More recently, such approaches have been linked more specifically with injury risk (Hulin et al., 2014; Malone et al., 2017). An understanding of the consequences of training is fundamental to the training process as they reflect the outcome of the process of planning. This is especially useful in a sport such as American football where the injury risk has been found to be higher than other team sports (Hootman et al., 2007). Positive training outcomes may therefore be an important component of injury avoidance and successful performance. Currently, no information exists regarding the relationship between training demands and injury risk in the NFL. Wilkerson et al (2016) recently evaluated training related injuries suggesting that training load, more specifically a consistent training load with little variation over time may increase the likelihood of injury in collegiate American football athletes (Wilkerson et al., 2016).

### 2.6.1 Approaches to Training Load Monitoring in Applied Sports Science

In an attempt to better understand the health and performance of athletes, the scientific community has looked to a variety of monitoring strategies to quantify the training process (Halson, 2014). Briefly, player monitoring may include methods to quantify activity (Aughey, 2011; Gregson et al., 2010; Dellaserra et al., 2014; Kempton et al., 2014), the physiological responses to that activity (Foster et al., 2001; Impellizzeri et al., 2004; Jeong et al., 2011; Clarke et al., 2013), and the adaptation to match and training demands (McLean et al., 2010; Thorpe et al., 2015; Thorpe et al., 2016). Collectively, these monitoring approaches have been developed to aid team sport practitioners in evaluating the dose-response relationship between the performed training loads and the athlete's ability to adapt to the training demands.

The dose-response relationship to training was originally proposed by Banister and colleagues (1975) to model the athlete's fitness and fatigue adaptations over the course of a training program. This model was initially conceptualized for an elite swimmer (Baniseter et al., 1975; Calvert & Bannister; 1976) and later extended to sedentary subjects performing cycle ergometer training (Busso et al., 1991). Training outcomes may be easier to model in these types of individual exercises where simple physiological measurements can serve as a basis for evaluating the dose-response relationship. As such, the applicability of this model to team sport is less clear given the range of training demands, tactical requirements, and the fact that the opposition can influence an athlete's performance in competition regardless of their physical preparation leading into the match.

Despite the above limitations in team sport athletes, Impellizzeri and colleagues (2005) have proposed a model of the training process, which identifies the interaction between the dose of training performed (external load) and the athlete's individual response (internal load). This training load model has been widely adopted in team sport as a means of providing data to describe performance outcomes, positional differences, or changes to the training program that take place overtime (e.g., periodization) (Moreira et al., 2015; Gregson et al, 2010). However, such an approach is not without limitation, as discussed in the subsequent section.

### 2.6.2 A Critical Commentary on the Internal and External Training Load Relationship in Team Sports

The current scientific literature differentiates between two types of training load – internal training load and external training load (Impellizzeri et al., 2005). Internal training load has been described as the athlete's physiological response to a given training stimulus (Foster et al., 2001; Impellizzeri et al., 2005; Halson, 2014) and can be quantified through methods such as session rating of perceived exertion (sRPE) and Heart Rate

(HR) (Foster et al., 2001; Impellizzeri et al., 2005; Halson, 2014). Conversely, external training load describes the athlete's physical output during training and competition (Aughey 2011; Dellaserra et al., 2014; Halson, 2014). In team sport athletes, external training load is frequently quantified through the use of integrated micro technology (Global Position System (GPS), accelerometer, and gyroscope) (Aughey, 2011; Boyd et al., 2013, Cummins et al., 2013; Halson et al., 2014).

This dichotomous breakdown of training load monitoring was born out of endurance sport athletes (Foster et al., 1996) and has been adopted in the team sport setting as a means of understanding and describing training loads (Impellizierri et al., 2004). However, upon further inspection, this approach may not be fully representative of the complexity of the training process within team sports. For example, in endurance sports, the external load is fixed (e.g., ride or run a specific distance at a specific pace) while the internal response is then evaluated (e.g., HR, Lactate, sRPE). This type of approach, while commonly accepted in team sport, is complicated by the fact that the external load is not fixed across all players. For example, the activity completed can depend on the context of the drills performed within the training session and/or the specific positional requirements. Additionally, different types of external training load (e.g., sprinting, change of direction, collisions) may elicit different physical responses, which potentially influence internal training load in different ways. As such, this type of variety in external load creates specific individual outputs for the athletes for each training activity as well as individual responses in internal load based on the stress imposed.

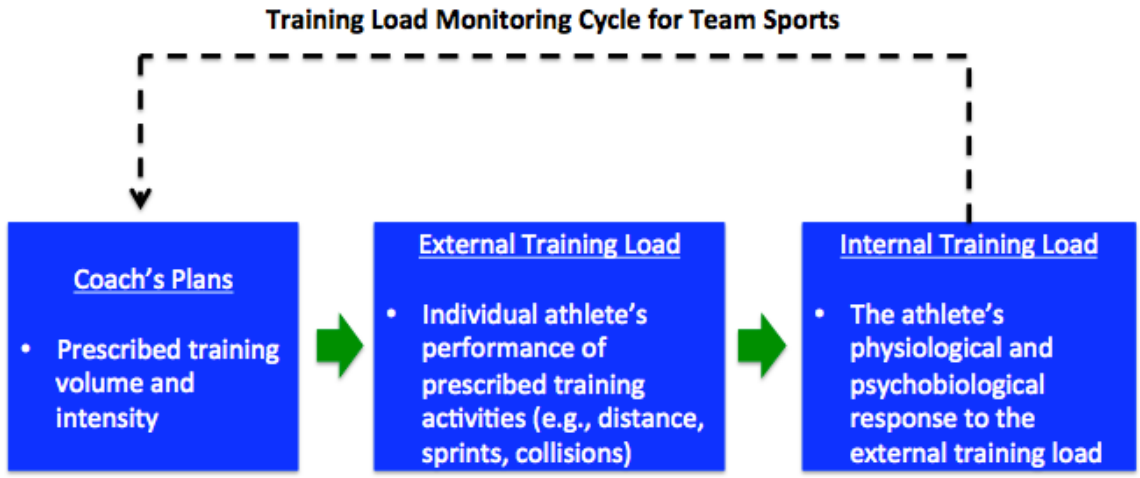


**Figure 2.2.** A comprehensive model for training load monitoring in team sport. This model considers the coaches prescription of training, the external training load based on how the individual performs the prescribed training, and the individual's physiological and psychobiological response to the external training load (internal training load).

This relationship is made further complex in collision sports as a consequence of the performance of sport-specific actions such as collisions and tackles, which will also be highly individual. These ideas are in line with contemporary models training load monitoring (Vanrenterghem, 2017). For these reasons, a more comprehensive model of training load monitoring seems relevant. This model would suggest that the coach plans and prescribes training for the team while the external load represents how the individual athlete performs this prescribed training, based on the context of their position specific activity profile (e.g., distance run, sprints, collisions).

Finally, internal load represents the individual athlete's physiological (e.g., HR) and psychobiological response to the prescribed training session (**Figure 2.2**).

### 2.6.3 Subjective Measures of Training Load Monitoring in Collision Sport

Evaluating the athlete's response to the training session and the activities that the individual performs is an important component of any training model. In team sport approaches to athlete monitoring have included subjective assessments of training load such as sRPE, the measurement of the physiological responses to exercise such as heart rate monitoring and the use of wearable integrated micro-technology units (Impellizzieri et al. 2004; Cardinale and Varely, 2017). Session rating of perceived exertion is one of the most well documented methods of quantifying internal load from a given training session and has a strong relationship with other indicators of the internal training response such as Banister's TRIMP ($r = .5 – .77$), Edwards' TL ($r = .54 – .78$), and Lucia's TRIMP ($r = .62 – .85$) (Impellizzeri et al., 2004). The lack of equipment needed to collect and analyze the data makes it a simple and cost-effective solution to monitor athletes (Impellizzeri et al., 2004). Athletes are asked to rate their perceived intensity of the training session using the Borg CR10 scale (Borg et al., 1987; Foster, 1998; Foster et al., 2001). This subjective rating is then multiplied by session duration, in minutes, to produce the daily training load in arbitrary units. Session RPE training load has been found to be an effective measure of internal training load in soccer (Impellizzeri et al., 2004; Scott et al., 2013; McLaren et al., 2018) and Canadian football (Clarke et al., 2013), a collision sport similar to American football, when compared to heart rate response. The use of sRPE in American football has not however been formally evaluated from a research perspective. While its application to the sport may be intuitive its use may be questionable given a number of important considerations that are specific to the sport. For example, the low volume of running and metabolic activity performed by several of the positional groups (Wellman et al., 2016) may mean that the usual relationships between the exercise that is completed, and the internal response do not hold. Additionally the large numbers of individuals involved in the squads may impact the utility of this approach through excessive variability in the data.  Another issue in American football for sRPE is the collision situations that exist within training and games. Recent research has suggested that sRPE may in fact be a useful marker of internal training load in sports that include collisions (Clarke et al., 2013; Johnston et al. 2015). For example, in Canadian football players sRPE was determined to be an accurate measure of internal training load when compared with two HR derived measures, Polar TRIMP ($r = 0.65 – 0.91$) and Edwards' TL ($r = 0.69 – 0.91$) (Clarke et al., 2013). This evidence while superficially useful may not however provide a strong rationale for the utility of sRPE as these relationships are not specifically generated for the collision component of the activity per se but rather the overall training load (i.e. collisions and movement demands). The relative disproportionate nature of collisions to movements in these circumstances may suggest that such models cannot accurately reflect the influence of collisions on the internal training load.

### 2.6.4 GPS Tracking for Monitoring External Load in American Football

The athlete's individual external training load relative to the coach's prescription of training can be quantified through the use of integrated micro technology (Global Position System (GPS), accelerometer, and gyroscope) (Aughey, 2011; Boyd et al., 2013, Cummins et al., 2013; Halson et al., 2014). These technologies provide a direct measure of the athlete's physical output allowing for quantification of both movement profiles and impacts during collision sports (Wisbey et al., 2010; Boyd et al., 2013; Cummins et al., 2013; Gabbett, 2015). GPS technology has been used for over a decade in professional team sports as a means of describing locomotor activity (Cardinale & Varley, 2017).

The reliability of commercially available GPS systems has been evaluated during various running tasks (Edgecomb et al., 2006; Coutts & Duffield, 2010; Castellano et al., 2011; Johnston et al., 2014; Rampinini et al., 2014). Castellano and colleagues (2011) found good accuracy of sprint distance and intra-device reliability for both 15 m (CV = 1.3%) and 30 m (CV = 0.7%) maximum effort sprints performed by 9 male athletes when using 10 Hz GPS devices. These findings suggested less variation in measured running distance when compared to earlier work from Coutts and Duffield (2010), who observed a CV of 3.6% to 7.1% for total distance when performing a standardized field circuit while using a 1 Hz GPS device. Additionally, 10 Hz GPS devices had better accuracy when measuring total distance (%TEM = 1.3) and peak speed (%TEM = 1.6) compared to units sampling at 15 Hz (%TEM for total distance = 1.9; %TEM for peak speed = 8.1) (Johnston et al., 2014). In collision sports, GPS tracking has recently been used as a means of categorizing locomotor activity (Hiscock et al., 2012; Chambers et al., 2015), classifying training drills (Loader et al., 2012; Boyd et al., 2013), and quantifying match demands (Wisbey et al., 2010; Wellman et al., 2016). Given the broad range of movement demands observed in American football (Picevero & Bompa, 1997), GPS may be useful for identifying the overall movement demands and quantifying between position group differences in activities within American football.

The locomotor demands in both games and training sessions have been evaluated within collegiate American Football athletes (DeMartini et al., 2011; Wellman et al., 2016). The first report of GPS in American football was focused on determining positional demands during NCAA football practice (DeMartini et al., 2011). DeMartini and colleagues (2011) classified 8 football position groups into two broad categories - linemen (defensive line, offensive line, and tight end) and non-linemen (defensive backs, linebackers, quarterback, fullback, and running back). Non-linemen performed more total distance and high-speed distance than linemen (DeMartini et al., 2011). These differences in running volume and intensity are in agreement with what has been recorded during collegiate football games. Wellman and colleagues (2016) found defensive backs and wide receivers performed greater total distance (5531 ± 997 m and 4696 ± 1,115 m, respectively), sprints (12.7 ± 5.7 m and 10.6 ± 4.3 m, respectively), maximal accelerations (21.9 ± 8.1 and 20.9 ± 8.6, respectively), and maximal decelerations (15.8 ± 5.4 and 14.0 ± 6.1, respectively) compared to other position groups. While these data suggest positional differences with regard to the running demands of the sport the output from GPS alone may not be suitable for the quantification of all aspects of the demands required of players. This may be specifically the case for actions such as collisions and other non-running actions (e.g., accelerations, decelerations, and jumping) (Dalen et al., 2016; Akenhead et al., 2016, Wellman et al., 2017) and tracking movements in small spaces (Jennings et al., 2010; Duffield et al., 2010) or movements over short distances (Castellano et al., 2011) and high velocities (Rampinini et al., 2014; Vickery et al., 2014; Akenhead et al, 2014). This may suggest that alternative methods of quantifying athlete collisions and other non-running activities may be required when attempting to describe the demands placed on some position groups, within American football, especially those that perform less running volumes than others (e.g., offense and defensive linemen).

### 2.6.5 The Use of Inertial Sensors to Evaluate Non-Locomotor Activities in American Football

To assist with the capture of on field movements and to offset some of the limitations of GPS described above, the data provided by integrated microtechnology systems are often combined within data from the indwelling inertial sensors (e.g., accelerometers, gyroscopes, and magnetometers). Inertial sensors sample at a higher rate that GPS sensors (100 Hz) and provide the ability to quantify accelerations taking place on 3 axes of movement (x, y, and z), angular velocities, and direction of movement. These inertial sensors can therefore quantify forces coming from all actions, not just locomotor tasks, and as a consequence are able to provide information regarding non-running activities (Dalen et al., 2016; Akenhead et al., 2016) and collisions (Gabbett et al., 2010; Gastin et al. 2013; Gabbett, 2015).

One commercially available metric, Player Load, is reported in arbitrary units and is derived by taking the square root of the sum of the squared instantaneous rate of change in acceleration on the 3 axes and dividing by 100 (**Figure 2.3**). This metric was found to have acceptable within- and between-device reliability during controlled oscillation of the accelerometers over 0.5 g and 3.0 g (Within CV = 0.91 to 1.05%; Between CV = 1.02 to 1.04%) (Boyd et al., 2011). Convergent validity has also been established during treadmill running where Player Load was found to have near perfect (r = 0.92 – 0.98) within-subject correlation to $VO_2$ max and average heart rate (Barrett et al., 2014). Aside from these lab-based tests, accelerometer units have also been evaluated during sports tasks. In the field, Player Load been shown to have acceptable between-device reliability during Australian football matches (Between CV = 1.9%) (Boyd et al., 2011) and moderate to large test-retest reliability during various ice hockey tasks

(Van Iterson et al., 2017). The placement of the accelerometer unit should be noted, as it has been shown that trunk-worn accelerometers (commonly used in practice) may not reflect ground reaction forces taking place at the limbs (Nedergaard et al., 2017). Therefore, practitioners should be aware that accelerometer data might not be reflecting whole-body mechanical loading but may still provide useful estimates of acceleration forces in in the applied setting (Nedergaard et al., 2017).

$$\text{Player Load} = \sqrt{\frac{(a_{y1} - a_{y-1})^2 + (a_{x1} - a_{x-1})^2 + (a_{z1} - a_{z-1})^2}{100}}$$

**Figure 2.3.** Player Load equation (Boyd et al., 2011). $a_y$ = forward acceleration, $a_x$ = sideways acceleration, $a_z$ = vertical accelerations.

Unlike GPS, Player Load does not provide a direct measure of distance run or running velocity; however, it does have a strong correlation with distance covered in team sport athletes (Boyd et al., 2010; Polglaze et al., 2015), which may suggest its utility in capturing locomotor-based activities. Player Load has also been evaluated for its ability to differentiate between positional demands in Australian football, quantify collisions in Rugby and quantify tackles in Australian football (Gabbett et al., 2010; Boyd, et al., 2013; Gastin et al., 2013). The ability of inertial sensor data, such as Player Load, to capture a variety of movements in collision-based sports (e.g., running and impacts), indicates it may be a valuable tool for determining the demands, above running activities, between position groups in American football as well as understanding training outcomes, such as injury risk. For example, Wilkerson (2016) and colleagues used Player Load for injury detection in collegiate athletes and concluded that low movement variability during practice (Player Load ≤ 15% CV) and high exposure to game conditions (≥ 289 plays over the season) was associated with a higher risk of injury (OR = 8.04; 90% CI: 2.39 - 27.03). While these findings provide a good initial first look at inertial sensor technology in American football, a more thorough evaluation of the specific ways in which Player Load describes positional movement actions is required to determine its utility within the sport and its ability to evaluate individual outputs relative to the prescribed external training load.

In an attempt to more specifically capture non-running movement such as physical impacts, collisions, and changes of direction derivations of the Player Load metric have also been created (Boyd et al., 2013; Gabbett 2015). For example, 2D Player Load removes the vertical vector from the Player Load equation, allowing for quantification of activities not biased towards upright running (Johnston et al., 2014; Gabbett 2015) while Player Load Slow records lower velocity movements, less than 2 m/s, reflecting the static exertion and contact type movements that collision sport athletes perform (Boyd et al., 2013). While these metrics have been investigated in collision-based sports their use in American football may be questioned. For example, 2D Player Load has been found to have a large correlation with Total Player load (Gabbett, 2015), suggesting that it may be describing a similar type of global training activity rather than anything that is specific to this unique category of movements. Player Load Slow also uses a component of the GPS output in its algorithm and was developed for more static collisions, such as rucking activity in Rugby union (McLaren et al., 2016; Roe et al., 2016). These factors may suggest that this metric may be either inaccurate for these purposes or reflect a movement unique to a different sport. Both of these factors may limit its usefulness in the description of movements performed by linemen (OL and DL) in American football.

Other attempts have been made to quantify collisions through the development of varying algorithms related to impacts. Wellman and colleagues (2017) quantified impacts during 12 NCAA Division I football games using one commercially available system (GPSport). Running Backs were found to sustain the most severe impacts (> 10 g force) while Defensive Tackles sustained the heaviest and very heavy impacts (7.1 – 10 g force) compared to any other offensive or defensive position group (Wellman et al., 2017). However, while the impact algorithms within the commercial systems may seem promising it has been suggested that impact algorithms created for one sport may be limited in their ability to detect similar activities in a different football code (Gastin et al., 2014). For example, Gastin and colleagues (2014) evaluated the tackle algorithm of one commercially available microtechnology system (Minimax S5, Catapult Innovations, Scoresby, Australia) and found it had incorrectly classified 82% of the events detected as a "tackle" during Australian football matches. These impact bands may also have a high correlation with other accelerometer variables (e.g., Player Load) and not therefore may not be adding additional understanding beyond that already attributed to other accelerometer related metrics. Future research should seek to develop a clearer understanding of how these types of accelerometer variables may reflect the requirements of these actions in American football specifically any positional differences with regard to locomotor and collisions-based activities. This type of preliminary research would benefit the scientific community in not only understanding the physical demands of American football but also the relationships between various accelerometer variables within collision-based sports.

## 2.7 Summary

At the present time limited evidence exists with respect to the physical demands of competition and training in American football at the NFL level. To date, much of the scientific work that has been conducted within the sport has been directed at describing the physical characteristics of players on a standardized test battery (NFL Scouting Combine). Beyond providing a relatively simplistic understanding of the general physical make up associated with different playing positions such an approach offers little in the way of a detailed understanding of the physical demands imposed on athletes on a day to day basis. This would seem to suggest that there is a need to complete research that investigates the demands of the sport. Understanding the training demands within the sport seems particularly important as practice represents both a model of the game and the stimulus to which players are most frequently exposed. Understanding the training strategies employed by coaches when preparing a team for competition and the potential consequences of these strategies would also represent a useful basis to identify potential areas to improve athlete health and performance.

The systematic approaches to periodization and planning of training have been previously investigated in various team sports (Moreira et al., 2015; Malone et al., 2015; Ritchie et al., 2016). In American football, such investigations have largely been focused on subjectively describing the resistance training periodization approaches of strength and conditioning coaches (Ebben & Blackard, 2001). These studies suggest that coaches within the sport seem to follow a form of systematic periodization throughout the competitive season. No specific attempts have, however, been made to describe the on-field planning strategies of coaches in the annual cycle. The use of wearable sensors makes it possible for scientists to study training demands in sport and objectively quantify the periodization structure that coaches may follow. Integrated micro-technology has been previously used to explore training demands within sport (Cardinale & Varely, 2017). While such systems have been used in collegiate American football to explore both training (DeMartini et al, 2011) and competition (Wellman et al., 2016; Wellman et al., 2017) there is little methodological underpinning associated with the utility of such measurements and what they may be able to provide regarding training demands in the sport. It would therefore seem useful to establish the basis for the use of such equipment for training load monitoring in American football by first understanding the utility of wearable technologies to capture relevant components of training.  This data may be useful from a methodological perspective for both scientists and practitioners as it may enable more sport-specific monitoring strategies to be developed in the future.

# CHAPTER 3

# AN INVESTIGATION INTO THE UTILITY OF WEARABLE INERTIAL SENSORS TO DIFFERENTIATE FUNDAMENTAL MOVEMENTS AND ACTIVITIES RELEVANT TO AMERICAN FOOTBALL TRAINING

## 3.1 Introduction

Activity demand requirements of team sport athletes vary greatly depending on both sport and positional demands (Wisbey et al., 2010; Cummins et al., 2013; Boyd et al., 2013). Aside from simple locomotor activity (e.g., walking, jogging, running), team sport athletes also perform movements such as accelerations, decelerations, change-of-direction, jumping, and collisions with other players. As such, objective quantification of these movements and their corresponding intensities is required for a detailed understanding of the demands associated with sports. This has led to the development of player monitoring approaches during training sessions (Halson, 2014).

One commonly used approach for quantifying on field movement demands is Global Positioning tracking (GPS) (Halson, 2014; Cardinale & Varley, 2017). While GPS monitoring appears to be most useful for locomotor activities, its reliability decreases with high intensity movements taking place in small spaces (10-20m) (Jennings et al., 2010; Cummins et al., 2013). To circumvent such a limitation, inertial sensors (accelerometer, gyroscope, and magnetometer) have been included in player tracking devices (i.e. integrated micro technology sensors) to quantify activities taking place in smaller spaces, non-locomotor actions (e.g., jumping, change-of-direction), and physical contact with other players, particularly in collision-based sports. Such inertial sensor measures are reliable in both the laboratory (Boyd et al., 2011, Nicolella et al., 2018) and field (Boyd et al., 2011; Meylan et al., 2016) settings. These data are useful to practitioners when attempting to quantify movements besides locomotor activity, particularly in collision-based sport where the addition of physical contact influences the overall training load (Roe et al., 2017).

American football is a collision-based sport consisting of brief bouts of high intensity activity followed by short rest intervals used to set up the next play (Iosia & Bishop, 2008). Research during collegiate games suggests that the physical actions of players are specific to their positional demands (Wellman et al., 2016 & 2017) with smaller, "skill" players (e.g., Wide Receivers and Defensive Backs) performing more running and the larger sized linemen (e.g., Offensive and Defensive Linemen) engaging in more frequent impacts as they collide with one another. While this research directly quantifies match demands, which had only been previously observed up until that point in the scientific literature (Pincevero & Bompa, 1997), no research to date has attempted to identify the ability of such technology to differentiate between different American football activities. Therefore, the aim of this study was to understand whether or not inertial sensors are able to differentiate between a series of fundamental American football activities. Such information may be useful to practitioners to enable them to better understand how specific metrics may be useful in the quantification of different types of on-field movements.

## 3.2 Methods

### 3.2.1 Research Approach

The objective of this study was directed at understanding the utility of inertial sensors for identifying different American football training activities. Six commonly performed American football activities were selected for evaluation as these movements represent the types of activities performed by players during training (e.g., straight line sprinting, backpedalling, decelerating, change-of-direction, and collision). Each participant was assigned an inertial sensor unit containing a 100 Hz accelerometer, gyroscope, and magnetometer (Minimax S5, Catapult Innovations, Scoresby, Australia). These units were worn between their shoulder blades in a custom made shirt, provided by the manufacturer, during all activities.

### 3.2.2 Participants

Three male participants (age: 37.1 ± 1.5 y; 1.83 ± 0.06 m; body mass: 95.9 ± 20.7 kg) were included in this study. Each participant was healthy and free from injury at the time of the study and currently engaged in a weekly training program (minimum 5x/week) consisting of resistance training, sprinting, and change-of-direction activities. Each participant works as a strength and conditioning professional in high level American football and is therefore familiar with the activities selected for this study. All participants were informed of the potential risks of taking part in this study and were provided a written informed consent form prior to their participation.

Ethical approval for this investigation was granted by a local university ethics committee.

### 3.2.3 Experimental Design

The eight positional groups within American football perform a variety of different locomotor and non-locomotor movements based on their tactical demand (Wellman et al., 2015 & 2016). As such, six different exercises were selected to represent some of the fundamental activities performed by each positional group: 36.6 m (40 yard) sprint (Forward Sprint), 9.1 m (10 yard) backpedal (Backpedal), 9.1 m sprint with a 90 degree turn (Sprint with Turn), 9.1 m backpedal – decelerate – 9.1 sprint (BDS), 18.3 m (5-10-5) pro agility shuttle (Pro Agility), Sled Drive (Collision). These actions have been previously observed in game play (Pincevero and Bompa, 1997) and also make up movements that are tested during the NFL Scouting Combine, as a means of identifying future talent (Robbins, 2010).

Exercises were classified as being either 'simple' or 'complex' and grouped into one of three movement categories (Linear, Change-of -Direction, Collision) (**Table 3.1**). The rationale for such a grouping is based on the complexity of the task from a movement perspective, whereby a task including a change-of-direction is more complex and has the potential to require a different demand than a task consisting of only linear based movement. These six activities were performed in the following order: (1) Forward Sprint; (2) Backpedal; (3) Sprint with Turn; (4) BDS; (5) Pro

Agility; (6) Collision. Participants were asked to perform each repetition for a maximal effort and were provided a 5 min recovery period between each activity.

**Table 3.1.** Details of the American football activity classification used in the current investigation.

| Activity | Classification | Movement Category |
|---|---|---|
| Forward Sprint | Simple | Linear |
| Back Pedal | Simple | Linear |
| BDS | Complex | Linear |
| Sprint with Turn | Simple | Change-of-Direction |
| Pro Agility | Complex | Change-of-Direction |
| Sled Drive | Simple | Collision |

***Forward Sprint***

The 36.5 m sprint represents a simple measure of linear speed and is one of the six performance tests completed at the NFL Scouting Combine. Five 36.5 m sprints were performed starting from a two-point staggered stance with a self-selected leg as the forward leg. Participants were provided 3 min of recovery between each repetition.

### *Backpedal*

Similar to the 36.6 m, the 9.1 m backpedal was used as a measure of a simple linear movement, however performed in the reverse direction. This movement was chosen, as it is specific to the type of activity a defensive player (e.g., Linebacker) would make during a play. Participants began in an athletic base stance and performed a maximal backpedal for 9.1 m. Five backpedal repetitions were performed with 3 minutes recovery between each.

### *Sprint with Turn*

The sprint with a right turn was classified as simple change-of-direction activity as it only consisted of one change-of-direction. This exercise was chosen as it mimics similar route running movements that a Wide Receiver or Tight End might perform in a game. During the sprint with right turn, participants began in a two-point staggered stance with a self-selected leg as the forward leg. Participants were asked to sprint forward for 9.1 m and then perform a 90-degree turn either left or right. Participants performed 3 repetitions in both the left and right directions and were provide 3 minutes of recovery between each.

### *BDS*

The backpedal-decelerate-sprint exercise represents the stop-and-start activity of several positional groups in American football and was classified in this study as a complex linear movement. Participants began in an athletic base stance, backpedaled 9.1 m, decelerated themselves, and then sprinted forward 9.1 m. Each of the 3 repetitions was followed by 3 minutes of recovery.

### *Pro Agility*

The 18.3 m pro agility shuttle is a commonly performed change-of-direction test in American football and represents one of the 6 physical output measures tested at the NFL Scouting Combine. Given the high number of change-of-directions per repetition and the intensity of decelerating and accelerating this task was classified as a complex change-of-direction movement. Participants began with their hand on the line in a 3-point stance and started by sprinting 4.6 m either right or left, decelerating themselves and touching the line, sprinting back 9.1 m, decelerate and touching the line, and then sprinting back 4.6 m to the original start line. Participants performed 3 repetitions starting to the right side and 3 repetitions starting to the left side with 3 minutes of rest between each repetition.

### *Sled Drive (Collision)*

The tackle sled drive was used to represent the collision type of activity performed during games. Participants began in a 3-point stance and exploded out of their stance to drive their shoulder into the tackle sled (Rogers Athletic Co.) and then proceeded to drive the sled forward for 5 seconds, to mimic play duration (Rhea et al., 2006; Iosia & Bishop, 2008), before ending their rep at the cue of the primary researcher. Each of the 3 repetitions was followed by a 3-minute recovery. To capture the intensity of the collision, an additional inertial sensor unit was placed onto the tackle sled, using a custom-made shirt from the manufacturer, in the same position it would be in for a human. A complex collision activity was not performed in this study due possible risk of injury to the participants when doing a live tackling drill.

### *Inertial Sensor Variables*

Three inertial sensor variables were used to quantify exercise activity (Minimax S5, Catapult Innovations, Scoresby, Australia). Total Player Load (PL) was used to quantify the volume of activity performed in each of the movements. PL has been used to track movements during a variety of team sport activities (Boyd et al., 2011; Van Iterson et al., 2017) and has been found to have a very large correlation ($r = .868$) with total running distance (Polglaze et al., 2015). Inertial movement analysis (IMA) was used to quantify the frequency of accelerations occurring in four directions (forward, backward, left, and right) above $3m \cdot s^{-2}$. IMA been used to represent intense movements taking place in small spaces during team sport competition (Meylan et al., 2016; Peterson et al., 2017) and may be a useful metric for identifying non-locomotor tasks inherent to American football (e.g., changes of direction). Finally, a count of the number of Impacts was quantified as any discrete acceleration actions taking place over 5g. Given the collision-based nature of the sport, a count of impacts is useful for quantifying the demands placed on the larger players who frequently collide with one another.

### 3.2.4 Statistical Analysis

Data are presented as mean ± SD. Comparisons between movement activities were made by calculating a t-statistic (Difference/SE) for the three inertial sensor variables. This t-statistic was converted to a probability via the corresponding t-distribution (Barrett et al., 2018). The magnitude of difference between movement activities was interpreted in reference to threshold values specific to each inertial sensor variable, represented as 1 * between-subject standard deviation. Differences were reported along with 95% CI and interpreted using a magnitude-based inference approach whereby differences were "positive", "negative", or "trivial". The probability of the observed effects was assessed as being "possibly" (25-75%), "likely" (75-95%), "very likely" (95-99.5%), and "most likely" (> 99.5%) (Batterham & Hopkins, 2006). In the event that the probability exceeded 5% in both the positive and negative directions, effects were reported as "unclear", indicating that no discernable difference could be detected (Batterham & Hopkins, 2006). All statistical analysis was performed in R statistical software (Version 3.3.4).

## 3.3 Results

The mean ± SD for each drill are displayed in **Table 3.2**. During the Forward Sprint, PL was most likely greater than Collision, BDS, Back Pedal, Sprint with Turn, and Pro Agility activities. Additionally, BDS (complex linear task) had a likely larger PL than the Collision activity and a possibly larger PL than Back Pedal (**Figure 3.1**).

**Table 3.2.** Mean ± SD of Player Load (au), IMA, and Impacts occurring during fundamental American football movements.

| Activity | Classification | Movement Category | Player Load (au) | IMA | Impacts |
|---|---|---|---|---|---|
| Forward Sprint | Simple | Linear | 9.46 ± 1.79 | 0.07 ± 0.26 | 0 ± 0 |
| Back Pedal | Simple | Linear | 2.48 ± 0.69 | 0.07 ± 0.26 | 0 ± 0 |
| BDS | Complex | Linear | 5.23 ± 0.53 | 0.33 ± 0.5 | 0 ± 0 |
| Sprint with Turn | Simple | Change of Direction | 4.68 ± 0.59 | 0.83 ± 0.38 | 0.06 ± 0.24 |
| Pro Agility | Complex | Change of Direction | 4.42 ± 0.51 | 1.44 ± 0.7 | 0.06 ± 0.24 |
| Collision | Simple | Collision | 2.15 ± 0.86 | 0.28 ± 0.46 | 1.33 ± 1.57 |

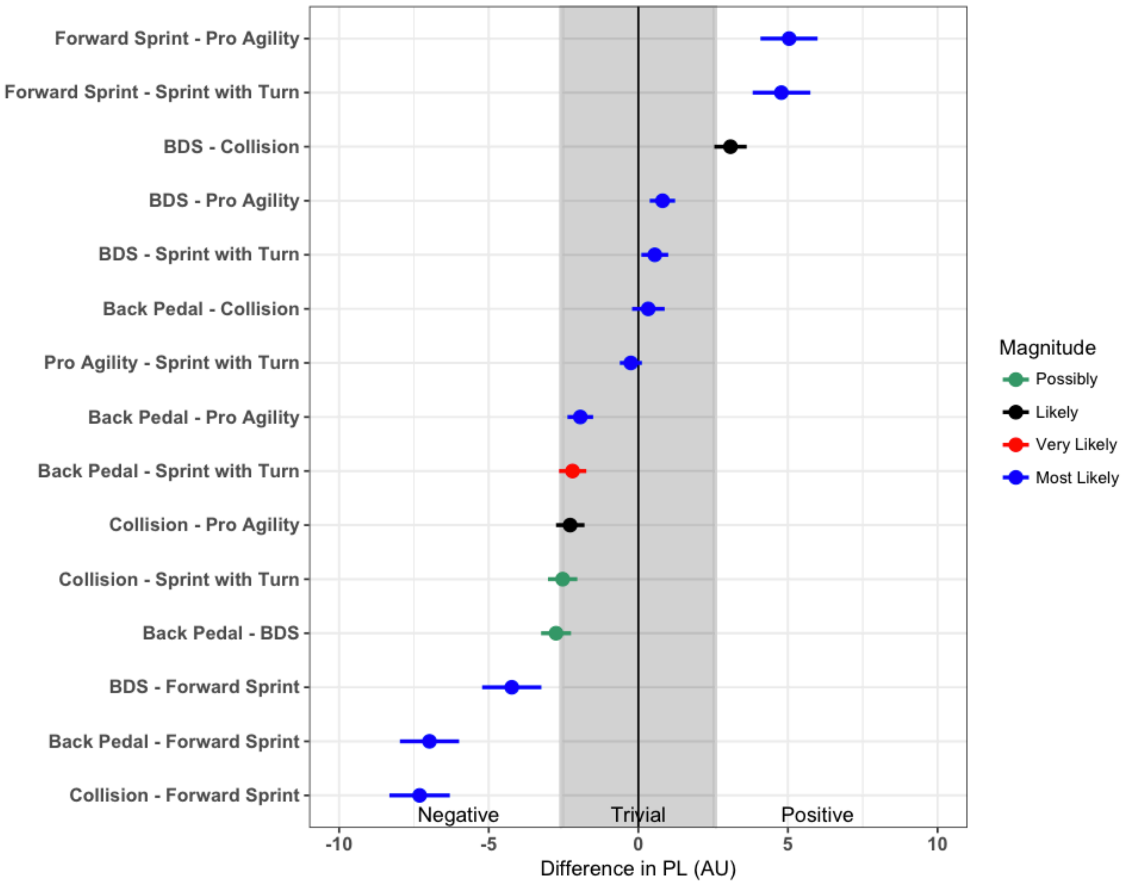


**Figure 3.1.** Mean difference ± 95% CI for Player Load (au) occurring different fundamental American football activities. Grey region represents a trivial difference. Colors of the differences represent the likelihood of the observed effect: Green (Possibly: 25-75%); Black (Likely: 75-95%); Red (Very Likely: 95-99.5%); Blue (Most Likely: > 99.5%).

