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Volume and Intensity are Important Training Related Factors in Injury Incidence in American Football Athletes

Other Sport: American Football
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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.[10] Due to the high rate of collisions, American football carries with it a high injury risk. Over a 16-year period, Hootman and colleagues[24] 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 observed to be the highest of 16 collegiate sports during the study period.[24] At the elite level, in the National Football League (NFL), a 10-year investigation of pre-season training camp injuries indicates that injuries occur at a rate of 12.7 per 1000 athlete exposures during training and 64.7 injuries per athlete exposure in games.[16] 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)[12, 15] and have been suggested to be a consequence of high training loads.[19]

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.[23] One of the most common methods of training load monitoring in team sport athletes is through the use of integrated micro technology sensors.[6] 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.[6] As such, integrated micro technology systems have been utilized to objectively quantify training demands in a variety of different sports.[4, 11, 36, 38] 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.[11, 38, 39, 40] For example, during training at both the collegiate[11] and NFL levels[38], 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 types of descriptions 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[2], a first step in mitigating risk lies in understanding the relationship between training load and injury.[34] Collision sports present a unique challenge for understanding injury due to the diverse demands of both locomotor tasks and physical contact.[20] The relationship between training demands, quantified using integrated micro technology, and non-contact injury has been explored in collision-based sports.[8, 9, 41] In American football, at the collegiate level, Wilkerson and colleagues[41] identified an association between inertial sensor derived training loads and increased injury risk in collegiate football athletes. However, one 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[31], however it may not identify the more high intensity actions observed in American football.[38, 39] Therefore, additional metrics may be required to evaluate the intensity of a session, in order 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[22], collegiate[11], and NFL levels[38], evidence describing the relationship between training load and non-contact soft-tissue injury in in the sport is currently lacking. Therefore, the aim of this study was to identify the relationship between inertial sensor training load metrics and non-contact injury in NFL athletes.

2. Methods

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.

2.1 Participants

101 participants competing for one NFL team were included in this study (mean ± SD; age: 24 ± 2 y; height: 1.88 ± 0.06 m; weight: 109.4 ± 19.9 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 as a consequence of this group's low sample size (n = 2). This study was approved by a local ethics committee and permission to publish was granted by the NFL club.

2.2 Data Collection

Each player was provided with an integrated micro technology unit (Minimax S4, 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.[33] 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 have been established for American football the recommendations set forth by the UEFA consensus statement were applied in this study.(17) This approach has been used previously in other sports besides soccer.(5) As American football is a contact sport, a substantial number of injuries occur due to player collisions.(12) 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 (which 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.(14, 17) 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.

2.3 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.(30, 38, 39, 40) Inertial sensors are useful in quantifying a number of relevant movement actions in team sport athletes.(3, 6, 29) Therefore, eleven inertial sensor variables were used in this study to quantify training load activities. These eleven variables 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.(4) The reliability of this metric for tracking a variety of movement activities has been previously established.(3, 37) 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.(6, 31) 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. 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 categories rather than a "global" continuous representation of accelerations performed by the player.

Non-running activities (e.g., changes of direction, shuffling, cutting) taking place within training 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.(29) IMA has been previously used to quantify explosive movements in soccer and basketball.(28, 29) 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).[38] 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.

2.4 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). In order 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 Bayesian Information Criterion (BIC) and out of sample likelihood[13] with the model consisting of the lowest BIC and the highest out of sample likelihood in each group being selected for presentation within the results of this manuscript. In order 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[1] 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.[26] 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.[25] 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).

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 1**.

Table 1. *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 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 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†	0.8	0.89§	0.06	0.34	0.64†	0.67†	0.78§

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** 3). Both PL and PL_{VH} were found to substantially increase the risk of injury on a given training day. A one-unit increase in the z-score for PL per minute increases the odds of non-contact soft tissue injury on a given training day 1.22 to 3.19 times (most likely harmful) when controlling for PL_{VH}. PL_{VH} per minute was also observed to have a positive association with non-contact soft tissue injury, increasing the odds by 2.06 to 3.99x for every one-unit increase in training day z-score (very likely harmful).

Table 3. *Player Load Model Parameters*

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%

3.2 IMA Models

Two IMA models were constructed. Model 1 consisted of all three IMA bands while model 2 included Position Group as a categorical predictor. 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 3** displays the model coefficients and magnitude based inferences for the effects of the model containing all three IMA bands. IMA_{High} per minute was observed to have the strongest relationship with non-contact soft tissue injury, with an increase of 1 standard deviation increasing injury risk by 3.18 to 11.4 times. Conversely, IMA_{Low} was found to have a very unlikely harmful association with non-contact soft tissue injury (0.47; 90% CI: 0.25 to 0.87) while the relationship between IMA_{Med} and injury was deemed unclear.

Table 3. *IMA Model Parameters*

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%

3.3 Impact Models

Two Impact models were compared with a model utilizing all three Impact bands describing the data better than a model that included position group (**Table 4**). While the effect of $Impacts_{Low}$ was unclear, $Impacts_{Med}$ was found to have a likely harmful effect, increasing the risk of non-contact soft tissue injury 1.83x (90% CI: 0.66 to 4.69) per one-unit increase. Similar to the Player Load and IMA models, the highest band of activity, $Impacts_{High}$, had a harmful association with non-contact soft tissue injury risk (OR: 2.66, 90% CI: 1.64, 4.49, most likely harmful).

