Relationships Between Training Load Metrics and Injury in Collegiate Women's Soccer

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ABSTRACT

Injury risk reduction is an ever-evolving topic within an athletic environment. Consequences from an injury include participation time loss, financial, social, and personal costs. Coaching and medical staff strive to reduce the risk through various manners. Training load monitoring is one method that is utilized in injury risk reduction through global positioning systems (GPS) with statistical modeling. The purpose of this study was to investigate the external loads for training sessions and competition in starters versus non-starters; to determine if there were control chart violations associated with sustained injuries; and to determine whether in-season injuries were associate with one or more control chart violations. NCAA Division I female soccer players were recruited during the fall 2019 season. Participants were provided a STATSports GPS unit to wear during all practice and competition sessions to analyze the following variables: total distance, high metabolic load distance, sprints, accelerations, decelerations, and dynamic stress load (DSL). These variables were analyzed using statistical process control charts (SPC Charts) and Nelson Rules. Overall, there were 1,235 violations for the team, with the highest amount coming from DSL. Throughout the season, there were 16 time-loss injuries. Within the 3- and 7-day periods prior to injury, there were only two cases in which the injured athlete had more violations when compared to the team average. Therefore, SPC Charts were not a good indicator of injury risk prediction within this population. Future research includes reassessing these methods within a larger population and for a longer duration (i.e. several seasons).

GENERAL AUDIENCE ABSTRACT

Reducing the risk of injury in athletes is a focal point for many coaches, training, and medical staffs in collegiate athletics. The consequences of injury range from loss of playing time to financial and long-term health costs. Being able to reduce the risk of injuries not only has personal implications for the athlete but also relates to overall team success. Using global positioning systems (GPS) to track the amount of work done in training can possibly reduce injury risk. This study planned to investigate the workload in NCAA Division 1 collegiate female soccer athletes and if any injuries were sustained during both training and competition settings. The results suggest that statistical process control (SPC) charts and the Nelson Rules did not predict injury risk within this population. There is limited research that has used these tools. Future work can reassess these methods within larger collegiate athletic populations, over a longer period of time.

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TABLE OF CONTENTS

CHAPTER 1: LITERATURE REVIEW

1.1 Introduction

Injury and injury risk are a commonality in athletes and can be a significant hindrance to both the individual and team success.[1] There are many costs that stem from an injury, ranging from missing competition, to financial and long-term health costs. While injuries are unavoidable, being able to decrease the risk of an injury is a responsibility that the coaching, training staff and athlete should take seriously. Physiological monitoring using wearable technology is a tool that can assist those involved in helping minimize and understand the risk of injury, as well as to help make better training decisions.

1.2 Injury and Prevalence

According to the National Collegiate Athletics Association (NCAA) an injury is defined as “those that occurred as a result of participation in an organized intercollegiate game or practice, required the attention of an athletic trainer or physician, and resulted in the restriction of participation one or more days beyond the day of injury”.[2] Up to 1.7 billion people worldwide are thought to be affected by musculoskeletal conditions, with roughly 166 million years lived with disability by those affected – an increase of 44.7% since 1990.[3–5] In fact, 1 in 2 adults in the United States are affected by musculoskeletal conditions.[6] Musculoskeletal conditions such as fractures, sprains/strains, contusions and dislocations, were the leading cause of health care visits (77%) in 2011, with 2.8 million visits being related to sports injuries annually.[7] The NCAA Injury Surveillance Program is a tool used by athletic trainers of 1,113 participating schools across the country.[8] Through this program, the participating team trainers voluntarily report student athlete injuries into a web-based platform. In a five-year span from 2009-10 to 2013-14, across 25 championship sports, there was an average of 210,674 injuries (includes practice and competition) per year in an estimated 35,333,250 athlete exposures.[8]

Table 1.1: Cumulative national estimates of the number and percentage of competition and practice injuries, by injury types and selected diagnoses[8]

	Injury type*			
	Injuries of all severity	Injuries requiring ≥7 days before return to full participation	Injuries requiring surgery	Injuries requiring emergency transport
Activity type/Diagnosis	No. (%)	No. (%)	No. (%)	No. (%)
Competition				
Concussion	26,394 (6.9)	14,888 (15.9)	96 (0.5)	1,174 (22.0)
Contusion	69,406 (18.2)	4,956 (5.3)	257 (1.2)	512 (9.6)
Fracture/Stress fracture/Dislocation/Subluxation	26,989 (7.1)	12,525 (13.4)	5,158 (24.9)	1,378 (25.8)
Inflammatory condition	22,918 (6.0)	3,272 (3.5)	376 (1.8)	39 (0.7)
Sprain/Strain	174,845 (45.9)	48,761 (52.1)	11,949 (57.7)	1,082 (20.2)
Other	60,327 (15.8)	9,189 (9.8)	2,868 (13.9)	1,158 (21.7)
Total	**380,879 (100.0)**	**93,591 (100.0)**	**20,704 (100.0)**	**5,342 (100.0)**
Practice				
Concussion	26,408 (3.9)	16,384 (11.9)	92 (0.4)	348 (8.3)
Contusion	49,781 (7.4)	4,198 (3.1)	410 (1.9)	355 (8.5)
Fracture/Stress fracture/Dislocation/Subluxation	38,292 (5.7)	15,817 (11.5)	4,558 (21.6)	734 (17.6)
Inflammatory condition	99,758 (14.8)	12,586 (9.1)	1,190 (5.6)	0 (—)
Sprain/Strain	302,288 (45.0)	65,736 (47.8)	11,188 (52.9)	1,228 (29.4)
Other	155,965 (23.2)	22,845 (16.6)	3,694 (17.5)	1,513 (36.2)
Total	**672,491 (100.0)**	**137,566 (100.0)**	**21,133 (100.0)**	**4,178 (100.0)**

* Categories are not mutually exclusive.

As seen in the Table 1.1, injuries are more common in practice than in competition.[8] However, the most common type of injury seen across both activity type is sprain/strain. When looking at time loss injuries and those requiring surgery, the cost to the athlete and team can be detrimental.

1.3 Injury Cost

The costs of injuries are not confined to just athletic performance. In fact, Hespanhol et al., reported that there are four typical classifications from a societal approach.[9] Direct healthcare costs often result after an injury and include everything from physician consultations, rehabilitation, medication and medical devices.[10–13] "In 2010, musculoskeletal problems resulted in an estimated $170 billion in health care spending in the United States, ranking third behind circulatory conditions ($234 billion) and prevention, colds, and other basic care ($207 billion)".[3,14] Among athletic injuries, anterior cruciate ligament (ACL) ruptures are one of the most common; in recent years, these injuries have become more common among younger age (< 20 years old) groups.[3,15–17] Using patients in the Truven Health Analytics MarketScan Commercial Claims and Encounters Database (2005-2013) the mean cost of an anterior cruciate ligament reconstruction (ACLR) was $14,234.05 while an ALCR with posterior cruciate ligament (PCL) reconstruction had a mean cost of $20,435.81.[3] The cost of musculoskeletal injuries in the United States are costly and have become more common.