The Pro Agility (complex change-of-direction) exercise was observed to have the highest IMA compared to all movements. IMA during Pro Agility was observed to be most likely larger than both Back Pedal and Forward Sprint activities and very likely larger than the Collision activity. Sprint with Turn (simple change-of-direction) had a possibly larger IMA than BDS (**Figure 3.2**).

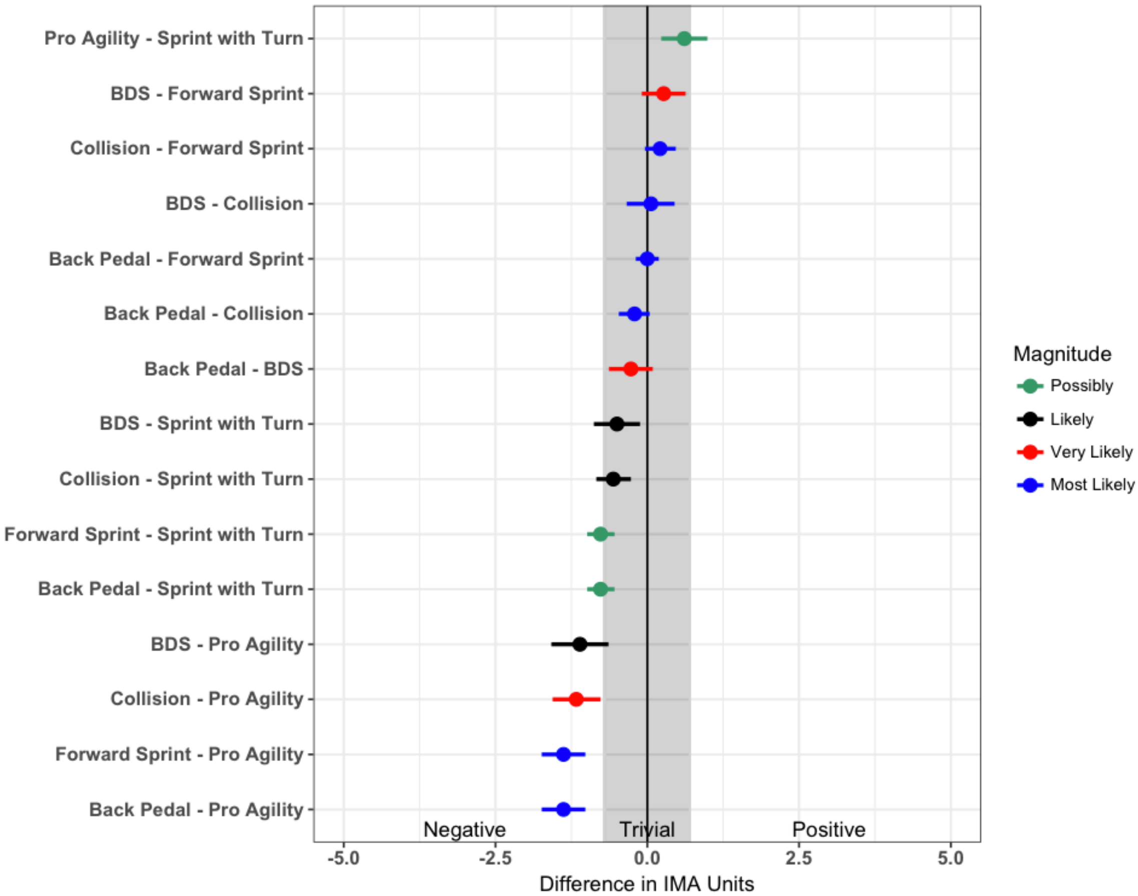


**Figure 3.2.** Mean difference ± 95% CI for IMA occurring different fundamental American football activities. Grey region represents a trivial difference. Colors of the differences represent the likelihood of the observed effect: Green (Possibly: 25-75%); Black (Likely: 75-95%); Red (Very Likely: 95-99.5%); Blue (Most Likely: > 99.5%).

The Collision activity had the largest impacts of all movement activities (very likely). While the two change-of-direction activities (Pro Agility and Sprint with Turn) registered a small amount of impacts, their differences were observed to be trivial relative to all other movement activities besides Collision (**Figure 3.3**). Comparisons between Back Pedal and BDS, Back Pedal and Forward Sprint, and BDS and Forward Sprint, could not be made as neither of these movement types produced impact loads and are therefore not presented.

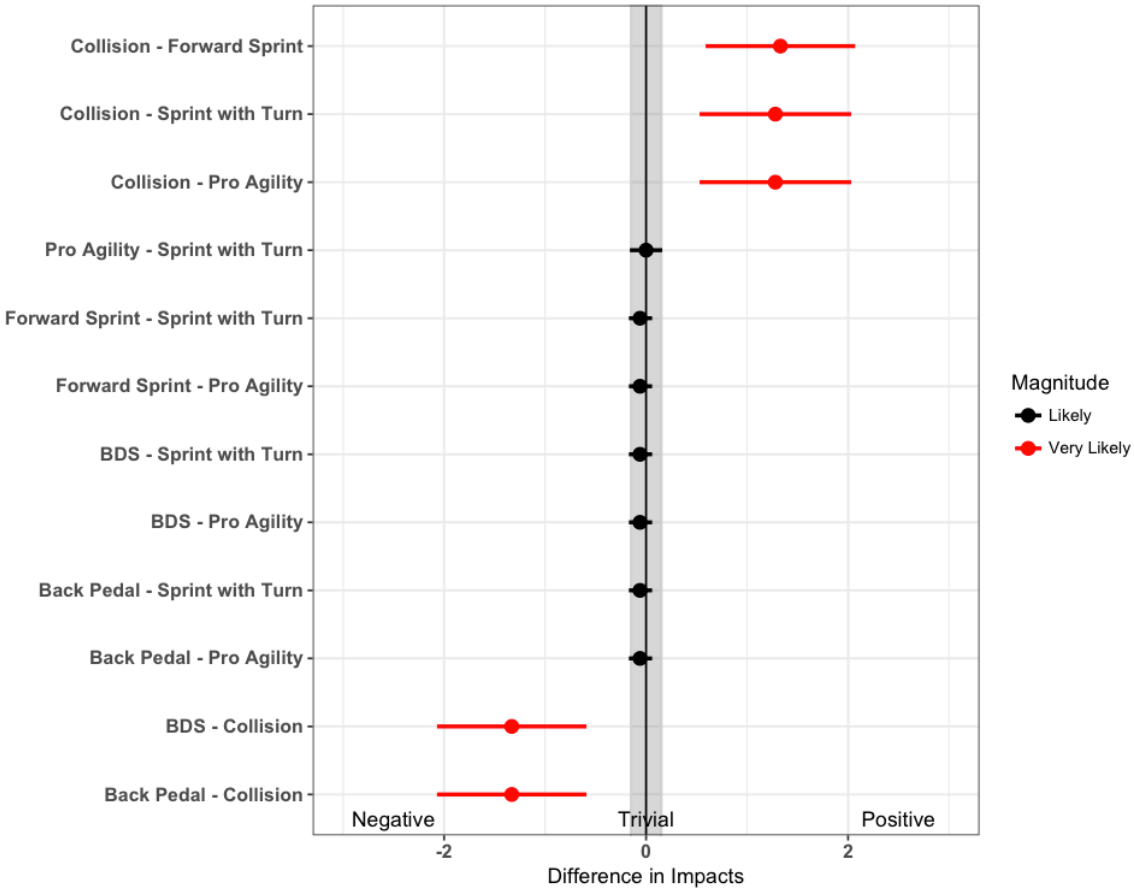


**Figure 3.3.** Mean difference ± 95% CI for Impacts occurring different fundamental American football activities. Grey region represents a trivial difference. Colors of the differences represent the likelihood of the observed effect: Green (Possibly: 25-75%); Black (Likely: 75-95%); Red (Very Likely: 95-99.5%); Blue (Most Likely: > 99.5%).

## 3.4 Discussion

The aim of the present study was to evaluate whether inertial sensors were able to differentiate between various football specific training activities.

Three inertial sensor variables were used to quantify activity during six American football exercises. These findings indicate that PL was larger during the simple linear activity (Forward Sprint) compared to all other movement activities with differences ranging from possibly to very likely. Conversely, the change-of-direction activities (Pro Agility and Sprint with Turn) were observed to have larger effects compared with other movements. Specially, IMA during the Pro Agility ranged from likely to very likely larger than Forward Sprint, BDS, and Tackle Sled Drive. The difference in IMA between the two change-of-direction exercises, Pro Agility and Sprint with Turn, was possibly trivial. Finally, the impacts metric was found to be very likely large in the Collision activity relative to all other activities. The findings suggest that the inertial sensor variables used in this study are able to detect differences in American football exercises. Specially, the PL variable appears to be influenced by linear running actions, to a greater extent. As expected, change-of-direction activities appear to register greater amounts of IMA and the impacts metric is influenced most by collision-based actions. As such, these sensors have potential to be used for quantifying the on-field demands of athletes in the sport of American football, during real training activities.

The ability of Player Load to quantify on field activities has been previously evaluated in Australian football (Boyd et al., 2011). However, no study has evaluated utility of this metric to detect differences in American football activities. We found PL to be most likely larger in the Forward Sprint activity compared to all other activities. Additionally, BDS was possibly larger than the Back Pedal and likely larger than the Collision exercise. These findings share similarities with previous research conducted by Polglaze and colleagues (2015) who observed a large correlation between PL and running (Total Distance) in field hockey athletes. As such, the PL metric may be useful for quantifying American football locomotor movements, particularly in position groups such as WR and DB, who perform larger amounts of running (Wellman et al., 2016). Additionally, even though PL was most sensitive to running-based movements, other football related activities such as COD and activities involving collisions also affected this metric (**Table 3.1**). This may be due to the position of these units on the torso, making them sensitive to a broad range of activities (i.e. any movement that may result in a change in position of the torso) (Nedergaard et al., 2017). Although this may seem problematic from a scientific perspective of identifying specific discrete movements, it remains useful from a practical standpoint for those practitioners interested in quantifying a global measure of training load and evaluating how this load impacts the players within the sport.

Change-of-direction movements are frequently observed during American football (Pincevero & Bompa, 1997) and are a key component of the game as offensive players attempt to evade defensive players and defensive players give chase. Although IMA has been a suggested metric for quantifying such directional type movements, limited research exists regarding its utility within the sport. The metric has been used, both in basketball (Petersen et al, 2017) and field hockey (Holme, 2015) to provide a count of high intensity activities. In women's soccer, IMA has been found to be a reliable measure of game-to-game "explosive actions" (Meylan et al., 2016). This study is the first to evaluate this metric in the sport of American football. The findings indicate that IMA was most sensitive to change-of-direction movements (Pro Agility and Sprint with Turn) compared to other movement types. In particular, IMA differences between Pro Agility and other movement types ranged from likely to very likely with the exception of Sprint with Turn, where the difference was seen to be possibly trivial. These findings are relevant to the sport of American football as a means of quantifying high intensity movements taking place in small spaces, where GPS reliability has been shown to be poor (Cummins et al, 2013). For example, players that play on the offensive and defensive line, perform a less running than other position groups due to their tactical requirements of blocking and tackling (Pincevero & Bompa, 1997; DeMartini et al., 2011; Wellman et al., 2017). It is possible that a metric such as IMA may be useful to practitioners looking to quantify the movement demands of players within these position groups.

Collisions comprise a large part of the sport of American football. Therefore, quantification of such activity is critical for practitioners in attempting to understand the physical load placed on athletes during training. The use of inertial sensors for quantifying impacts has been previously evaluated in professional Rugby League and semi-professional Rugby Union athletes (Gabbet et al., 2010; Gabbett, 2015; Wundersitz et al., 2015). Research evaluating the amount and magnitude of impacts taking place in collegiate football matches has indicated that, compared to other offensive position groups, running backs are exposed to more severe impacts (> 10 g) while the defensive linemen engage in the greatest amount of heavy and very high impacts (7.1 – 10 g), compared to other defensive position groups (Wellman et al., 2017). However, this type of impact metric has yet to be explored in American football to determine if it is able to pick up these types of actions. The findings of this current study indicate that the collision activity had very likely larger impacts than all other movement activities. Likely trivial differences in impacts were found between the two change-of-direction movements (Sprint with Turn and Pro Agility) and the three linear running movements (Forward Sprint, Back Pedal, and Backpedal, Decelerate, and Sprint). These findings are interesting given that the change-of-direction movements did not include physical contact. This may be due to the threshold for impacts (>5g) being too low and thus miss-classifying non-collision actives performed at a high intensity. Alternatively, this may be an issue related to the way impacts are calculated within the manufacturers software. This measure was originally devised for the sport of Rugby (Gabbet et al., 2010). Therefore, the impacts metric has been shown to misclassify tackling events in other collision sports, such as Australian football due to differences in tackling technique, (Gastin et al., 2014). As such, it is possible that the impacts measure is not specifically calibrated to American football tackling technique and may capture non-impact activities that are high intensity in nature (e.g., change of direction). Practitioners in American football should be aware that, while the impacts variable was most sensitive to collision type activities, during the course of a training session it might also quantify other high intensity actions. As such, impacts may provide a false count of the amount of physical collisions taking place in a given session. These findings indicate that the impacts variable can be useful for providing a measure of high intensity during a training session but is not always specific to physical collisions, per se, as it appears to register units during high intensity non-contact actives.

## 3.5 Conclusions

This study was the first to evaluate the use inertial sensors for differentiating between various American football activities. Findings indicated that the three inertial sensor variables evaluated were sensitive to different types of movements and may therefore provide practitioners with a useful way of differentiating training activities in the applied setting. This study, however, was conducted on a non-elite population. It is possible that elite level athletes would perform such movements with greater amounts of acceleration forces and perhaps more refined movement strategies. Additionally, the movements tested within this study are a small subset of the types of actions that athletes in American football may perform during training or competition. It is possible that the data generated from these movements become noisier in a training environment where the context of how these actions are performed is influenced by a number of factors (e.g., tactical demand, opposition).

While the finding of PL being most influenced by linear running movements is supported by previous literature in other sports (Polglaze et al., 2015), this study is the first to show the utility of IMA for measuring change-of-direction actions. As such, IMA may have high relevance to positional groups that perform less locomotor activity (e.g., offensive and defensive linemen) as more commonly used measures in team sport, such as GPS, may not be able to adequately capture these demands (Cummins et al., 2013). Finally, while the impacts variable was sensitive to the collision-based movement in this study, a low amount of impacts were detected during change-of-direction activities. As such, practitioners should be aware that, in practice, this measure might misclassify some high-intensity activities (e.g., change of direction) as impacts, providing a false count of collision in a training session. Collectively, the three inertial sensor measures used in this study should help practitioners working in American football quantify training demands and aid in informing daily training habits.

# CHAPTER 4

# IS SESSION RATING OF PERCEIVED EXERTION A VIABLE MEASURE OF TRAINING DEMANDS IN AMERICAN FOOTBALL?

## 4.1 Introduction

Monitoring strategies have been employed in team sport to evaluate the athletes' response to training in an effort to improve performance and reduce injury risk (Halson, 2014). Within the scope of athlete monitoring, scientists have suggested that training load be differentiated in two ways: internal training load and external training load (Lambert & Borresen, 2010; Halson, 2014). External training load refers to the physical output of the athletes (e.g., distance, speed) (Halson, 2014) and is frequently quantified in team sport athletes through the use of integrated micro technology sensors (GPS, accelerometer, gyroscope, magnetometer) (Cardinale & Varley, 2017). Conversely, internal training load represents the physiological and psychological stress imposed on the athlete from a given training session (Lambert & Borresen, 2010; Halson 2014). The two most commonly used measures of internal training load are Heart Rate and sRPE. When measured together, external and internal training loads have been proposed as a load-monitoring model for team sport as they provide practitioners with an overview of the training process and outcomes (Impellizzeri et al., 2005).

Although sports science practitioners have adopted this training load model, its applicability to team sport athletes is not without limitation. Originally, this conceptual approach was pioneered in endurance sport where the external load is generally "fixed" across athletes (e.g., individuals will run or ride a specific distance at a specific pace), thereby allowing the internal load to be easily quantified for each athlete using methods such as HR and Lactate (Borg et al., 1987; Foster, 1998). Further, exercise in endurance sport is unimodal (e.g., bike, run, etc.) making quantification of training loads less complex. Conversely, team sport athletes perform a diverse range of movement demands at varying intensities and are also required to cope with high technical/tactical demands, which may influence the stress they are placed under (Farrow et al., 2008). Additionally, the training load in team sport is prescribed by the coach and is directed at the team as a whole, which may lead to individualized physical responses from the athletes across the club (Morgans et al., 2014). This relationship has the potential to be further compounded in collision-based sports where physical contact with other players, in addition to the locomotor requirements, may alter the stress placed on an individual (Weston et al., 2014) (e.g., a running back sprinting forward and contacting a linebacker to block them from making a tackle). For these reasons, collision sport athletes training on the same team, in the same session, may experience a large variation in the internal training load response based on their unique physical demands.

Due to its limited technological requirements and ease of data collection, sRPE has been favored as an internal training load measure for those working in team sport (Impellizierri et al., 2004). Initially, it was believed that this method would not provide an accurate evaluation of training load for collision-based team sport athletes' due to the intermittent nature of activity and the various non-running activities (e.g., collisions and change of direction) performed (Lambert & Borresen, 2010). However, recent research has indicated that sRPE may provide a useful measure of the training load in AFL matches (Scott et al., 2013; Weston et al., 2014), AFL training (Scott et al., 2013; Johnston et al., 2015), and Rugby League (Lovell et al., 2013) training. The individual's sRPE is frequently multiplied by session duration (minutes) to achieve the sRPE Training Load (Foster et al., 1999). Large to very large correlations ($r = .65 - .84$) have been found between sRPE Training Load and absolute measures of external training load quantified by integrated microtechnology sensors (e.g., Total Distance, Total High-Speed Distance, and Player Load) (Scott et al., 2013). However, this correlation has been shown to only be small when sRPE Training Load is compared to measures of intensity during Rugby skills training (e.g., high-speed running/min ($r = .23 \pm .22$), body load/min ($r = .23 \pm .23$)) (Lovell et al., 2013). This may indicate that sRPE is more influenced by total training duration rather than the actual intensity or density of the session or, perhaps, the relationship between the two variables is due to mathematical coupling (McLaren et al., 2018). Alternatively, these findings may indicate that a gestalt measure, such as sRPE may not adequately represent the complexity of training demands (Hutchinson et al., 2006). The highly individual nature of the perceptual sensations that may be experienced by different athletes, either as a consequence of their specific movement and technical/tactical demands or their own internal processing of any exercise stimulus, may limit the appropriateness of anything but bespoke interpretation of the response.

American football is a team sport characterized by brief bouts of intense activity and collisions followed by a short rest interval (Iosia & Bishop, 2008). Previous research has indicated that the both the physical and psychological demands of the sport are influenced by the positional requirements of the players (Cox & Sang, 1995; Wellman et al., 2016; Wellman et al., 2017; Chapter 5). At the present time, no scientific evidence exists on the internal load of National Football League (NFL) athletes during training or how these two training load constructs may be linked within the sport. The relationship between these two training load constructs would help provide an understanding how the athlete's internal responses are impacted by the physical demands of training. Therefore, the aim of this study is to evaluate the relationship between sRPE and constructs of external training load during American football training. Given the variety of inter-individual demands in the sport, a secondary aim was to explore individual differences in the internal training load of athletes during the same training sessions.

## 4.2 Methods

### 4.2.1 Research Approach

This study sought to understand the relationship between markers of external training load and sRPE in American football players. The club performed a total of 47 training sessions during the 17-week in-season period. In order to ensure that players were sufficiently educated on using the sRPE scale, only those players who were with the club during the 5.5-week pre-season period were eligible for inclusion in the in-season data. During the pre-season players were briefed on what sRPE was and how to use the sRPE scale. Players were taught to rate the session using the verbal anchor question, *"How difficult did I feel today's session was compared to the hardest session I've ever performed?"* Only players who completed at least 70% (33 session) of all in-season training sessions were retained for the final analysis. All sessions were directed by the coaching staff and were designed to prepare the team for the upcoming weekly competition.

### 4.2.2 Participants

Thirty participants belonging to one NFL team participated in the study (mean ± SD; age: 24 ± 2 y; height: 1.88 ± 0.06 m; body mass: 109.4 ± 19.9 kg). Participants were classified by the coaching staff into one of seven positional groups: Defensive Back (DB; n = 4), Defensive Line (DL; n = 3), Linebackers (LB; n = 5), Offensive Line (OL; n = 8), Quarterback (QB; n = 1), Running Back (RB; n = 1), Tight End (TE; n = 2), and Wide Receiver (WR; n = 6). These positional groups were further categorized into their respective squad, Offense (OFF: OL, QB, RB, TE, WR) and Defense (DEF: DB, DL, LB). This study was approved by a local ethics committee and permission to publish was granted by the NFL club.

### 4.2.3 Experimental Design

Internal training load was quantified using the sRPE method (Foster, 1998; Foster et al., 2001). Participants were asked to rate how hard they felt the training session was on a 1-10 scale approximately 15-30 minutes following the completion of training (Foster, 1998; Impellizzeri et al., 2004). This 1-10 scale differed from the commonly used CR10 scale proposed by Foster (1998) in that the scale is anchored at "5" with the verbiage "moderate". As such, the 1-10 scale represents a linear scale of perceptual responses while the CR10 scale is exponential ("5" being anchored to the verbiage of "hard"), reflecting its relationship to lactate response during cardiovascular exercise (Foster, 1998). Given the intermittent nature of the American football (Rhea et al., 2006) the player's have a lack of understanding of maximum cardiovascular training and, therefore, were more comfortable working off of a 1-10 scale that presented the anchors in a fashion that made logical sense. A proprietary web application was designed to collect each player's individual sRPE response following each training session. This data was then exported from the application for further analysis. The use of sRPE for monitoring internal training load has been validated against heart rate and lactate responses in endurance training and Canadian football training as a means of internal training load monitoring (Foster et al., 2001; Coutts et al., 2009; Clarke et al., 2013). While sRPE is often multiplied by the duration of training minutes to obtain a sRPE Training Load value (Foster et al., 2001), we chose to only analyze the single sRPE value. The rationale for using the single sRPE value was based on the fact that the training duration is a "constant" that influences all other measured training load variables. Therefore, any correlation between sRPE Training Load and other external training load measures may simply determine the mathematical coupling of variables influenced by time as opposed to identifying meaningful relationships (McLaren et al., 2018).

On-field training activities were quantified through the use of integrated micro technology units (Minimax S5, Catapult Innovations, Scoresby, Australia). Athletes wore the units between their shoulders blades in a custom-made pouch provided by the manufacturer. Players were provided their own unit for the duration of the season to ensure inter-unit reliability (Rampinini et al., 2015). Following each training session, data was downloaded using manufacturer software (Catapult Sports, Openfield Software) and imported into Microsoft Excel (Microsoft, Redmond, WA) for further analysis.

Aside from locomotor activity, the sport of American football also consists of high intensity actions and physical collisions (Wellman et al., 2016; Wellman et al., 2017). Therefore, we chose to use four inertial sensor derived metrics, Player Load, Total Inertial Movement Analysis ($IMA_{Total}$), Player Load/min, and IMA/min. These metrics have been used to quantify external training load during American football training sessions (Chapter 5). Player Load represents the total amount of accelerations taking place on three axes (x, y, and z) and is reported in arbitrary units. The reliability of Player Load for tracking various movement actions, such as locomotor and collision-based activities, in team sport athletes has been previously established (Boyd, et al., 2011; Van Iterson 2017). Player Load has a strong correlation with running volume (Polglaze et al., 2015; Cardinale & Varley, 2017) and has been used as a metric to differentiate positional group training demands in American football athletes (Chapter 5). Because of the variety of movement actions that can influence the Player Load value, we used Player Load to provide an overall measure of training load. Player Load was also normalized (Player Load/min) for the duration of each session to provide an additional indication of the intensity of the training sessions.

$IMA_{Total}$ was used to quantify non-running activities (e.g., changes of direction, shuffling, cutting). Utilizing data from the tri-axial accelerometer, tri-axial gyroscope, and magnetometer, $IMA_{Total}$ generates a count of accelerations greater than 3.5 $m{\cdot}s^{-2}$ occurring in all movement vectors (forward, backward, right, and left) (Peterson et al., 2017). When evaluating match-to-match movement activity, $IMA_{Total}$ also has reasonable reliability (CV = 14%) (Meylan et al., 2016) and has been used to quantify training activities in other sports, such as professional basketball (Peterson et al., 2017). In American football athletes $IMA_{Total}$ was observed to be higher for linemen, who engage in a large amount of physical contacts, compared with position groups who require more locomotor demands (e.g., WR and DB) (Chapter 5). Exploring the correlation between $IMA_{Total}$ and sRPE may provide greater understanding around the relationship between non-running activity and internal training load within American football while also providing validation of IMA as a construct of load. $IMA_{Total}$ was also normalized (IMA/min) for the duration of the session to provide a measure of the density of discrete accelerations per session.

### 4.2.4 Statistical Analysis

Data are represented as mean ± SD. These data were generated for thirty players as they participated in football training across the entire in-season phase. As such, the data represents repeated measures for each athlete, which needs to be appropriately taken into account when evaluating the correlation between two variables (Bland & Altman, 1995). Indeed, pooling all of the data when individuals have provided multiple observations to the data set violates the assumption of independence and leads to misleading interpretations for correlation due to an incorrect representation of degrees of freedom (Bakdash, 2017; Kelly, 2016). Previously, Bland & Altman (1995) have suggested a statistical approach to calculating correlation in the presence of repeated measures. This approach is similar to a mixed model approach with a fixed slope and random intercepts allowed to vary for each individual (Bakdash, 2017). Therefore, to account for the repeated observations in the data we employed a mixed effects model to create a repeated measures correlation ($r_{rep}$) between sRPE and measures of external training load by dividing the sum of squares of the slope by the sum of squares of the slope plus the sum of squared residuals from the model (Bland & Altman, 1995). One of the advantages of a mixed model approach is that the random effects of the model can be used to describe how individuals vary from the average of the group (fixed effects). In this way, a mixed model can be described as balance between a completely pooled model (single regression line representing the average response of all individuals) and non-pooled model (individualized regression lines for each individual) (Gelman & Hill, 2010).

Models were built to evaluate the relationship between sRPE and duration and sRPE and the four external load variables. Due to a low sample size within several of the position groups "Position" was not included into the models; however, players were evaluated relative to their squad general category (OFF, DEF). Individual models were built for the OFF and DEF. In all models, sRPE served as the dependent variable while fixed effects were represented by the respective external training load variable. Random effects were established to allow for varying intercepts for each athlete. The magnitude of correlation between sRPE and each external training load was interpreted as: trivial ($r < 0.1$), small (0.1 to 0.3), moderate (0.3 to 0.5), large (0.5 to 0.7), very large (0.7 to 0.9), almost perfect (0.9 to 0.99), and perfect ($r = 1$) (Kelly et al., 2016). Differences (± 95% CI) in correlation coefficients between OFF and DEF were made using the statistical approach suggested by Zou (2007). To further examine individual differences, individualized correlation coefficients were built for each athlete and presented to provide an understanding of the variation in responses between players. All statistical analysis was carried out using R Statistical Software (R version 3.3.2) with the *lme4* package for linear mixed effects model analysis and the *cocor* package for comparison between correlation coefficients.

## 4.3 Results

In total, 1225 complete training load files (OFF = 745 / DEF = 480) were obtained from the thirty athletes during the in-season training period. Out of the 47 available training sessions athletes had complete data sets for an average of 41 ± 4 sessions. The pooled mean ± SD for all training variables are displayed in **Table 4.1**.

**Table 4.1.** Mean ± SD of training load variables.

| Variable | Mean ± SD |
|---|---|
| Session Duration (min) | 106 ± 16.6 |
| sRPE | 5.3 ± 1.7 |
| sRPE TL | 576 ± 237 |
| Player Load (au) | 337 ± 89 |
| Player Load/min (au) | 3.2 ± 0.6 |
| $IMA_{Total}$ | 40 ± 20 |
| IMA/min | 0.37 ± 0.16 |

The repeated measures correlation between external training load variables, duration and sRPE for both OFF and DFF in shown in **Table 4.2**. Both groups observed large $r_{rep}$ between sRPE and duration (OFF: 0.58; DEF: 0.54) and sRPE and PL (OFF: 0.63; DEF: 0.52). Additionally, both groups observed moderate $r_{rpe}$ between sRPE and Player Load/min (OFF: 0.44; DEF: 0.48) and sRPE and IMA/min (OFF: 0.48; 0.35). The OFF had a large $r_{rep}$ between sRPE and $IMA_{Total}$ (0.59) while the DEF had a moderate $r_{rep}$ between sRPE and $IMA_{Total}$ (0.48).

**Table 4.2.** Repeated measures correlation (± 95% CI) between sRPE and duration and sRPE and other measures of external training load in Offensive and Defensive groups.

| Variable | Offense Correlation with sRPE | Magnitude | Defense Correlation with sRPE | Magnitude |
|---|---|---|---|---|
| Session Duration (min) | 0.58 [0.53, 0.63] | Large | 0.54 [0.47, 0.60] | Large |
| Player Load (au) | 0.63 [0.58, 0.67] | Large | 0.52 [0.45, 0.58] | Large |
| Player Load/min (au) | 0.44 [0.38, 0.50] | Moderate | 0.39 [0.31, 0.46] | Moderate |
| $IMA_{Total}$ | 0.59 [0.54, 0.64] | Large | 0.48 [0.41, 0.55] | Moderate |
| IMA/min | 0.48 [0.42, 0.53] | Moderate | 0.35 [0.27, 0.43] | Moderate |

The OFF observed a "larger" $r_{rep}$ than the DEF in all cases. The differences in $r_{rep}$ between these two groups are displayed in **Table 4.3.** With the exception of duration and Player Load/min, differences ranged from trivial to small for all other variables. These findings show that the OFF observes a stronger relationship between sRPE and PL, $IMA_{Total}$, and IMA/min than the DEF while differences in sRPE and duration and sRPE and Player Load/min have greater amount of uncertainty and no evidence of a population difference.

**Table 4.3.** Differences in repeated measures correlation (± 95% CI) between Offensive and Defensive groups.

| Variable | Offense - Defense<br>Difference in Correlation ± 95% CI |
|---|---|
| Session Duration (min) | 0.04 [-0.04, 0.12] |
| Player Load (au) | 0.11 [0.03, 0.19] |
| Player Load/min (au) | 0.05 [-0.05, 0.15] |
| $IMA_{Total}$ | 0.11 [0.03, 0.20] |
| IMA/min | 0.13 [0.03, 0.23] |

Individual correlation coefficients represent a no-pooling model, where data is not shared across participants. The individualized correlation coefficients between sRPE and each of the external load measures can be observes in **Table 4.4.** The range of individual correlation coefficients is large, as noted by the minimum and maximum correlations by variable at the bottom of the table. For the measure of intensity (Player Load/min and IMA/min) the minimum correlation is negative, indicating that there were players who had an inverse relationship between internal and external load.

**Table 4.4.** Individualized correlation coefficients between sRPE and external training load measures for all athletes.

| Individual | Player Load | Player Load/min | IMA | IMA/min |
|---|---|---|---|---|
| DB 1 | 0.41 | 0.17 | 0.43 | 0.33 |
| DB 2 | 0.61 | 0.37 | 0.58 | 0.42 |
| DB 3 | 0.35 | 0.21 | 0.38 | 0.30 |
| DB 4 | 0.79 | 0.64 | 0.67 | 0.49 |
| DL 1 | 0.08 | 0.11 | 0.14 | 0.17 |
| DL 2 | 0.17 | -0.01 | 0.09 | -0.01 |
| DL 3 | 0.69 | 0.43 | 0.55 | 0.36 |
| LB 1 | 0.76 | 0.71 | 0.67 | 0.62 |
| LB 2 | 0.86 | 0.84 | 0.79 | 0.67 |
| LB 3 | 0.38 | 0.15 | 0.34 | 0.15 |
| LB 4 | 0.42 | 0.25 | 0.38 | 0.26 |
| LB 5 | 0.42 | 0.24 | 0.38 | 0.26 |
| OL 1 | 0.61 | 0.44 | 0.58 | 0.47 |
| OL 2 | 0.72 | 0.34 | 0.67 | 0.51 |
| OL 3 | 0.68 | 0.31 | 0.67 | 0.50 |
| OL 4 | 0.70 | 0.59 | 0.59 | 0.50 |
| OL 5 | 0.72 | 0.59 | 0.75 | 0.69 |
| OL 6 | 0.72 | 0.56 | 0.73 | 0.62 |
| OL 7 | 0.76 | 0.60 | 0.78 | 0.70 |
| OL 8 | 0.81 | 0.56 | 0.76 | 0.57 |
| QB 1 | 0.24 | 0.31 | 0.18 | 0.19 |
| RB 1 | 0.54 | 0.26 | 0.52 | 0.38 |
| TE 1 | 0.67 | 0.49 | 0.74 | 0.64 |
| TE 2 | 0.71 | 0.55 | 0.62 | 0.55 |
| WR 1 | 0.61 | -0.09 | 0.55 | 0.27 |
| WR 2 | 0.41 | 0.10 | 0.45 | 0.30 |
| WR 3 | 0.30 | 0.50 | 0.27 | 0.29 |
| WR 4 | 0.68 | 0.41 | 0.59 | 0.39 |
| WR 5 | 0.80 | 0.72 | 0.84 | 0.77 |
| WR 6 | 0.43 | 0.07 | 0.25 | 0.03 |
| **Minimum Correlation** | 0.08 | -0.09 | 0.09 | -0.01 |
| **Maximum Correlation** | 0.86 | 0.84 | 0.84 | 0.77 |

**Figures 4.1-4.4** present the linear relationship between sRPE and the external training load variables for each individual. Individual variability in the relationship between sRPE and PL is visually represented by how much the individual athlete's random effects regression line (thick black line) deviates from the fixed effect regression line (dashed line) (e.g., how much their intercept varies). In addition to the fixed and random regression lines, the red line in each plot represents the individual's (non-pooled) regression line, taken from the individualized correlation analysis described above. These plots allow for a visual understanding of individual responses between training load and sRPE. They also reflect how specific athletes perceive the demands of training relative to their peers. In several instances, the individual regression line (red line) aligns with the random effects line (black line), indicating the model is appropriately capturing that player's relationship between sRPE and external load variables. However, in other instances, there is a large disparity between the individual regression line and the random effects line, indicating that the model may not be useful for the given athlete. This type of analysis allows for a clear evaluation of the responses that individual athletes have to the prescribed training dose and how these responses may deviate from the expected responses based on empirical data contained within the model.

