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The Correlation of Biometrics and Game Performance in Division I Collegiate Women's Soccer Team

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THE CORRELATION OF BIOMETRICS AND GAME PERFORMANCE IN A DIVISION I COLLEGIATE WOMEN'S SOCCER TEAM

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In competitive sports, the ultimate goal is to win as many matches, competitions, or games as possible. In an attempt to optimize this goal, the use of data analytics has risen. Soccer, a particularly popular sport across the globe, has been using data analytics for this optimization for multiple decades. One common practice for this data collection is the use of heart rate monitors paired with GPS tracking in order to collect data. Some of the data collected includes training load, total distance, sprints, and time spent in various heart rate percentage zones. Additionally, InStat Index has been used to collect skill specific data about various competition related variables such as shots completed, passes completed and goals conceded. In conjunction with the performance data, coaches can make informed decisions based off of this information to improve the outcome of winning. A University Women's Soccer team used Polar Team Pro and InStat to analyze their performance. It was found that training load, total distance, sprints and time spent at or above 70% of heart rate maximum are weakly correlated with InStat Index.

DEDICATION

I would like to dedicate this thesis to my wonderfully supportive parents, who, without their help, I would not be here today.

- Finn

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I would like to make several acknowledgements. First I would like to acknowledge Doctor Lehnhard, who worked extremely closely with me on completing this thesis and always encouraged me to push myself that little bit extra. Second I would like to acknowledge my friend Pete, who consistently had me questioning my own biases and beliefs. Without that, I would not have been as critical in my research. I would also like to acknowledge two great friends, Ozzy and Tomo, who sat through many hours of my frustrations during the data organization process and patiently listened to my problems. I appreciate you guys for that. I would like to acknowledge Jen for being a fantastic person and always being there for me during the tough moments. Lastly I would like to acknowledge the University of Maine Kinesiology and Physical Education department for being my home these past couple of years and providing me with a space in which I could collaborate freely and develop into the person I strive to be.

PERSONAL STATEMENT

Since graduating with my Bachelor's degree in 2016 I have had the goal of working in professional sport, ideally in the sport of soccer. The sport of soccer has been a part of my life since I can remember and has filled my life with a passion no other sport could rival. From playing to sitting on the sidelines, there is no other sport in the world that brings such emotion out of me as a person. This is what drives me on towards my goal and this is what has helped to motivate me throughout this process.

I have been able to research in depth the sport that I love and dive even deeper into my understanding of it. This has continued to fuel my passion for soccer and has helped to alleviate some of the burden that inevitably comes with the research process. With this thesis I hope to demonstrate my deep understanding of soccer from a physiological standpoint, but also to make clear that the sport goes beyond the physical nature of the human experience.

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INTRODUCTION

Methodologies that employ a system of logical analysis to the decision making process are broadly termed "analytics" [1]. In a more complete sense, Bernard Marr defines analytics as "our ability to collect and use data to generate insights that inform fact based decision making" [2]. The collection and interpretation of data (analytics) is widely used in decision making across a variety of domains including health care, public safety and sport [2]. For example, decisions in health care are guided by the use of electronic health records to provide efficient and safe care to patients [3]. Public safety officials collect data on supply chains to help guide their decisions regarding resource gaps [4]. In athletics, the use of analytics has become commonplace [5]. Regardless of the sport in question, the common desirable competitive outcome is winning. To this end, the data collected in sport can be divided into two groups. Competition-related variables (i.e. - number of passes completed, number of shots on net, time of possession, etc.) and individual physiological variables such as heart rate, blood lactate and running speed [6, 7, 8, 9].