Indirect or lost productivity costs refer to a loss of productivity from work or study or the inability to fully perform due to injury.[9] One result from an athlete being injured is the effect on the team; when a player is not available (secondary to injury) there is a strong negative relationship between team success and the player's availability.[18] Societal costs include insurance administration costs, or those related to insurance programs (i.e. litigation or overhead costs).[9] Social costs refers to the psychological aspects of the injury including but not limited to depression, social isolation or economic dependence.[9] The psychological aspects that an athlete may experience are important when rehabilitating from an injury and returning to play.[19] Common psychological reactions that might come with an athlete's injury include: unreasonable fear of re-injury, extreme guilt about letting the team down and obsession with the question of return-to-play.[19] Should these responses become more problematic for the athlete, they should be referred to a licensed mental health provider.[19]

1.4 Monitoring Training Load

Monitoring training load is a useful tool for coaches, strength and conditioning staff and athletes.[20] When done appropriately, load monitoring can assist in determining whether an athlete responds to their current training program, as well as decreases the risk of developing non-functional overreaching, illness and/or injury.[21] Currently, internal and external training loads are monitored routinely. Internal training load can be defined as “the summation of the physiological and psychological stimulation/stress imposed during training activities”.[22,23] Internal training load includes measures such as heart rate, rate of perceived exertion (RPE), blood lactate and training impulse.[21] External training is “the work completed by the athlete, measured independently of their internal characteristics”.[23] External training load includes variables such as power output, time motion analysis, duration, speed, distance covered body load acceleration, metabolic power and sport-specific movements.[21,23] These types of monitoring can provide useful information to the coaches and athletes, however, the monitoring systems should be intuitive, provide simple reporting, analysis and interpretation while also scientifically valid.[21]

1.5 Variables

There are a multitude of variables that can be collected in both internal and external monitoring systems. Internal training load variables such as RPE, session RPE (sRPE) and heart rate monitoring are commonly used with athletes.[21,24,25] External training load variables such as total distance, number of sprints, average speed, distance covered in speed zones, new body load (accumulation of forces measured by a triaxial accelerometer in the GPS units sampling at 100Hz), and meters per minutes are also commonly used in monitoring systems.[25,26] One example is the StatSports system, which has the capability to monitor over 108 different variables.[27] The variables that will be utilized in this investigation include, Distance Total, High Metabolic Load Distance (HMLD), Sprints, Accelerations, Decelerations and Dynamic Stress Load (DSL).

1.5.1 Distance

Total distance is the distance in meters (m) covered by the athlete while wearing the GPS monitor. HMLD is a metric which measures the total amount of high-speed running completed by an athlete, coupled with the total distance of accelerations and decelerations throughout a training session.[27]

1.5.2 Speed

Sprints are based on an athlete's speed above a certain threshold, with 5.5 m/s as the default. To register as a sprint, it must be maintained for at least one second and will stop when the speed falls below 80% of the sprint threshold. Accelerations occur when there is an increase in speed for at least half of a second, with a maximum acceleration in the period of at least 0.5 m/s^2. This measure stops when the athlete stops accelerating. Deceleration measurements require a decrease in speed for at least half of a second, with the maximum deceleration in the period being at least 0.5 m/s^2.[27]

1.5.3 Load

DSL is the total of weighted impacts at a magnitude above 2g (using a proprietary algorithm). This measure includes both collisions and step impacts while the athlete is running and is individualized based on running style. This provides coaches with a quality insight of how each player physiologically responds to a training session and can allow the coach to individualize training loads to ensure the training elicits an adaptation without unnecessary load.[27]

1.6 What Technology Has Been Used

Internal training load monitoring can be broken down into three main categories: cardiorespiratory parameters, humoral parameters and neuromuscular and muscle metabolism parameters.[23] While internal monitoring systems are important to gauge the athlete's response to training, they can be less feasible and more invasive in larger research studies. For instance, in order to monitor markers from the previously mentioned categories, the athlete would be wearing multiple devices and require invasive testing, which may interfere with their training and create increased difficulty to collect data.[23]

Research has shown, that one of the most common ways to assess external training load is via global positioning system (GPS).[26,28–33] In fact, an 18 Hz GPS unit is a valid tool for use in team sports and research in sport specific metrics.[34] Along with GPS, other common ways to measure external load in training or competition include inertial sensors (accelerometers), magnetometers and gyroscopes. Most of the GPS units used in sport contain a triaxial accelerometer or a magnetometer and/or gyroscope.[23] This type of monitoring has become routine within many collegiate and professional sports and teams. It has been utilized in nearly all top-level professional soccer teams to track GPS, accelerometry and heart rates. This type of non-invasive monitoring has become an expected and accepted piece of participation by numerous professional athletes. In addition, player monitoring has become more widespread among collegiate sports teams and the information generated by these devices can evaluate and design training schedules.

1.7 Monitoring Unit

STATSports offers a variety of GPS monitoring units that report anywhere between four and 260+ variables and can be customized for individual and team-based usage.[35] For this study, the APEX Pro Series will be used. This unit is an 18Hz GPS that also includes an accelerometer (952 Hz), magnetometer (10 Hz) and a gyroscope (952 Hz) as well as Bluetooth connectivity.[35] The APEX Pro Series allows for custom data exports, as well as individual and group data display and analysis.[35] The monitoring system from STATSports has provided valid and reliable results when monitoring distances and speed in athletic movements in soccer and rugby athletes.[34,36–38]

1.8 Statistical Process Control Charts

Statistical process control charts (SPC charts) are graphs that determine how a process changes over a particular time period.[39] The central line of the control chart displays the average of the data, whereas the upper and lower control limits are determined by ± 3 standard deviations from the mean. The historical data was used to create these lines and then current data is compared to them.[39] SPC charts are commonly used for:

- controlling ongoing processes by finding and correcting problems as they occur
- predicting the expected range of outcomes from a process
- determining whether a process is stable (in statistical control)
- analyzing patterns of process variation from special causes (non-routine events) or common causes (build into the process)
- determining whether your quality improvement project should aim to prevent specific problems or to make fundamental changes to the process[39]