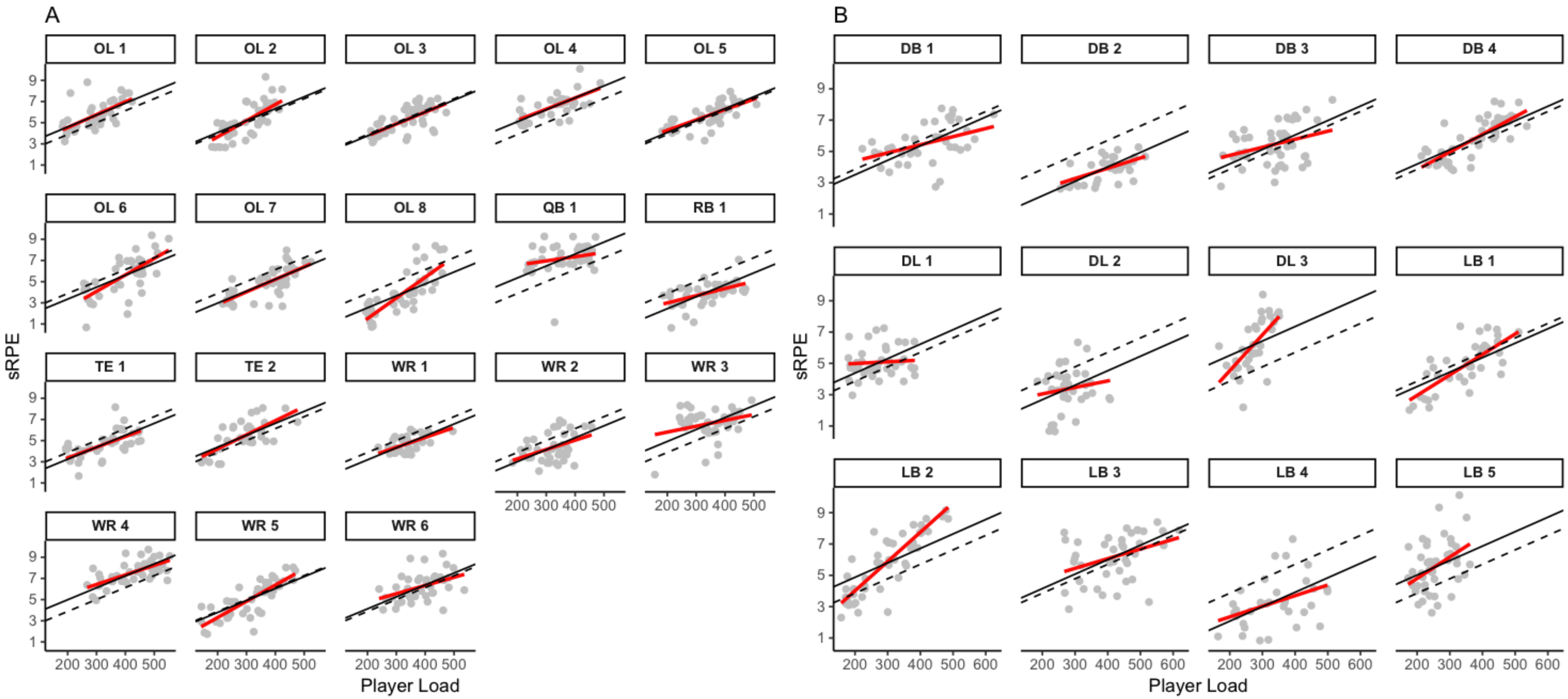


**Figure 4.1.** Relationship between sRPE and Player Load (au) for each athlete separated by Offense (A) and Defense (B). Solid black line represents mixed model fixed effects regression line. Dashed line represents mixed model random intercepts line. Red line represents individualized regression line.

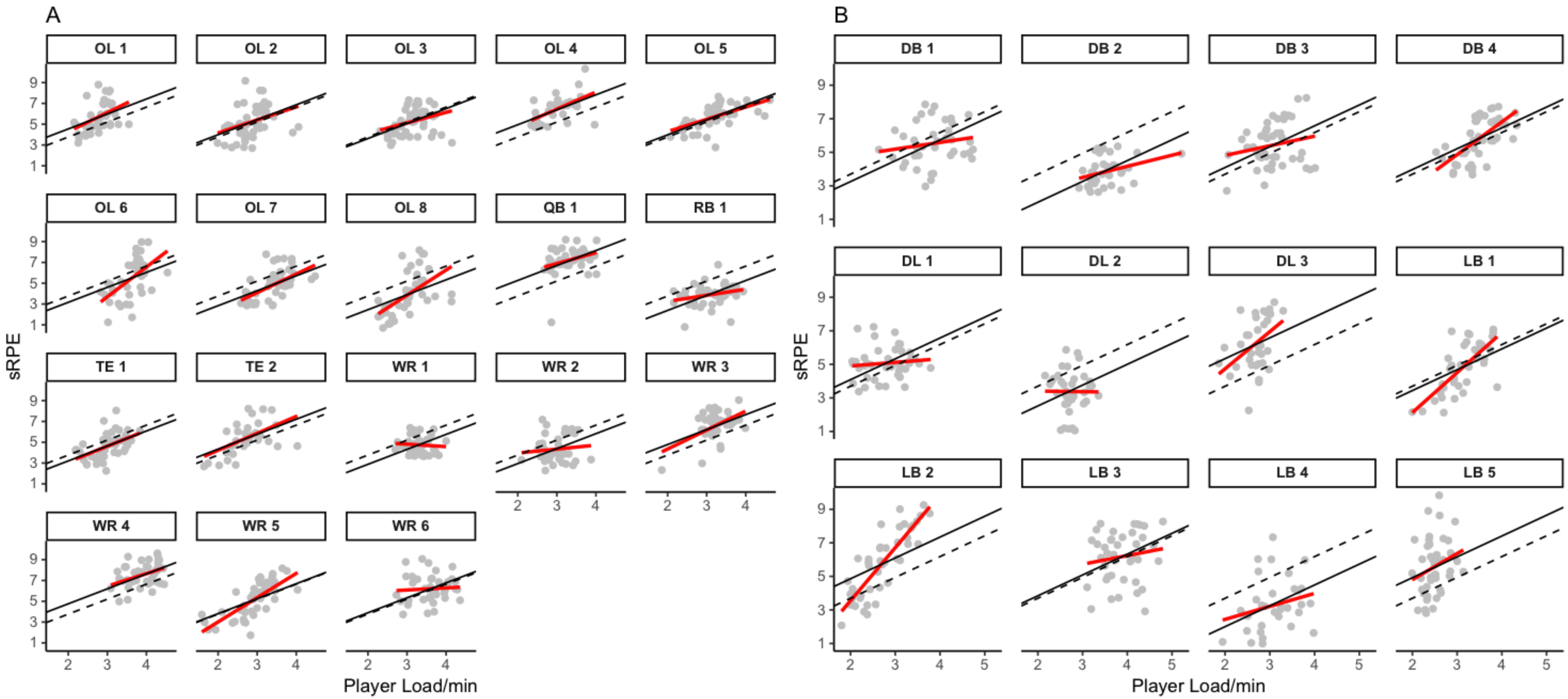


**Figure 4.2.** Relationship between sRPE and Player Load/min (au) for each athlete separated by Offense (A) and Defense (B). Solid black line represents mixed model fixed effects regression line. Dashed line represents mixed model random intercepts line. Red line represents individualized regression line.

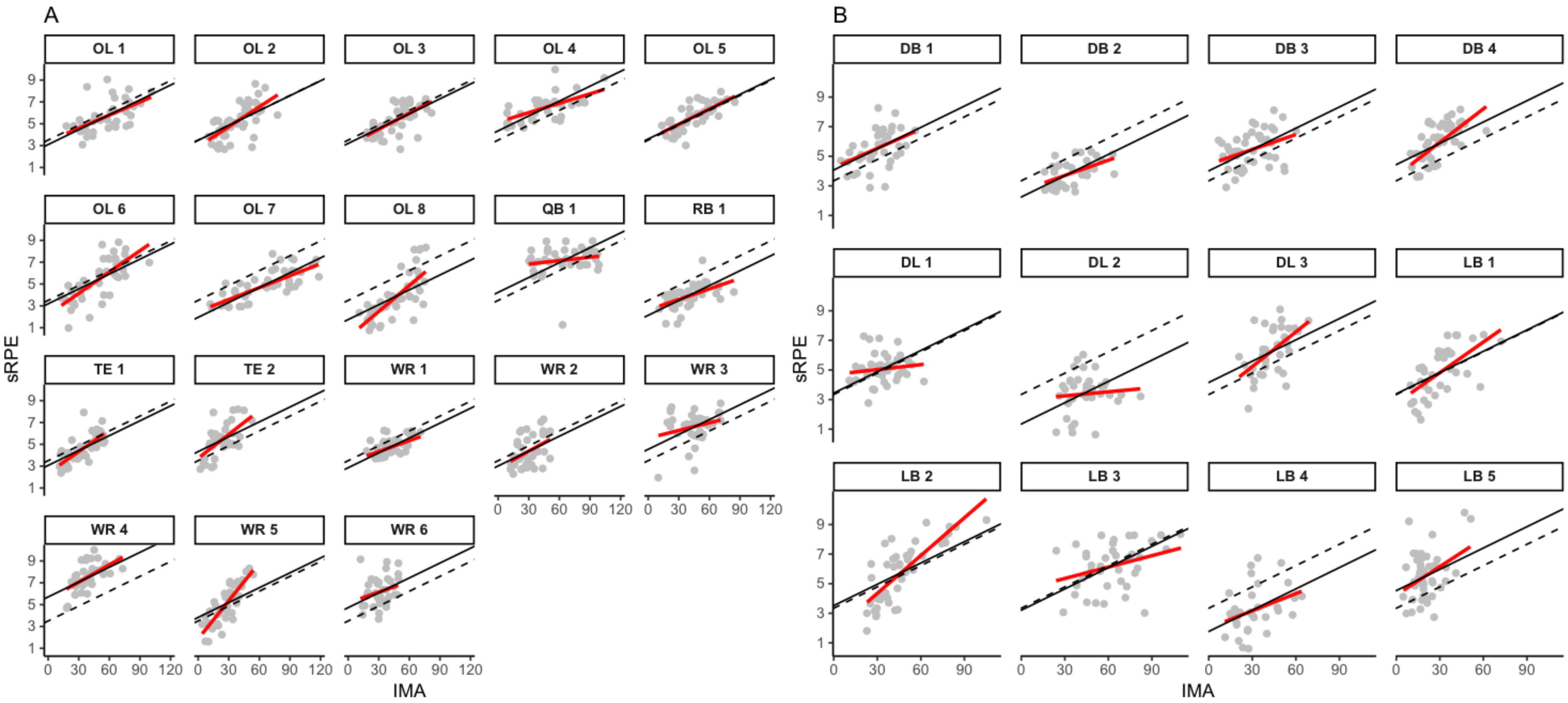


**Figure 4.3.** Relationship between sRPE and IMA for each athlete separated by Offense (A) and Defense (B). Solid black line represents mixed model fixed effects regression line. Dashed line represents mixed model random intercepts line. Red line represents individualized regression line.

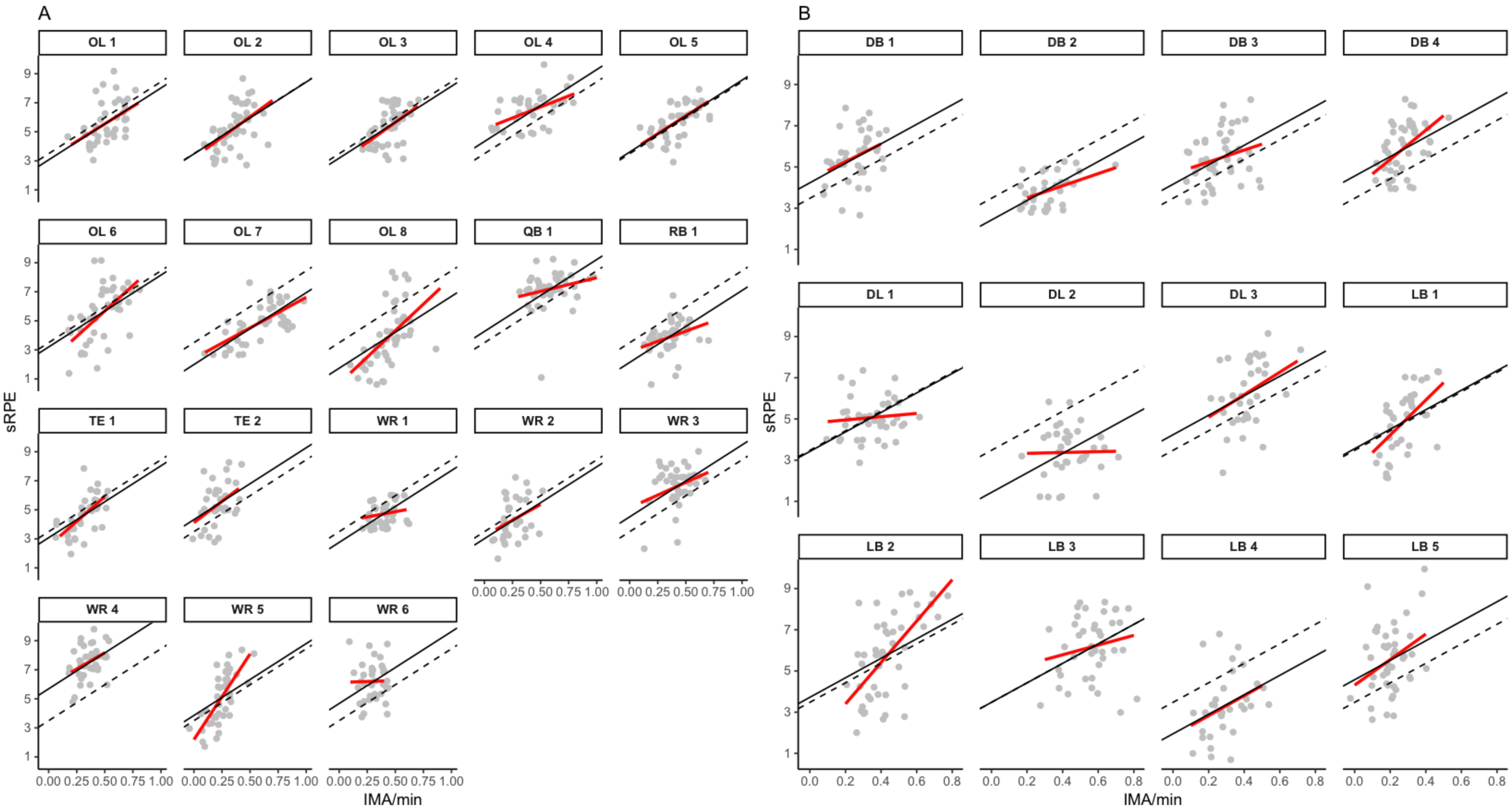


**Figure 4.4.** Relationship between sRPE and IMA/min for each athlete separated by Offense (A) and Defense (B). Solid black line represents mixed model fixed effects regression line. Dashed line represents mixed model random intercepts line. Red line represents individualized regression line.

## 4.4 Discussion

While external training load has previously been quantified in American football practices (Chapter 5 & 6) and collegiate games (Wellman et al., 2016; Wellman et al., 2017) it is currently not understood how these measures are reflected in an individual's perception of training volume or intensity. Therefore, this paper aimed to investigate the relationship between sRPE, a measure of internal training load, and four external training load variables in American football. Additionally, we sought to describe individual perceptions of sRPE, which is important to consider given the range of factors that can influence the perceptual sensations of training (Hutchinson et al., 2006). The main findings were that sRPE had large $r_{rep}$ with PL and Duration and a moderate $r_{rep}$ between Player Load/min and IMA/min for both OFF and DEF. The $r_{rep}$ between sRPE and $IMA_{Total}$ was observed to be large for the OFF and moderate for the DEF. In all instances, the OFF observed a "larger" $r_{rep}$ than the DEF with the difference ranging from trivial to small in all relationships except sRPE and Player Load/min and sRPE and duration, where the relationship was uncertain. These findings have relevance for practitioners working within the sport as sRPE offers a low cost method of monitoring overall training load and affords practitioners the opportunity to evaluate inter-individual differences of internal training loads. However, practitioners should be aware of the decrease in $r_{rep}$ between sRPE and training intensity (Player Load/min) and sRPE and training density (IMA/min). This latter finding is important given the sport is comprised of brief, high intensity efforts (Iosia

& Bishop, 2008) and collisions between athletes (Wellman et al., 2017), which means direct quantification of training intensity is still required as the relationship between sRPE and external training load is not the same between various external training load constructs or between players. Finally, the statistical approach used in this study allows practitioners to identify inter-individual differences in specific athletes' sRPE responses. These findings indicated a large variation in the individual relationships between sRPE and indicators of external load. Such individual differences are a consequence of the fact that all of the possible variables that may influence an individual's perceptual response to training are never measured.

While this study is the first to investigate these relationships in American football it is not the first study to evaluate the relationship between sRPE and measures of external training load in collision sports. Scott and colleagues (2013) validated the use sRPE Training Load (sRPE-TL; sRPE * Duration) in Australian football and found large correlations between sRPE-TL and running distance (r = 0.81), high-speed running (0.71), and Player Load (0.83). The correlation between sRPE-TL and Player Load found by Scott and colleagues (2013) is "larger" than what was observed in this study of American football athletes. This may be due to the current study using the standalone sRPE score instead of sRPE-TL. These differences may also be due to the use of a linear 1-10 scale, which may lead to differences in athlete responses compared to the more commonly used CR10 Scale (exponential scale) by Scott (2013), making comparisons between the two studies challenging. Alternatively, this relationship may reflect different ergonomic demands between the sports, given the more intermittent activity profile observed in NFL athletes (Rhea et al., 2006). The large correlation between sRPE and PL in this study, as well as Scott's (2013), may lead practitioners to conclude that sRPE is able to provide a crude measure of overall training load. However, practitioners should be aware of the individual differences (**Figure 4.1-4.4**) exhibited by players in the observed relationship between sRPE and PL. Such individual differences indicate that players differ substantially in their perceptions of total training activities, which may impact the consistency of any given response following training.

When Player Load was normalized per minute, the relationship between sRPE and Player Load/min was found to be moderate for OFF ($r_{rep}$ = 0.44) and DEF ($r_{rep}$ = 0.39). Lovell and colleagues (2013) found a similar relationship between Body Load/min and sRPE in professional Rugby training. This smaller relationship, relative to an absolute measure such as PL, has been raised as a potential issue more recently in a meta-analysis of the relationship between internal and external measures of training load by McLaren and colleagues (2018). Pooling results from 15 data sets McLaren (2018) found smaller correlations between sRPE and measures of intensity (e.g., Total Distance/min (r = .29), Total Accelerometer load/min (r = .25)) than those of sRPE training load and measures of total volume (e.g., Total Distance (r = .79), Total Accelerometer load (r = .63)). The reason for such a low correlation between sRPE and constructs of training intensity is not understood but indicate that sRPE is possibly influenced by a variety of training related factors. Alternatively, it is important to consider that sRPE was theoretically developed as a measure of internal training load (Foster et al., 1999). As such, sRPE may be influenced by a myriad of factors besides just physical output and using a single measure to represent a full range of perceptual responses during training may be misleading (Hutchinson et al., 2006; McLaren et al., 2018). This limitation has led to the investigation of differential RPE scales for evaluating various perceptual aspects of training (Weston et al., 2014). Such an approach may be useful in American football where a broad range of movement and psychological demands are imposed on the players based on their positional and tactical requirements (Cox & Sand, 1995; Chapter 5).

This study is the first to quantify the relationship between sRPE and $IMA_{Total}$ and sRPE and IMA/min. $IMA_{Total}$ has been previously used as a measure of external training load in American football given that it can be used to quantify non-running activities and directional movements (Chapter 3 & 5). Similar to the Player Load/min findings, a moderate $r_{rep}$ was found between sRPE and IMA/min for both OFF (0.48) and DEF (0.35). When evaluating the $r_{rep}$ between sRPE and IMA, the relationship was observed to be large for OFF (0.59) and moderate for DEF (0.48). In both instances, the difference in $r_{rpe}$ between squads was found to be small ($IMA_{Total}$: 0.11; IMA/min: 0.13). The difference in $r_{rep}$ between these two squads is interesting given the "mirroring" in the physical demands that have been previously observed between position groups that oppose each other on offense and defense (Chapter 5). These finding seem to suggest that the sRPE of players on different squads may be influenced by other factors not captured in this relationship. For example, certain position groups have been observed to require a higher level of mental skill and awareness (Cox & Sand, 1995) to perform the tactical aspects of game preparation compared to other positions. These findings are important for practitioners to consider as using sRPE alone, without an objective measure of non-running activities, may mislead practitioners in their interpretation of a player's training load in a given session.

The statistical modeling strategy employed in this paper offers practitioners with a novel way of investigating individual responses. While these perceptual responses may be influenced by a number of factors besides just physical demands (Hutchinson et al., 2006) the statistical approach can be used in a practical sense by comparing the expected sRPE, provided by the model, to the actual sRPE, provided by the athlete following the given training session. Large discrepancies between these two values may indicate a different psychological response by the athlete than expected for the training dose performed. Such discrepancies may warrant further investigation as to the athlete's current physical state (Ward et al., 2018). This type of approach has the potential to extend beyond American football and provide value for sports scientists looking to evaluate individual responses of perceptual measures in other sports.

## 4.5 Conclusions

This investigation is the first to explore the relationship between different external training load metrics and sRPE in American football training. While these initial findings may suggest that sRPE can be a useful measure of overall training activity in American football, practitioners need to keep in mind that individual differences of perceptual responses to training do exist. It is important to note that the individual athlete and between squad (OFF and DEF) correlations observed here may be unique to the team and coaching staff in which the study was conducted on. Different teams may have different practice routines or place different levels of cognitive demand on specific position groups based on style of play, which has the potential to alter perceptual responses. Given the vast amount of physical and psychological inputs that can influence perceptual responses (Hutchinson et al. 2006), sRPE may be limited in its utility to describe the physical demands of training in American football. When attempting to quantify the physical demands of sport, a broader limitation of sRPE is more likely due to the notion that sport scientists are, at the present time, unaware of or are unable to capture all of the measures that can influence an athlete's perceptual responses. As such, sRPE may be useful for informing practitioners about more than just the physical demands of a given session, however the responses provided are highly individualized.

# CHAPTER 5

# POSITIONAL DIFFERENCES IN RUNNING AND NON-RUNNING ACTIVITIES DURING ELITE AMERICAN FOOTBALL TRAINING

## 5.1 Introduction

Field-based team sports require that players compete in different positions that have specific technical, tactical and physical activity demands. Indeed, with increased use of micro technologies such as GPS and accelerometers, recent studies have described different positional activity profiles for a variety of team sports (Austin et al., 2013; Boyd et al., 2013; Cummins et al., 2013; Suarez-Arrones et al, 2014). These studies have been used to gain greater insight into sport specific requirements and may be used to aid in the design of specific training sessions (Torres-Ronda et al., 2016). Widespread profiling of activity profiles have been conducted in most field-based team sports (Austin et al., 2013; Boyd et al., 2013; Cummins et al., 2013; Suarez-Arrones et al, 2014), as well as collegiate American football (DeMartini et al, 2011; Wellman et al., 2016).

American football is a collision-based sport characterized by high intensity efforts separated by brief periods of rest (Rhea et al., 2006; Iosia & Bishop, 2008). The game is played at the collegiate level in the NCAA and the professional level in the National Football League (NFL). Players are divided into eight positional groups: Defensive Backs (DB), Defensive Linemen (DL), Linebackers (LB), Offensive Linemen (OL), Quarterback (QB), Running Back (RB), Tight End (TE), and Wide Receiver (WR)), each with different tactical and physical demands (Pincevero & Bompa, 1997). The limited quantification of such physical demands in the literature revealed that non-linemen (e.g., WR, DB, RB, QB) perform greater amounts of running activities compared to linemen during collegiate football training (DeMartini et al., 2011). Similarly, during Division 1 college football games, WR and DB cover greater total distance (5531 ± 997 m and 4696 ± 1115 m, respectively) and perform a higher number of sprints (21.9 ± 8.1 and 20.9 ± 8.6, respectively) than other position groups (Wellman et al., 2016). An evaluation of impacts and collisions during collegiate football games revealed that RB and Defensive Tackles (a position on the DL) engage in a larger amount of severe (> 10 g-forces) and heavy impacts (7.1 – 10 G force), respectively, than other position groups (Wellman et al., 2017). These data support the idea that positional differences in the physical demands exist in American football.

There are several limitations in the previous studies that have described the position demands of American football. Indeed, previous studies have divided playing positions into two broad groups (i.e. linemen and non-linemen) (DeMartini et al., 2011), which limited the ability to describe the discrete activity demands of the unique playing positions that exist within these two groups. Additionally, two previous studies that described positional differences in 12 collegiate American football games only examined position group differences between players who fulfilled the same function within the team (e.g., offensive players compared with other offensive players) (Wellman et al., 2016; Wellman et al., 2017), which limits the ability to understand how competition between position groups may influence activity. This study also monitored the same players across the season using repeated measures from the same players, which violates fundamental assumptions of the statistical analysis applied (Cnaan et al., 1997). A final limitation is that these data are specific to the collegiate competitions, which limits the generalizability of these results to professional American football (i.e. the NFL).

Presently, little is known about the specific positional differences in American football in players competing at the highest level within the NFL. Therefore, the aim of this study is to investigate the differences among position groups during an NFL training camp.

## 5.2 Methods

### 5.2.1 Research Approach

This study investigated the positional differences in training demands during an NFL training camp consisting of four match preparation weeks prior to the upcoming NFL season. The first 10 days of the training camp were dedicated to team practices with the remainder of the time devoted to preparing for four pre-season games (1x/week). For the purposes of this study, only the preparation weeks for the 4 games were considered as these weeks were used to prepare for competition and follow the typical in-season training structure. Eleven training sessions over this 4-week period were therefore included in the final analysis. The contents of the training sessions were determined by the coach with the goal of preparing the team for the upcoming opponent. Training sessions were divided into five key periods: warm up, position specific training drills, special teams' drills, preparatory plays, and team plays that represent the offense running plays against the defense and make up the bulk of the training session. The contents of these periods consisted of a diverse number of sporting actions, with certain position groups performing running and cutting activities (e.g., DB and WR), other groups performing a greater number of collisions and physical contact (e.g., OL and DL), and some position groups performing a combination of both locomotor and collision-based actions (e.g., TE and LB) (**Tables 5.1-5.2**).

**Table 5.1.** Weekly schematic of training duration and percentage of time devoted to specific drills across training days in relationship to the upcoming match (GD -4 = Game Day -4; GD – 3 = Game Day -3; GD -2 = Game Day -2).

| Practice Activity | GD -4 | GD -3 | GD -2 |
|---|---|---|---|
| Duration | 115.6 ± 4.5 min | 115.6 ± 8.9 min | 102.2 ± 14.7 min |
| Warm Up | 8.1% | 7.7% | 8.8% |
| Position Specific Drills | 9.9% | 9.7% | 10.8% |
| Special Teams Drills | 21.5% | 20.8% | 20.0% |
| Preparatory Plays | 8.6% | 9.8% | 9.7% |
| Team Plays | 52.6% | 53.9% | 54.9% |

**Table 5.2.** General overview of training activities performed by each positional group during specific training activities (table columns).

| Position | Warm Up | Position Specific Drills | Special Teams Drills | Preparatory Plays | Team Plays |
|---|---|---|---|---|---|
| DB | General Warm up (stretching, mobility, skipping, running) | • Running<br>• Cutting<br>• Catching balls | Kickoff and Punt Return drills (sprinting, blocking, physical contact) | Slow speed walk thru of plays to be run during the Team Plays period | Full speed plays (Offense vs. Defense) |
| DL | General Warm up (stretching, mobility, skipping, running) | • Accelerations<br>• Bag hitting<br>• Physical contact | Kickoff and Punt Return drills (sprinting, blocking, physical contact) | Slow speed walk thru of plays to be run during the Team Plays period | Full speed plays (Offense vs. Defense) |
| LB | General Warm up (stretching, mobility, skipping, running) | • Sprinting<br>• Change of direction<br>• Bag hitting | Kickoff and Punt Return drills (sprinting, blocking, physical contact) | Slow speed walk thru of plays to be run during the Team Plays period | Full speed plays (Offense vs. Defense) |
| OL | General Warm up (stretching, mobility, skipping, running) | • Accelerations<br>• Bag hitting<br>• Blocking drills<br>• Physical contact | Kickoff and Punt Return drills (sprinting, blocking, physical contact) | Slow speed walk thru of plays to be run during the Team Plays period | Full speed plays (Offense vs. Defense) |
| QB | General Warm up (stretching, mobility, skipping, running) | • Throwing to WR and RB | Throwing and route timing drills | Slow speed walk thru of plays to be run during the Team Plays period | Full speed plays (Offense vs. Defense) |
| RB | General Warm up (stretching, mobility, skipping, running) | • Sprinting<br>• Change of direction<br>• Play running<br>• Catching balls | Kickoff and Punt Return drills (sprinting, blocking, physical contact) | Slow speed walk thru of plays to be run during the Team Plays period | Full speed plays (Offense vs. Defense) |
| TE | General Warm up (stretching, mobility, skipping, running) | • Sprinting<br>• Change of direction<br>• Bag hitting<br>• Blocking drills | Kickoff and Punt Return drills (sprinting, blocking, physical contact) | Slow speed walk thru of plays to be run during the Team Plays period | Full speed plays (Offense vs. Defense) |
| WR | General Warm up (stretching, mobility, skipping, running) | • Route Running<br>• Cutting<br>• Catching balls | Kickoff and Punt Return drills (sprinting, blocking, physical contact) | | Full speed plays (Offense vs. Defense) |

### 5.2.2 Participants

Sixty-three American football players from the same NFL team were included in this study (mean ± SD; age: 24 ± 2 y; height: 1.88 ± 0.06 m; body mass: 109.4 ± 19.9 kg). The position groups consisted of DB (n = 12), DL (n = 7), LB (n = 10), OL (n = 11), QB (n = 2), RB (n = 8), TE (n = 5), and WR (n = 11). A total of 541 individual training files were obtained. The number of sessions performed by the athletes can be observed in **Table 5.3**. The variation in session number is a consequence of the availability of participants (e.g. non-availability through injury and participants being released or added to the playing staff). This study constitutes a retrospective analysis of archived data collected in an applied sports science setting where training load monitoring is considered best practice and within occupational purview (Winter et al., 2009). All data was de-identified prior to analysis. Ethical approval for the methodology of this study was granted by a local university ethics committee and permission to publish was granted from the NFL team.

**Table 5.3.** Training completed by each participant within the study period. (**Note**: For example, 28 participants (44.4%) completed 11 out of 11 training sessions while 2 participants (3.2%) completed 3 out of 11 sessions.)

| Number of Players | Sessions Completed (n = 11) | % Of Athletes |
|---|---|---|
| 28 | 11 | 44.4% |
| 7 | 10 | 11.1% |
| 5 | 9 | 7.9% |
| 5 | 8 | 7.9% |
| 2 | 7 | 3.2% |
| 4 | 6 | 6.3% |
| 5 | 5 | 7.9% |
| 1 | 4 | 1.6% |
| 2 | 3 | 3.2% |
| 1 | 2 | 1.6% |
| 3 | 1 | 4.8% |

### 5.2.3 Experimental Design

During training, players wore an integrated micro technology unit (Minimax S5, Catapult Innovations, Scoresby, Australia) contained within a custom pouch, provided by the manufacture, sewn between the shoulder blades, on the inside of their practice shirt. These units contain a GPS sensor (10 Hz), accelerometer (100 Hz), gyroscope (100 Hz), and magnetometer (100 Hz). Following each training session, data was downloaded using the manufactures software (Catapult Sports Openfield software) and exported to Excel (Microsoft, Redmond, WA) for further analysis. To ensure intra-unit reliability, athletes were assigned their own individual units (Rampinini et al., 2015). The reliability and validity of these units have been previously established (Boyd et al., 2011; Castellano et al., 2011; Vickery et al., 2014; Rampinini et al., 2015).

Training sessions were classified specific to the number of days until the upcoming game. For example, day to game -4 (GD -4) indicates that there are 4 days until the next game. Three main training sessions were performed each week: GD -4 (n = 3), GD – 3 (n = 4), and GD – 2 (n = 4). The final session of the week, GD -1, included a brief review of the game plan, which did not include significant physical activity and therefore was not included in the study. Total distance (TD) and high-speed distance were analyzed to compare running demands between position groups. High-speed distance (HSD) was defined as distances run above 70% of the maximum speed for the respective position group. This threshold was established using all training data from the previous season, collected via the GPSport system (SPI Pro X; GPSports, Canberra, Australia). As such, this data reflect the most frequently performed max speeds of each positional group during real training sessions. These position group thresholds were determined using the median maximum speed observed for each group during training sessions within the previous year (DB: > 6.8 $m{\cdot}s^{-1}$; DL > 5.9 $m{\cdot}s^{-1}$; LB > 5.9 $m{\cdot}s^{-1}$; OL > 4.5 $m{\cdot}s^{-1}$; QB: > 5.9 $m{\cdot}s^{-1}$; RB: 6.2 $m{\cdot}s^{-1}$; TE > 6.3 $m{\cdot}s^{-1}$; WR > 7.1 $m{\cdot}s^{-1}$).