The sport of soccer is no exception in its use of analytics in the hopes of improving overall performance and the probability of winning [6, 7, 9, 10]. The collection of competition-related variables in soccer is performed notationally through skilled notational analysts or by commercial means via data specialist companies [5, 11, 12, 13]. Examples of these variables include passes completed, shots on goal, total possession (typically reflected as a percent out of 100), clearances, and shots blocked [5, 11, 12]. A common system for this data collection is the InStat system [14, 15, 16]. According to Modric et al. 2020 "the InStat Index is a unique parameter that provides an assessment of a player's game performance" [15]. It is mentioned by Modric that the exact algorithm used for calculating the InStat is trademarked and therefore only known by the manufacturer of the platform. These data can be further analyzed when taking into consideration situational variables such as strength of the opposition (technical skill), the level of competition, match outcomes, and location [5, 13]. Srgo et al. 2016 reports that the influence of the situational variables has been assessed in the past, but states that "the evidence on the link between performance profiles and situational variables are limited" [5]. Hughes et al. 2007 reflected on this link in regards to the 2004 European Championship; "The successful teams during the early rounds had higher technique scores in all positions, but in the semi finals and finals the losing teams had the higher technique scorers" [12]. Perhaps the only non disputable claim about success in a match is that the team who scores more goals than the other will win [11, 13]. To that end (winning), a large amount of research has been collected on physiological, competition, and situational variables in an effort to understand and improve the outcome of competition [6, 9, 17-19, 20, 21-39].

Physiological assessment within soccer has explored a variety of different variables such as player load, VO_{2Max}, lactate threshold, heart rate maximum, heart rate minimum, heart rate average, and power output. Player load, sometimes referred to as a training load or match load can be divided into external and internal load. Player load is used to represent the various aspects that stress the body during exercise, both internally through the use of heart rate tracking and externally through the use tracking distances covered. Separation of player load is done in order to determine the physical demands of the sport at high intensities [9, 29]. A player's external load is determined through tracking total distance covered in addition to sprinting metrics such as total sprints [7, 22, 29]. Internal load on the other hand is determined through the use of heart rate monitoring and the time spent in specific heart rate zones [7, 9, 22, 29]. These zones are based off of a percentage of each player's maximum heart rate during the tracking period, whether that be training or match play [9, 29]. These data are then used to improve a player's physical fitness, prevent injury, and achieve greater performance [6, 9, 29].

Important physiological implications of player load can be found in previous research performed on accelerations and decelerations within soccer match play. Mara et al. (2017) reported across 7 matches that elite female players aged 24 (+/-4) years performed 423 (+/-126) accelerations and 430 (+/- 125) decelerations per match. It was also reported that the difference in the total number was due to positional differences within the match [32]. Most importantly, research about accelerations and decelerations has focused on their impact on performance [27, 32]. It was noted by Harper et al. 2018 that the load per meter of decelerations is 65% greater than that of accelerations. This type of data represents the potential sustained impact high intensity eccentric muscular contractions can have over the course of a 90 minute soccer match.

VO_{2Max} and blood lactate threshold have also been seen as important indicators of match performance [21, 24, 25]. In fact, "The VO_{2Max} and the various indices associated with the blood lactate response to exercise are among the most widely used parameters for aerobic evaluation" [24]. As reported by Castanga et al. 2002, "Because of the positive relationship between VO_{2Max} and physical match performance, international bodies such as Fédération Internationale de Football Association (FIFA) and Union of European Football Associations (UEFA) consider a high VO_{2Max} as a requirement for good refereeing. This is likely because it allows the referee to get closer to the action, providing them with an improved view" [21]. Additionally, Eniseler 2005 reported that "the reason for high anaerobic energy expenditure during match play, was as a result of the frequent accelerations, decelerations, changes of direction, intermittent sprinting, jumping, tackling, and backward and side-ways movements" [25]. It is important to remember that the match performance is held in high regard in hopes that it will improve the outcome of competition. As such, Helegrad et al. 2001 provided evidence that high intensity aerobic training increased VO_{2Max} and the lactate threshold. More importantly, Helegrad showed a percentage increase in total distance covered (20%), number of sprints (100%), and number of involvements with the ball (24%) during match play when players increased their VO_{2Max} [28].

Developing fitness profiles by position, through the assessment of various physiological variables, is becoming an increasing practice for professional soccer organizations [37]. Sporis et al. 2009 report that goalkeepers outperform outfield players in tests of explosive power, whereas there was no statistically significant difference between the outfield players (defenders, midfielders and attackers). Additionally, it was found that midfielders had statistically significant superior values for VO_{2Max}, maximal heart rate, maximal running speed, and blood lactate concentration than defenders and attackers. It was noted by Sporis et al that the anaerobic portion of soccer, albeit only a small portion, is important when performing actions such as sprinting, high intensity running and duels, all of which may contribute to the outcome of the match [18, 26, 37].