Table 4. Impacts Model Parameters

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

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 models are displayed in **Figure 1**. The joint model displaying the lowest BIC value included PL, PL_{Low}, and $Impacts_{High}$. Therefore, this model was retained as the "best" joint model and was used for interpretation and comparison to the sub-group models.

Model parameters and qualitative inference for the best joint model can be seen in **Table 5**. A one-unit increase in training day z-score of PL was associated with a most likely harmful increase in injury risk (OR = 2.79 to 15.8x). Moreover, an increase in $Impacts_{High}$ during a training session was found to lead to a 1.42 to 2.86x likelihood of non-contact injury risk (most likely harmful). Conversely, PL_{Low} had a negative coefficient in the model and was observed to have a most unlikely harmful relationship to injury as a one-unit increase in training day z-score led to a 0.15 to 0.61 decrease in injury risk.

	Model 1	Model 1	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	
Posterior Probability	21.9%	12.2%	9.8%	9.4%	8.2%

Figure 1. *Visualization of the variables contained in the top 5 models according to BIC. Shaded regions indicate that variables inclusion to the specific model. Coefficients displayed within the shaded regions are represented in log odds and the posterior probability for each model is displayed below each model.*

Table 5. *Joint Model Parameters*

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 2 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 11% greater than the non-injured group.

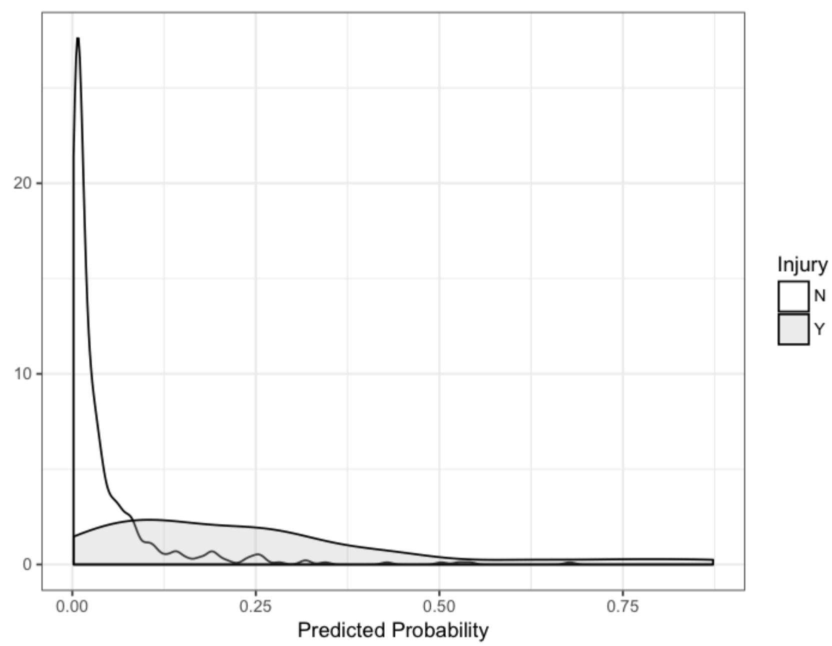

Figure 2. *Probability density for the non-injured (N) and injured (Y) groups.*

The out-of-sample log likelihood and BIC comparison between each sub-group model and the best joint model is presented in **Table 6.** 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 6. *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

4. Discussion

The present study is the first to evaluate the relationship between training load variables and non-contact injury in an NFL population 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. Overall, these findings suggest that a combination of inertial sensor variables may be useful in describing injury risk within the sport of American football.

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 never 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 may 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[18] and, therefore may misclassify these actions in other collision-based sports.[21] 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 be reliable when quantifying on field activities in collision sport athletes.[3] This metric has recently been used to describe training loads across positional groups in American football at the NFL level.[38] In our study, we used Player Load as an overall measure of total training volume. Our 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. This indicates that training volume plays an important role in describing injury risk in American football. In collegiate American footballers, Wilkerson and colleagues 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).[41] Our study did not take into account game exposure as our main interest was in understanding training related injuries. Additionally, our approach differed from that of Wilkerson[41] whereby we did not take into account the variability in training load over time. Rather we sought to understand the utility of different inertial sensor variables to identify injury risk during American football training in the NFL. We found that 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[41] only used Player Load in their analysis, it is clear from our study 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, PL_{Low} was identified as having a negative relationship with non-contact injury. Intuitively, this makes sense 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 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 IMA_{High}) variable. This volume-intensity relationship is supported in previous literature evaluating positional differences during American football training.[38] 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, in our study 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, our 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.

This study evaluated the relationship between injury and training load in American footballers at the elite level. Our key findings reveal that, regardless of the position group, training days with high amounts of volume and intensity share an association with increased risk of injury while training days of a high amount of low intensity training share a relationship with a decreased risk of 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 is 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[9, 27, 35] 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. This allows us borrow 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[32] and take into account the repeated nature of training

sessions across a season.[7] While, this paper looked only at training load on a given training day it's 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 training sessions.

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