Player Load (PL) and Inertial Movement Analysis (IMA) were used to quantify non-running activities such as collisions, impacts, or changes of direction and movements taking place in small spaces. Player Load represents the total amount of acceleration taking place on three axes of movement (X, Y, and Z) and is reported in arbitrary units (Boyd et al., 2011). We evaluated PL in both absolute and relative (Player Load per Minute (PL/min)) forms. IMA has been reported to quantify the displacement of force over different vectors of movement (Forward, Backward, Left, and Right) through the combined use of accelerometer, gyroscope, and magnetometer data (Abbott, 2015). Total IMA (the sum of IMA activities taking place above 3.5 $m.s^{-2}$) was used to investigate positional differences within this study. Player Load and IMA have good reliability when measuring on field movement activities (Boyd et al., 2011) and game-to-game explosive actions (Meylan et al., 2016).

### 5.2.4 Statistical Analysis

Training data was pooled together by day (e.g., all GD -4 sessions were grouped together) in order to reflect the training demands during each day of a training week. Mixed models have been suggested as an analytical approach to deal with repeated measures data and unbalanced data sets, for example players performing different numbers of training sessions during the monitoring period (Cnaan et al., 1997). A separate mixed model for each dependent variable (TD, HSD, PL, PL/min, and Total IMA) was constructed. Position group and Day to Game were treated as fixed effect independent variables. Random effects within the models were represented as the individual player and the training day. Models were fit iteratively and candidate models were compared using likelihood ratio tests with significance set at $p < 0.05$.

Data are represented as mean ± SD. Standardized mean differences (effect sizes) with 95% Confidence Limits (CL), were used to evaluate the difference between position groups. Standardized differences relative to the between subject SD of the random effects within each model were interpreted as trivial (< 0.2), small (0.2 – 0.6), moderate (0.6 – 1.2), large (1.2 – 2.0), and very large (2.0 – 4.0). Qualitative statements about the effect were made based on the probability of a real difference between groups (75% - 95% probability indicated a "likely" difference, 95% - 99.5% probability indicated a "very likely" difference, and > 99.5% indicated a "most likely" difference) (Batterham & Hopkins, 2006). In the event that the probability exceeded 5% in both the positive and negative directions, the effect was reported as "unclear", indicating that no clear difference could be detected given the data. This type of statistical approach was selected to provide a qualitative interpretation of the uncertainty surrounding the observed differences (Batterham & Hopkins, 2006). All analysis was conducted using the statistical software R (Version 3.1.2).

## 5.3 Results

### 5.3.1 Overview of Mixed Models

The final model consisted of a main effect interaction between Position Group and Day to Game and a random effect allowing the slope and intercept to vary for the individual player and Day to Game. These models show training load was influenced by the interaction between playing position and the training day.

### 5.3.2 Running Demands

Significant main effects were observed for the interaction between position groups and Day to Game for both TD ($\chi^2(21) = 92.1$, $p < 0.0001$) and HSD ($\chi^2(21) = 71.3$, $p < 0.0001$). Between-athlete standard deviations of 318 m and 39 m were observed for TD and HSD, respectively (**Tables 5.4-5.5, Figure 5.1**).

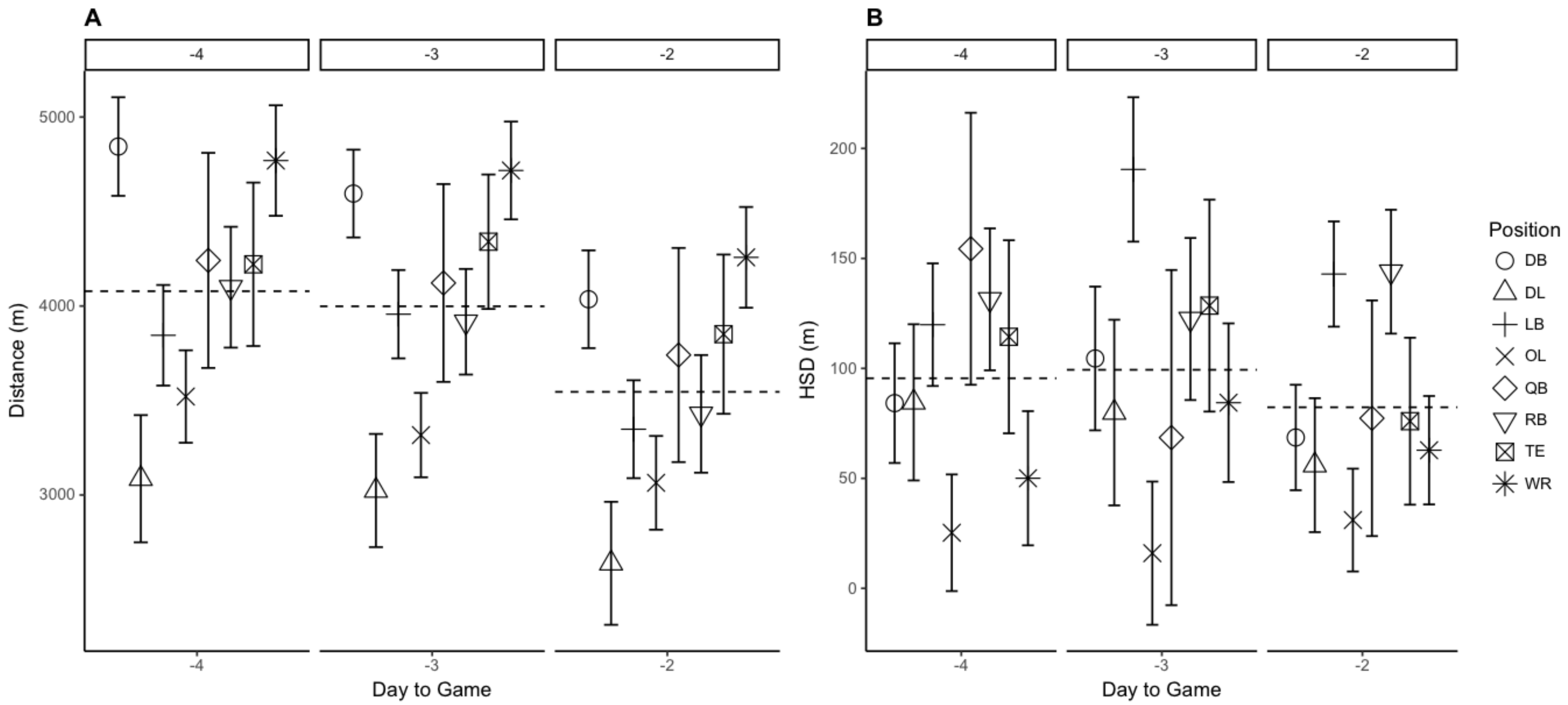


**Figure 5.1.** Mean ± 95% CI for Total Distance (A) and High-Speed Distance (B) relative to each training day. The horizontal dashed lines represent the mean Total Distance (A) and High-Speed Distance (B) for the entire group on each training day.

**Table 5.4.** Total running differences and qualitative inference for the interaction between Position Group and Training Day. (Unclear differences have been omitted.)

| Day to Game | Group 1 | Group 2 | Difference (m) ± 95% CL | Qualitative Inference |
|---|---|---|---|---|
| -4 | DB | DL | 1758 ± 426 | Most Likely Very Large |
| -4 | DB | LB | 999 ± 372 | Most Likely Very Large |
| -4 | DB | OL | 1323 ± 358 | Most Likely Very Large |
| -4 | DB | QB | 603 ± 626 | Possibly Large |
| -4 | DB | RB | 744 ± 406 | Possibly Large |
| -4 | DB | TE | 623 ± 505 | Likely Large |
| -4 | DL | LB | -759 ± 429 | Likely Large |
| -4 | DL | OL | -435 ± 416 | Likely Moderate |
| -4 | DL | QB | -1155 ± 661 | Likely Very Large |
| -4 | DL | RB | -1013 ± 464 | Likely Very Large |
| -4 | DL | TE | -1135 ± 548 | Likely Very Large |
| -4 | DL | WR | -1684 ± 446 | Most Likely Very Large |
| -4 | LB | OL | 324 ± 362 | Possibly Moderate |
| -4 | LB | RB | -254 ± 408 | Possibly Moderate |
| -4 | LB | TE | -376 ± 508 | Likely Moderate |
| -4 | LB | WR | -925 ± 395 | Likely Very Large |
| -4 | OL | QB | -720 ± 619 | Likely Large |
| -4 | OL | RB | -578 ± 403 | Likely Large |
| -4 | OL | TE | -700 ± 497 | Likely Large |
| -4 | OL | WR | -1249 ± 381 | Most Likely Very Large |
| -4 | QB | WR | -528 ± 640 | Possibly Large |
| -4 | RB | WR | -670 ± 433 | Likely Large |
| -4 | TE | WR | -549 ± 519 | Possibly Large |
| -3 | DB | DL | 1572 ± 379 | Most Likely Very Large |
| -3 | DB | LB | 638 ± 329 | Likely Large |
| -3 | DB | OL | 1278 ± 322 | Most Likely Very Large |
| -3 | DB | QB | 473 ± 573 | Possibly Large |
| -3 | DB | RB | 678 ± 360 | Likely Large |
| -3 | DB | TE | 255 ± 425 | Possibly Moderate |
| -3 | DL | LB | -933 ± 380 | Likely Very Large |
| -3 | DL | OL | -293 ± 373 | Possibly Moderate |
| -3 | DL | QB | -1098 ± 603 | Likely Very Large |
| -3 | DL | RB | -893 ± 410 | Possibly Very Large |
| -3 | DL | TE | -1317 ± 465 | Most Likely Very Large |
| -3 | DL | WR | -1694 ± 396 | Most Likely Very Large |
| -3 | LB | OL | 640 ± 323 | Possibly Large |
| -3 | LB | TE | -384 ± 426 | Possibly Moderate |
| -3 | LB | WR | -761 ± 349 | Likely Large |
| -3 | OL | QB | -805 ± 569 | Possibly Very Large |
| -3 | OL | RB | -600 ± 358 | Likely Large |
| -3 | OL | TE | -1023 ± 420 | Likely Very Large |
| -3 | OL | WR | -1400 ± 342 | Most Likely Very Large |
| -3 | QB | WR | -595 ± 584 | Possibly Large |
| -3 | RB | TE | -424 ± 452 | Likely Moderate |
| -3 | RB | WR | -801 ± 381 | Possibly Very Large |
| -3 | TE | WR | -377 ± 434 | Likely Moderate |
| -2 | DB | DL | 1397 ± 416 | Most Likely Very Large |
| -2 | DB | LB | 688 ± 366 | Likely Large |
| -2 | DB | OL | 972 ± 358 | Most Likely Very Large |
| -2 | DB | RB | 607 ± 401 | Likely Large |
| -2 | DL | LB | -710 ± 416 | Likely Large |

| | | | | |
|---|---|---|---|---|
| -2 | DL | OL | -426 ± 409 | Likely Moderate |
| -2 | DL | QB | -1102 ± 653 | Likely Very Large |
| -2 | DL | RB | -791 ± 450 | Possibly Very Large |
| -2 | DL | TE | -1212 ± 533 | Likely Very Large |
| -2 | DL | WR | -1619 ± 421 | Most Likely Very Large |
| -2 | LB | OL | 284 ± 359 | Possibly Moderate |
| -2 | LB | QB | -393 ± 623 | Possibly Moderate |
| -2 | LB | TE | -503 ± 495 | Possibly Large |
| -2 | LB | WR | -909 ± 372 | Possibly Very Large |
| -2 | OL | QB | -676 ± 618 | Possibly Large |
| -2 | OL | RB | -365 ± 398 | Possibly Moderate |
| -2 | OL | TE | -787 ± 489 | Possibly Very Large |
| -2 | OL | WR | -1193 ± 364 | Most Likely Very Large |
| -2 | QB | WR | -517 ± 626 | Possibly Large |
| -2 | RB | TE | -422 ± 524 | Possibly Moderate |
| -2 | RB | WR | -828 ± 410 | Possibly Very Large |
| -2 | TE | WR | -407 ± 495 | Possibly Moderate |

**Table 5.5.** High-Speed Distance differences and qualitative inference for the interaction between Position Group and Training Day. (Unclear differences have been omitted.)

| Day to Game | Group 1 | Group 2 | Difference (m) ± 95% CL | Qualitative Inference |
|---|---|---|---|---|
| -4 | DB | LB | -35.7 ± 38.8 | Possibly Moderate |
| -4 | DB | OL | 58.9 ± 38 | Likely Moderate |
| -4 | DB | QB | -70.2 ± 67.6 | Possibly Large |
| -4 | DB | RB | -47.2 ± 41 | Likely Moderate |
| -4 | DB | WR | 34.1 ± 40.9 | Possibly Moderate |
| -4 | DL | LB | -35.3 ± 45.1 | Possibly Moderate |
| -4 | DL | OL | 59.3 ± 44.3 | Likely Moderate |
| -4 | DL | QB | -69.8 ± 71.3 | Possibly Large |
| -4 | DL | RB | -46.8 ± 48 | Likely Moderate |
| -4 | DL | WR | 34.5 ± 46.8 | Possibly Moderate |
| -4 | LB | OL | 94.6 ± 38.5 | Very Likely Large |
| -4 | LB | WR | 69.8 ± 41.3 | Likely Large |
| -4 | OL | QB | -129.1 ± 67.3 | Likely Very Large |
| -4 | OL | RB | -106.1 ± 41.8 | Likely Very Large |
| -4 | OL | TE | -89.1 ± 51.3 | Likely Large |
| -4 | QB | WR | 104.3 ± 69 | Possibly Very Large |
| -4 | RB | WR | 81.3 ± 44.4 | Likely Large |
| -4 | TE | WR | 64.3 ± 51.8 | Possibly Large |
| -3 | DB | LB | -85.9 ± 46.2 | Possibly Large |
| -3 | DB | OL | 88.5 ± 46.1 | Possibly Large |
| -3 | DL | LB | -110.5 ± 53.5 | Likely Large |
| -3 | DL | OL | 63.9 ± 53.3 | Likely Moderate |
| -3 | DL | RB | -42.5 ± 56 | Possibly Moderate |
| -3 | DL | TE | -48.6 ± 64 | Possibly Moderate |
| -3 | LB | OL | 174.5 ± 46.2 | Most Likely Very Large |
| -3 | LB | QB | 121.9 ± 83 | Possibly Very Large |
| -3 | LB | RB | 68 ± 46 | Likely Moderate |
| -3 | LB | TE | 61.9 ± 58.3 | Likely Moderate |
| -3 | LB | WR | 106 ± 48.8 | Likely Large |
| -3 | OL | QB | -52.6 ± 82.9 | Possibly Moderate |
| -3 | OL | RB | -106.5 ± 49.2 | Likely Large |

| | | | | |
|---|---|---|---|---|
| -3 | OL | TE | -112.6 ± 58.1 | Likely Large |
| -3 | OL | WR | -68.4 ± 48.6 | Likely Moderate |
| -3 | QB | RB | -53.9 ± 84.6 | Possibly Moderate |
| -3 | QB | TE | -60 ± 90.1 | Possibly Moderate |
| -3 | RB | WR | 38 ± 51.6 | Possibly Moderate |
| -3 | TE | WR | 44.1 ± 57 | Possibly Moderate |
| -2 | DB | LB | -74.3 ± 33.8 | Possibly Large |
| -2 | DB | OL | 37.5 ± 33.5 | Possibly Moderate |
| -2 | DB | RB | -75.4 ± 36.4 | Possibly Large |
| -2 | DL | LB | -86.9 ± 38.7 | Likely Large |
| -2 | DL | RB | -88 ± 41.5 | Likely Large |
| -2 | LB | OL | 111.8 ± 33.4 | Likely Very Large |
| -2 | LB | QB | 65.6 ± 58.7 | Possibly Large |
| -2 | LB | TE | 66.9 ± 44.9 | Possibly Large |
| -2 | LB | WR | 80.1 ± 34.3 | Likely Large |
| -2 | OL | QB | -46.3 ± 58.4 | Possibly Moderate |
| -2 | OL | RB | -112.9 ± 36.6 | Likely Very Large |
| -2 | OL | TE | -45 ± 44.6 | Possibly Moderate |
| -2 | OL | WR | -31.8 ± 34 | Possibly Moderate |
| -2 | QB | RB | -66.6 ± 60.5 | Possibly Large |
| -2 | RB | TE | 68 ± 47.3 | Possibly Large |
| -2 | RB | WR | 81.2 ± 37.4 | Likely Large |

Defensive Backs and WR showed unclear differences in TD covered (GD -4: 74 ± 392 m; GD -3: -122 ± 348; GD – 2: -222 ± 371 m). However, when compared with all other positional groups, these two groups performed greater TD (moderate to large differences), with the exception of the TE and QB, who had an unclear difference with the DB on GD -2. The DL and OL positions were found to cover the least amount of distance.

There were variable responses in HSD between the playing positions. Tight Ends and RB performed more HSD than WR on GD -4 (64.3 ± 51.8 m, possibly large, and 81.3 ± 44 m, likely large, respectively). HSD differences between OL and RB were likely very large (-106.1 ± 41.8 m) on GD -4, likely large (-106.5 ± 49.2 m) on GD -3, and likely very large (-112.9 ± 36.6 m) on GD -2. Defensive backs performed less HSD than LB on GD -2 (-35.7 + 38.8

m, possibly moderate), GD -3 (-85.9 ± 46.2 m, possibly large), and GD -4 (-75.3 ± 33.8 m, possibly large). Linebackers performed more HSD than DL (GD -4: -35.3 ± 45.1, possibly moderate; GD -3: -110.5 ± 53.5, likely large; GD -2: -86.9 ± 38.7, likely large).

### 5.3.3 Sport Specific Movements

Significant main effects were observed for the interaction between Position and Day to Game for PL ($\chi^2(21) = 131.2$, $p < .0001$), PL/min ($\chi^2(21) = 48.0$, $p = .0007$), and Total IMA ($\chi^2(21) = 965$, $p < .0001$). Between athletes standard deviations of 41 AU, 0.4 AU, and 9 were observed for Player Load, PL/min, and Total IMA, respectively (**Tables 5.6-5.8, Figure 5.2**).

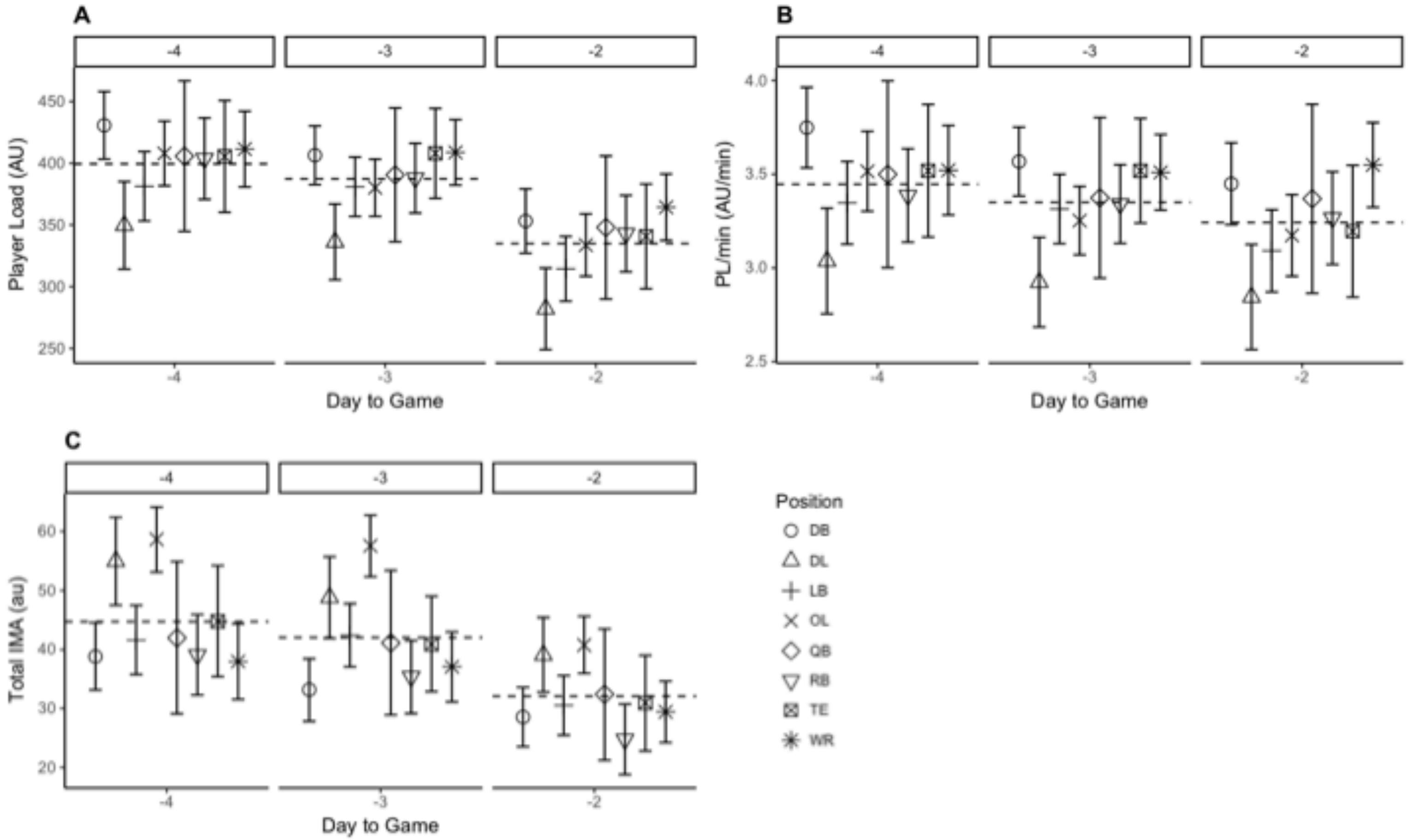


**Figure 5.2.** Mean ± 95% CI for Player Load (au) (A), Player Load per minute (au) (B), and Total IMA (C) relative to each training day. The horizontal dashed lines represent the mean Player Load (au) (A), Player Load per minute (au) (B), and Total IMA (C) for the entire group on each training day.

**Table 5.6.** Player Load (au) differences and qualitative inference for the interaction between Position Group and Training Day. (Unclear differences have been omitted.)

| Day to Game | Group 1 | Group 2 | Difference ± 95% CL | Qualitative Inference |
|---|---|---|---|---|
| -4 | DB | DL | 81 ± 45 | Likely Large |
| -4 | DB | LB | 49.3 ± 39 | Likely Moderate |
| -4 | DL | LB | -31.7 ± 45 | Possibly Moderate |
| -4 | DL | OL | -58.2 ± 44 | Likely Large |
| -4 | DL | QB | -56.1 ± 71 | Possibly Large |
| -4 | DL | RB | -54.1 ± 48 | Possibly Large |
| -4 | DL | TE | -55.8 ± 57 | Possibly Large |
| -4 | DL | WR | -61.8 ± 47 | Possibly Large |
| -4 | LB | WR | -30.1 ± 42 | Possibly Moderate |
| -3 | DB | DL | 70.2 ± 39 | Likely Large |
| -3 | DB | LB | 25.5 ± 34 | Possibly Trivial |
| -3 | DB | OL | 26.3 ± 33 | Possibly Trivial |
| -3 | DL | LB | -44.7 ± 39 | Likely Moderate |
| -3 | DL | OL | -43.9 ± 38 | Likely Moderate |
| -3 | DL | QB | -54.3 ± 62 | Likely Moderate |
| -3 | DL | RB | -51.7 ± 42 | Likely Moderate |
| -3 | DL | TE | -71.7 ± 48 | Likely Large |
| -3 | DL | WR | -72.5 ± 41 | Likely Large |
| -3 | LB | TE | -27 ± 44 | Possibly Trivial |
| -3 | LB | WR | -27.8 ± 36 | Likely Small |
| -3 | OL | TE | -27.8 ± 43 | Likely Moderate |
| -3 | OL | WR | -28.6 ± 35 | Possibly Moderate |
| -2 | DB | DL | 71.1 ± 42 | Likely Large |
| -2 | DB | LB | 38.7 ± 37 | Possibly Moderate |
| -2 | DL | LB | -32.5 ± 42 | Possibly Moderate |
| -2 | DL | OL | -51.7 ± 42 | Possibly Large |
| -2 | DL | QB | -65.9 ± 67 | Possibly Large |
| -2 | DL | RB | -61 ± 45 | Possibly Large |
| -2 | DL | TE | -58.7 ± 54 | Possibly Large |
| -2 | DL | WR | -82.4 ± 43 | Likely Large |
| -2 | LB | RB | -28.5 ± 39 | Possibly Moderate |
| -2 | LB | TE | -26.2 ± 50 | Possibly Moderate |
| -2 | LB | WR | -49.9 ± 38 | Possibly Large |
| -2 | OL | WR | -30.7 ± 37 | Possibly Moderate |

**Table 5.7.** Player Load per minute (au) differences and qualitative inference for the interaction between Position Group and Training Day. (Unclear differences have been omitted.)

| Day to Game | Group 1 | Group 2 | Difference ± 95% CL | Qualitative Inference |
|---|---|---|---|---|
| -4 | DB | DL | 0.7 ± 0.35 | Likely Large |
| -4 | DB | LB | 0.4 ± 0.31 | Likely Moderate |
| -4 | DB | OL | 0.2 ± 0.3 | Likely Small |
| -4 | DB | RB | 0.4 ± 0.32 | Likely Moderate |
| -4 | DL | LB | -0.3 ± 0.36 | Possibly Moderate |
| -4 | DL | OL | -0.5 ± 0.35 | Possibly Large |
| -4 | DL | QB | -0.5 ± 0.57 | Possibly Large |
| -4 | DL | RB | -0.3 ± 0.38 | Possibly Large |
| -4 | DL | TE | -0.5 ± 0.45 | Possibly Large |
| -4 | DL | WR | -0.5 ± 0.37 | Possibly Large |
| -4 | LB | RB | 0 ± 0.31 | Most Likely Trivial |
| -4 | OL | QB | 0 ± 0.54 | Most Likely Trivial |
| -4 | OL | TE | 0 ± 0.41 | Most Likely Trivial |
| -4 | OL | WR | 0 ± 0.32 | Most Likely Trivial |
| -4 | QB | TE | 0 ± 0.61 | Most Likely Trivial |
| -4 | QB | WR | 0 ± 0.55 | Most Likely Trivial |
| -4 | TE | WR | 0 ± 0.42 | Most Likely Trivial |
| -3 | DB | DL | 0.6 ± 0.3 | Possibly Large |
| -3 | DB | LB | 0.3 ± 0.26 | Possibly Moderate |
| -3 | DB | OL | 0.3 ± 0.26 | Possibly Moderate |
| -3 | DB | RB | 0.2 ± 0.27 | Likely Small |
| -3 | DB | TE | 0.1 ± 0.33 | Most Likely Trivial |
| -3 | DL | LB | -0.4 ± 0.3 | Likely Moderate |
| -3 | DL | OL | -0.3 ± 0.3 | Possibly Moderate |
| -3 | DL | QB | -0.5 ± 0.49 | Likely Moderate |
| -3 | DL | RB | -0.4 ± 0.32 | Likely Moderate |
| -3 | DL | TE | -0.6 ± 0.37 | Possibly Large |
| -3 | DL | WR | -0.6 ± 0.31 | Possibly Large |
| -3 | LB | RB | 0 ± 0.26 | Most Likely Trivial |
| -3 | LB | WR | -0.2 ± 0.27 | Possibly Small |
| -3 | OL | TE | -0.3 ± 0.33 | Possibly Moderate |
| -3 | OL | WR | -0.3 ± 0.27 | Possibly Moderate |
| -3 | QB | RB | 0 ± 0.48 | Most Likely Trivial |
| -3 | TE | WR | 0 ± 0.33 | Most Likely Trivial |
| -2 | DB | DL | 0.6 ± 0.36 | Most Likely Moderate |
| -2 | DB | LB | 0.4 ± 0.31 | Likely Moderate |
| -2 | DB | OL | 0.3 ± 0.31 | Possibly Moderate |
| -2 | DB | TE | 0.3 ± 0.41 | Possibly Moderate |
| -2 | DL | LB | -0.3 ± 0.36 | Possibly Trivial |
| -2 | DL | OL | -0.3 ± 0.35 | Possibly Moderate |
| -2 | DL | QB | -0.5 ± 0.58 | Possibly Large |
| -2 | DL | RB | -0.4 ± 0.37 | Likely Moderate |
| -2 | DL | TE | -0.4 ± 0.45 | Possibly Moderate |
| -2 | DL | WR | -0.7 ± 0.36 | Likely Large |
| -2 | LB | WR | -0.5 ± 0.31 | Possibly Large |
| -2 | OL | TE | 0 ± 0.41 | Most Likely Trivial |
| -2 | OL | WR | -0.4 ± 0.31 | Likely Moderate |
| -2 | RB | WR | -0.3 ± 0.33 | Possibly Moderate |
| -2 | TE | WR | -0.4 ± 0.41 | Possibly Moderate |

**Table 5.8.** Total IMA differences and qualitative inference for the interaction between Position Group and Training Day. (Unclear differences have been omitted.)

| Day to Game | Group 1 | Group 2 | Difference ± 95% CL | Qualitative Inference |
|---|---|---|---|---|
| -4 | DB | DL | -16 ± 9 | Possibly Large |
| -4 | DB | OL | -20 ± 8 | Possibly Very Large |
| -4 | DB | TE | -6 ± 11 | Possibly Small |
| -4 | DL | QB | 13 ± 15 | Possibly Moderate |
| -4 | DL | RB | 16 ± 10 | Likely Large |
| -4 | DL | TE | 10 ± 12 | Possibly Moderate |
| -4 | DL | WR | 17 ± 10 | Likely Large |
| -4 | LB | OL | -17 ± 8 | Likely Large |
| -4 | OL | QB | 17 ± 14 | Likely Large |
| -4 | OL | RB | 20 ± 9 | Possibly Very Large |
| -4 | OL | TE | 14 ± 11 | Likely Moderate |
| -4 | OL | WR | 21 ± 8 | Possibly Very Large |
| -3 | DB | DL | -16 ± 9 | Likely Large |
| -3 | DB | LB | -9 ± 8 | Likely Moderate |
| -3 | DB | OL | -24 ± 7 | Most Likely Very Large |
| -3 | DL | LB | 6 ± 9 | Possibly Moderate |
| -3 | DL | OL | -9 ± 9 | Likely Moderate |
| -3 | DL | RB | 14 ± 9 | Possibly Large |
| -3 | DL | WR | 12 ± 9 | Likely Moderate |
| -3 | LB | OL | -15 ± 8 | Very Likely Moderate |
| -3 | LB | RB | 7 ± 8 | Possibly Moderate |
| -3 | OL | QB | 16 ± 13 | Possibly Large |
| -3 | OL | RB | 22 ± 8 | Likely Very Large |
| -3 | OL | TE | 17 ± 10 | Likely Large |
| -3 | OL | WR | 21 ± 8 | Possibly Very Large |
| -2 | DB | DL | -11 ± 8 | Likely Moderate |
| -2 | DB | OL | -12 ± 7 | Likely Moderate |
| -2 | DL | LB | 9 ± 8 | Likely Moderate |
| -2 | DL | RB | 14 ± 9 | Very Likely Moderate |
| -2 | DL | WR | 10 ± 8 | Likely Moderate |
| -2 | LB | OL | -10 ± 7 | Likely Moderate |
| -2 | OL | RB | 16 ± 8 | Likely Large |
| -2 | OL | TE | 10 ± 9 | Likely Moderate |
| -2 | OL | WR | 11 ± 7 | Likely Moderate |

Defensive Backs and WR performed the highest amount of PL compared to other position groups, with unclear between-position differences observed between them (GD -4: 19 ± 41 AU; GD – 3: -2 ± 36 AU; GD -2: -11 ± 38 AU). Defensive linemen performed the lowest PL relative to all other positions. Conversely, the OL, the position group that opposes the DL on offense, performed more PL than the DL with effects ranging from moderate to large (GD -4: -58 ± 44 AU, likely large; GD -3: -44 ± 38 AU, likely moderate; -52 ± 42 AU, possibly Large). The DL group also performed the lowest PL/min, with differences ranging from likely small to likely large when compared to other positional groups.

Position groups that oppose each other on offense and defense showed unclear differences in Total IMA. Defensive Line and OL performed a higher number of Total IMA compared to all other position groups with unclear differences between the two groups on GD -4 and GD -2 and OL performing more Total IMA on GD -3 (-9 ± 9, Likely Moderate). Wide Receivers and DB's had unclear differences in IMA as did LB's and TE's and LB's and RB's, with the exception of GD -3, where a possibly moderate difference was observed (7 ± 8).

## 5.4 Discussion

This is the first study to investigate the positional differences in external training loads (both running and non-running activity) in American football players during a NFL training camp. The main findings show positional differences in both running and sports specific movements. Specifically, DB's and WR's exhibited moderate to most likely very large positive differences in TD covered compared to other position groups. Conversely, DL and OL performed a larger number of sports specific movements, as measured via Total IMA. The observed variations in training load between positions groups also appear to be influenced by the microcycle structure, whereby training intensity appears to decrease as the training days progress closer to competition. This decrease in training intensity across the week is a consequence of the training sessions being aimed at preparing for the game (e.g., installing plays) and may reflect a tapering approach as competition nears. These findings may have practical relevance in illustrating differences in the training loads completed by different positions in the NFL, during the training camp period.

Total distance is often reported as a measure of training volume in field-based team sport athletes (Akenhead & Nassis, 2016). The heterogeneous nature of position demands in American football requires some positions to perform more running than others (DeMartini et al., 2011). Differences in locomotor activity between position groups in the present study are similar to previous findings in collegiate (DeMartini et al., 2011; Wellman et al., 2016; Wellman et al., 2017) and high school (Gleason et al., 2017) American football athletes. For example, WR and DBs in the college ranks were observed to have a higher amount of running distance and sprints during a season compared to all other positions (Wellman et al., 2016). Similarly, college non-linemen performed a higher amount of TD than linemen (DeMartini et al., 2011). These findings are similar to the present observations for DB and WR who had a greater amount of running distance during training compared to other position groups. Notably, total distances observed in this sample of NFL players are greater than during a collegiate football practice (DeMartini et al., 2011). This may be a direct consequence of playing at the higher NFL level where there are fewer players on training squads than college teams. While college football teams often support between 110-120 players, NFL teams are regulated by the number of players they can employ by the rules of the league. These lower numbers of available players may also result in lower opportunities for recovery periods from practice drills in NFL athletes thereby increasing the need to be involved in practice activities. It is also possible that these differences may simply reflect a higher level of physical demand at the elite end of the game (Gabbett, 2005; Gorostiaga et al., 2005).