FIGURE 1.1. Depiction of a Statistical Process Control

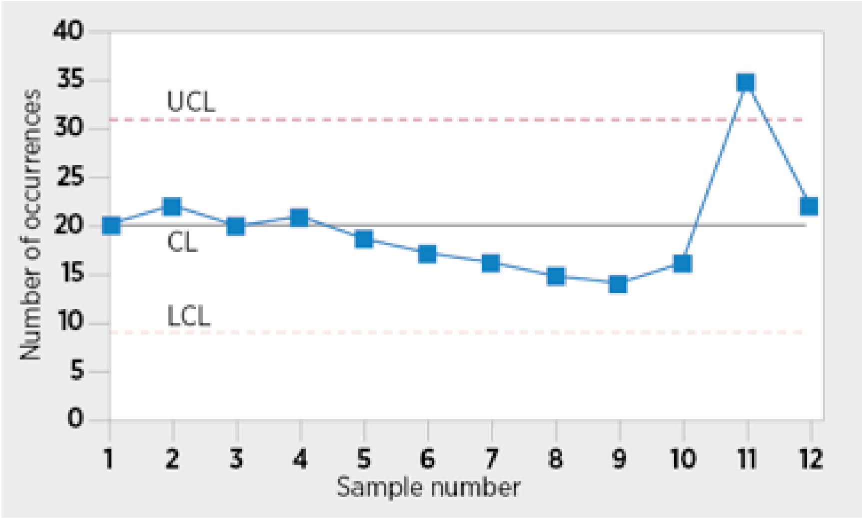

Image from asq.org

When analyzing the graph, the data points are compared to the established Nelson Rules and if there are any violations to the Nelson Rules, that constitutes a violation.[40]

SPC charts have been used in medical research involving infection control, outcomes in children's surgery, and monitoring military injuries.[41–43] Specifically, Wiemken et.al., utilized SPC Charts to determine quality improvement within infection prevention and control programs. They found that this tool was easily adaptable in meeting the needs of their facilities and could provide benefit to other programs of quality control.[41] Researchers have also utilized SPC Charts to determine the quality of pediatric surgery outcomes. By providing a visual representation of the surgeon's performance in a graphical manner, researchers and practitioners can detect minute changes within patient outcomes. In addition, this study found that these charts did not require a deep knowledge of statistics in order to interpret the data.[42] A study by Schuh et. al., studied existing medical surveillance data and how it related to injury trends. They found that SPC Charts can be used to move towards an injury reduction goal by identifying significant increases or decrease in injury rates. However, there are currently no studies that have applied a SPC chart to athletic injuries and load monitoring in the athletic population.

1.9 Conclusions

While injuries are not entirely preventable, having the ability to help reduce the risk of injuries in athletes is an ever-evolving process. Injury costs are multifaceted and range from direct medical costs to athlete health and team performance.[3,9,14–18] The use of external load monitoring is only one metric that can be used to stratify risk based on the workload. Using variables such as distance, speed and load that are gathered using a GPS unit is a common way to monitor an athlete's external workload.[21,23,25,26]

The use of SPC charts is common across industry and medical fields and can be beneficial when analyzing patterns and finding problems as they occur.[39] When using SPC Charts with the application of the Nelson Rules, violations can be detected to warn of potential problems or quality control issues. The potential to combine SPC charts and external load monitoring to assist in reducing the injury risk in athletes is a novel idea that will be explored further.

CHAPTER 2: INTRODUCTION

2.1 Introduction

Injuries in athletes are common and have a plethora of ramifications for the player they affect, including costs, participation in their respective sport and potential lifelong physical dysfunction.[44,45] Physical performance can be significantly affected, as well as financial and personal costs. Finding means to reduce the chance of an injury can significantly benefit an athlete's long-term performance, including individual and team goals. This can be done by using a training load monitoring system that can provide data and analysis to both coaching staff and athletes. Utilizing this data analysis can assist in the proper application of training and return to sport programming, which can aid in the reduction of injury or reinjury.[20,26,28–31]

There has been growing interest in the field of training load and its relationship to injury among coaches, players and team administrators.[46] While research has found that sports injuries compromise a team's success, the implementation of evidenced-based guidelines in the reduction of workload related injures is deficient.[1,46,47] This can often be due to the expertise or under-standing of the coaching or medical staff or their biases towards the guidelines.[46]

Findings ways to monitor and potentially reduce the risk of injury in the athlete are important tasks for coaching and training staff. Creating and applying a statistical model with easy to analyze inputs and outputs, as well as a visual component may assist the team staff in this task. Based on the available research, currently the use of a statistical process control chart and sports season data to assess whether it would be a viable tool for measuring injury risk has not been studied in athletic populations.

2.2 Specific Aims

The overall aim of this study was to determine if statistical process control charts are viable tools to use when assessing player load and injury occurrence. This investigation will seek to:

Specific Aim 1: Characterize the external load for training sessions and matches in starters vs non-starters.

Specific Aim 2: Determine if there were control chart violations that are associated with sustained injuries.

Specific Aim 3: Determine whether in season injuries were associated with one or more control chart violations.

CHAPTER 3: METHODS

3.1 Participants

NCAA Division 1 collegiate female soccer players were recruited for this retrospective observational study between June and November of 2019. Eligibility criteria for the study includes: Sports Medicine clearance to play prior to season, aged ≥ 18 years old, and a varsity level soccer player at Virginia Tech. Informed consent was provided during an individual team meeting during the first study session, where data collection methods, analysis and data security are clearly described. The participants were asked not to perform any activities other than those which would be required of them normally during training and competition as directed by coaching and sports medicine staffs. The participants were asked not to provide any information other than what is normally communicated between the coaching and sports medicine staff. Participants were not compensated for their time. This research was approved by the Virginia Tech Institutional Review Board prior to recruitment.

Once recruited, each subject was assigned a randomly generated identification number. During the initial meeting, players were asked to complete a brief demographic survey, which included age and weight, in order to calculate body mass index (BMI). Body mass was measured using a certified scale (Fairbanks Scales, Model 1100) and be supervised by one of the investigators.

3.2 Monitoring Units

Each subsequent study session took place during each team scheduled training session and competition. A STATSport GPS monitoring unit was used to capture player movements, such as running distances, speeds, etc., during each training session and competition.[34,36–38,48]. The signals from the units were transmitted in real time to a receiver, through a two-way wireless encryption for security, that was located adjacent to the playing field. After each training session or competition, data from the units was downloaded onto a laptop computer and stored on a secured hard drive; this data was analyzed off-line.

Players were issued two STATSport vests, that include a pocket for the GPS unit, to be worn over their sports bra or training gear. However, during competition, it was worn under their game day jersey. The investigators inserted the GPS units into the “pockets’ located on the vest, prior to the start of the session and collected them following the training session or competition. In the case that one or both vests are damaged or lost, additional vests were issued.

Virginia Tech Sports Medicine staff provided information on all injuries sustained including they type of injury and injury location throughout the season. The Sports Medicine staff also notified the researchers if the participant’s participation is limited or restricted on each day.