According to Gentles et al. 2018, total distance covered across varying positions during a match shows a range of 9km to 11km covered in 90 minutes. The relationship between total distance and speed is also of importance. Gentles et al found that the majority of match play is typically spent in the speed zone representing walking speed. Speed zones are simply a way of categorizing different ranges of speeds during competition or training. For example the speed zone referred to by Gentles as representing walking would be zone one ranging from one mile per hour and four miles per hour. As an athlete progresses in speed the various ranges of speed can be categorized into different zones, each pertaining to a moment of that athlete's running velocity. Even though a large portion of a match is spent in these walking speed zones, the high speed running zones are critical to the match outcome [18, 26, 37]. It has been reported that sprinting, or high speed running, has been shown to be the most common action before scoring a goal [20, 23, 27, 31, 32, 35]. Since the team with more goals wins the match, it is important to maximize these high speed running moments to capitalize on the chances created to score more goals, and therefore win the match. These high speed running zones can include a variety of different actions. Carling et al. 2008 reports that a total of 1563 'purposeful movement' passages were observed for 55 players during 15-minute periods of Premier League soccer, which involved 487 changes in movement, direction, perceived intensity or individual soccer-specific events (e.g. pass, dribble, shoot).

Sprinting distances are also going to vary depending on the position that a player has on the field. Central and wide midfielders perform more explosive sprints, whereas forwards and fullbacks perform a higher percentage of overall sprints [18, 20, 33]. Wide and central midfielders, forwards, and fullbacks all cover more high speed running distances than central defenders [9, 20, 33]. Other considerations for speed distances are the tactical set-ups for each team. Depending on how a team decides to play in terms of their choice to attack more or defend and counterattack will determine the total number of sprints a team and its players will perform during a match [17, 18].

For the purpose of quantifying intensity (ie - walking vs sprinting), the use of heart rate monitors has become quite common in the sport of soccer data analytics [19, 22, 34, 36, 39, 41]. The first wireless heart rate monitor was developed by Finland based Polar Electro OY in 1977. Since then Polar has gone on to operate in more than 80 countries worldwide [34]. As recently as 2012, the United States Soccer Federation (USSF), adopted Polar as their Official Heart Rate Technology Supplier [41]. In addition to the USSF utilizing this heart rate technology, many University teams and researchers have found value in this equipment [19, 22, 34, 36, 39].

For Polar studies, a common use of the data is assessing training load [19, 22, 34, 36, 39]. It is important to note that training load can be separated into two domains, external and internal load. A player's external load is determined through tracking total distance covered in relation to sprinting metrics, such as time spent in a high speed running zone [7, 22, 29]. Internal load, on the other hand, is determined through the use of heart rate data and analyzing the time spent in specific heart rate zones [7, 9, 22, 29]. These zones are based on a percentage of each player's maximum heart rate during the tracking period, whether that be training or match play [9, 22, 29]. For example, heart rate zone one would relate to any heart rate between fifty and fifty nine percent of a specific player's heart rate max. The subsequent zones then follow along sequentially. Zone two would be sixty to sixty nine percent, zone three seventy to seventy nine percent and so forth until one hundred percent (zone five). During the tracking period athletes are typically wearing a strap that wraps around their chest, just below the sternum so as to be as unobtrusive as possible while still collecting the data of interest.

A study conducted, by Curtis et al. 2020, examined contextual factors impacting training load during National Collegiate Athletic Association Division I Men's soccer seasons in 2016 and 2017. With the use of Polar Team Pro (Polar Electro, Lake Success, NY), the authors examined the differences in training load when looking at starters vs reserves, playing position, pre-season, in-season, postseason as well as 1, 2, 3, 4, and 5 days prior to a match. External load was defined by total distance covered in meters and distance covered in high speed running zones(>14.4 km*h^{-1}, m). Internal load was assessed using time spent above 70% of maximum heart rate. They found that there were no significant differences in total distance, high speed running, or session rate of perceived exertion between starters and reserves. Curtis et al. 2020 also reported that preseason training load was on average higher than in-season training load. Additionally training load was lower when there were less than four days between matches, but greater when there were more than 5 days between matches. Most importantly, Curtis et al. 2020 reported that there was no significant difference between training loads when examining the outcome of the match (win, loss or draw).