In addition to TD, differences in HSD between NFL position groups were also evaluated. HSD differences were observed between positions whereby WR performed less than TE's on GD -4 and GD -3 and RB on all three training days. In the defensive position groups, the LB's were found to perform more HSD than the other two position groups (DB and DL). These findings describe a difference in the positional requirements for HSD irrespective of total distance that is covered across positions. The findings are in contrast to previous findings, from collegiate games, where WR and DB performed greater sprint distance (> 6.4 $m \cdot s^{-1}$) than other position groups (Wellman et al., 2016). These authors, however, used absolute speed zones for the entire team, which may overestimate and underestimate HSD for faster and slower athletes respectively (Gabbett, 2015). In contrast, the present study utilized a relative speed criteria specific to each position group. This may explain some of the observed differences between position groups. Alternatively, these findings may indicate a potential volume-intensity relationship in position groups that perform larger amounts of total distance during training. For example, it is possible that the amount of total distance the WR and DB groups are required to perform impedes their ability to perform greater HSD during training and may implicate within-session fatigue for those positional groups.

To investigate sports specific movements, we utilized three accelerometer metrics – PL, PL/min, and Total IMA. This study revealed that high PL values may be associated with the completion of a variety of specific actions other than running, such as collisions and tackles. This is evidenced by some positions demonstrating relatively high PL values in the context of low total distances. For example, differences in PL and PL/min between OL and WR ranged from unclear to possibly moderate across all three training days, despite WR's performing very large amounts of total distance. Similarly, the DB group performed greater running than the LB group, though the PL differences between these two groups were less substantial. These findings indicate that PL is capturing a variety of different running and non-running activities and may provide practitioners with a global measure of training load, regardless of position demands. Further validation of PL in American football is required to confirm its utility.

The DL produced the lowest PL and PL/min compared to all other position groups. Observed differences between DL and OL are interesting given the OL is the main opposition of the DL. These findings may be a consequence of the practice style for this group in this team. Practice is divided in such a way that portions of the sessions are dedicated towards position groups competing against each other in game specific tasks (e.g. running plays) while other parts of practice are devoted to individual position groups working on technical elements of play. It is possible that even though position groups like the OL and DL compete against each other during structured periods of practice, their position specific training periods may provide different training load intensities for these groups when compared to other positions. A more thorough evaluation of within-session training drills would allow for a better understanding of how positional groups are affected by these training demands.

While PL is influenced by a variety of actions, previous literature has suggested that PL is correlated with upright running (Jennings et al., 2010; Polglaze et al., 2015). Therefore, we attempted to further quantify the sports specific movements using Total IMA. Differences in Total IMA were unclear between position groups that compete against each other on offense and defense. These findings indicate that more data is required to make a more thorough determination regarding differences in positional demands between position groups that directly oppose one another. The DL and OL groups performed the highest Total IMA compared to other position groups. The main actions of these two groups typically occur through collisions with one another to block or tackle. The findings suggest that while the OL perform a greater amount of total distance and PL compared to the DL, a similar number of sports specific movements are performed between the two groups during training. These observed differences show that Total IMA could be used to identify the contribution of sports specific movements to the total training load in American football. This suggests that there is also a need for training load measures other than speed and distance in groups that perform greater sport specific actions (e.g., OL and DL) in this sport.

While this is the first study to describe training demands in NFL football, it is important to recognize that these data are only specific to a single period of training completed during the training camp of one team. Therefore, these findings may not reflect training during the in-season phase when competitive demands are greater and the roster size is smaller. For example, during the pre-season phase teams are allowed to maintain a roster of 90 players, as opposed to 63 during the regular season, which allows training to be dispersed amongst a greater number of players. Therefore, the key players on the team are not required to train with the same amount of volume as they would during the in-season phase. Thus, this data may not reflect the outputs of the most elite players within the sport.

## 5.5 Conclusions

This study has described positional training loads during training of American football in the NFL. The results showed differences in running volume, intensity and sport specific movements. These data have implications for aiding coaches when it comes to specific training drill design and for establishing periodization strategies when preparing for competition. For example, the observed decreases in physical output across the microcycle may be reflective of tapering as the competition nears. However, the findings here may lack generalizability to other American football teams given the practice demands are unique to the coaching style of each positional coach and the play style specific to the head coach who designs the playbook. Practitioners are encouraged to take a similar approach to evaluating the training demands of their team in order to understand the unique physical demands imposed on their athletes.

A novel finding of this study is that inertial sensor data provides the basis for a different conceptual approach to quantifying training load, as GPS metrics may be limited in identifying all of the training demands. These inertial sensor measures provide value in collision-based sports where players perform different types of actions that may not be solely running based. Future research should seek to better understand these metrics and their utility for determining not only training demands but also performance outcomes and injury risk.

# CHAPTER 6

# AN INVESTIGATION OF THE RELATIONSHIP BETWEEN INERTIAL SENSOR METRICS FOR MONITORING TRAINING LOAD IN AMERICAN FOOTBALL

## 6.1 Introduction

American football is a collision-based sport consisting of brief bouts of high intensity activity interspersed with longer rest intervals (Rhea et al., 2006; Iosia & Bishop, 2008). Each team is allowed 11 players on the field at one time with those players being dedicated to one of eight positional groups. The defense includes three positions - Defensive Backs (DB), Defensive Line (DL), and Linebackers (LB) - while the offense is based on five positions; Offensive Line (OL), Quarterback (QB), Tight Ends (TE), Running Backs (RB), and Wide Receivers (WR). Players have been observed to perform a variety of actions including sprinting, decelerating, changing direction, blocking and tackling (Pincevero & Bompa, 1997). These physical demands are thought to vary amongst position groups with these activity profiles depending on each positions tactical requirement. For example, during matches, larger players on the defensive and offensive line will collide with one another to block and tackle while smaller sized players, such as WR, will sprint with the ball in an effort to gain field position while the DB players will attempt to stop them (Pincevero & Bompa, 1997).

Recently, GPS technology has allowed for more direct quantification of training and match activity within the sport of American football. The application of such technology has provided a platform for the deeper understanding of the physical demands of the sport by providing objective quantification of the activities performed by players (DeMartini et al., 2011; Wellman et al., 2016; Wellman et al., 2017). For example, during collegiate football matches, the WR and DB position groups performed greater running (4696 ± 1,115 m and 5531 ± 997 m, respectively) and sprinting (10.6 ± 4.3 m and 12.7 ± 5.7 m, respectively) volumes than other position groups. Similar running volumes to those in matches have also been observed for these groups in collegiate football training, with the non-linemen (DB, LB, WR, QB, and RB) performing a larger total running volume (3532 ± 943 m) compared to linemen (DL, OL, and TE) (2573 ± 489 m) (DeMartini et al., 2011). The quantification of running based activities during practice may however only partially describe the demands placed on certain positional groups. This is a consequence of each positions tactical need to complete specific actions (e.g., blocking, change of direction) and the collision-based nature of the game. For example, while lineman may perform less running distance than other position groups they are required to engage in a greater amount of collisions and physical contact (Chapter 5). There would seem to be a need for the quantification of training load metrics, that quantify both running and non-running based actions, to fully understand the demands placed on players and the true nature of the differences in activity demands between positions.

Integrated micro technology systems combine GPS with inertial-sensor metrics (e.g., Player Load, Inertial Movement Analysis (IMA), and Impacts) in an attempt to provide data around non-running activities (Boyd et al., 2011; Meylan et al., 2016; Gastin et al., 2013). These metrics have recently been used within American football. For instance, RB's and Defensive Tackles (a position on the DL) performed the highest amount of heavy (7.1 –

8 g) and very heavy (8.1 – 10 g) impacts during a season of collegiate matches (Wellman et al., 2017). The Player Load metric has also been used, during training, to identify players at risk of injury and provide an understanding of the ramifications of playing the sport at the collegiate level (Wilkerson et al., 2016). While these examples enhance the discussion around the physical demands of American football it is still not clear which inertial sensor variables may be most effective at classifying positional differences in training/match demands. This challenge may be made more difficult by the large variety of training load metrics in commercially available integrated micro technology systems (Cardinale & Varley, 2017). Additionally, several of the available metrics may be highly correlated, indicating that they are not discrete descriptors of activity but are instead describing similar physical constructs (Gabbett, 2015). Due to these limitations, an approach to reduce the number of variables and determine which metrics may be most related and therefore describe similar physical constructs seems warranted.

Principal components analysis (PCA) is a statistical method that seeks to reduce the dimension of a dataset that consists of highly correlated variables down to a few key factors or "principal components" that explain similar constructs (Witte et al., 2010; Clark & Ma'ayan, 2011; Federolf et al., 2012). In this way, PCA can be thought of as a parsimonious approach to data analysis. The weighting of each of the variables within their respective principal component can be used as coefficients, similar to regression, and produce a single metric describing a specific training load construct. This type of statistical approach has practical relevance as it allows for an understanding of the relationship between various training metrics while helping reduce the number of variables. This may ultimately simplify any reporting structures in an applied setting. Therefore, the aim of this paper is to utilize Principal Component Analysis (PCA) to understand the relationship between different inertial sensor metrics within American football. A secondary aim is to use the loadings of these principal components to evaluate if there are new training constructs that may be used to better represent the physical requirements of each positional group.

## 6.2 Methods

### 6.2.1 Research Design

This study evaluated training load data, quantified with inertial sensors, in American football players through the use of PCA. The motivation to use such a statistical approach was to attempt to understand the relationship between different inertial sensor variables and through this process reduce these variables down to key principal components. This process may be useful in identifying outcome measures that describe the same physical constructs. This study is descriptive in nature and utilized a longitudinal research design whereby training load data to be used in the analysis was collected over the course of an NFL in-season for one team. The season consisted of 16 games in 17 weeks with the majority of weeks consisting of 3 training sessions that lead into the upcoming competitive fixture. Fortyeight training sessions were recorded in total giving 2332 individual training files obtained during the course of the study. All training sessions were dictated by the coaching staff and were broadly aimed at preparing the players for the upcoming competition.

### 6.2.2 Participants

Training load data was collected on 82 American football athletes belonging to one NFL team (mean ± SD; age: 24 ± 2 years; height: 1.88 ± 0.07 m; body mass: 113.3 ± 21.0 kg). Players were categorized into one of eight different positional groups: DB (n = 12), DL (n = 14), LB (n = 9), OL (n = 14), QB (n = 3), RB (n = 15), TE (n = 5), WR (n = 10). This study received ethical approval from a local research ethics committee and permission to publish was granted from the NFL club.

### 6.2.3 Experimental Design

Integrated micro technology sensors (Minimax S5, Catapult Innovations, Scoresby, Australia) were used to capture training load during each training session. These sensors house a 10 Hz GPS unit and a 100 Hz accelerometer, gyroscope, and magnetometer. Units were worn by each player between their shoulder blades in a custom designed pouch provided by the manufacturer. Following the completion of each training session, data was downloaded using the manufactures software (Catapult Sports, Openfield software) and exported into Excel (Microsoft, Redmond, WA) for further analysis. To help ensure the reliability of the data, each player was assigned his own micro technology unit for the duration of the study (Rampinini et al., 2015). These units are valid and reliable for tracking the on-field activities, such as running and collisions, in team sport athletes (Boyd et al., 2011; Wundersitz et al., 2015; Van Iterson et al., 2017).

American football players perform a variety of movement actions, consisting of both running and non-running (e.g., physical collisions) activities. The extent that each position produces these actions is partly dependent on the tactical requirements of the position (Pincevero & Bompa, 1997). To capture such diverse movements, eleven inertial sensor variables were selected for PCA (i.e., Total Player Load, Player Load Low Effort Band, Player Load Medium Effort Band, Player Load High Effort Band, Player Load Very High Effort Band, Low IMA, Medium IMA, High IMA, Low Impacts, Medium Impacts, and High Impacts). While GPS and velocity-based measures are commonly applied in team sports, such as soccer (Akenhead & Nassis, 2016), the inertial sensor metrics we chose to utilize in this study were selected for their ability to potentially quantify both running movements and non-running movements. Relevant movements include changes of direction, decelerations, and physical contacts (Boyd et al., 2011; Petersen et al., 2017; Gabbett, 2015); activities that are specific to American football training (Chapter 3 & 5).

Given the diverse nature of actions performed by American football players during training, Total Player Load was chosen as an overall proxy for total training activity. Total Player Load was derived from the tri-axial accelerometer and was calculated as the square root of the sum of squared instantaneous rate of change in acceleration in each of the three movement planes (X, Y, and Z) (Boyd et al., 2011). Player Load is reported in arbitrary units (AU) and reflects physical stress resulting from accelerations, decelerations, change of directions, and impacts. Additionally, this metric has been reported to have a strong relationship with the total distance covered, making it useful for describing total running volume (Cardinale & Varley, 2017; Gabbett, 2015; Polglaze et al., 2015).

In addition to the use of Player Load to reflect the overall load, Player Load Effort Bands were analyzed. The thresholds for these bands were specific to manufacturer pre-sets: Player Load Low Effort Band (1 – 2 g), Player Load Medium Effort Band (2 – 3 g), Player Load High Effort Band (3 – 4 g), and Player Load Very High Effort Band (> 4 g). These bands were used to represent discrete movement efforts (e.g., running, jumping, etc.) performed within each pre-designated threshold during training. Such distinctions may be useful for understanding how acceleration forces during training are distributed. For example, lower intensity movements such as walking, and jogging would be represented as actions in lower effort bands while intense changes of direction or collisions with other players would register actions in higher effort bands. These types of discrete activities may help to differentiate positional differences more clearly than a single continuous measure of force, such as Total Player Load.

Both IMA and Impacts were selected to represent non-running activities during training as position groups perform less running and more physical contact activities (DeMartini et al., 2011; Wellman et al., 2016; Wellman et al., 2017). IMA utilizes the three inertial sensors (accelerometer, gyroscope, and magnetometer) to quantify how acceleration forces are displaced in specific directions (Forward, Backward, Left, and Right). This metric has good reliability when measuring game-to-game explosive activities (CV = 14%) (Meylan et al., 2016) and has been used to quantify explosive actions taking place in confined spaces in the sport of basketball (Petersen et al, 2017). IMA activity was classified into Low (1.5 – 2.5 $m{\cdot}s^{-2}$), Medium (2.5 – 3.5 $m{\cdot}s^{-2}$), and High (> 3.5 $m{\cdot}s^{-2}$) bands, which were pre-set by the manufacturer. Finally, three "Impact" Bands were used to describe the amount and intensity of collision-based activities performed by the players during training. Impacts were grouped into Low (5 – 6 g), Medium (6 – 7 g), and High (> 7 g) categories. The use of inertial sensors to calculate collisions and impacts has been previously established (Wundersitz et al., 2015; Kelly et al., 2012) and these types of measures have been used to quantify the volume and magnitude of impact during collegiate football matches (Wellman et al., 2017).

### 6.2.4 Statistical Analysis

Training variables were first normalized by dividing the value by the duration of training (min) in a given session. Prior to PCA analysis, all variables were scaled to have a mean of 0 and SD of 1. To determine the appropriateness for PCA, Bartlett's Test of Sphericity was used to evaluate whether correlations between variables were sufficiently large and the Kaiser-Meyer-Olkin (KMO) measure was used to determine sample size adequacy. Bartlett's Test of Sphericity was found to be significant ($p < 0.001$) indicating the correlations between variables were acceptable for PCA. The overall KMO score was 0.81 with each individual variable having a KMO between 0.76 – 0.91. This exceeds the minimum criteria of 0.50 established by Kaiser (1974). These tests indicate acceptability for PCA therefore permitting the eleven training variables to be subjected to further analysis. Three principal components were found to have eigenvalues greater than 1 and were thus retained for extraction (Kaiser, 1960). These three components explained a cumulative variance of 79%. Due to the correlation between the 3 principal components, oblique rotation (promax) was applied to improve interpretation of the loading values. Variables with loading values greater than 0.4 were highlighted as being most important for a given principal component (Burnett et al., 1997). Loading values were applied as coefficients to their respective variables within the data set to create single values that describe the specific construct of the given principal component. The mean of each position group was calculated for the three principal components and then standardized so that the principal components could be compared to one another. Statistical analysis was carried out in the statistical software R (Version 3.1.2).

## 6.3 Results

Descriptive statistics (mean ± SD) of the 11 training variables for each position group are displayed in **Table 6.1**. The rotated loadings for the three principal components along with their eigenvalues, proportional variance, and cumulative variance are displayed in **Table 6.2**. Variables with a loading of > 0.4 are highlighted as the most important variables within that principal component. The correlation between the three components is shown in **Table 6.3**.

**Table 6.1.** Normalized (per minute of training) mean ± SD for all training load variables.

| Position | Player Load | Player Load Low Effort | Player Load Medium Effort Band | Player Load High Effort Band | Player Load Very High Effort Band | Low IMA | Medium IMA | High IMA | Low Impacts | Medium Impacts | High Impacts |
|---|---|---|---|---|---|---|---|---|---|---|---|
| DB | 3.41 ± 0.55 | 2.05 ± 0.39 | 0.62 ± 0.25 | 0.15 ± 0.12 | 0.022 ± 0.028 | 1.63 ± 0.34 | 0.48 ± 0.13 | 0.24 ± 0.09 | 0.11 ± 0.128 | 0.025 ± 0.03 | 0.013 ± 0.016 |
| DL | 2.88 ± 0.51 | 2.04 ± 0.45 | 0.75 ± 0.35 | 0.21 ± 0.18 | 0.046 ± 0.062 | 2.14 ± 0.76 | 0.65 ± 0.24 | 0.45 ± 0.16 | 0.192 ± 0.17 | 0.066 ± 0.075 | 0.04 ± 0.044 |
| LB | 3.07 ± 0.66 | 2 ± 0.51 | 0.68 ± 0.38 | 0.19 ± 0.2 | 0.037 ± 0.061 | 2.33 ± 0.79 | 0.62 ± 0.22 | 0.32 ± 0.16 | 0.127 ± 0.139 | 0.029 ± 0.035 | 0.022 ± 0.037 |
| OL | 3.07 ± 0.52 | 2.51 ± 0.56 | 0.74 ± 0.43 | 0.19 ± 0.19 | 0.037 ± 0.052 | 3.26 ± 0.62 | 0.9 ± 0.22 | 0.44 ± 0.17 | 0.167 ± 0.116 | 0.05 ± 0.04 | 0.031 ± 0.033 |
| QB | 3.24 ± 0.43 | 2.55 ± 0.46 | 1.08 ± 0.31 | 0.38 ± 0.19 | 0.033 ± 0.029 | 2.49 ± 0.55 | 0.56 ± 0.22 | 0.36 ± 0.26 | 0.201 ± 0.124 | 0.059 ± 0.062 | 0.013 ± 0.024 |
| RB | 3.34 ± 0.74 | 1.85 ± 0.56 | 0.68 ± 0.25 | 0.28 ± 0.17 | 0.058 ± 0.063 | 1.83 ± 0.69 | 0.56 ± 0.2 | 0.31 ± 0.14 | 0.196 ± 0.214 | 0.045 ± 0.053 | 0.022 ± 0.034 |
| TE | 3.15 ± 0.55 | 2 ± 0.49 | 0.63 ± 0.3 | 0.19 ± 0.15 | 0.029 ± 0.044 | 2.21 ± 0.62 | 0.61 ± 0.19 | 0.31 ± 0.12 | 0.111 ± 0.115 | 0.023 ± 0.025 | 0.015 ± 0.023 |
| WR | 3.32 ± 0.54 | 2.16 ± 0.55 | 0.64 ± 0.22 | 0.22 ± 0.15 | 0.039 ± 0.042 | 1.72 ± 0.45 | 0.54 ± 0.15 | 0.32 ± 0.11 | 0.088 ± 0.082 | 0.024 ± 0.025 | 0.017 ± 0.023 |

**Table 6.2.** Principal component loadings, eigenvalues, and variance explained for each principal component following oblique rotation. Variables with a weighting greater than 0.4 are bolded to show their relevance to the given principal component.

| **Variable (per minute)** | **Principal Component 1** | **Principal Component 2** | **Principal Component 3** |
|---|---|---|---|
| Player Load | -0.14 | 0 | **0.98** |
| Low IMA | -0.11 | **0.98** | -0.07 |
| Medium IMA | 0.08 | **0.90** | 0.01 |
| High IMA | 0.39 | **0.6** | 0.06 |
| Player Load Low Effort Band | -0.22 | **0.58** | **0.58** |
| Player Load Medium Effort Band | 0.33 | 0.15 | **0.63** |
| Player Load High Effort Band | **0.61** | -0.2 | **0.55** |
| Player Load Very High Effort Band | **0.77** | -0.23 | 0.28 |
| Low Impacts | **0.77** | 0.05 | 0 |
| Medium Impacts | **0.91** | 0.13 | -0.22 |
| High Impacts | **0.93** | 0.04 | -0.18 |
| **Eigenvalue** | 3.67 | 2.7 | 2.35 |
| **% Variance** | 33% | 25% | 21% |
| **Cumulative Variance** | 33% | 58% | 79% |

**Table 6.3.** Correlation matrix representing the relationship between the 3 principal components. (PC = Principal Component)

| | **PC 1** | **PC 2** | **PC 3** |
|---|---|---|---|
| **PC 1** | 1 | | |
| **PC 2** | 0.33 | 1 | |
| **PC 3** | 0.49 | 0.47 | 1 |

Evaluation of the weighting applied to the variables within the 3 rotated principal components demonstrated that each described a specific construct. Principal Component 1 has greater emphasis placed on all 3 of the impact bands as well as high and very high player load effort bands. Alternatively, Principal Component 2 was weighted higher on all 3 IMA bands. Finally, the third Principal Component was weighted most heavily on Player Load and low, medium, and high Player Load Effort bands. The weightings of the variables within the respective principal components were then used as coefficients and applied to the dataset. In this way, we are able to describe positional group training loads using the three principal components instead of the 11 different inertial sensor metrics. Each principal component was represented as a single score and used in an attempt to describe the different physical constructs for each position group. This allows for a clear representation of the how each positional group may be reflected by different physical constructs. The relationship of the three principal components to each position group is shown in **Figure 6.1.**

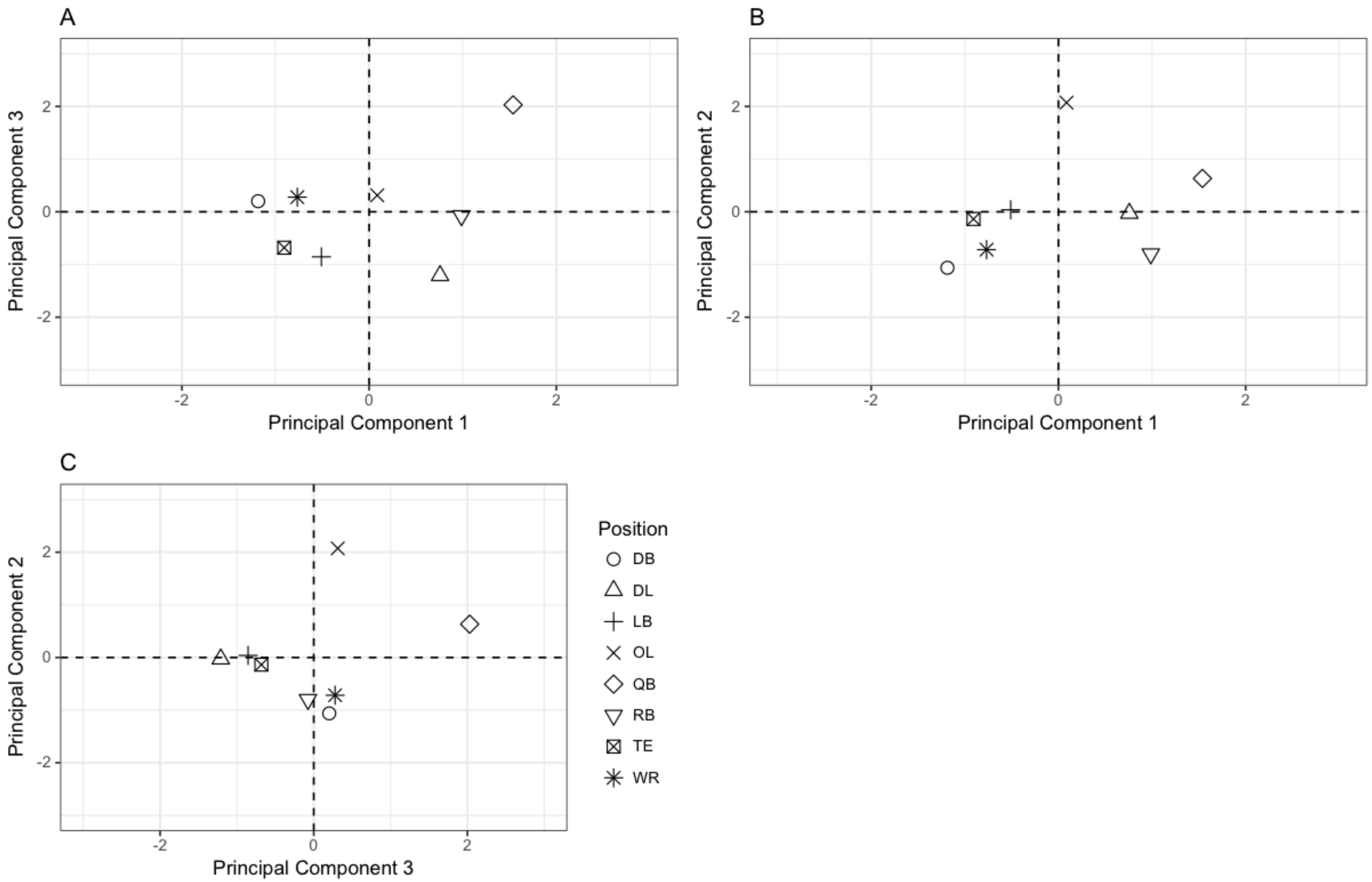


**Figure 6.1.** Relationship between positional groups across the three principal components. (A) Principal Components 1 and 3; (B) Principal Components 1 and 2; (C) Principal Components 3 and 2.

Positional groups that compete against each other on defense and offense such as the DB and WR and the TE and LB were found to be similar (e.g., similar z-scores) for all three principal components in most cases. Conversely, the OL and DL groups, two groups that also compete against each other, differed in all three principal components. The QB and RB groups had a unique relationship with the principal components. The QBs are represented by the highest weighting in all three principal components, while the RB group only had a positive weighting in Principal Component 1 (consisting of all Impact variables and the Player Load High and Very High effort bands).

## 6.4 Discussion

The primary aim of this paper was to utilize PCA to identify the relationship between different inertial sensor metrics during the training of American football athletes to simplify reporting of training load variables in practice. PCA analysis identified three principal components that described 79% of the variance within the data. These three principal components revealed a difference in the emphasis placed on specific inertial sensor metrics thereby indicating that the three components that are described may identify unique physical constructs during training. For example, Principal Component 1 had a high weighting on all three of the impact bands and the high and very high Player Load effort bands whilst Principal Component 2 was loaded more heavily on all three IMA bands. Principal Component 3 placed more weight on Player Load and the low, medium, and high Player Load effort bands. The loadings of these three principal components, once identified, were then applied to the data in an attempt to describe the physical requirements of eight positional groups within American football. The present findings suggest that certain positional groups are more heavily weighted in different principal components than others while some position groups that oppose each other on offense and defense share similar physical requirements. Collectively, these results indicate that the three observed principal components could be utilized to provide context around specific training load constructs within American football.

For data sets consisting of a large number of highly correlated variables PCA has been suggested as a statistical method to reduce the dimension of a dataset to "principal components", which can then be used to explain similar constructs (Clark & Ma'ayan, 2011; Federolf et al., 2012; Witte et al., 2010). This statistical method has been used previously in sports science literature to identify different sRPE (Williams et al., 2017) constructs and classify training drills in Rugby athletes (Weaving et al., 2014). However, this is the first investigation to use PCA to create a parsimonious model that attempts to reflect inertial sensor data within a collision-based sport. Given the large variety of potential metrics for the practitioner to choose from this approach was necessary in order to reduce these metrics down to a smaller number that may identify specific physical constructs. This approach may aid practitioners in identifying key training load variables that best describe the sport and help to reduce the presentation of redundant variables that are highly correlated.

Previous research into American football training has revealed that groups, which play opposite each other on offense and defense share similar physical demands (Chapter 5). In agreement, this study reveals that the DB and WR groups and the TE and LB groups are similarly weighted in all three principal components. Interestingly, this relationship was not found between the OL and DL groups, who also compete against each other during activities of blocking and tackling. The DL group performed lower than the OL group in both Principal Component 3 and Principal Component 2 while having higher values in Principal Component 1. These findings may be a consequence of the tactical demands exhibited by these position groups. For example, the offensive linemen are seldom substituted out when their positional group is performing a consecutive series of plays. This will clearly lead to a larger total training load compared to the DL group (Chapter 5). Conversely, players on the DL engage in a large volume of physical collisions (Chapter 5) and are frequently substituted in and out depending on the tactics of the offense. This would make their demands more intermittent collision-based in nature. As such, this may explain why the disparity between competing positions and why DL group was so highly loaded in Principal Component 1 compared to the other two principal components. These findings indicate the potential role that exercise-to-rest ratio has on influencing the physical demands for certain positional groups.

The OL and QB position group were the only two groups that revealed a high emphasis in all three principal component indices. These two positional groups play a critical role in the offense as the team attempts to drive down the field and score. As such, these positional groups may engage in larger amounts of diverse training activities compared to other groups given they are required to stay on the field for the entire offensive series. Interestingly, the QB position observed a high weighting in Principal Component 1 in this study, which places an emphasis on impacts and high and very high Player Load. These findings are surprising given that the QB position is the only position that does not engage in contact at any time during training. Because the inertial sensor unit is worn on the torso, it is possible that the impact metrics are related instead to activities that are not specific to collisions, particularly in the lower band (e.g., torso movements when throwing a ball or intense changes of direction and sprinting) (Cunniffe et al., 2009). These findings may reflect the need for specific QB metrics that are able to quantify torso movements during throwing activities.

## 6.5 Conclusions

This study was the first to utilize PCA with the aim of creating a parsimonious description of several training load variables for one team within the sport of American football. The findings indicate that three principal components could be used to summarize 11 inertial sensor metrics and provide an overall description of the training loads relative to eight positional groups. From a practical perspective, the reduction of variables into three principal components may ease the processes of reporting such data to coaches and support staff members who need to make daily decisions regarding training load prescription. To assist with reporting, principal components are often named to help identify the constructs they are describing. As such, we've provided the following naming conventions for the three principal components (**Table 6.4**). While these names are convenient for practical purposes, caution should be used when interpreting them scientifically given the limitations surrounding a more thorough understanding of the types of movement activities these metrics are truly quantifying. For example, these findings show that the variables within each of the principal components are related in some way. However, it is possible that adjustments in how some of these specific values are derived needs to be investigated to improve the identification of more specific actions and not add redundancy into the monitoring process. While these findings may be limited to the specific training style of the team and players which the study was conducted on, thus potentially lacking generalizability to other American football clubs, the statistical approach taken highlights a way for sports scientists to evaluate large data sets consisting of a number of correlated features. Additionally, the findings presented in this study are limited by the fact that they do not include internal training load metrics in the PCA. It is possible that internal training load measures may have unique relationships with the external training load measures examined here, leading to different training load constructs which describe the ways in which players perform the prescribed training dose. Finally, this analysis was conducted at the team level and therefore is not specific to positional demands. Each position groups may require a different principal component structure given their unique ergonomic demands (Chapter 5); however, a lack of sample size for each position group did not provide confidence that the principal components generated from such analysis would offer stability or generalizability. Therefore, data was pooled in this study to borrow statistical strength from the large sample of team training data. Future research should seek to address these limitations and add to the knowledge of how various internal and external training load measures may be aligned in similar constructs across positional groups.

**Table 6.4.** Proposed naming convention for the three principal components specific to the training load variables with the highest weighting in each.

| Principal Component | Main Training Load Variables | Name |
|---|---|---|
| PC 1 | Low Impacts, Medium Impacts, High Impacts, High Player Load, Very High Player Load | Impact Index |
| PC 2 | Low IMA, Medium IMA, High IMA | Mutli-Directional Movement Index |
| PC 3 | Player Load, Player Load Low Effort Band, Player Load Medium Effort Band, Player Load High Effort Band | Action Index |

# CHAPTER 7

# AN EVALUATION OF THE MICROCYCLE AND SEASON LONG POSITION GROUP RATE OF CHANGE IN TRAINING VOLUME AND INTENSITY

## 7.1 Introduction

Periodization refers to the planned manipulation of training variables to provide a specific stimulus to the body (Gamble et al, 2006). The manipulation of such training variables is parsed into phases or training blocks, termed mesocycles (~3-6 weeks) and microcycles (~1 week) each with specific training goals (Plisk & Stone, 2003). Recently, the use of GPS and integrated micro technology sensors has provided practitioners with the ability to quantify external training load; the physical output of the athlete, during training (Halson, 2014; Cardinale & Varley, 2017). Quantification of such training demands has allowed for investigations of periodization strategies in team sport athletes (Manzi et al., 2010; Malone et al., 2015; Ritchie et al., 2016). Although little evidence supports the use of a completely structured periodization model in team sports (Morgans et al., 2014) small changes in training load patterns have been identified across different team sport training phases (Ritchie et al., 2016), which may indicate coaches are intuitively adjusting training in a systematic way. In particular, these fluctuations in training load appear to be most evident in the smallest training phase, the weekly micro-cycle, as teams prepare for the upcoming competition (Morgans et al., 2014; Malone et al., 2015). For example, Malone and colleagues (2015) identified weekly micro-cycle periodization patterns for one English Premier League team whereby training was incrementally reduced in the sessions closest to match day.

The NFL is the highest level of American football competition. Aside from one report on pre-season training (Chapter 5), little is known about the in-season training characteristics of athletes at this level. The NFL in-season consists of 16 games played in 17 weeks with each team being provided a one-week "bye" (a period where no game is played which is assigned by the league prior to the commencement of the upcoming season). The most common training week within the NFL consists of Wednesday, Thursday, and Friday training, with games played on Sunday. However, deviations from this common week occur when teams are designated to play on Monday or Thursday or when half of the teams play on Saturday, during the last two weeks of the season. An investigation of weekly preparation during game weeks in pre-season has identified positional differences in movement demands, which are thought to be due to the tactical demands placed on each position (Chapter 5). For example, linemen engage in more collisions and impacts compared to receivers and defensive backs, who perform a greater amount of locomotor activity (Wellman et al., 2016; Wellman et al., 2017; Chapter 5). While these studies define the physical demands of position groups within sport, details about how the volume and intensity are adjusted within the training week and across the season to prepare the players for competition has yet to be explored.