3.3 Statistical Analysis

The main data set from the STATSports unit started with 221,616 data points from 108 variables and 28 participants. From this data, six valued variables were chosen to reflect both the volume and intensity of training: total distance, HMLD, sprints, accelerations, decelerations, and DSL. These six variables narrowed down the data set to 14,856 points which were then analyzed using SPC Charts, Nelson Rules and descriptive statistics.

Descriptive statistics were used to characterize study participant demographics. Variable averages ($\bar{x} \pm SD$) were calculated for two subgroups: starters (>800 minutes played, n=12) and non-starters (<800 minutes played, n=16). Additionally, time series analysis was also used (statistical control charts, spectral analysis). Statistical process control (SPC) charts were used in combination with the Nelson Rules (Rules 1, 5, 6, 8) to determine violations and if there were correlations with player injuries.[43,44] The rules used for this study are shown in Table 3.1. Data points from each of the six variables were used to create six individual SPC charts per participant. The data was normalized to the participant using z-scores and then plotted in the SPC chart. The upper- and lower- control limits were created using z-score ± 3 standard deviations. The plotted data was then used to determine any Nelson Rule violations that occurred.

TABLE 3.1. List of Nelson Rule violations used in this study

Rule	Violation Description
1	One point beyond three standard errors.
2	Nine consecutive points on the same side of the center line within one standard error of the center line.
3	Six consecutive points increasing or decreasing.
4	Fourteen consecutive points alternating, increasing and decreasing.
5	Two of three consecutive points between two and three standard errors on either side of the center line.
6	Four of five consecutive points on either side of the center line beyond one standard error from the center line.
7	Fifteen consecutive points within one stander error of the center line.
8	Eight consecutive points on either or both sides of the center line – with none within one standard error of the center line.

Violations were then stratified between starters and non-starters to determine the difference between the two groups. A two-sample t-test assuming unequal variances was used to determine any significant differences between the two groups in each of the six variables (total violations and mean difference per group).

Using SPC Charts and Nelson violations, three- and seven-day time windows were analyzed to determine how many violations occurred for both the injured participant as well as how many violations occurred for the rest of the team during that same time frame. The total number of violations for each time was then divided by how many players experienced a violation to determine the average violation for injury period.

Injured participants and injury dates were collected from the sports medicine injury reports. The previous three- and seven-day time windows were analyzed from each injury date to determine the violations that occurred for both the subject and the team. The total number of participant violations were then compared with the mean team violations during the same time window.

CHAPTER 4: RESULTS

4.1 Participant Results

Twenty-eight participants completed the study during the 2019 season with an average age of 19.7 ± 1.6 years and BMI of 21.1 ± 1.3 kg/m^2. Across all practice sessions and competitions, the team averaged a total distance of 5,764.54 ± 3,504.15 meters, an HMLD of 1,410.51 ± 19,231.60 (au), sprints 7.25 ± 8.85 (n), accelerations 35.85 ± 24.68 (n), decelerations 34.87 ± 26.94 (n) and a DSL of 349.52 ± 2,988.88 (au). The team was divided up into starters (12) and non-starters (16) for study comparisons.

Table 4.1 demonstrates the mean±SD for starters and non-starters for each of the six variables. Total distance, HMLD, sprints, accelerations, decelerations, and DSL differences between the two groups were all statistically significant ($p \leq 0.05$) with the starters experiencing greater external workloads.

Using the data from the GPS monitoring units in conjunction with the SPC Charts, there were a total of 1,235 violations across the team's season (including preseason). The highest number of violations for the team occurred with DSL and the lowest was Sprints (Table 4.2)

Table 4.1 Variable Averages and Differences for Starters, Non-Starters

	Starters (x̄ ± SD)	**Non-Starters** (x̄ ± SD)	**Difference** (x̄ ± SD)
Total Distance (m)	6,833.25 ± 4,010.84	5,034.98 ± 2,870.61	1,798.26 ± 1271.56*
HMLD (au)	1,130.16 ± 909.85	836.13 ± 717.54	294.36 ± 192.31*
Sprints (n)	9.88 ± 10.80	5.35 ± 6.43	4.53 ± 3.20*
Accelerations (n)	40.40 ± 26.67	32.88 ± 22.69	7.52 ± 5.31*
Decelerations (n)	40.00 ± 29.72	31.26 ± 23.83	8.74 ± 6.18*
DSL (au)	572.48 ± 4,400.25	172.30 ± 593.69	400.18 ± 282.97*

*significant difference between starters vs non-starters ($p \leq 0.05$)

m: meters; au: arbitrary unit; n: number of instances

A representation of the SPC Charts for each variable and the team average for each data are found in Figure 4.1. All values are expressed as z-scores. The team, as a whole, did not show any violations. SPCs for individual players revealed multiple violations. Using the data from the GPS monitoring units in conjunction with the SPC Charts, there were a total of 1,235 violations by individual players across the team's season (including preseason). The highest number of violations within the team occurred with DSL and the lowest was Sprints (Table 4.2). Each player showed at least one violation during the season. The lowest number of individual violations was 6 and the greatest was 286. The median for all players was 29.5 violations. Three players showed many violations across the season, more than 100 (combined 43% of all violations). All three of these players were injured much of the season and most of the violations occurred in the days following each being cleared for full training.

TABLE 4.2 Violations per Variable

Variable	**Violations**
Total Distance	208
HMLD	188
Sprints	134
Accelerations	253
Decelerations	162
DSL	290
Total	**1,235**

To better understand the relationship between SPC violations and injury occurrence, the number of violations experienced by each player were summed (across the six variable). This gave a single violation value for each player on each day.

Over the course of the 2019 season there were a total of 16 time-loss injuries between 13 participants (8 starters, 5 non-starters) that were used for data analysis. Using the dates that the injuries were sustained, three- and seven-day previous time windows were analyzed for SPC Chart violations that occurred in both the participant sustaining the injury as well as the how many violations the team accrued in that same period (Table 4.3). To calculate the team average violations, the injured participant's violations were subtracted from the team total and then divided by the remaining 27 participants.

The data for violations occurring to injured players and the team average were not normally distributed. As a result, statistical group comparisons were done using a Mann-Whitney U test. The median number of violations in the three-day period leading up to an injury was zero. For the same period, the median number of violations committed by the non-injured players was 1.31. These values were not significantly different. For the seven-day period leading to the injury, injured players experienced a median of 1 violation whereas the non-injured group experienced 3.2. For this comparison, the Mann-Whitney U value was significant, indicating greater violations occurring in the non-injured group.

Graphical depictions of the three- and seven-day violations for the injured players vs the rest of the team are shown in Figure 4.2. As can be seen, in only two cases were the number of violations experienced prior to injury noticeably different from those experienced by the remainder of the players. In fact, in many cases, the injured player showed no violations in the days preceding an injury.