Similarly, Curtis et al. 2019 investigated the accumulated workloads over the course of an entire NCAA Division I Men's soccer season between starters and reserves. It is important to note that this analysis was conducted on a total of 5 teams over the 2016 and 2017 competitive seasons. With the use of the Polar Team Pro (Polar Electro, Lake Success, NY) Curtis et al. examined various data collected by the heart rate technology. Total distance covered, total distance in various speed zones, minutes recorded in a range of percent of maximum heart rate zones, and acceleration in various speed zones. It was to no surprise that Curtis et al. discovered that starters covered more total distance across the season than reserves during match play, however this trend was reversed for training. Additionally, starters accumulated more accelerations, and therefore decelerations, in match play than reserves, but this trend was not the case during training, as both groups accumulated similar totals across the season. The author also reported that total distance in all speed zones, all acceleration zones, and time spent between

70-90% of maximum heart rate was higher for starters than reserves. Finally, starters accumulated more time in matches above 60% of their maximum heart rate than reserves, while this trend was reversed for training. This trend is explained by reserve players needing to be match fit if called upon to play so they typically will perform extra conditioning in training in order to be prepared for game time.

An investigation by McFadden et al. 2020 compared internal and external training loads in NCAA Division I Collegiate Men's and Women's soccer players for both games and training. With the use of the Polar Team Pro (Polar Electro, Lake Success, NY) players were evaluated during match play and training. Training load, time spent in heart rate zones as a percent of maximum heart rate, total distance, number of sprints, average speed, and distance covered in various speed zones were collected using the Polar Team Pro. McFadden et al. 2020 reported that there were no significant differences for training load in match play between men and women. It was found that men accumulated a significantly greater number of total sprints, whereas the women covered more total distance during match play. There were no significant differences in practice training load, total distance, sprints, and time spent in all heart rate zones, however men had higher average speed across training sessions.

Swenson 2019 utilized the Polar Team Pro Heart Rate Monitoring System in an analysis of internal and external workloads in NCAA Division I Collegiate Women's soccer players. With the use of the Polar Team Pro, Swensen examined both the acute and chronic workloads internally and externally for all players on a 23 women roster. Swensen reported that there was a trend for the internal and external workloads to increase over the course of the season both for acute and chronic workloads. “This tends to be the case due to the volume of games played throughout the competitive season, which institute high internal and external workloads” [39].

In a positional specific study by Babic et al. 2018, the Polar Team Pro was utilized to analyze the internal load of young adolescent soccer goalkeepers (15 years of age). Because there is only one goalkeeper per match day team, rosters do not typically hold a large number of goalkeepers, so this study was conducted on four goalkeepers from Club SK Slovan Bratislava in Slovakia. Each goalkeeper’s heart rate maximum, minimum and average were collected during two small sided games in order to track the internal load. With the aim to expand the understanding of the functional response of goalkeepers, Babic et al. reported that “both small sided games have brought about adequate adaptations and the development of the proficiency potential” [19].

A study by Sapp et al. 2017 compared the data collected using the Polar Team Pro Heart Rate Monitoring System of a Division I collegiate Men’s soccer team over two seasons, against the best player on the roster. This player had won the MAC Herman trophy two seasons in a row which has only been achieved by four other athletes in the history of the award [36]. The MAC Herman trophy is awarded to the best player in Division I Men’s and Women’s soccer each season based on voting from all the coaches. Sapp et al. compared the players (Player A) recorded metrics against that of his teammates in maximal oxygen consumption, match play heart rate, and match play training load over the course of the 2012 and 2013 competitive seasons. It was reported that Player A was 1.28 ($\pm$ 0.58) below the average VO2max for the 2012 and 2013 seasons respectively. Additionally, Player A had a similar heart rate average to his teammates during match play, and in only 1 of 22 games did his average percent of heart rate max significantly differ from his teammates. Player A's average training load per minute during match play was lower than all but one of his teammates. Sapp et al. also reported that Player A spent more time in heart rate zones 3 and 4 compared to his teammates.