From an analytical standpoint, the statistical approaches taken in team sport periodization studies (Malone et al., 2015; Moreiera et al., 2015; Ritchie et al. 2016) have focused mainly on comparing training loads between various phases of the pre- and competitive season. Other than providing a description of training periodization, these studies have limited use for practitioners, as relevant information can often get lost in a substantial number of planned comparisons. Conversely, a statistical approach that identifies how training volume and load change across a season may be more in-line with the type of information practitioners require when planning training sessions. For example, rate at which training is changing over time can be used by practitioners to adjust training session load based on identified trends from previous phases of training. In this way, training volume outcomes can be viewed as time series measurements across the season. As such, a summary measures approach (Matthews et al., 1990) can be used to analyze serial measurements and may provide a useful starting point for an explanatory study of this kind (Weston et al, 2011).

Therefore, the aim of this study is to understand the rate of change in training load (i.e., volume and intensity), both within and between positional groups, across a competitive NFL season and within training microcycles between competitive games. Understanding the changes in training demands within and between positional groups across these training cycles may help practitioners to better prescribe training and mitigate unwanted trends in training outcomes.

## 7.2 Methods

### 7.2.1 Research Approach

The training load and intensity of one NFL team was quantified for 47 training sessions over the course of the 17-week competitive season. The number of training sessions per weekly microcycle and number of days between games can be viewed in **Table 7.1.** Training session volume and intensity was quantified through the use of integrated micro technology units. The weekly training plan was developed by the coaching staff with the objective of preparing the team for the upcoming opponent (Weston, 2018).

**Table 7.1.** Seasonal overview of the breakdown of the number weekly training sessions and days between matches in each microcycle.

| Weekly Microcycle (Training Week) | Number of Days Between Games | Number of Training Sessions Per Microcycle |
|---|---|---|
| 1 | 10 (since last pre-season game) | 4 |
| 2 | 7 | 3 |
| 3 | 7 | 3 |
| 4 | 7 | 3 |
| 5 | Bye Week | |
| 6 | 14 | 4 |
| 7 | 7 | 3 |
| 8 | 7 | 3 |
| 9 | 8 | 3 |
| 10 | 6 | 3 |
| 11 | 7 | 3 |
| 12 | 7 | 3 |
| 13 | 7 | 3 |
| 14 | 7 | 3 |
| 15 | 4 | 1 |
| 16 | 9 | 3 |
| 17 | 8 | 3 |

### 7.2.2 Participants

Inclusion criteria for this investigation consisted of players who participated in ≥ 80% (38) of the 47 total sessions in the season, as this represents between 2-3 sessions per week, on average, being completed by the athlete (38/16 = 2.4 sessions). In total, thirty-six American football players from the same NFL club were included in the final analysis (mean ± SD; age: 24 ± 2 y; height: 1.88 ± 0.06 m; body mass: 109.4 ± 19.9 kg). Reasons for missing sessions consisted of injury or the player being granted an "off day" by his position group coach to allow for more recovery before the next match. Players were assigned by the coaching staff to one of seven positional groups; these were used for the classification of position groups in this investigation: Defensive Back (DB, n = 7), Defensive Line (DL, n = 3), Linebacker (LB, n = 6), Offensive Line (OL, n = 9), Quarterback (QB, n = 2), Tight End (TE, n = 5), and Wide Receiver (WR, n = 7). The running backs group was excluded from this analysis due to the low sample size of players who met the inclusion criteria across the season (n = 1). This data represents retrospective data collected as a best practice approach in professional sport (Winter et al., 2009) and is used solely for descriptive purposes. All data was anonymized prior to analysis and ethical approval for this study was granted by a local university ethics committee. Permission to publish was granted by the NFL club in question.

### 7.2.3 Experimental Design

During training, players wore an integrated micro technology unit (Minimax S5, Catapult Innovations, Scoresby, Australia) situated within a manufacturer provided custom pouch, which was sewn into their practice shirt in a position that situated it between the two scapula. These micro technology units consist of a GPS sensor (10 Hz), tri-axial accelerometer (100 Hz), tri-axial gyroscope (100 Hz), and magnetometer (100 Hz). Each player was issued his own micro technology unit to be worn for all training sessions to ensure intra-unit reliability (Rampinini et al., 2015). Data was downloaded immediately following each training session, using the manufacturers software (Catapult Sports Openfield software) and exported into Excel (Microsoft, Redmond, WA) for further analysis.

The physical requirements of American football consist of both running and non-running (e.g., collisions, cutting, change of direction) activities (Wellman et al., 2016; Wellman et al., 2017; Chapter 5 & 6). Therefore, the physical demands associated with each training session were quantified using two accelerometer-derived metrics, Player Load (PL) and Total Inertial Movement Analysis (IMA). Player Load is quantified by taking the square root of the rate of change in acceleration occurring in each of the three movement vectors (x, y, and z) divided by 100 (Boyd et al., 2011). Thus, PL represents the cumulative amount of acceleration force experienced by the individual during training and is used to reflect the total volume of the training session. The validity and reliability of PL has been established in both laboratory and on-field team sport running activities (Boyd et al., 2011) and has a strong relationship with running volume (Polglaze et al., 2015). Non-running actions (e.g., cutting, collisions, etc) make up a large portion of American football (Pincevero & Bompa, 1997; Chapter 3 & 5) for several of the positional groups. These actions were quantified using the IMA metric. Through the use of the tri-axial accelerometer, tri-axial gyroscope, and magnetometer, IMA provides a count of the number of accelerations occurring above 3.5 $m \cdot s^{-2}$ in four movement vectors (forward, backward, right, and left). The number of IMA actions taking place in each direction was summed to produce a total IMA count for each training session. This cumulative number was used as an indicator of session intensity. Both IMA and PL have been previously used to describe American football training activities (Chapter 3) and to differentiate the volume and intensity of training between position groups during an American football training camp (Chapter 5).

### 7.2.4 Statistical Analysis

Training during the 17-week competitive season was evaluated by summing both PL and IMA to obtain a total weekly PL and total weekly IMA values for each player. Each player's data is represented as a time series, whereby repeated training load data is represented for each training week across the season. Because of the serial nature of the data we employed a summary measures approach to the analysis, as proposed by Mathews et al (1990).

The summary measure chosen was the regression slope, as this statistic quantifies the rate of change in training load over time (e.g., a negative slope is indicative of a decrease in training load). Two linear regression models were built for each player: PL Model and IMA Model. Both of these models consisted of the microcycle week as a continuous independent variable (week 1 to 17) and the respective inertial sensor metric (PL or IMA) as the dependent variable. A "Team" rate of change was evaluated by taking the average rate of change for PL and IMA across all players. To create a position average rate of change for both PL and IMA, a mean of the regression slope for each player in each positional group was then calculated. Both within and between position group comparisons were made by obtaining a t-statistic (effect statistic – threshold value / SE), which was then converted to a probability via the t-distribution (Barrett et al., 2018).

Microcycle periodization was evaluated for the commonly performed, 3-day training weeks, which occurred 13 out of the 16 game weeks in the given season. During these weeks, players performed training on Game Day (GD) -4, -3, and -2. Game Day -1 consisted of a 45 min walk through that serves to review the playbook for the upcoming match but is not strenuous and does not constitute a true training session. Game Day -6 is the day immediately following the previous Game. This day does not consist of any football training and players, instead, perform light activities in the gym. Therefore, GD -6 and GD -1 received a training load of 0 (AU) to reflect the fact that on-field training activities are not performed on those days. Game Day -5 is a mandatory day away from the training grounds, per league rules, and is therefore not represented in this analysis.

Microcycle training has been previously explored in other team sports and found to be larger early in the week and decrease as the game nears (Malone et al., 2015). Traditionally, this type of periodization model has been analyzed by making comparisons between discrete training days (e.g., GD -4 compared to GD -2). However, given the time series nature of weekly training we chose to take a summary measures approach (Matthews et al, 1990) and model the microcycle training using a quadratic curve to reflect the rise and fall of training across the week. Using this approach, two polynomial models were built for each individual athlete (Player Load model and IMA model). To determine the microcycle training load trend, the coefficients of these models were then averaged across players within each position group. Additionally, Team models were built for PL and IMA to determine the weekly trend in training for the squad. The parameter of interest in these models is the squared regression coefficient as this represents the direction (increase or decrease) and rate of change in training load from the peak training day in the microcycle. The peak training day was identified using the beta coefficients from the respective models and applying the equation $-b / (2 * b^2)$. Within and between position group comparisons were made by obtaining a t-statistic (effect statistic – threshold value / SE), which was then converted to a probability via the t-distribution (Barrett et al., 2018).

Differences in the rate of change in training load between position groups are presented along with 99% CI, to account for type I error due to the large number of inferences (Ritchie et al., 2016). The magnitude of the effects for within and between position comparisons were interpreted in reference to a threshold value of 10 PL units, for the PL Model, and 2 IMA units, for the IMA Model, in the seasonal periodization analysis and 66 PL units, for the PL Model, and 3 IMA units, for the IMA model, in the weekly microcycle analysis. These threshold values reflect 1 * between subject SD of the regression slopes value across the entire sample of athletes. Effects were assessed mechanistically as being "increasing", "decreasing", or "trivial" for within position comparisons and "positive", "negative", or "trivial", for between position comparisons. Qualitative statements regarding the probability of the effects were assessed as "trivial" (< 25%), "possibly" (25-75%), "likely" (75-95%), "very likely" (95-99.5%), and "most likely" (> 99.5%). If the probability exceeded 5% in both the positive and negative directions, effects were reported as "unclear", indicating that no discernable difference could be detected (Batterham & Hopkins, 2006). All statistical analysis was performed in R statistical software (Version 3.3.4).

## 7.3 Results

### 7.3.1 Seasonal Periodization

The rate of change in the PL and IMA, presented in **Figure 7.1 (Team PL and IMA), Figure 7.2 (Position Group PL)** and **Figure 7.3 (Position**

**Group IMA)**, was negative for the entire team and for all position groups, indicating a decrease in training load across the 17-week competitive season. Across the season, decreases in weekly PL were most likely for Team, DB, and OL, very likely for LB and WR, and likely for DL and TE. Decreases in IMA across the season were most likely for Team, LB, and OL, likely for DB and TE, and possible for DL and WR (**Table 7.2**). In both models, the rate of change for QB was deemed unclear. The across-season rate of change in PL between position groups was unclear to trivial (**Table 7.3**). Differences for the rate of change in IMA were likely for DB compared to OL, and OL compared to WR, and possible for DB compared to LB, DL compared to OL, and both LB and TE compared to WR (**Table 7.4**).

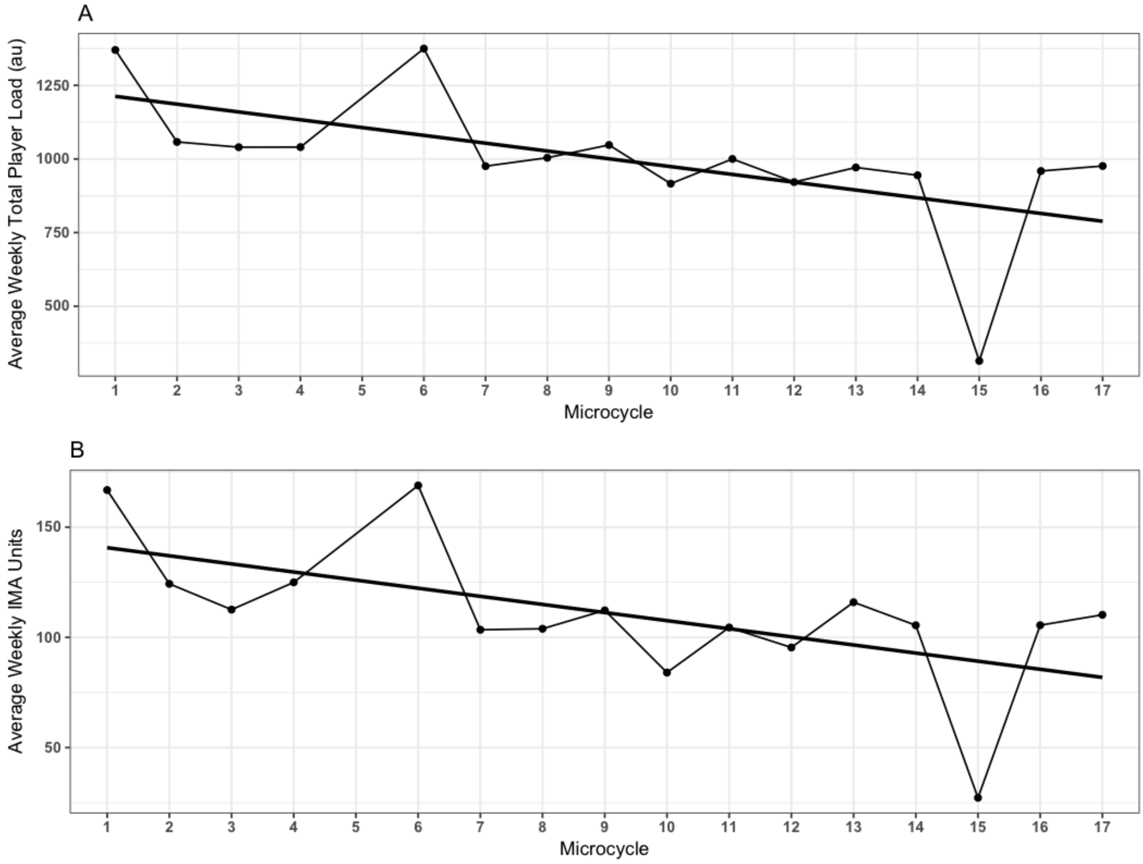


**Figure 7.1.** The trend in total weekly Player Load (au) (A) and IMA (B) across the 17-week season for one NFL team.

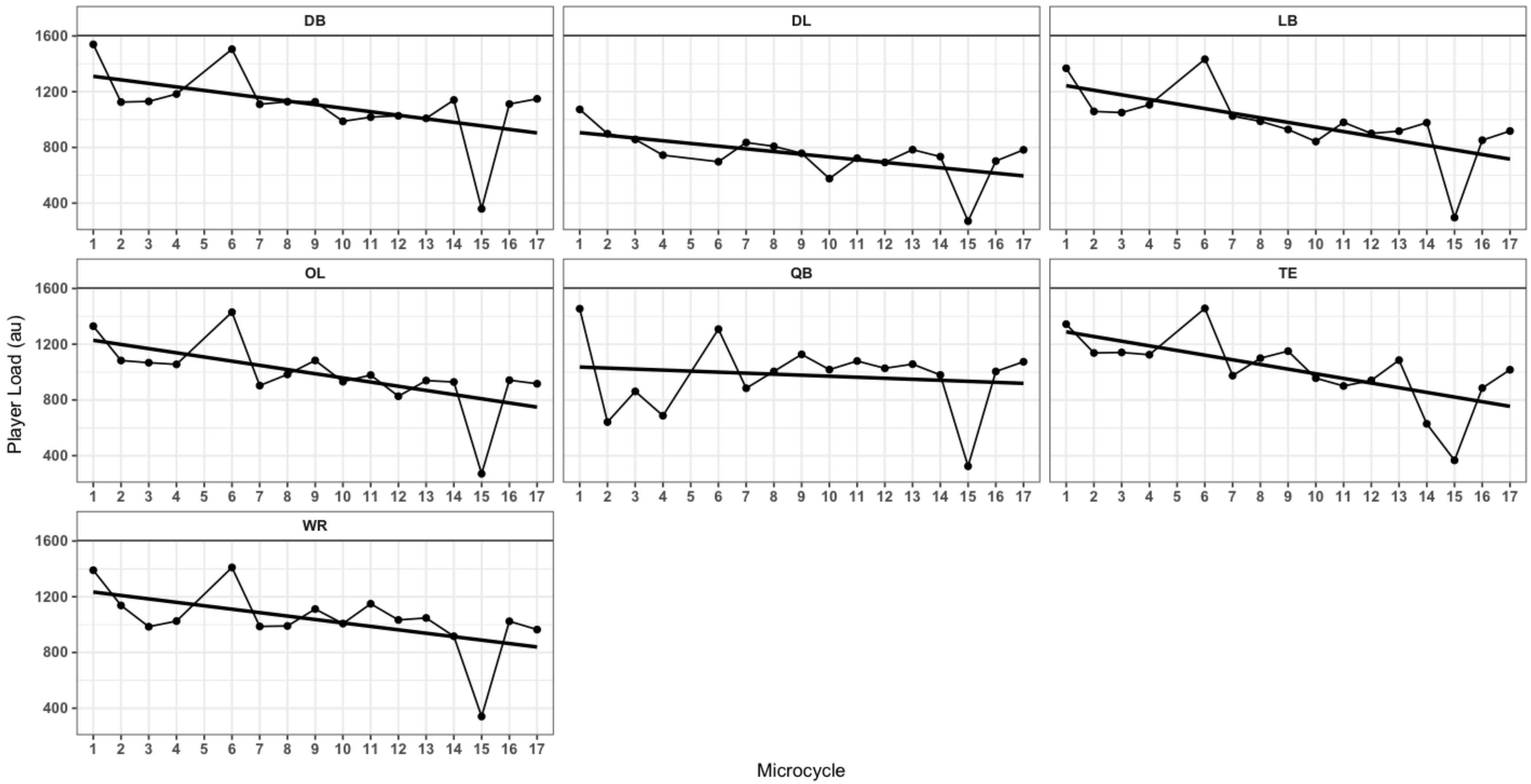


**Figure 7.2.** The trend in total weekly Player Load (au) across the 17-week season for each positional group of one NFL team.

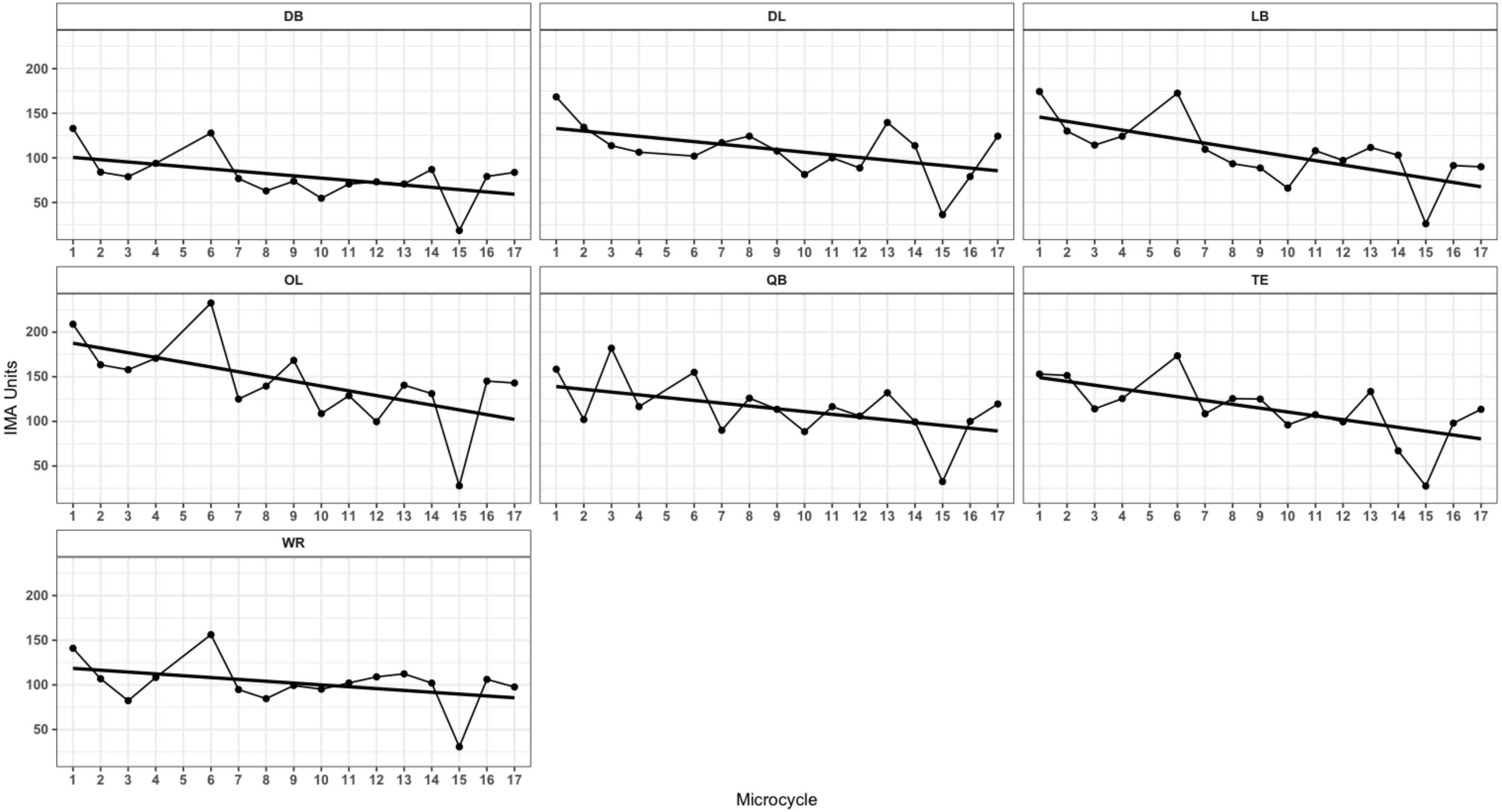


**Figure 7.3.** The trend in total weekly IMA across the 17-week season for each positional group of one NFL team.

**Table 7.2.** Mean ± SD rate of change across the season for Player Load (au) and IMA. (↓ = decreasing rate of change)

| Position | Player Load Model Mean ± SD | Player Load Model Inference | IMA Model Mean ± SD | IMA Model Inference |
|---|---|---|---|---|
| Team | -25.9 ± 10.7 | Most Likely ↓ | -3.6 ± 1.9 | Most Likely ↓ |
| DB | -25.7 ± 6.6 | Most Likely ↓ | -2.5 ± 1.2 | Likely ↓ |
| DL | -19.4 ± 14.1 | Likely ↓ | -3 ± 2.4 | Possibly ↓ |
| LB | -31.5 ± 3.1 | Very Likely ↓ | -4.6 ± 1.2 | Most Likely ↓ |
| OL | -28.7 ± 8.4 | Most Likely ↓ | -5.3 ± 1.4 | Most Likely ↓ |
| QB | -5.7 ± 24.5 | Unclear | -2.3 ± 4.5 | Unclear |
| TE | -33.4 ± 8.9 | Likely ↓ | -4.3 ± 0.9 | Likely ↓ |
| WR | -24.3 ± 10.9 | Very Likely ↓ | -2.2 ± 1.1 | Possibly ↓ |

**Table 7.3.** Comparison of the mean difference ± 99% Confidence Interval (CI) for the between position season long rate of change in Player Load (au).

| Comparison | Difference (± 99% CI) | Inference |
|---|---|---|
| DB - DL | -6.3 (-71.4 to 58.7) | Possibly Trivial |
| DB - LB | 5.8 (-3.4 to 14.8) | Likely Trivial |
| DB - OL | 3.0 (-8.1 to 14.2) | Very Likely Trivial |
| DB - QB | -20.1 (-974.4 to 934.2) | Unclear |
| DB - TE | 7.7 (-158.1 to 173.4) | Possibly Trivial |
| DB - WR | -1.4 (-16.7 to 13.8) | Likely Trivial |
| DL - LB | 12.1 (-63.7 to 87.9) | Unclear |
| DL - OL | 9.3 (-52.7 to 71.3) | Unclear |
| DL - QB | -13.8 (-382 to 354.5) | Unclear |
| DL - TE | 14.0 (-46.6 to 74.6) | Unclear |
| DL - WR | 4.9 (-47.2 to 56.9) | Possibly Trivial |
| LB - OL | -2.8 (-12.3 to 6.8) | Very Likely Trivial |
| LB - QB | -25.9 (-1087.9 to 1036.1) | Unclear |
| LB - TE | 1.9 (-301.4 to 305.2) | Possibly Trivial |
| LB - WR | -7.2 (-22.2 to 7.7) | Possibly Trivial |
| OL - QB | -23.1 (-940.7 to 894.6) | Unclear |
| OL - TE | 4.7 (-134.1 to 143.4) | Likely Trivial |
| OL - WR | -4.4 (-19.9 to 10.9) | Likely Trivial |
| QB - TE | 27.8 (-500.7 to 566.2) | Unclear |
| QB - WR | 18.7 (-739.2 to 776.4) | Unclear |
| TE - WR | -9.1 (-85.6 to 67.3) | Possibly Trivial |

**Table 7.4.** Comparison of the mean difference ± 99% Confidence Interval (CI) for the between position season long rate of change in IMA. (↓ = negative effect, indicating the second group in the comparison is larger than the first. ↑ = positive effect indicating the first group in the comparison is larger than the second)

| Comparison | Difference (± 99% CI) | Inference |
|---|---|---|
| DB - DL | 0.44 (-10.1 to 11.0) | Possibly Trivial |
| DB - LB | 2.08 (-0.06 to 4.23) | Possibly ↑ |
| DB - OL | 2.73 (0.78 to 4.69) | Likely ↑ |
| DB - QB | -0.23 (-172.8 to 172.4) | Possibly Trivial |
| DB - TE | 1.74 (-5.64 to 9.12) | Possibly Trivial |
| DB - WR | -0.35 (-2.27 to 1.59) | Very Likely Trivial |
| DL - LB | 1.64 (-8.58 to 11.86) | Possibly Trivial |
| DL - OL | 2.29 (-8.31 to 12.89) | Possibly ↑ |
| DL - QB | -0.67 (-75.44 to 74.08) | Unclear |
| DL - TE | 1.30 (-8.50 to 11.09) | Possibly Trivial |
| DL - WR | -0.79 (-11.71 to 10.14) | Possibly trivial |
| LB - OL | 0.65 (-1.45 to 2.75) | Very Likely Trivial |
| LB - QB | -2.31 (-170.53 to 165.90) | Unclear |
| LB - TE | -0.34 (-7.02 to 6.33) | Likely Trivial |
| LB - WR | -2.43 (-4.51 to -0.35) | Possibly ↓ |
| OL - QB | -2.96 (-176.26 to 170.32) | Unclear |
| OL - TE | -0.99 (-8.42 to 6.43) | Likely Trivial |
| OL - WR | -3.08 (-4.94 to -1.21) | Likely ↓ |
| QB - TE | 1.97 (-147.14 to 151.09) | Unclear |
| QB - WR | -0.12 (-177.08 to 176.85) | Possibly Trivial |
| TE - WR | -2.09 (-10.57 to 6.39) | Possibly ↓ |

From a practical perspective, the full linear regression model can be used to understand how training changed across the season. For example, the model coefficients for the DL group as a whole and for each of the three players within in that group are displayed in **Table 7.5.** For the DL group, the rate of change indicates that for each week of the season there is a corresponding 19.4 unit decrease in Player Load. Correspondingly, the parameter values for each player within that group reveal their individual differences from the group model. For example, Player 1 is seen to have a larger overall Player Load during training than Player 3. However, Player 1 also has a more rapid decline in Player Load across the season than the other players in this group.

**Table 7.5.** Player Load regression model coefficients for the DL group as a whole and each individual.

| | **DL Group** | **Player 1** | **Player 2** | **Player 3** |
|---|---|---|---|---|
| Intercept | 925.4 | 1073 | 966.7 | 736.7 |
| Rate of Change | -19.40 | -31.71 | -22.51 | -3.98 |

### 7.3.2 Microcycle Periodization

Microcycle peak training day and rate of decrease from peak to game day for PL and IMA are displayed in **Table 7.6** and visually presented in **Figure 7.4 (Team PL and IMA)**, **Figure 7.5 (Position Group PL),** and **Figure 7.6 (Position Group IMA)**. The peak training day was observed to differ between positional groups with some groups experiencing their highest weekly PL or IMA on GD -4 while others experiencing their highest weekly loads on GD -3. Clear decreases in PL and IMA, from the peak day, as game day approached, were observed for all positional groups. Although these decreases were clear for the PL model, all effects were trivial. Conversely, a likely decrease in microcycle IMA was observed in the QB and TE group with all other groups showing a most likely decrease from their peak training day.

**Table 7.6.** Microcycle peak training day and the mean ± SD in the rate of change for Player Load (au) and IMA from the peak training day for the team and each positional group. (↓ = decreasing rate of change)

| | Player Load Model | | | IMA Model | | |
|---|---|---|---|---|---|---|
| **Position** | **Microcycle Peak Day** | **Mean ± SD** | **Inference** | **Microcycle Peak Day** | **Mean ± SD** | **Inference** |
| Team | -4 | -63.8 ± 7.2 | Very Likely Trivial | -3 | -12.1 ± 6 | Most Likely ↓ |
| DB | -4 | -69.7 ± 6.9 | Likely ↓ | -3 | -5.5 ± 1.1 | Most Likely ↓ |
| DL | -3 | -46.7 ± 4.3 | Very Likely Trivial | -3 | -7 ± 1.2 | Most Likely ↓ |
| LB | -3 | -63.7 ± 8.3 | Possibly ↓ | -3 | -7 ± 2 | Most Likely ↓ |
| OL | -4 | -64 ± 5.4 | Likely Trivial | -3 | -11.1 ± 1.8 | Most Likely ↓ |
| QB | -4 | -63.3 ± 4.8 | Possibly ↓ | -4 | -8.6 ± 3.3 | Likely ↓ |
| TE | -3 | -65.2 ± 5.7 | Possibly ↓ | -3 | -8.1 ± 1.3 | Likely ↓ |
| WR | -3 | -64.5 ± 6.6 | Possibly ↓ | -3 | -6.9 ± 1.3 | Most Likely ↓ |

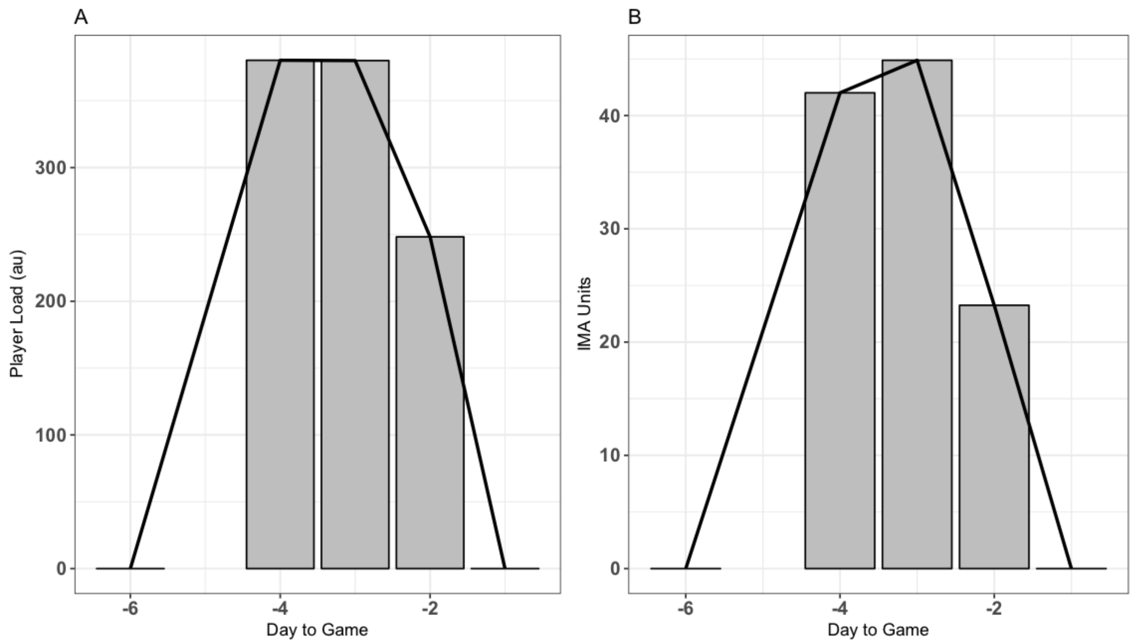


**Figure 7.4.** The microcycle trend in Player Load (au) (A) and IMA (B) for one NFL team.

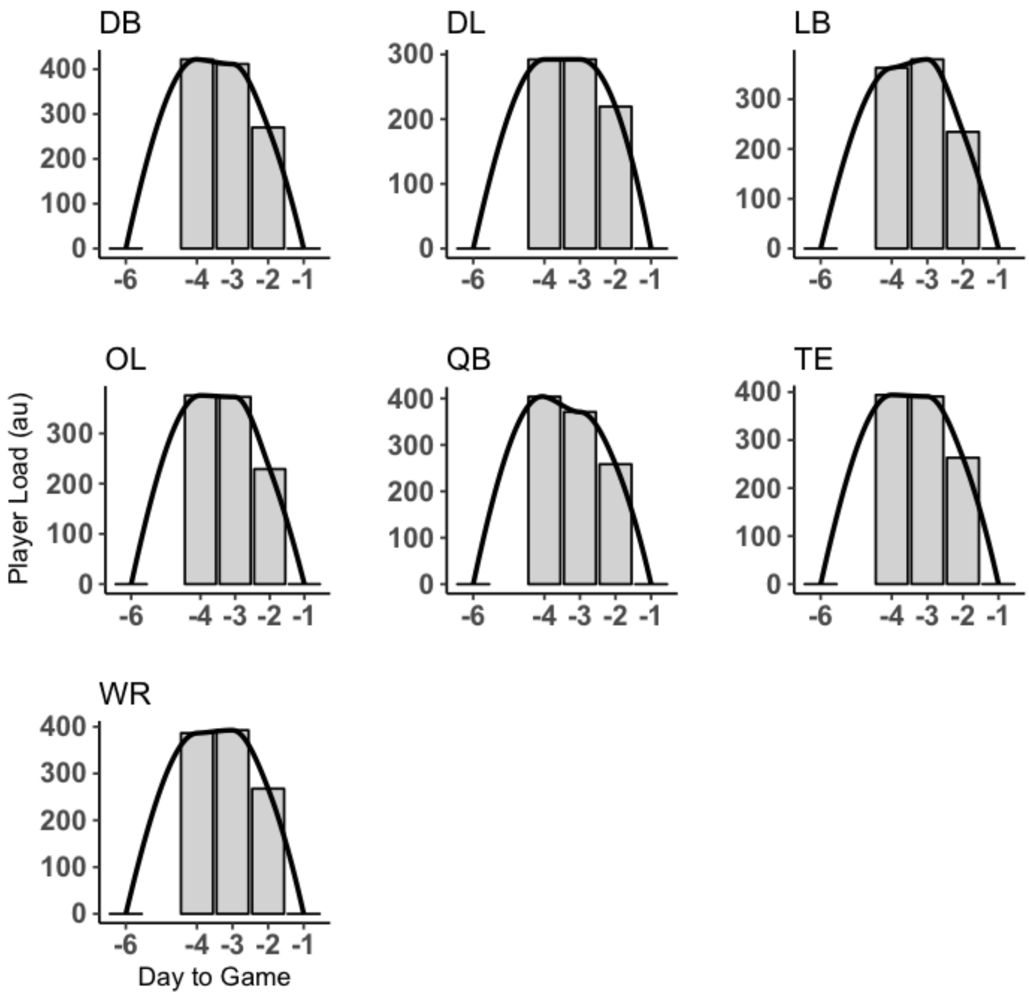


**Figure 7.5.** Microcycle trend in Player Load (au) for each positional group of one NFL team.

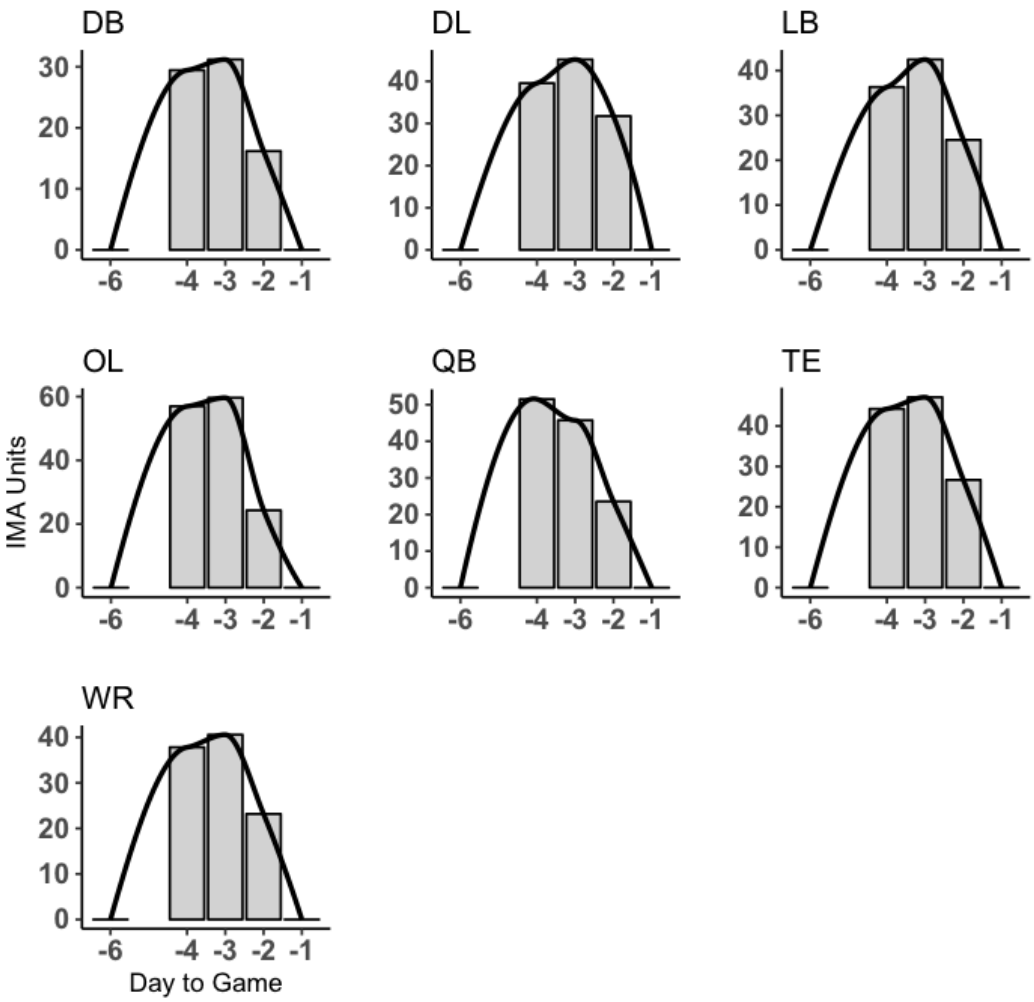


**Figure 7.6.** Microcycle trend in IMA for each positional group of one NFL team.

All between-group differences for PL were observed to be most likely trivial. Differences in the decrease of IMA ranged from possibly to very likely for all comparisons with the exception of unclear differences between the LB and TE groups and the QB and TE groups. Differences in the microcycle decrease in IMA were likely for DB compared to DL, LB, OL, and WR; DL compared to LB, OL, and WR; LB compared to OL, QB, and WR; OL compared to WR; and, WR compared to QB and TE (**Table 7.7**).