TABLE 4.3 Injury, Injury Date, and Violations per Injury

Participant ID	Injury	Injury Session Number	3 Day Violation (participant)	3 Day Violation (team avg)	7 Day Violation (participant)	7 Day Violation (team avg)
TLM1ǂ	Right Calf Strain	4	2	6.30	2	6.30
	Left Meniscus Tear	19	0	1.26	0	3.56
TLM4	Left ACL Tear	59	1	0.70	8	2.63
TLM5	Left Ankle Sprain	15	3	0.93	3	1.33
TLM6ǂ	Right UCL Sprain	35	0	1.96	0	2.30
	Right Ankle Sprain	62	0	0.48	0	1.96
TLM10	Concussion	10	12	1.37	41	8.04
TLM11	Right ACL Tear	14	0	0.78	0	0.96
TLM16	Concussion	62	5	1.22	5	4.93
TLM17ǂ	Left ACL Tear	37	1	1.33	2	3.52
TLM18ǂ	Left Foot Sprain	31	1	0.26	1	1.52
TLM20ǂ	Left Meniscus Tear	45	0	0.89	1	3.15
TLM24ǂ	Concussion	45	0	0.59	0	3.26
TLM27ǂ	Right Ankle Sprain	72	0	0.48	3	2.81
TLM28ǂ	Right Knee Pain	36	0	1.52	0	4.04
	Right Ankle Sprain	37	0	0.81	0	3.67
	Mean		1.6	1.31	4.1	3.37
	SD		3.1	1.40	10.1	1.84
	Median		0	0.91	1	3.20
	Mann-Whitney U		88		69	
	p-value		0.1321		0.0266	

ǂ denotes team starter

Table (4.4) shows the total number on violations between starters and non-starters. Both number of violations and violations normalized by the number of players within the group are shown. The non-starters had significantly more total violations over the course of the season than the other group. Within individual variables, non-starters experienced more violations than starters, with the exception of accelerations.

TABLE 4.4 Variable violations of starters and non-starters

Variables	**Starters**		**Non-Starters**	
	Mean±SD	Median	Mean±SD	Median
Total Distance	0.7 ± 0.6	1.0	12.4 ± 12.7	9.5 *
HMLD	0.9 ± 1.1	0.5	11.1 ± 10.4	8.0 *
Sprints	1.3 ± 2.2	1.0	7.4 ± 7.8	5.0 *
Accelerations	4.92 ± 3.6	4.0	12.1 ± 15.8	8.0
Decelerations	2.1 ± 2.4	1.5	8.56 ± 12.1	4.5 *
DSL	6.0 ± 11.0	2.0	13.6 ± 18.9	5.0 *
Totals	16.0 ± 14.5	10.5	65.2 ± 67.1	41.5 *

*significant difference between starters vs non-starters ($p \leq 0.05$)

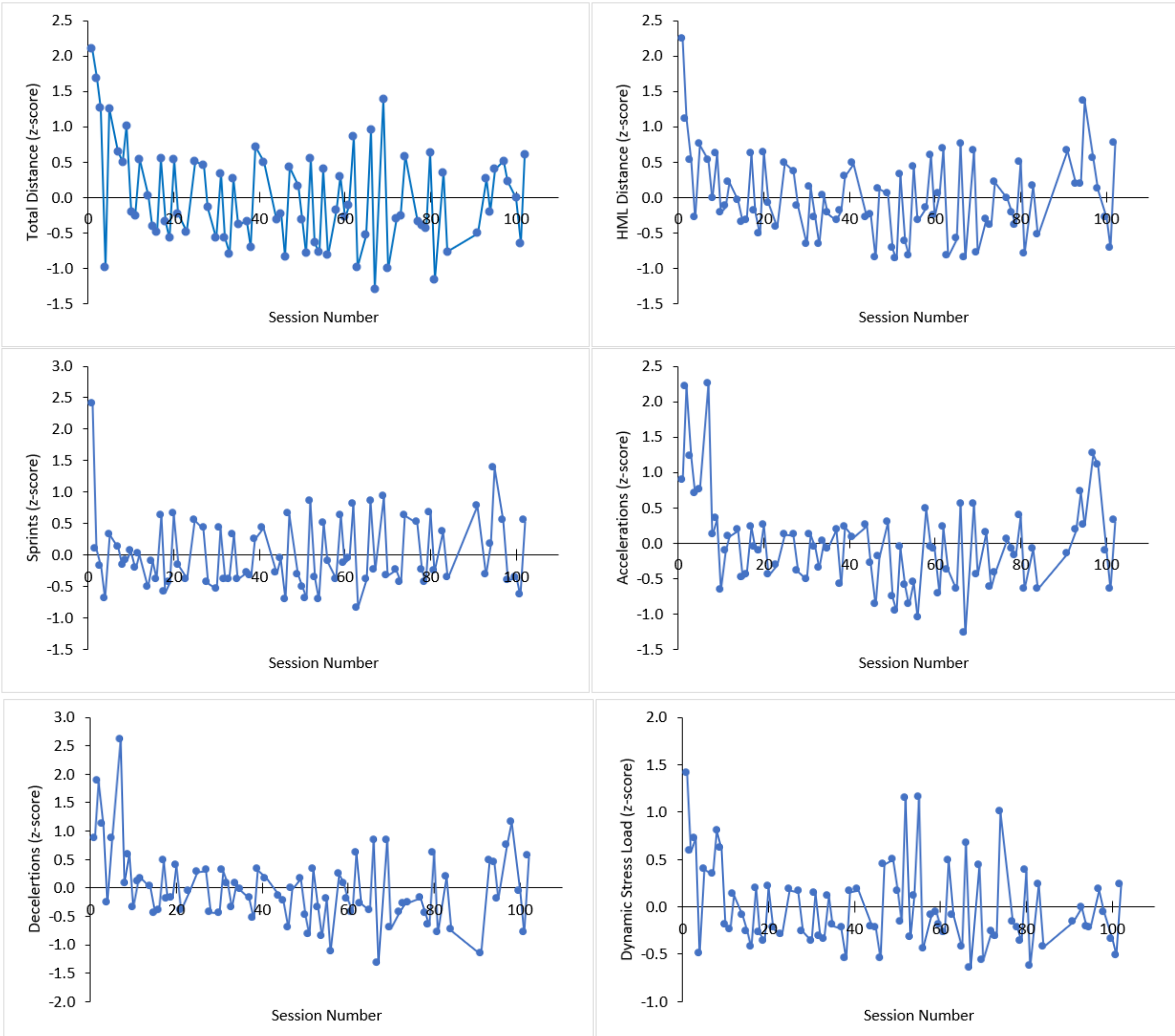

FIGURE 4.1. Representation of SPC Charts from each variable for entire team.