It is well described that physical match performance is related to training efforts in female soccer players, male soccer players and officials [30]. Unfortunately, there is a paucity of research on whether the tracking of these physical performance outcomes, both in training or match play, can accurately predict the outcome of a soccer match. It is safe to say that there is evidence suggesting that improved physical performance is important in soccer. However, why is the key to winning still so elusive? In a study examining how the result impacted physical performance outcomes across an entire professional season, Andrzejewski et al. (2019) found that the result of a match influenced both the total distance covered, and the number of sprints of individual players. It was also noted that situational variables such as the score of the match, tactical set-up, and level of the team may have also been an explanation for the reduction in total distance and sprints.

Prior research has shown physical performance and skill performance are associated with one another. We hypothesize that data collected through the Polar (Polar Team Pro) Monitor will be correlated with match performance as graded by the InStat system. More specifically, I hypothesize that training load score and InStat will be weakly correlated. Additionally, I believe that total distance, sprints, and time spent at or above 70% of heart rate maximum will be weakly correlated with match performance through the InStat Index.

METHODS

Subjects

All subjects were rostered players on a 2019/2020 Division I Women's Soccer Team. The age range of the players was 17 to 22 years of age.

Procedure

The Polar Heart Rate monitor was used for all training sessions and all matches. Each player was assigned a monitor at the start of the season that they would use throughout the season for both training and matches. Once training or match were complete they would put their monitor on the Polar Pro Team Dock for charging and data sync. The data would sync to the Polar electro online platform, where it was downloaded to Microsoft Excel for Mac 2011 Version 14.5.1.

The 2019/2020 season began in the last week of August and extended until the end of October. A typical weekly schedule for the team was to play matches on a Wednesday and Sunday with training in between. Mondays were the mandatory day off for all athletes at the University. In total there were 14 matches and 39 training sessions recorded. Training times were typically during the morning, starting at 7 AM and lasting anywhere from one hour to three hours, and matches were typically played during the afternoon, starting around 1 PM.

Statistical Analysis

In order to analyze the data, the excel (xls) documents were converted into SPSS Version 26 (sav) documents. Once each training session and match was converted, the data was organized so that the files could be merged into one master file. A final condensed file containing the variables of interest was put together to complete the analysis. A total of 1735 cases were included in the file pertaining to the 68 days of the season and the variables included. The statistical analysis used was Pearson correlation coefficients.

RESULTS

There were five variables analyzed in the correlational analysis: InStat score, total distance covered in yards, total sprints, training load score, and time spent at or above 70% of heart rate maximum. It is important to note that the higher the InStat score the better in regards to player performance. A range of 0-230 was reflected in the data for InStat. Additionally, for training load score, being a reflection of total impact on the body, a higher score is generally considered worse due to the requirements for longer recovery between training sessions. A range of 0-310 was reflected in the data for training load score.

I hypothesized that training load score and InStat would be correlated. There was a correlation between InStat and training load score. As reported by SPSS, the R value was 0.181 and was flagged as significant at the 0.01 level (2-tailed). Table 1 and Figure 1 provide visual representation of this relationship and can be found in Appendix A.

It was also hypothesized that total distance, sprints, and time spent at or above 70% of heart rate maximum would be correlated with InStat. I found that total distance (r=0.196), sprints (r=0.130) and time spent at or above 70% of heart rate maximum (r=0.146) were all correlated with InStat. Total distance was flagged as significant at the 0.01 level (2-tailed), while sprints and time spent at or above 70% of heart rate maximum were flagged as significant at the 0.05 level (2-tailed). Table 1 and Figures 2-4 provide visual representation of these relationships and can be found in Appendix A.