**Table 7.7.** Comparison of the mean difference ± 99% Confidence Interval (CI) for the between position microcycle rate of change in IMA. (↓ = negative effect, indicating the second group in the comparison is larger than the first. ↑ = positive effect indicating the first group in the comparison is larger than the second)

| Comparison | Difference (± 99% CI) | Inference |
|---|---|---|
| DB - DL | 1.5 (-0.6 to 3.6) | Very Likely Trivial |
| DB - LB | 1.5 (-0.8 to 3.8) | Likely Trivial |
| DB - OL | 5.6 (3.7 to 7.5) | Very Likely ↑ |
| DB - QB | 3.1 (-2.9 to 9.1) | Possibly ↑ |
| DB - TE | 2.6 (0.1 to 5.1) | Possibly ↑ |
| DB - WR | 1.4 (-0.3 to 3.1) | Likely Trivial |
| DL - LB | 0 (-2.7 to 2.7) | Very Likely Trivial |
| DL - OL | 4.1 (1.7 to 6.5) | Likely ↑ |
| DL - QB | 1.6 (-4.6 to 7.8) | Possibly Trivial |
| DL - TE | 1.1 (-1.8 to 4) | Possibly Trivial |
| DL - WR | -0.1 (-2.3 to 2.1) | Very Likely Trivial |
| LB - OL | 4.1 (1.5 to 6.7) | Likely ↑ |
| LB - QB | 1.6 (-4.7 to 7.9) | Likely Trivial |
| LB - TE | 1.1 (-2 to 4.2) | Unclear |
| LB - WR | -0.1 (-2.5 to 2.3) | Very Likely Trivial |
| OL - QB | -2.5 (-8.6 to 3.6) | Possibly ↓ |
| OL - TE | -3 (-5.8 to -0.2) | Possibly ↓ |
| OL - WR | -4.2 (-6.2 to -2.2) | Likely ↓ |
| QB - TE | -0.5 (-6.9 to 5.9) | Unclear |
| QB - WR | -1.7 (-7.8 to 4.4) | Likely Trivial |
| TE - WR | -1.2 (-3.9 to 1.5) | Likely Trivial |

## 7.4 Discussion

The aim of this study was to investigate and attempt to understand the rate of change in indicators of training load both within and between positional groups, across both a competitive NFL season and within training microcycles between competitive games. While much of the periodization research in team sport has made comparisons between discrete training phases (Malone et al., 2015; Moreira et al., 2015; Ritchie et al., 2016), the approach taken in this study was to evaluate the rate of change in serial measurements across the time periods of a competitive season and within training microcycles. The data suggests that all positional groups, with the exception of QB, demonstrated decreases in both the volume (PL) and intensity (IMA) of training over the course of the season. The across season trend for volume and intensity was observed to be unclear for the QB group, indicating no discernable effect could be detected. The between position across-season rate of change in PL ranged from unclear to trivial. Conversely playing position had an effect on the rate of cross-season change in IMA, with clear differences observed between groups. Changes in training load were also observed across a microcycle. These shorter periods of training indicated that specific position groups were different in their peak training day for volume (PL) and intensity (IMA). Between position group differences in these decreases in training load were most likely trivial for PL, however clear differences were found for the decrease in IMA from the peak training day for all groups except LB compared to TE and QB compared to TE. These findings suggest that a lack of periodization is observed across the season though there does appear to be a systematic decrease in training load as the season progresses for all positional groups. It does, however, appear that coaches employ some form of periodization between games. This is illustrated by a training load decrease as the days within the week moves closer to the game. Such information can provide a basis for an evaluation of the effectiveness of such approaches to planning. For example, analyzing the rate of change in training across the week in relationships to cumulative training load, injury risk, and performance outcomes. Evaluating training using a summary measures approach also seems useful in providing a more specific understanding of how players training changes over the course of a season and within the microcycle. These insights provide an opportunity to develop more appropriate strategies to ensure that more effective training stimuli are delivered to enable players to cope with the demands of the sport. For example, depending on the amount of fatigue experienced by the players from the previous game, training could be modulated across the week to have a larger reduction from the peak day leading, allowing for greater recovery.

The approach to data analysis used in the present study differed from previous approaches that have been utilized to evaluate periodization strategies in team sport athletes (Malone et al., 2015; Moreira et al., 2015; Ritchie et al., 2016). Rather than treating phases of the season as discrete periods of time, we used a summary measures approach (Mattews et al., 1990; Weston et al., 2011) to identify the rate of change in serial measures. Training volume is an important component of the training stimulus as it is an important determinant of the adaptive response (Stone et al., 2009). The findings from this study showed a systematic decrease in PL (ranging from 5.7 to 33.4 au) across the season in all playing positions aside from QB. These trends have been observed in other team sports such as soccer (Malone et al, 2015) and AFL (Moriera et al., 2015; Ritchie et al., 2016).

The observed decrease in PL for all groups maybe a consequence of specific coaching strategies to reduce the training volume across the season to mitigate any fatigue experienced by the athletes These strategies may be a reflection of planning traditions that have been passed down from other more experienced coaches (Weston, 2018). It is also possible that this trend in the data is simply a reflection of the response to other situational factors experienced in the later stages of the season that are not linked to physical preparation (e.g. the success of the team, the monotony of the training/competition routine). This investigation did not attempt to evaluate the reasons for any changes in training load and so the specific reasons for these declines remain unknown. A more thorough understanding of how coaches within the sport of American football consider periodization and the planning of training is required to fully understand the reasons behind the outcomes in this study.

Understanding how coaches periodize training in a microcycle is critical in team-sports as this represents the most important unit of the yearly training program given that each week ends with a competition (Morgans et al., 2014). We found a decrease in PL from the peak training day of the week (range from -46.7 to -69.7 au) across the seven positional groups. As a whole, the team exhibited a 63.8 au decrease in PL from the peak training day of the week (GD -4). Between group comparisons revealed most likely trivial differences indicating that positional groups are, for the most part, experiencing similar weekly declines in PL from their peak training day, as the game nears. While the peak PL training day for each position group may differ the decline in PL for all groups suggests that there is a systematic strategy used by coaches to decrease training volume as the week progresses and the game nears. This would seem to make sense from a physiological perspective as it provides an opportunity for players to arrive at match day in "peak" physical condition. This would in some way mirror the tapering strategies observed in other sports (Manzi et al., 2010), however at this time we do not know if this strategy is optimal for American football.

Intensity, as reflected by IMA, was found to decrease across the season for all position groups, by a range of 2.2 to 5.3 IMA units. In contrast to the observations on training volume, clear effects in the rate of change in IMA across the season were only observed for some position groups. The smallest decline in IMA was found in players typically associated with skill positions (DB, WR, and QB) while a larger decline was observed for the positions that require physical contact such as the LB and TE and linemen (OL and DL). While the exact reasons for these changes are unknown they may be a consequence of the rule changes imposed by the sport's governing body. For example, after the 14$^{th}$ week of the season teams are no longer allowed to hold padded practices, which results in a decrease in the amount of hitting and collisions that take place within a given training session. This change would clearly impact the OL, DL, TE, and LB groups given the physical nature of these positions and the type of activities they perform (Pincevero & Bompa, 1997). Other groups that perform more locomotor activity (DB and WR) may however be less influenced by these changes as their dominant training stimulus would remain unchanged.

All positional groups observed likely to most likely decreases in IMA from the peak IMA training day across the microcycle. Aside from the QB group, positional groups observed their peak IMA training day to be GD -3. Reasons for this may be due to how coaches choose to install the plays for the upcoming game with less intense, more "learning-based", plays taking place on GD -4 before attempting to perform them at full pace on GD -3. Interestingly, the peak training day for IMA (GD -3) was observed to be different from the day in which peak PL was observed (GD -4). This may support the notion that coaches prioritize a higher training volume earlier in the post-game phase of the microcycle before then increasing the intensity of training on GD -3. While the specific reasons for such loading patterns are currently unknown, they may either reflect the coaches "intuitively" feel that players require extra days of recovery prior to increasing training intensity or simply favor higher intensity training on certain days for game preparation reasons. These ideas are in-line with those proposed by Fullagar and colleagues (2016) in collegiate American football, who observed reductions in self-reported soreness and wellness measures up to

GD -3. The rationale for such an approach should be the subject of future research.

## 7.5 Conclusions

This is the first study to evaluate the periodization strategies used by one team in the sport of American football. This study showed likely decreases in training volume (PL) and possible to likely decreases in training intensity (IMA) across the season as well as decreases in volume (PL) and intensity (IMA) across position groups within the microcycle. These findings are consistent with findings from other sport where training has been found to decrease across the season as well as decrease within the microcycle, as the competition nears (Weston et al., 2011; Malone et al., 2015). The present results also revealed different days for the completion of peak training volumes and intensity within the microcycles analyzed. This data together illustrates that the training loads completed by this team would seem to follow some pattern of systematic change as would be expected in periodization. The exact reasons for these changes are however currently unknown. Potential explanations could include specific strategies to respond to changes in the fatigue status of players, situational factors that may influence planning and/or important considerations in the short-term preparation strategies for the upcoming competition. Future research should therefore attempt to understand the implications of such programs for performance and/or injury outcomes. Additionally, a limitation of the study, that requires future investigation, is that the weekly microcycle models presented here do not differentiate between player ranks within the club. It is possible that players who are going to be featured in the upcoming game (rank = 1) exhibit a different periodization strategy across the week than those who are back up players (rank = 2) or players on the practice squad, who are not available to participate in the game and only participate in team activities during training (rank = 3). Finally, future research is required to evaluate the periodization strategies of other coaches across the sport. Other teams may utilize different microcycle or season long periodization strategies, however, the current landscape of such approaches is not well understood at this time.

The statistical approach taken in this study has value across multiple team sports besides American football. Traditional approaches to investigating periodization in team-sport have been limited to making discrete comparisons between training phases (Malone et al., 2015; Moreira et al., 2015; Ritchie et al., 2016). Such an approach to analysis does not provide the practitioner with an understanding of the athlete's adaptation as training progresses overtime (serial measures). The approach taken in this study has the potential to assist sports scientists in better understanding the dose-response relationship of training (Bannister et al., 1975) as it honors the time-series nature of training across a competitive season.

# CHAPTER 8

# VOLUME AND INTENSITY ARE IMPORTANT TRAINING-RELATED FACTORS IN INJURY INCIDENCE IN AMERICAN FOOTBALL ATHLETES

## 8.1 Introduction

Injury is an unintended consequence of participating in sport. In America, an estimated 7 million individuals participating in sport require medical attention each year (Conn et al., 2003). Due to the physical nature of the sport, American football carries with it a high injury risk. Over a 16-year period, Hootman and colleagues (2007) observed the risk of injury in American college football to be 9.6 injuries per 1000 athlete practice exposures and 35.9 injuries per 1000 athlete game exposures. These figures were the highest of 16 collegiate sports during the study period (Hootman et al., 2007). At the elite level, in the National Football League (NFL), a 10-year investigation of pre-season training camp injuries indicated that injuries occur at a rate of 12.7 per 1000 athlete exposures during training and 64.7 injuries per athlete exposure in games (Feeley et al., 2008). While some of these injuries may be related to contact with another player, a large number of injuries are non-contact in nature (e.g., muscle strains) (Dick et al., 2007; Elliot et al., 2011) and have been suggested to be a consequence of high training loads (Gabbett, 2010).

Prescription of training load can be aided by the use of player-monitoring strategies, which help to inform on the different physical responses experienced by the athletes (Halson et al., 2014). One of the most common methods of training load monitoring in team sport athletes is through the use of integrated micro technology sensors (Cardinale & Varley, 2017). These wearable technologies consist of GPS and inertial sensor units making them useful for quantifying both running and non-running (e.g., change of direction and collisions) actions in team sport athletes (Cardinale & Varley, 2017). As such, integrated micro technology systems have been utilized to objectively quantify training demands in a variety of different sports (DeMartini et al., 2011; Boyd et al., 2013; Schelling et al., 2016; Chapters 3, 5-7). The use of such technologies has recently been explored in American football, where positional groups were observed to experience different physical loads based on their tactical demands (DeMartini et al., 2011; Wellman et al., 2016; Wellman et al., 2017; Chapter 5 & 6). For example, during training at both the collegiate (DeMartini et al., 2011) and NFL levels (Chapter 5), players in the wide receiver and defensive backs group performed greater amounts of running volume while those on the line (e.g., Defensive and Offensive Linemen) engaged in a higher number of collision and physical contact. These descriptions of training demands provide a unique perspective on the ergonomic demands of the sport but offer little in the way of understanding the physical consequences of the game for either positive (e.g. performance) or negative (e.g., muscle injury) outcomes.

While the multi-faceted nature of injury makes it challenging to predict (Bittencourt et al., 2016), a first step in mitigating risk lies in understanding the relationship between training load and injury (Roe et al., 2017). Collision sports present a unique challenge for understanding injury due to the diverse demands of both locomotor tasks and physical contact (Gabbett et al., 2011). In American football, Wilkerson and colleagues (2016) identified an association between inertial sensor derived training loads and increased injury risk in collegiate football athletes. However, a limitation of this study was that only one inertial sensor variable, Player Load, was utilized in the investigation. Player Load may help to quantify the total volume of practice, given its large correlation with running distance (Polglaze et al., 2015), although it may not identify the more high intensity actions observed in American football (Wellman et al., 2017; Chapter 5 & 6). Therefore, additional metrics may be required to evaluate the intensity of a session, to better understand the volume-intensity relationship of training and what this might mean for non-contact injury. Additionally, given the diverse positional demands in American football it is still not understood which metrics provide the best option for describing training load. Therefore, it is possible that other inertial sensor variables or a combination of inertial sensor variables may provide greater detail regarding injury risk because they quantify different aspects of the players' movement demands. Finally, it is not clear whether similar findings are applicable to higher levels of American Football such as the NFL.

While the physical demands of American football training have been described at the high school (Gleason et al., 2017), collegiate (DeMartini et al., 2011), and NFL levels (Chapters 5-7), the relationship between training load and non-contact soft-tissue injury in the sport is poorly understood. Therefore, the aim of this study was to identify the relationship between inertial sensor training load metrics and non-contact injury in NFL athletes.

## 8.2 Methods

### 8.2.1 Research Approach

This study investigated the relationship between training load and non-contact soft tissue injury in NFL football players. The study period consisted of 24 weeks of training from the pre-season, regular season, and playoff periods for one NFL team. During this time 76 training sessions in total were completed. Training load was evaluated through the use of integrated micro technology sensors worn by the players during all on-field training sessions. Injury data was recorded by the team physical therapist using a proprietary injury database and was subsequently combined with training data for further evaluation. All training sessions were directed by the coaching staff with the aim of preparing the players for the upcoming opponent.

### 8.2.2 Participants

One hundred and one participants competing for one NFL team were included in this study (mean ± SD; age: 25 ± 3 y; height: 1.88 ± 0.06 m; body mass: 112.9 ± 20.2 kg). Participants were classified by the coaching staff into one of 7 positional groups: Defensive Backs (DB; n = 16), Defensive Line (DL; n = 18), Linebackers (LB; n = 13), Offensive Line (OL; n = 17), Running Back (RB; n = 18), Tight End (TE; n = 7), and Wide Receiver (WR; n = 12). All playing positions were included in this study with the exception of the Quarterback position given their unique training actions compared to other position groups (e.g., throwing passes) and the lack of clarity in the inertial sensor readings due to these actions (Chapter 6). This study was approved by a local ethics committee and permission to publish was granted by the NFL club.

### 8.2.3 Experimental Approach

Each player was provided with an integrated micro technology unit (Minimax S5, Catapult Innovations, Scoresby, Australia) to be worn during on-field training activities. These integrated micro technology units contain three inertial sensors - tri-axial accelerometer, tri-axial gyroscope, and magnetometer - each sampling at 100 Hz. The units were worn between the shoulder blades in a custom-made pouch provided by the manufacturer. In order to ensure inter-unit reliability, each player was provided their own unit for the duration of their time with the team (Rampinini et al., 2015). At the completion of each training session data was downloaded from the units using the manufacturer's software (Catapult Sports, Openfield Software) and imported into Microsoft Excel (Microsoft, Redmond, WA) for further analysis.

A bespoke injury database was created to code the injury status of players throughout the study period. At the completion of each week the team's sports scientist and physiotherapist coded the injury type (contact/non-contact) and whether the injury resulted in time loss for the players suffering injury during that week of training. While no consensus on injury data collection and coding methods has been established for American football the recommendations set forth by the UEFA consensus statement were applied in this study (Fuller et al., 2006). This approach has been used previously in other sports besides soccer (Caparrós et al., 2017). As American football is a contact sport, a substantial number of injuries occur due to player collisions (Dick et al., 2011). These collision injuries are a consequence of playing the sport and are thus frequently recognized as being unavoidable and not attributable to changes in training load. Therefore, this study focused on the relationship between training load and non-contact injuries (e.g., injuries that may be a consequence of the training load performed by the athlete). As such, a non-contact soft tissue injury was defined as any injury that did not occur due to contact with another player and which resulted in the player having to miss a subsequent training session or game (Fuller et al., 2006; Ehrmann et al., 2016). Additionally, if a player was removed from a training session due to injury their data was excluded from the data on the given injury day. This is necessary to ensure that the group-training load is not biased downward due to the injured athlete being unable to complete the session or potentially limiting their overall activity during training due to pain or discomfort.

### 8.2.4 Inertial Sensor Training Load Metrics

American football is comprised of a variety of movement actions with players performing different volumes of running, cutting, and collisions depending on their positional and tactical requirements (Pincevero &

Bompa, 1997; Wellman et al., 2016; Wellman et al., 2017; Chapter 5 & 6). Inertial sensors are useful in quantifying a number of relevant movement actions in team sport athletes (Boyd et al., 2011; Cardinale & Varley, 2017; Peterson et al., 2017). Therefore, eleven inertial sensor variables were used in this study to quantify training load activities. These eleven variables, defined in detail later, consisted of total Player Load (PL), Player Load effort bands such as Low ($PL_{Low}$), Medium ($PL_{Med}$), High ($PL_{High}$), and Very High ($PL_{VH}$), IMA bands including Low ($IMA_{Low}$), Medium ($IMA_{Med}$), and High ($IMA_{High}$), and three Impact Bands (Low ($Impacts_{Low}$), Medium ($Impacts_{Med}$), and High ($Impacts_{High}$)). Utilizing the tri-axial accelerometer, Player Load reports the amount of acceleration taking place in three axes of movement (x, y, and z) in arbitrary units (Boyd et al., 2013). The reliability of this metric for tracking a variety of movement activities has been previously established (Boyd et al., 2011; Van Iterson et al., 2017). Due to its high correlation with total running distance in team sport athletes Player Load was selected in this study as a measure of overall movement activity (Polglaze et al., 2015; Cardinale & Varley, 2017). Conversely, counts of activity in Player Load effort bands were used to reflect the amount of training performed with different levels of acceleration within a training session. Unlike Player Load, a continuous variable, effort bands are not time dependent; rather, they provide a count activities taking place above pre-set thresholds. These effort bands were discretized into four categories: $PL_{Low}$ (1-2 g); $PL_{Med}$ (2-3 g); $PL_{High}$ (3-4 g); $PL_{VH}$ (> 4g). As such, Player Load effort bands would seem to report a different type of activity than PL as they likely represent discrete accelerations across a range of categories rather than a "global" continuous representation of accelerations performed by the player.

Non-running training activities (e.g., changes of direction, shuffling, cutting) were quantified through data collectively generated from the tri-axial accelerometer, tri-axial gyroscope, and magnetometer and were provided as a count via the IMA metric (Peterson et al., 2017). IMA has been previously used to quantify explosive movements in soccer and basketball (Meylan et al., 2016; Peterson et al., 2017). Recently, this metric was used to describe positional differences during American football training, where linemen (e.g. OL and DL) were found to perform a larger volume of IMA actions compared to skill position players (e.g., WR and DB) (Chapter 5). These explosive actions were classified into three IMA band levels: $IMA_{Low}$ = 1.5 – 2.5 m•s$^{-2}$, $IMA_{med}$ = 2.5 – 3.5 m•s$^{-2}$, $IMA_{high}$ > 3.5 m•s$^{-2}$). Finally, three Impact Bands ($Impacts_{Low}$ = 5-6 g, $Impacts_{Med}$ = 6-7 g, and $Impacts_{High}$ > 7 g) were used in an attempt to identify the amount and magnitude of collisions during training for each player.

### 8.2.5 Statistical Analysis

Average training load per minute for the eleven inertial sensor variables was calculated for each position group following each training session. To better understand the relationship between these eleven variables correlation was assessed using Pearson's correlation coefficient and interpreted as trivial ($r < 0.1$), small (0.1 – 0.3), moderate (0.3 – 0.5), large (0.5 – 0.7), very large (0.7 – 0.9), almost perfect ($r > 0.9$) and perfect ($r = 1$).

Logistic regression models were constructed in an attempt to understand the relationship between training load, position group, and non-contact soft tissue injury (the dependent response). To compare the intensity of training equally across all sessions, inertial sensor variables were normalized to reflect the amount of training activity per minute of practice in a given training session and then standardized to have a mean 0 and SD 1. Models were first fit, both with and without position group as a categorical predictor, for each of the training load variable sub-groups (e.g., Player Load variables only, IMA variables only, and Impact Variables only). A final joint model consisted of iteratively fitting all training load variables with and without position group.

Model comparison was made using the Bayesian Information Criterion (BIC) and out of sample likelihood (Drichoutis et al., 2014) with the model consisting of the lowest BIC and the highest out of sample likelihood in each group being retained. To understand the relationship that these eleven variables have on non-contact soft tissue injury we present the five best joint models, according to BIC. Finally, the joint model with the strongest relationship to non-contact soft tissue injury was compared with the sub-group models using out of sample likelihood. The top model in each category was interpreted practically using a magnitude-based inference approach (Batterham & Hopkins, 2006) whereby the smallest worthwhile increase in risk for non-contact injury was an odds ratio of 1.11 and the smallest worthwhile decrease in risk was an odds ratio of 0.90 (Hopkins et al. 2009). Effects were qualified in probabilistic terms: < 0.5%, most unlikely; 0.5% to 5%, very unlikely; 5% to 25%, unlikely; 25% to 75%, possible; 75% to 95%, likely; 95% to 99%, very likely; and > 99.5%, most likely (Hopkins, 2007). If the chance that the true value was beneficial was >25%, with an odds ratio of < 66 (or vice versa) the effect was deemed unclear. Model results are presented as OR ×/÷ 90% CI. All statistical analysis was performed in the statistical software R (Version 3.2.2).

## 8.3 Results

Twenty-eight non-contact soft tissue injuries resulting in time loss were recorded during the 76 training sessions completed by this team. The breakdown of these injuries and injury type per positional group is represented in **Table 8.1**.

**Table 8.1.** Breakdown of the number of non-contact soft tissue injuries by positional group.

| Position | Number of Players | Non-Contact Soft Tissue Injuries | Injury Type |
|---|---|---|---|
| DB | 16 | 4 | Groin (n = 3), Knee (n = 1) |
| DL | 18 | 7 | Calf (n = 4), Elbow (n = 1), Hamstring (n = 1), Knee (n = 1) |
| LB | 13 | 3 | Foot (n = 1), Groin (n = 1), Oblique (n = 1) |
| OL | 17 | 1 | Ankle (n = 1) |
| RB | 18 | 4 | Achilles (n = 1), Ankle (n = 1), Hamstring (n = 1) |
| TE | 7 | 5 | Achilles (n = 1), Ankle (n = 1), Foot (n = 1), Hamstring (n = 1), Low Back (n = 1) |
| WR | 12 | 4 | Groin (n = 1), Hamstring (n = 3) |

**Table 8.2** displays the correlation matrix for all 11 inertial sensor variables. Several large and very large relationships were found between the inertial sensor variables with an *almost perfect* relationship existing for $PL_{High}$ and $PL_{VH}$. These findings may introduce collinearity between predictor variables that may confound statistical models.

**Table 8.2.** Correlation matrix of all inertial sensor variables († = Large, § = Very Large, • = Almost Perfect).

| | **PL** | **$PL_{Low}$** | **$PL_{Med}$** | **$PL_{High}$** | **$PL_{VH}$** | **$IMA_{Low}$** | **$IMA_{Med}$** | **$IMA_{High}$** | **$Impacts_{Low}$** | **$Impacts_{Med}$** |
|---|---|---|---|---|---|---|---|---|---|---|
| **PL** | 1 | | | | | | | | | |
| **$PL_{Low}$** | 0.6† | 1 | | | | | | | | |
| **$PL_{Med}$** | 0.71§ | 0.59† | 1 | | | | | | | |
| **$PL_{High}$** | 0.63† | 0.25 | 0.83 | 1 | | | | | | |
| **$PL_{VH}$** | 0.46 | 0.1 | 0.67† | 0.93• | 1 | | | | | |
| **$IMA_{Low}$** | 0.07 | 0.67† | 0.28 | -0.02 | -0.06 | 1 | | | | |
| **$IMA_{Med}$** | 0.34 | 0.79§ | 0.62† | 0.32 | 0.23 | 0.87§ | 1 | | | |
| **$IMA_{High}$** | 0.43 | 0.63† | 0.82 | 0.64† | 0.56† | 0.52† | 0.79§ | 1 | | |
| **$Impacts_{Low}$** | 0.53† | 0.37 | 0.76§ | 0.76§ | 0.68† | 0.2 | 0.47 | 0.68† | 1 | |
| **$Impacts_{Med}$** | 0.4 | 0.31 | 0.72§ | 0.75§ | 0.74§ | 0.18 | 0.46 | 0.73§ | 0.89§ | 1 |
| **$Impacts_{High}$** | 0.35 | 0.17 | 0.64† | 0.80§ | 0.89§ | 0.06 | 0.34 | 0.64† | 0.67† | 0.78§ |

### 8.3.1 Player Load Models

Player load models were compared with and without position group as a categorical predictor. A model consisting of total PL and $PL_{VH}$ was found to have the highest association with injury (BIC = 180.2, out of sample log likelihood = -84.4) and was retained for interpretation. The model parameters and qualitative inference are displayed in (**Table 8.3**). The probability of non-contact soft tissue injury in a given training session was very likely higher with a one-unit increase in z-score for PL (OR = 1.96; 90% CI: 1.22 – 3.19) and most likely higher with a one-unit increase in z-score for $PL_{VH}$ (OR = 2.84; 90% CI: 2.06 – 3.99).

**Table 8.3**. Model Parameters for the best Player Load model.

| Variable | OR | 90% CI | Clinical Inference | % Likelihood effect is beneficial/trivial/harmful |
|---|---|---|---|---|
| Constant | 0.02 | 0.01, 0.03 | | |
| PL | 1.96 | 1.22, 3.19 | Very Likely Harmful | 0.4% / 2.1% / 97.5% |
| $PL_{VH}$ | 2.84 | 2.06, 3.99 | Most Likely Harmful | 0.0% / 0.0% / 100.0% |

### 8.3.2 IMA Models

IMA models both with and without positional group as a categorical predictor were evaluated for their associated risk with non-contact soft tissue injury. The inclusion of position group along with all 3 IMA bands did not have a substantial improvement over the model consisting of only IMA variables. **Table 8.4** displays the model coefficients and magnitude-based inferences for the effects of the best model according to BIC, containing all three IMA bands. A one-unit increase in $IMA_{High}$ z-score was associated with a most likely higher risk of non-contact soft tissue injury (OR = 5.89; 90% CI: 3.18 – 11.4) while a one unit increase in $IMA_{Low}$ was associated with a very unlikely increase in the probability of non-contact soft tissue injury (OR = 0.47; 90% CI: 0.24 – 0.87). An unclear relationship was observed between $IMA_{Med}$ and non-contact soft tissue injury (OR = 1.05; 90% CI: 0.45 – 2.42).

**Table 8.4.** Model Parameters for the best IMA model.

| Variable | OR | 90% CI | Clinical Inference | % Likelihood effect is beneficial/trivial/harmful |
|---|---|---|---|---|
| Constant | 0.02 | 0.01, 0.036 | | |
| $IMA_{Low}$ | 0.47 | 0.24, 0.87 | Very Unlikely Harmful | 95.4% / 3.3% / 1.3% |
| $IMA_{Med}$ | 1.05 | 0.45, 2.42 | Unclear | 37.6% / 17.1% / 45.4% |
| $IMA_{High}$ | 5.89 | 3.18, 11.4 | Most Likely Harmful | 0.0% / 0.0% / 100% |

### 8.3.3 Impact Models

Similar to the Player Load and IMA models, positional group was not found to improve model performance when attempting to describe the association between impacts during training and non-contact soft tissue injury. As such a model utilizing all three Impact bands was retained for the final interpretation (**Table 8.5**). An unclear association was found between non-contact soft tissue injury and $\text{Impacts}_{\text{Low}}$ (OR = 0.64; 90% CI: 0.29 – 1.38) and $\text{Impacts}_{\text{Med}}$ (OR = 1.83; 90% CI: 0.78 – 4.23). However, similar to the Player Load and IMA models, the highest band of activity, $\text{Impacts}_{\text{High}}$, had a most likely harmful association with non-contact soft tissue injury risk (OR = 2.66; 90% CI: 1.77 - 4.11).

**Table 8.5.** Model Parameters for the best Impact model.

| Variable | OR | 90% CI | Clinical Inference | % Likelihood effect is beneficial/trivial/harmful |
|---|---|---|---|---|
| Constant | 0.03 | 0.016, 0.042 | | |
| $\text{Impacts}_{\text{Low}}$ | 0.64 | 0.29, 1.38 | Unclear | 76.7% / 11.4% / 11.9% |
| $\text{Impacts}_{\text{Med}}$ | 1.83 | 0.78, 4.23 | Unclear | 8.4% / 8.2% / 83.4% |
| $\text{Impacts}_{\text{High}}$ | 2.66 | 1.77, 4.11 | Most Likely Harmful | 0.0% / 0.0% / 100% |

### 8.3.4 Joint Model

Joint models were compared using BIC due to the large combination of variables that could be fitted in a model. The variables contained in each of the top five joint models are displayed in **Table 8.6**. The joint model displaying the lowest BIC value included PL, $\text{PL}_{\text{Low}}$, and $\text{Impacts}_{\text{High}}$. Therefore, this model was retained as the “best” joint model and was used for interpretation and comparison to the sub-group models.