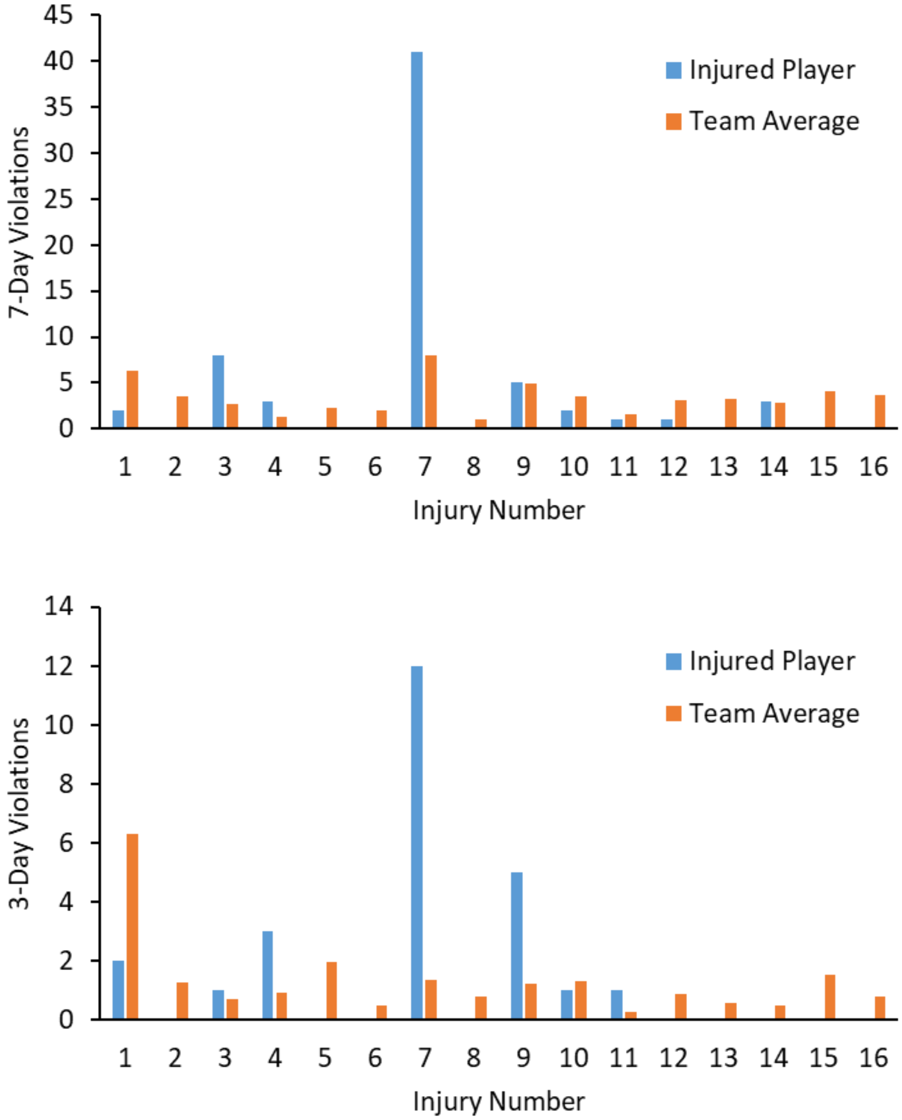

FIGURE 4.2. 7- and 3-Day violations experienced by the injured player and the remainder of the team average. Data are for all 16 injuries occurring during the season.

CHAPTER 5: DISCUSSION

5.1 Discussion

This study aimed to quantify the external load associated with training sessions and matches between starters and non-starters, use SPC Charts to determine if there were violations associated with sustained injuries and if those injuries were associated with one or more control chart violations. Using GPS data from a Division I women's soccer program Fall 2019 season; six variables were selected to analyze external workload. This was the first time that SPC charts had been used to analyze workload along with these variables.

This study found a significant difference in total distance (m), HMLD (au), number of sprints, accelerations, decelerations, and DSL (au) when comparing starters vs. non-starters. Typically, starters play longer minutes in competition, giving them the greater probability of recording a higher total distance and number of sprints, accelerations, and decelerations. Therefore, those who played higher competition minutes also had a higher DSL, as it was a measurement of fatigue in the participant. The findings from this research are novel as currently there are no other investigations that have utilized these variables between these two groups.

Overall, there were a total of 1,235 SPC Chart violations for the 2019 season between 28 participants. DSL had the highest number of violations, followed closely by accelerations and total distance traveled (290 violations, 253 violations, 208 violations, respectively). Starters averaged a significantly lower number of violations at 16 per player, whereas non-starters averaged 65.19 per player with total distance, HMLD and sprints. There are several explanations as to why non-starters had a significantly higher total number of violations when compared to the starter subgroup. Firstly, there were a higher number of non-starters than starters, 16 and 12, respectively. Secondly, since non-starters do not often play as much as the starters during competition, their mean for an SPC chart was lower. When a non-starter was active in a competition, this raised their SPC chart mean creating violations for lower workloads. A spike in workload (like participating in a competition match) would not only create violations for previous lower workload by raising the average, it could also create a violation for a significantly higher workload than previously recorded.

There were 16 total injuries between the starter and non-starter subgroups. Eight starters sustained 11 injuries while five non-starters sustained only five injuries. The most common injury within the study population was ACL rupture (3), concussion (3) and ankle sprains (3). There were no significant differences for any of the six variables between injured and non-injured players.

There were six participants (2 starters, 4 non-starters) who sustained an injury and had a higher violation total compared to the rest of the team. Of those 6, four participants (non-starters) had higher totals in both the three- and seven-day windows, while one participant (starter) had a higher three-day total and one (starter) had a higher seven-day total. This may show that there is some relation between higher individual violations when compared to the team average and an increased injury risk.

Comparing the total number of violations that occurred between starters and non-starters, there was a significant difference in total distance, HMLD, sprints and total violations. Therefore, it was more common for non-starters to present a violation either above or below the mean for each of those categories, when compared to the starters.

Another area that should be discussed includes the idea of minor or moderate non-training load complaints, referred to as “niggles” by Whalan et. al.[49] Their study found that there was a 3.6 to 6.9x higher risk of a training load injury when there was a report of a non-training load injury. Their study also concluded that when there was a complaint in all four of the categories (OSTRC Questionnaire - participation, performance, volume, severity), this showed a "good" prediction of experiencing a training load injury in the next 7 days.[49] In addition, these results demonstrate that there are factors outside of actual training load variables that can have an effect on injury risk. In competitive team sports, it could be hypothesized that reporting complaints such as niggles could influence playing time from the perspective of a player. While monitoring for injury, this is something that should be accounted for in addition to the physiological monitoring that is commonly done.