**Table 8.6.** Variables contained within the top 5 joint models according to BIC. Shaded regions indicate the variables included in each of the specific models. Coefficients displayed within the shaded regions are represented in log-odds.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| **Intercept** | -4.12 | -3.6 | -4.26 | -3.86 | -4.35 |
| **PL** | 1.87 | | 2.45 | 0.69 | 2.08 |
| **$PL_{Low}$** | -1.18 | | -1.20 | | -1.83 |
| **$PL_{Med}$** | | | | | |
| **$PL_{High}$** | | | | | |
| **$PL_{VH}$** | | | | | |
| **$IMA_{Low}$** | | | | | |
| **$IMA_{Med}$** | | | | | |
| **$IMA_{High}$** | | | | | 1.13 |
| **$Impacts_{Low}$** | | | -0.79 | | |
| **$Impacts_{Med}$** | | | | | |
| **$Impacts_{High}$** | 0.7 | 1.14 | 0.97 | 1.0 | |

Model parameters and qualitative inference for the best joint model can be seen in **Table 8.7**. A one-unit increase in PL z-score was associated with a most likely higher risk of non-contact soft tissue injury (OR = 6.48; 90% CI: 2.79 - 15.8). Similarly, a one-unit increase in $Impacts_{High}$ was also found to have a most likely higher association with non-contact soft tissue injury (OR = 2.01; 90% CI: 1.42 - 2.86). Conversely, $PL_{Low}$ had a negative coefficient in the model and was observed to have a most unlikely harmful relationship with non-contact soft tissue injury (OR = 0.31; 90% CI: 0.15 - 0.61).

**Table 8.7.** Model Parameters for the best Joint model.

| Variable | OR | 90% CI | Clinical Inference | % Likelihood effect is beneficial/trivial/harmful |
|---|---|---|---|---|
| Constant | 0.02 | 0.008, 0.03 | | |
| Player Load | 6.48 | 2.79, 15.8 | Most Likely Harmful | 0.0% / 0.0% / 100% |
| $PL_{Low}$ | 0.31 | 0.15, 0.61 | Most Unlikely Harmful | 99.4% / 0.5% / 0.1% |
| $Impacts_{High}$ | 2.01 | 1.42, 2.86 | Most Likely Harmful | 0.0% / 0.3% / 99.7% |

**Figure 8.1** displays the predicted probability densities for both the injured and non-injured groups within the observed data. The mean probability of injury in the injured group is 25% while the mean probability of injury for in the uninjured group is 4.2%. While there is overlap in the model predictions, the injured group is observed to have a larger range of probability values with the average predicted probability in the injured group being 20.8% greater than the non-injured group.

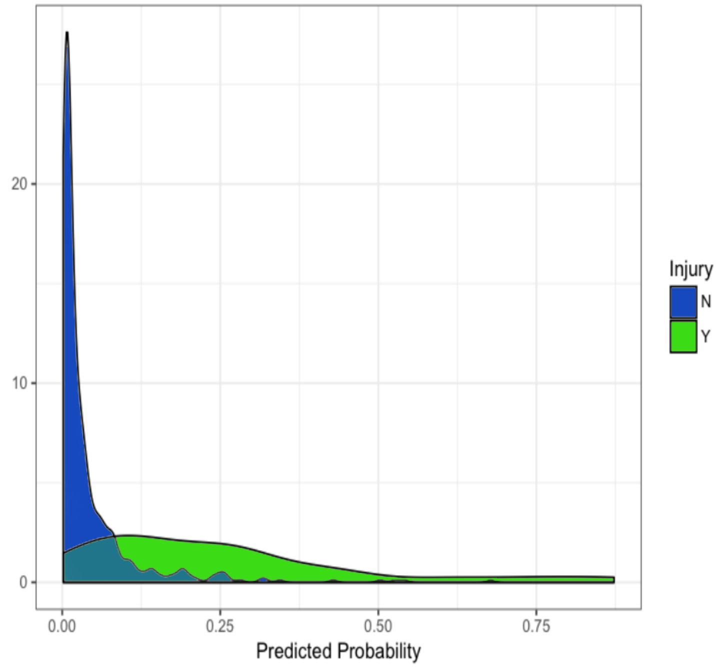


**Figure 8.1.** Probability density for the non-injured (N) and injured (Y) groups. The injured group is observed to have a higher predicted mean probability of injury (25%) compared to the non-injured group (4.2%).

The out-of-sample log likelihood and BIC comparison between each sub-group model and the best joint model is presented in **Table 8.8**. The joint model out performs each of the top sub-group models and should be accepted as the preferred model to explain the association between inertial sensor training load variables and non-contact soft tissue injury in NFL athletes.

**Table 8.8.** Out of sample log likelihood and BIC for the top models in each category.

| Model Category | Model | Out of Sample Log Likelihood | BIC |
|---|---|---|---|
| Player Load Model | $PL + PL_{VH}$ | -84.4 | 180.2 |
| IMA Model | $IMA_{Low} + IMA_{Med} + IMA_{High}$ | -91.3 | 197.9 |
| Impacts Model | $Impacts_{Low} + Imacts_{Med} + Impacts_{High}$ | -86.6 | 189.0 |
| Joint Model | $PL + PL_{Low} + Impacts_{High}$ | -80.5 | 176.6 |

## 8.4 Discussion

The present study is the first to evaluate the relationship between training load variables and non-contact injury in an NFL sample across a single season. Training load was evaluated using 11 inertial sensor metrics that were defined according to three sub-categories: (1) Player Load variables; (2) IMA variables; and, (3) Impact variables. Twenty-eight non-contact soft tissue injuries were observed during 76 training sessions for one NFL club. Logistic regression models were built for each of these three sub-categories. Following the development of sub-category models, five "joint models", which combined all of the variables, were iteratively fit in an effort to identify the model that had the strongest relationship with injury. Models were compared against each other using BIC and out of sample log likelihood. The best models in each sub-category consisted of a Player Load model with PL and $PL_{VH}$, an IMA model with $IMA_{Low}$, $IMA_{Med}$, and $IMA_{High}$, and an Impact model with $Impacts_{Low}$, $Impacts_{Med}$, and $Impacts_{High}$. Evaluation of the five joint models indicated a variety of different metrics identified as having a relationship with non-contact injury. Interestingly, PL was included in four out of the five joint models and may therefore represent a useful measure of overall training activity for practitioners to consider when designing training sessions. Of the five joint models the model consisting of PL, $PL_{Low}$, and $Impacts_{High}$ had the strongest relationship with non-contact soft tissue injury as it had the lowest BIC and highest out of sample log likelihood. Collectively, these findings suggest that a combination of inertial sensor variables may be useful in describing injury risk in American football players.

While the best model identified in this study as having the largest relationship with non-contact soft tissue injury was a joint model consisting of PL, $PL_{Low}$, and $Impacts_{High}$, it is important to acknowledge that differences between the joint model and sub-group models were not very large. This finding may be due to the fact that several of the inertial sensor variables are highly correlated with each other and may be describing similar training constructs. For example, when evaluating the five joint models, $Impacts_{High}$ is observed in four out of the 5 top models though it is not included in a model with $PL_{High}$, $PL_{VH}$, or $IMA_{High}$. Understandably, $PL_{High}$ and $PL_{VH}$ share a very large correlation with $Impacts_{High}$ ($r = 0.80$ and 0.89, respectively) while $IMA_{High}$ shares a large correlation ($r = 0.64$) with $Impacts_{High}$. These findings indicate that these metrics are potentially describing the same types of activities. Therefore, perhaps practitioners only need to focus on one of the variables for monitoring purposes. Additionally, these findings suggest that the thresholds utilized for these inertial sensor variables need to be evaluated to ensure that they are describing the intended actions in American football. For example, threshold bands for the Impacts metric have been created based on work in Rugby (Gabbett, 2013) and, therefore may misclassify these actions in other collision-based sports (Gastin et al., 2014; Chapter 6). More specific validation work is required to determine whether different metrics are truly measuring the same types of activities or whether more specific thresholds need to be defined for American football to ensure proper activity classification.

The inertial sensor variable, Player Load, has been previously shown to reliably quantify on-field activities in collision sport athletes (Boyd et al., 2011) and has recently been used to describe training loads across positional groups in American football at the NFL level (Chapter 5). The best joint model identified Player Load as having the highest relationship to non-contact soft tissue injury (OR = 6.48, 95% CI: 2.79, 15.8) of the three variables in the model. Training load variables were standardized per minute prior to analysis, however, because the duration of training across all sessions was similar, PL provided a proxy for overall movement activity. As such, these findings indicate that training volume plays an important role in describing injury risk in American football. In collegiate American footballers, Wilkerson and colleagues (2016) evaluated the relationship between Player Load and injury and concluded that both high levels of game exposure and low variability in Player Load (coefficient of variation) led to significant increases in injury (OR = 8.04; 90% CI: 2.39, 27.03). The present study did not take into account game exposure as, as in-game data was not available at this that time due to NFL regulations. Additionally, the present approach differed from that of Wilkerson (2016) whereby it did not take into account the variability in training load over time. Rather this study sought to understand the utility of different inertial sensor variables to identify injury risk during American football training in the NFL. The incorporation of metrics, which quantify training intensity into the injury model may aid in describing the relationship between training and injury more succinctly. While Wilkerson and colleagues (2016) only used Player Load in their analysis, the present findings indicate that some measure of intensity may be additionally useful for understanding injury risk.

Player Load and $\text{Impacts}_{\text{High}}$ were observed to have a most likely harmful relationship to non-contact injury within the joint model. Conversely, $\text{PL}_{\text{Low}}$ demonstrated a negative relationship with non-contact injury. Intuitively, these findings are logical given that sessions with a substantial amount of low intensity activity cannot also consist of large amounts of high intensity activity, which was related to greater injury risk. Collectively, these findings suggest a volume-intensity relationship whereby one metric is quantifying the overall activity of the session while the other is more sensitive to the intensity of the activities being performed. Indeed, when evaluating the 5 joint models presented in **Figure 8.1** it is important to consider that all models except for one (Model 2) contained both a volume (Player Load) and intensity (e.g. $\text{Impacts}_{\text{High}}$ or $\text{IMA}_{\text{High}}$) variable. This volume-intensity relationship is supported in previous literature evaluating positional differences during American football training (Chapters 5-7). Differences between position groups were observed whereby certain groups (e.g., WR and DB) performed a greater volume of running and Player Load while the DL and OL group had higher volumes of IMA compared to the rest of the positions. Thus, it is possible that metrics quantifying volume and intensity help not only describe positional differences but also the physical consequences of players actions within their respective positional groups. For example, three non-contact injuries observed in this study were not specific to locomotor actions – Elbow (DL), Oblique (LB), and Low Back (TE). These injuries were repetitive, overuse injuries and specific to the types of training activities these groups are asked to perform (e.g., hitting bags and working on collision techniques). Unfortunately, the categorical predictor "position group" was not found to be useful in any model. The limited number of injuries observed within the each positional group makes it challenging to infer anything specific about the relationship between injury risk and training load for each position. Thus, a larger sample set would be required to identify if a relationship between position group, training load, and injury truly exists. Despite this, the results indicate that both volume and intensity should be evaluated when trying to understand injury risk, as one single metric (e.g., Player Load) may not adequately describe the training activities of all positional groups.

## 8.5 Conclusions

This study evaluated the relationship between injury and training load for one American football at the elite level. As such, these findings may lack generalizability to other American football teams who may adopt different practice strategies or approaches to player management (e.g., interventions to modify training). For the NFL team in this study, the key findings reveal that, regardless of the position group, training days with high amounts of volume and intensity share an association with risk of non-contact soft tissue injury while training days with a high amount of low intensity training are negatively associated with the risk of non-contact soft tissue injury. These findings indicate a volume-intensity relationship that is important for practitioners to be aware of in a sport where players perform a wide variety of movement activities. For sessions where a player is injured, that individual's data are often censored (when the session gets cut off after the injury) or biased (as player finishes the session with the injury). As a result, we diverge from recent investigations which have attempted to understand injury at the individual athlete level (Rogalski et al., 2013; Hulin et al., 2016; Colby et al., 2017) and take a pooled position group approach to predicting injury, looking retrodictively at the group as a whole to predict the likelihood of an injury in a given group session. Such a retrodictive approach is key to the research aim of identifying injury risk factors inherent to the training session rather than attempting to identify risk factors prior to the training session. As such, the approach taken in this study allowed for a borrowing of strength within a position group to understand how differences in training sessions impact injury risk, while also mitigating the class imbalance that occurs due to the relative rarity of individual injuries. Future research should seek to solve these issues and develop the concept of individual injury prediction further using different statistical modeling approaches which can handle issues such as class imbalance (Rahman et al., 2013) and take into account the repeated nature of training sessions across a season (Cnaan et al., 1997). While this study examined only at training load on a given training day, practical application for practitioners and coaches lies in the ability to understand the volume-intensity factors that have an association with injury as the monitoring and manipulation of these factors may help to mitigate risk when designing future training sessions.

# CHAPTER 9

# SYNTHESIS OF FINDINGS

## 9.1 Introduction

The purpose of this chapter is to firstly review the completion of the aims and objectives associated with this project. This will be followed by a general discussion section that will orientate the outcomes of the research within this project to broader theoretical and methodological frameworks associated with the area of training and monitoring in American football. Practical considerations for the sport that may come from the data are also presented. Finally, suggestions for future research based on the insights gained from this project will be made.

## 9.2 Completion of Aims and Objectives

The primary aim of this thesis was to investigate the physical demands of training for American football at the highest level, in the NFL. This framework established to fulfill this aim included three phases: (1) Methodological Evaluation of Monitoring Strategies (Chapters 3-6); (2) Description of Training Demands (Chapter 7); (3) Consequences of Training (Chapter 8).

### 9.2.1. Determining the Utility of Integrated Micro Technology Units for Quantifying Commonly Performed Training Activities in American Football.

A proof-of-concept study (Chapter 3) was designed to evaluate whether integrated micro technology sensors could detect and differentiate between "football actions" commonly performed by positional groups during training. The results demonstrated that various inertial sensor metrics were sensitive to different types American football movement activities. Therefore, it was deemed that integrated micro technology sensors provide a measure of position specific movements within American football indicating its use for quantifying training demands within in this thesis.

### 9.2.2. Evaluating the Usefulness of Subjective Rating of Perceived Exertion to Quantify American Football Training.

Session RPE represents a frequently reported marker of training load used in collision-based sport (Scott et al., 2013; Lovell et al., 2013; Weston et al., 2014; Johnston et al., 2015). This measure had yet to be investigated within NFL football training prior to this thesis (Chapter 4). At the group level, moderate to large correlations between sRPE and measures of external training load were observed between the offensive and defensive groups with lower correlation being observed between measures of sRPE and training load (Player Load) and intensity (IMA). These results suggest that sRPE may not provide as a strong a measure of training intensity as it does total training volume. A large amount of individual variability was observed in the relationship between sRPE and external load factors. While individual perceptual responses to training may be useful for answering other research questions, the results of Chapter 4 call into question the utility of sRPE to provide a measure of external training load intensity in American football.

### 9.2.3 Evaluating Between Position Group Differences in On-Field Activities During Training

To investigate between group differences in movement demands, a study was conducted to evaluate pre-season training sessions of an American football team using integrated micro technology (Chapter 5). The results confirm previous studies of match analysis in lower levels of the sport (Wellman et al., 2016; Wellman et al., 2017) and suggest that some position groups perform a greater volume of running while other position groups engage in a larger number of non-locomotor actions. More specifically, the smaller players in the "skill" position groups (e.g., DB and WR) performed a high amount of locomotor actions, as their role is to get downfield and attempt to make plays. Conversely, the linemen (offense and defense) are engaged in more physical contact between each other as they block and tackle. Importantly, the results of this chapter suggest that commonly used measures of locomotor activity (e.g., GPS) are not appropriate for describing the movement demands faced by some of the position groups (e.g., DL and

OL), which perform a low volume of locomotor activity. Therefore, the use of inertial sensors to quantify training load within American football may provide a more thorough representation of the sport's demands, as such measures are able to capture both locomotor and non-locomotor actions.

### 9.2.4 Use of a Parsimonious Statistical Approach to Help Reduce the Number of Integrated Micro Technology Features when Reporting Training Demands in American Football

To understand the relationship between these various measures in American football the sixth chapter in this thesis used a Principal Components Analysis to parsimoniously reduce the training load variables into correlated components, which represent similar training constructs. Results revealed three principal components, each component containing several variables that share a correlation between them. These findings show that several variables are providing details about similar training load constructs indicating that such a large number of available variables may not be necessary. For example, PC1 consisted of all of the impacts variables as well as the high and very high player load effect bands, PC2 was heavily weighted on all three IMA bands, and PC3 consisted of total Player Load as well as Player Load effort bands low, medium, and high. A proposed naming convention of the three identified principal components was developed, for practical purposes, to highlight the physical constructs of each (Impact

Index (PC1), Multi-Directional Movement Index (PC2), and Action Index (PC3)). The results of this chapter should indicate to practitioners that reporting to a coach or athlete a large number of variables is not required and rather, only one or two variables may be needed to adequately describe training. For example, knowledge about training volume (e.g., Player Load) and intensity (e.g., IMA) may only be required for practitioners to report to coaches, in which case only two metrics are needed to describe those constructs.

### 9.2.5 Describing the Periodization Strategies of Coaches During the In-Season Period for One American Football Team

To understand the role that periodization plays in the preparation of American Football athletes Chapter 7 investigated the weekly microcycle and season long periodization strategies of coaches within the sport. In doing so, this study employed a summary measures approach to analysis (Matthews et al., 1990; Weston et al., 2011) to evaluate the rate of change in training load overtime. These findings suggest that training does change across the season; with position groups showing meaningful decreases in both training volume (Player Load) and intensity (IMA). At the weekly microcycle level, training loads were observed to decrease in training days closer to the match. The analytical approach used in this chapter may be beneficial to practitioners as the serial measurements of athletes are routinely collected within the applied sports setting. Such an approach allows for an understanding of the rate at which individuals change overtime allowing for a more specific understanding of constructs such as ‘dose-response’ to training, which may not be as clear with more discrete measures of analysis (e.g., t-test, ANOVA, etc).

### 9.2.6 Identifying the Relationship Between Training Load and Injury in One American Football Team

The final study of this thesis aimed to understand the consequences of training within American football by evaluating the likelihood of injury during training (Chapter 8). A relationship between training sessions with high volume and intensity and non-contact soft tissue injury was identified. More specifically, training sessions consisting of large amounts of Player Load (volume) and $\text{Impacts}_{\text{VeryHigh}}$ were identified as increasing the risk of injury within the session. A key finding of this study is the increase risk of non-contact soft tissue injury with training sessions that also had a high amount of $\text{Impacts}_{\text{VeryHigh}}$. This evidence suggests that more intense training sessions, with higher amounts of physical contact, also have implications towards the increased risk of non-contact injuries. The reason for this is not clear but it is possible that athletes become more fatigued during these physical training sessions, exposing them to greater injury risk.

## 9.3 General Discussion

Monitoring athlete's during training activities has become commonplace in team sports over the past decade or more. Such data has helped to provide a unique understanding of the physical demands of team sports and the implications of training practice (e.g. changes in performance and/or injury). American football is a popular collision-based sport yet only limited data exists on the physical demands at the collegiate level (DeMartini et al., 2011; Wellman et al., 2016; Wellman et al., 2017; Wilkerson et al., 2016) and no data exists at the elite level in the NFL. The paucity of research surrounding the sport provided the primary motivation for the present thesis. As a means to facilitate the structure of the research projects within this thesis we identified three discrete phases of experimental work:

1) Methodological Evaluation of Monitoring Strategies
2) Description of Training Demands
3) Consequences of Training

### 9.3.1 Phase 1: Methodological Evaluation of Monitoring Strategies

When evaluating the demands of a sport it is important to first understand which methods are most useful for monitoring training or competition. Practitioners may be faced with a number of monitoring strategies when attempting to quantify training demands. However, not all of these strategies may be useful or relevant within the context of their given sport. Phase 1 of this thesis was established to evaluate a number of measures that may be useful for describing the demands of American football (e.g. GPS, sRPE, and inertial sensors).

The varied nature of movement actions performed by athletes in American Football (Pincevero & Bompa, 1997) may indicate that inertial sensors offer a way for practitioners to quantify training loads of players in positional groups that perform lower volumes of locomotor activity (e.g., DL and OL). Prior to doing so, a more formal evaluation of whether or not such measures can differentiate between more fundamental sports movements was required. Chapter 3 of this thesis established that such inertial sensors variables are able to differentiate between movement demands in movements that would seem important to American Football. For example, Player Load appeared to be sensitive to locomotor-based movements while a greater amount of IMA was registered during change of direction activities. However, there did seem to be some crossover between inertial sensor variables during the majority of movement tasks (e.g., Player Load was registered during change of direction and collision activities). These results show that these measurements may not be identifying discrete movements per se but rather activity at a more general level.  These findings would agree with the outcomes of other methodologically based chapters (Chapters 3-6) particularly the research focused on the use of Principal Components Analysis (PCA) (Chapter 6).

While these findings are novel contributions to the understanding of American football, the reason for the relationship between some of these variables was not full understood. For example, these variables may be identifying similar training load constructs or maybe recording similar activities thereby representing a redundancy within the measures provided by the technology. Such issues may simply be a consequence of the positioning of the sensor unit on the torso meaning that any number of movement activities is able to register different inertial sensor loads. These ideas may be supported by the observations on the QB position in Chapter 6. In this chapter the QB was identified as having the highest values in all three of the principal components even though the QB position is the only position during training that does not engage in physical contact. This suggests that the sensor unit, in such situations may be picking up a more general movement process linked to the throwing action performed by this position.

While such an implication suggest the need for more specific movement templates (i.e. throwing measurements etc) it may also suggest that the data can only really reflect a measure of overall 'training load' not how that load has been achieved (e.g., running, cutting, colliding). While these findings warrant further investigation, practitioners may still be able to utilize such measures usefully to provide a 'gross' account of training demands. From a practical perspective it may also indicate that practitioners do not need to report all inertial sensor variables when describing daily training activities. Indeed, practitioners may be able to describe the demands of American football using a measure of training volume, such as Player Load, and intensity, such as IMA. These reasoning for these two variables is their ability to differentiate position demands during training (Chapter 5) and the demonstration that they registered some form of load during all fundamental American football movement tasks (Chapter 3).

Perceptual measures (e.g., sRPE) of training are often used in sport to evaluate the athlete's subjective response to training activities (Halson, 2014). The use of sRPE in American Football has yet to be explored. The findings in this thesis suggest that sRPE exhibits a large number of inter-individual differences. Such differences may be brought upon by different levels of psychological demand required by different position groups (Cox et al., 1995) or by different physical requirements of training (McLaren et al., 2017). These specific individual factors are not precisely exhibited in a gestalt measure such as sRPE (Hutchinson et al., 2006). Additionally, while anchoring can help the players calibrate to the scale, it is important to consider that different players may still interpret the RPE scale in different ways. Finally, as with all subjective measures, we should consider the fact that players may not be honest with their responses or only interact with a small range of values on the sRPE scale, therefore, making the relationship between sRPE and external load variables nothing more than a statistical artifact. While the present results provide new information, more research is warranted to understand the nature of inter-individual responses to sRPE in American football. At the present time, it would appear that sRPE is unable to inform on discrete training activities. More refined subjective assessments of training load may help counter some of these methodological issues. Differential Rating of Perceived Exertion scales have been used to quantify specific internal load constructs such as breathlessness, leg muscle exertion, upper-body muscle exertion, or cognitive/technical demands in Rugby athletes (McLaren et al., 2017). It is possible that this type of approach may be more useful in a sport such as American football where the positional requirements create a number of different physical and psychological demands (Chapter 4).

Chapter 3 revealed that inertial sensors have some capability to differentiate between fundamental American football movements (albeit at a more 'gross level') while Chapter 4 suggested sRPE is confounded by inter-individual differences and is influenced by training load constructs of volume and intensity in different ways, making it challenging to use when attempting to describe sporting demands as a whole. Therefore, Chapter 5 investigated the utility of GPS and inertial sensor technology by evaluating whether they could differentiate between positional demands during American football training in the NFL. When evaluating GPS data, similar to research conducted in the collegiate game (DeMartinin et al., 2011; Wellman et al., 2016), different positional groups exhibited different amounts of locomotor activity. While this finding may be useful for describing locomotor activity, in American football such metrics may not adequately depict the training demands of position groups that perform less running-based movements.

Inertial sensor variables offer a number of unique ways for exploring training load, which may have greater utility in American football and more broadly within other collision-based sports. These measures may provide a more comprehensive way for scientists and practitioners to understand sporting demands and conceptualize new ways of looking at the activities performed by position groups (e.g., training prescription and periodization). A limitation of the current technology is however still related to the fact that it is only identifying training load at a gross level (see above and Chapter 3). Additionally, it is important to note that within each position group there are more nuanced positional differences (e.g., Cornerbacks, Free Safeties, and Strong Safeties, make up the DB group) that may magnify those observed due to very specific tactical requirements. It is therefore possible that subtle ergonomic differences exist both within and between position groups in American Football. Unfortunately, the number of players at these nuanced positions is small within a single team and therefore we were not able to explore such differences with the present sample.

### 9.3.2 Phase 2: Description of Training Demands

An understanding of the training demands of athletes in a sport can be investigated by examining the training loads imposed on them by the coaching staff. Coaches adjust specific aspects of training based on their perception of the team's needs as they prepare for the upcoming competition. These adjustments can be related to both longer (months) and shorter (weeks) periods of time. Such adjustments should ideally require a systematic processes regarding planning and periodization. Phase 2 of this thesis revealed that training volume and intensity appear to decline across the season. Moreover, these changes do not seem to be a result of any clear pattern of a periodized program. The reason for such a decline is uncertain at this time but such trends have been observed previously in team sports (Malone et al, 2015). It's possible that coaches and performance staffs are intuitively adjusting training demands as the players accrue fatigue as the season progresses. However, without measures of fatigue or markers of muscle damage, it is difficult to say what type of consequences these observed decrease in training volume and intensity may have on the fitness-fatigue relationship. In addition, this insight into the training process is only specific to on-field training activities and thus may not provide a complete overview of all training demands. It is common for American footballers to spend time in the gym completing additional strength and conditioning activity. As this training has been omitted in this thesis future research should seek to include gym-based sessions in the evaluation of total training load.  A final consideration is that the structure of training explored within this study is specific to one out of thirty-two NFL teams and may not reflect the periodization strategies adopted by coaches at other clubs.

At the weekly microcycle level, a periodization structure similar to that previously observed in other sports was discovered. American football coaches appear to decrease training load, at different rates of training decline for different positions, as the week progresses towards match day. This decrease is training load occurs from different time points within the week as different position groups seem to experience different peak training days. Such variety may indicate that coaches are more concerned with tactical periodization and teaching the players the playbook for the upcoming match rather than considering the physical ramifications of their program.

In light of such findings it is possible to consider the traditional concept of periodization in American football needs to be reconsidered. The coaching staff studied within this investigation utilized a plan that emphasized training for different position groups on specific days, which varies for positional groups, directed towards tactical requirements. This may be an overly rigid approach to weekly planning that is effectively unidimensional in its considerations to team preparation. Such strategies may prove to be challenging from an athlete health standpoint given that players may recover from game day at different rates (Fullagar et al., 2017) and not be ready to be exposed to different types of load at different times. Rather than having a standard weekly training template, as coaches appear to have, it may be more useful for to adopt a flexible approach to weekly periodization (Kiely, 2012) whereby the most intense training day of the week is allowed to fluctuate based on the team's recovery from the previous competition. This type of approach would therefore allow coaches to teach the necessary tactical components to prepare the team for the upcoming opponent while obeying the dose-response relationship of training. Such an approach requires further investigation with regards to the implications this may have not only on decreasing injury outcomes but also on team performance.

### 9.3.3 Phase 3: Consequence Training

The physically demanding nature of the sport is reflected in the fact that the risk of injury in American football is higher compared to other team sports (Hootman et al., 2007). Ideas discussed in the above section have also provided a rationale for how the training loads that are completed by the team could also be implicated in this high injury rate. Phase 3 of this thesis provide information regarding the risk of injury during American football training. Specifically, sessions with higher amounts of either Player Load or $\text{Impacts}_{\text{VeryHigh}}$ appear to increase the risk of injury within the training session. From a practical perspective, such information may allow practitioners to plan training sessions that limit the amount of to such volumes or intensities of training.

The present research provides a basis for understanding injury risk as it relates to external training load for one NFL club. However, it is important to point out that this study was conducted on training injuries only and such a study is retrodictive in nature, i.e. it provides a historic account of how injuries occurred, and lacks the predictive ability to forecast injury risk prior to the training session taking place. Given the multi-faceted nature of injury, more variables are required to understand the true risk of injury and gain a full picture of the training process. For example, understanding the internal response to the training session performed and the daily wellness of the athletes may be useful for evaluating fatigue, which could influence injury risk in subsequent sessions. Additionally, other intrinsic factors such as prior injury history, age, and positional group could be useful for identifying a link to future injury. Collectively, such information could be used to build more specific predictive modeling of injury, which may require more specific statistical approaches that can handle the non-linear relationships between such a broad variety of intrinsic and extrinsic factors (Meeuwise et al, 2007; Bittencourt et al., 2016).

## 9.4 Future Research

In light of the findings contained within this thesis, a number of future research opportunities may be relevant to further understanding the demands of American football training.

### 9.4.1 Determining the Effectiveness of Inertial Sensor Devices to Identify Specific Movements in American Football

The uncertainty around the extent that inertial sensor devices can detect specific movements suggests that future research should attempt to complete investigations that help identify what specific movements these metrics may be measuring in American football. This type of research could be done by (i) identifying specific movements completed by all players and evaluating these in isolation or (ii) by examining specific movements completed by certain positions. Potential studies in this area would include:

***i) Evaluation of an inertial sensor analysis specific to throwing***

A more specific evaluation of the inertial sensor variables contained within this thesis is required to determine their use for evaluating the movement demands at the QB position. Such a study requires the capture of throwing movements in a controlled laboratory setting using both inertial sensors and high-speed motion capture. Data from the inertial sensor variables would need to be evaluated with respective to the torso movements taking place during various throwing actions recorded from the motion capture so that a 'throwing signature' can be detected within the data. This 'throw signature' could then be used develop a metric that is able to categorize throw intensities. Such a methodological study would then need to be followed up with on-field research, conducted during actual training sessions. Using the inertial sensors and video footage the 'throw signature' algorithm could be critically evaluated to ensure that it is correctly classifying throwing movements during training.

***ii) The development of linemen specific metrics***

The OL and DL produce unique movements within the sport of American football. Their actions are non-locomotor in nature and occur within a confined space of movement as the OL creates a wall of protection for the QB and the DL attempt to breach that wall. The present results show that the inertial sensor technology is able to provide a general measure of training load for these position groups, although a more discrete measure is currently lacking. This study would need to be set up in a controlled environment where offensive and defensive linemen can compete against one another in a fashion similar to what takes place during training and competition. The inertial sensor trace could be used to identify a brief period of non-movement (i.e., before the ball is snapped) and then the movement actions after that non-movement phase where the players come out of their stance and collide with each other. For defensive linemen, a metric could be developed to identify the force at which they come out of their stance and make impact with the offensive linemen. Opposite to that, the offensive linemen would require a metric that identifies the way in which they receive force from the defensive lineman and are pushed back. Collectively, such measures could be used to provide a count of these collision actions that are specific to the positional demands.

### 9.4.2 The Use of Differential RPE in American Football

Perceptual responses in American football were found to exhibit inter-individual differences that may indicate that athletes perceive training demands in different ways. Reasons for this may be due to individual physical or psychological requirements specific tactical demands. Future investigations into the utility of dRPE are warranted to gain perspective on the specific training related demands that influence the athlete's perception. Prior research into dRPE has evaluated scales for breathlessness, lower bod exertion, upper body exertion, and psychological strain (McLaren et al, 2018). Given the unique positional demands of American football, dRPE scales should be designed to record the player's perceptions of the locomotor activity, physicality and collisions, and psychological effort occurring during training. This type of research project should be conducted on training days where the coaches have specific goals (e.g., tactical, physical, or psychological) to evaluate the face validity of such measurements.

### 9.4.3 Periodization Strategies Across the NFL

The data contained within this thesis is specific to a single NFL football club and therefore reflects the strategies unique to that coaching staff. A more thorough investigation of periodization and planning strategies across the NFL is required to better understand these practices at the highest level. A study of this nature could be conducted by circulating an anonymous questionnaire to all 32 head coaches within the league asking about their approach to planning both weekly and seasonal training for their team.

### 9.4.4 The Physical Consequences of Training Demands Relative to Fitness and Fatigue

Research contained in this thesis suggests that training decreases across the competitive season. The consequences of such changes in training are currently unknown and may have implications towards declines in performance or increased injury risk. The application of sub-maximal fitness testing (Thorpe et al., 2015), jumping testing (McLean et al., 2010), or musculoskeletal screening (e.g., hamstring range of motion, groin strength)

(Esmaeili et al., 2018) have been employed on a weekly basis within other competitive sports. Such approaches should be explored in American football to understand if the yearly training plan is appropriate for maintaining athlete fitness across the season while mitigating large increases in fatigue.

### 9.4.5 Forecasting Injury Risk in American Football Players

The present thesis provided an initial understanding of the relationship between training load and injury risk. However, injury is multi-faceted and related to a number of interactions between both intrinsic and extrinsic variables (Meeuwise, 2007). Future research should seek to incorporate these variables into a more holistic model of injury within the sport. To handle such interactions, some of which may be non-linear, and the fact that the group of interest, the injury group, is often under-sampled relative to the non-injured group, new statistical approaches should be undertaken. Such approaches would allow for the classification of risk prior to the training session, which may then aid in the alteration of training for individual athletes and the fluid periodization structure that has been discussed in prior parts of this thesis.

## 9.5 Conclusion

The aim of this thesis was to examine the physical demands of American football training in the NFL. This thesis was written using a "flat" structure, which differs from the more commonly used approach to a PhD thesis. Using this structure, this thesis was able to examine a variety of pertinent questions relevant to practitioners who are required to examine the physical demands of the sport, model training load demands overtime, and understand the potential negative outcomes (e.g., injury) associated with training. A key finding of this thesis was that, while traditional velocity and distance based measures (GPS) of training may be useful in sports with substantial locomotor demands, the unique requirements of different position groups within American football make these measures less applicable. As such, it is recommended that practitioners seek to understand training through the use of inertial sensors, which offer more flexibility for capturing a wide range of movement activities. It should be noted that, while this thesis has accomplished its aim of beginning the journey into evaluating the demands American football it merely scratches the surface. A substantial amount of future research is required to fully understand the sport and catch up with the body of knowledge generated in other team sports (e.g., AFL, Rugby, Association Football). Hopefully this thesis provides scientists with a jumping off point to investigate the sport more thoroughly and the "future research" section of this thesis may provide a road map in doing so. Finally, while this thesis was conducted on the sport of American football, the goal was to provide approaches that may be useful across the landscape of sports science. As such, several of the statistical approaches contained within the chapters of this thesis may be of value to scientists investigating other sports. For example, the time series approach to periodization (Chapter 7) offers a new way of evaluating training demands across a training program or season and may assist those looking to understand the dose-response relationship to training more explicitly. Collectively, the knowledge generated from this thesis is novel given such a paucity of research within the sport of American football, however, the approaches to analysis taken here will hopefully have broader implications within the area of sports science research.

# CHAPTER 10

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