5.2 Limitations

The investigator is aware of the limitations of the investigation. Data was collected from one NCAA collegiate female soccer team. Therefore, the results from this study may not be generalizable to other NCAA collegiate teams. In addition, these results may not be generalizable to collegiate male sports. Another limitation includes the time-period of data collection, which did not include off season training. If a longer timeline were available, such as that of a professional offseason, the SPC charts would be a more accurate representation of the workload of the participant

5.3 Conclusion

This evaluation of the utilization of SPC Charts in conjunction with Nelson Rules was an important area for investigation of workload and its relationship to injury risk. However, there are a limited number of studies using this methodology that have been conducted to assess injury risk within collegiate athletes. While the results from this study may not show that the use of SPC Charts and Nelson Rule violations as a monitoring system for injury risk are successful tools, there is a possibility that with a greater sample size and longer sample period that it may be of use to a team. Due to the outcomes and limitations of this study, further research using this method may be warranted to test the validity and specificity of this tool.

CHAPTER 6: FUTURE DIRECTION

6.1 Future Direction

The main finding of this novel study was that there may be a correlation between an individual's SPC Chart violations and the team's violations when assessing for injury risk. Reducing injury risk is always a priority when working with athletes, especially in a competitive environment. The use of a SPC Chart and the Nelson Rules had not been used to decipher workload variables and injury occurrences in the available literature. This study filled the gap in the literature by demonstrating that the use of those two analyses may be of benefit when addressing workload and potential injury risk in competitive athletes.

Due to the limitations of this study, there are several areas in which this study could be improved upon for future research. Since this study only used data from one specific team and over only one season the sample is small. Using the same data collection techniques and analysis for multiple teams and tracking those players over multiple seasons would increase the statistical relevance for the SPC Charts and violations. Another area that could be improved upon would be tracking the athletes in their off season. Since the NCAA does not allow this type of monitoring in the athlete's offseason, it is difficult to know what kind of workloads they are exposed to before the preseason and season start. While this limitation is not likely to change in a NCAA program, the opportunity exists in a professional program where the season is longer and there is more of a structured off-season training program. Having the ability to track a player's workload over the off-season would allow for a more accurate values when it comes to the SPC Charts mean and upper-/lower-control limits.

Future studies using this method may benefit coaching, medical and strength and conditioning staffs through evaluating players for injury risk as they participate in practices and competitions. The data could potentially be viewed in real time allowing observers to track when a player may be approaching a period of a higher injury risk. Being able to monitor an athlete's workload and when they are at a higher risk for injury would be of benefit not only to the player themselves, but also to the overall success of the team as mentioned earlier.

REFERENCES

1. Hägglund M, Waldén M, Magnusson H, Kristenson K, Bengtsson H, Ekstrand J. Injuries affect team performance negatively in professional football: An 11-year follow-up of the UEFA Champions League injury study. *Br J Sports Med*. 2013. doi:10.1136/bjsports-2013-092215

2. Women's soccer injures: data from the 2204/2005-2008/2009 season. https://www.ncaa.org/sites/default/files/NCAA_W_Soccer_Injuries_WEB.pdf.

3. Herzog MM, Marshall SW, Lund JL, Pate V, Spang JT. Cost of outpatient arthroscopic anterior aruciate ligament reconstruction among commercially insured patients in the United States, 2005-2013. *Orthop J Sport Med*. 2017. doi:10.1177/2325967116684776

4. Vos T, Flaxman AD, Naghavi M, et al. Years lived with disability (YLDs) for 1160 sequelae of 289 diseases and injuries 1990-2010: A systematic analysis for the Global Burden of Disease Study 2010. *Lancet*. 2012. doi:10.1016/S0140-6736(12)61729-2

5. Yelin EH. The Big Picture | BMUS : The burden of musculoskeletal diseases in the United States *Bone Jt Burd*. 2014.

6. By the numbers *Musculoskeletal Conditions*. www.usbji.org. Accessed March 28, 2020.

7. https://www.boneandjointburden.org/docs/By The Numbers - MSK Injuries.pdf. Accessed March 28, 2020.

8. Kerr ZY, Marshall SW, Dompier TP, Corlette J, Klossner DA, Gilchrist J. College sports–related injuries — United States, 2009–10 through 2013–14 academic years. *Morb Mortal Wkly Rep*. 2015;64(48):1330-1336. doi:10.15585/mmwr.mm6448a2

9. Hespanhol Junior LC, Barboza SD, van Mechelen W, Verhagen E. Measuring sports injuries on the pitch: A guide to use in practice. *Brazilian J Phys Ther*. 2015;19(5):369-380. doi:10.1590/bjpt-rbf.2014.0110

10. Van Mechelen W. The severity of sports injuries. *Sport Med*. 1997. doi:10.2165/00007256-199724030-00006

11. Davis JC, Verhagen E, Bryan S, et al. 2014 consensus statement from the first economics of physical inactivity consensus (EPIC) conference (Vancouver). In: *British Journal of Sports Medicine*. ; 2014. doi:10.1136/bjsports-2014-093575

12. van Dongen JM, van Wier MF, Tompa E, et al. Trial-based economic evaluations in occupational health. *J Occup Environ Med*. 2014. doi:10.1097/jom.0000000000000165

13. Tolpin HG, Vinger PF, Tolpin DW. Ocular sports injuries. Economic considerations. *Int Ophthalmol Clin*. 1981. doi:10.1097/00004397-198102140-00013

14. The Diseases We Spend Our Health Dollars On - Washington Wire - WSJ. https://blogs.wsj.com/washwire/2015/03/03/the-diseases-we-spend-our-health-dollars-on/. Accessed March 28, 2020.

15. Caine D, Maffulli N, Caine C. Epidemiology of injury in child and adolescent sports: injury rates, risk factors, and prevention. *Clin Sports Med*. 2008. doi:10.1016/j.csm.2007.10.008

16. Maffulli N, Longo UG, Gougoulias N, Loppini M, Denaro V. Long-term health outcomes of youth sports injuries. *Br J Sports Med*. 2010. doi:10.1136/bjsm.2009.069526

17. Mall NA, Chalmers PN, Moric M, et al. Incidence and trends of anterior cruciate ligament

reconstruction in the United States. *Am J Sports Med*. 2014. doi:10.1177/0363546514542796

18. Drew MK, Raysmith BP, Charlton PC. Injuries impair the chance of successful performance by sportspeople: A systematic review. *Br J Sports Med*. 2017. doi:10.1136/bjsports-2016-096731

19. Herring SA, Boyajian-O'Neill LA, Coppel DB, et al. Psychological issues related to injury in athletes and the team physician: A consensus statement. *Med Sci Sports Exerc*. 2006. doi:10.1249/mss.0b013e31802b37a6

20. Jones CM, Griffiths PC, Mellalieu SD. Training load and fatigue marker associations with injury and illness: a systematic review of longitudinal studies. *Sport Med*. 2017. doi:10.1007/s40279-016-0619-5

21. Halson SL. Monitoring training load to understand fatigue in athletes. *Sport Med*. 2014. doi:10.1007/s40279-014-0253-z

22. Impellizzeri FM, Rampinini E, Marcora SM. Physiological assessment of aerobic training in soccer. *J Sports Sci*. 2005. doi:10.1080/02640410400021278

23. Cardinale M, Varley MC. Wearable training-monitoring technology: Applications, challenges, and opportunities. *Int J Sports Physiol Perform*. 2017. doi:10.1123/ijspp.2016-0423

24. Williams S, Trewartha G, Cross MJ, Kemp SPT, Stokes KA. Monitoring what matters: A systematic process for selecting training-load measures. *Int J Sports Physiol Perform*. 2017. doi:10.1123/ijspp.2016-0337

25. McFadden BA, Walker AJ, Bozzini BN, Sanders DJ, Arent SM. Comparison of internal and external training loads in male and female collegiate soccer players during practices vs. games. *J Strength Cond Res*. 2020. doi:10.1519/jsc.0000000000003485

26. Ehrmann FE, Duncan CS, Sindhusake D, Franzsen WN, Greene DA. GPS and injury prevention in professional soccer. *J Strength Cond Res*. 2016. doi:10.1519/JSC.0000000000001093

27. STATSports | World leading gps tracker & sports performance analysis. https://statsports.com/. Accessed March 26, 2020.

28. Cummins C, Welch M, Inkster B, et al. Modelling the relationships between volume, intensity and injury-risk in professional rugby league players. *J Sci Med Sport*. 2019. doi:10.1016/j.jsams.2018.11.028

29. Li RT, Salata MJ, Rambhia S, Sheehan J, Voos JE. Does overexertion correlate with increased injury? The relationship between player workload and soft tissue injury in professional American football players using wearable technology. *Sports Health*. 2020. doi:10.1177/1941738119868477

30. Enright K, Green M, Hay G, Malone JJ. Workload and injury in professional soccer players: role of injury tissue type and injury severity. *Int J Sports Med*. 2019. doi:10.1055/a-0997-6741

31. Bowen L, Gross AS, Gimpel M, Li FX. Accumulated workloads and the acute: Chronic workload ratio relate to injury risk in elite youth football players. *Br J Sports Med*. 2017. doi:10.1136/bjsports-2015-095820

32. Cousins BEW, Morris JG, Sunderland C, Bennett AM, Shahtahmassebi G, Cooper SB. Match and training load exposure and time-loss incidence in elite rugby union players. *Front Physiol*. 2019;10. doi:10.3389/fphys.2019.01413

33. Bowen L, Gross AS, Gimpel M, Bruce-Low S, Li FX. Spikes in acute:chronic workload ratio (ACWR) associated with a 5-7 times greater injury rate in English Premier League football players: A comprehensive 3-year study. *Br J Sports Med*. 2019. doi:10.1136/bjsports-2018-099422

34. Beato M, de Keijzer KL. The inter-unit and inter-model reliability of GNSS STATSports Apex and Viper units in measuring peak speed over 5, 10, 15, 20 and 30 meters. *Biol Sport*. 2019;36(4):317-321. doi:10.5114/biolsport.2019.88754

35. STATSports | STATSports APEX Team Series Software | GPS player tracking and performance analysis. https://statsports.com/apex-team-series/. Accessed March 31, 2020.

36. Moreno-Pérez V, Malone S, Sala-Pérez L, Lapuente-Sagarra M, Campos-Vazquez MA, Del Coso J. Activity monitoring in professional soccer goalkeepers during training and match play. *Int J Perform Anal Sport*. 2020;20(1):19-30. doi:10.1080/24748668.2019.1699386

37. Johnston RD, Devlin P, Wade JA, Duthie GM. There is little difference in the peak movement demands of professional and semi-professional rugby league competition. *Front Physiol*. 2019;10(OCT):1285. doi:10.3389/fphys.2019.01285

38. Beato M, Devereux G, Stiff A. Validity and reliability of global positioning system units (STATSports Viper) for measuring distance and peak speed in sports. *J Strength Cond Res*. 2018;32(10):2831-2837. doi:10.1519/JSC.0000000000002778

39. Control Chart - Statistical Process Control Charts | ASQ. https://asq.org/quality-resources/control-chart. Accessed March 31, 2020.

40. Statistics Roundtable: Follow the Rules. http://asq.org/quality-progress/2013/01/statistics-roundtable/follow-the-rules.html. Accessed March 31, 2020.

41. Wiemken TL, Furmanek SP, Carrico RM, et al. Process control charts in infection prevention: Make it simple to make it happen. *Am J Infect Control*. 2017. doi:10.1016/j.ajic.2016.09.021

42. Jaffray B. Am I out of control? The application of statistical process control charts to children’s surgery. *J Pediatr Surg*. 2020. doi:10.1016/j.jpedsurg.2019.12.027

43. Schuh A, Canham-Chervak M, Jones BH. Statistical process control charts for monitoring military injuries. *Inj Prev*. 2017;23(6):416-422. doi:10.1136/injuryprev-2016-042089

44. Andrew N, Gabbe BJ, Wolfe R, Cameron PA. The impact of serious sport and active recreation injuries on physical activity levels. *Br J Sports Med*. 2011. doi:10.1136/bjsm.2011.084038.71

45. Schneider S, Seither B, Tönges S, Schmitt H. Sports injuries: Population based representative data on incidence, diagnosis, sequelae, and high risk groups. *Br J Sports Med*. 2006. doi:10.1136/bjsm.2005.022889

46. Gabbett TJ. Debunking the myths about training load, injury and performance: empirical evidence, hot topics and recommendations for practitioners. *Br J Sports Med*. 2020. doi:10.1136/bjsports-2018-099784

47. Williams S, Trewartha G, Kemp SPT, et al. Time loss injuries compromise team success

in Elite Rugby Union: A 7-year prospective study. *Br J Sports Med*. 2016. doi:10.1136/bjsports-2015-094798

48. Heart Rate Monitors, activity trackers and bike computers | Polar USA. https://www.polar.com/us-en. Accessed April 13, 2020.

49. Whalan M, Lovell R, Sampson JA. Do Niggles Matter? - Increased injury risk following physical complaints in football (soccer). *Sci Med Footb*. 2020. doi:10.1080/24733938.2019.1705996