DISCUSSION

The correlations between various biometrics and match performance were assessed. There was a fairly weak correlation between InStat and the various physical metrics investigated (training load, total distance, sprints and time spent at or above 70% maximum heart rate). While the mathematical calculation of InStat score (number) is proprietary, we know that it assesses situational variables such as pass completion, shots on target, dribbles completed and other such areas of soccer related to technical performance (14). To see a weak correlation between InStat and the physical performance variables makes sense. As Srgo et al. 2016 reports, the influence of the situational variables has been assessed in the past, but states that "the evidence on the link between performance profiles and situational variables are limited" (5). The statistical significance of these correlations is due to the large sample size in the data. Although the team size is only about 30 athletes, because we analyzed across all matches (25), the sample size goes up considerably. Despite the lack of strength in the correlations (all being between 0.1 and 0.2) the significance resides in the size of the correlation showing the truth of the analysis.

There were several measures used in previous research utilizing POLAR to calculate training load score. As described earlier, a player's external load is determined through tracking total distance covered in addition to sprinting metrics such as total sprints (7, 22, 29). Internal load on the other hand is determined through the use of heart rate monitoring and the time spent in specific heart rate zones (7, 9, 22, 29). These zones are based off of a percentage of each player's maximum heart rate during the tracking period, whether that be training or match play (9, 29). Because of this understanding there was value in analyzing the correlations between training load score, total distance, sprints and time spent at or above 70 percent of maximum heart rate as these defined our internal or external training loads found in the literature. We discovered that training load score was correlated with both total distance (r=0.939) and sprints (r=0.777). Additionally training load score was correlated with time spent at or above 70 percent of maximum heart rate, with a reported r value of 0.960. Table 1 and Figures 5-7 provide visual representation of these relationships and can be found in Appendix A.

These findings are unsurprising. As is reflected in prior research, external load is determined using total distance and sprints and as such we see that these variables are strongly correlated with training load. Additionally, time spent at or above 70% of heart rate maximum represents internal load, and so it makes sense that we see a positive correlation between that and training load in this study.

It is important for coaches who are training their soccer athletes to be aware of this information for a few reasons. First, we cannot allow data to control our behavior in training. We can use it to inform our decision making. As stated by Paul Gamble, “The data are not sentient, so it is nonsensical that they be granted the role of driving our decisions and behaviors...Any meaning is borne out of our interpretation of the data. Accordingly, being data-informed seems a more worthy proposition” [(42)]. We must be willing to accept that the data is not everything and can be used to enhance our understanding of match play, but ultimately it is a tool not a rule. Second, emphasizing the importance of these data can influence the actions of players in training and match play. Again, Paul Gamble states, “As specific players’ performance are being evaluated (and rewarded) based on selected metrics, this inevitably drives how they subsequently operate on the field, on the court, or on the ice” [(42)]. This is incredibly important in how, as coaches, we decide to relay the information collected during training and match play. To say that more distance covered or sprinting more is key to performance is not necessarily wrong, but we do not want to influence our athletes to just run or sprint without a purpose. Lastly, soccer is a complex, multivariate sport with a large amount of influences on player performance. We must consider the mental status of our athletes as well as the physical to get the best from them in the hopes of improved outcomes.

LIMITATIONS AND FUTURE CONSIDERATIONS

There are a few limitations to this study. First, InStat is a very in-depth tool that looks at individual player positions when evaluating them and providing a score. We did not take into account individual positions when analyzing our data. Second, human error is always a limitation when organizing and filtering data. Lastly, correlational analysis is fairly basic and only paints so much of a picture for us to understand. In order to truly evaluate this moving forward, a more detailed analysis by player position is recommended.

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APPENDIX A

Table 1 - Correlation for all variables

Correlations

		Instat	Training load score	Total distance [yd]	Time at 70-100% of heart rate max	Number of sprints performed
Instat	Pearson Correlation	1	.181**	.196**	.146*	.130*
	Sig. (2-tailed)		.006	.003	.026	.047
	N	233	233	233	233	233
Training load score	Pearson Correlation	.181**	1	.939**	.960**	.777**
	Sig. (2-tailed)	.006		.000	.000	.000
	N	233	1735	1735	1735	1735
Total distance [yd]	Pearson Correlation	.196**	.939**	1	.913**	.818**
	Sig. (2-tailed)	.003	.000		.000	.000
	N	233	1735	1735	1735	1735
Time at 70-100% of heart rate max	Pearson Correlation	.146*	.960**	.913**	1	.748**
	Sig. (2-tailed)	.026	.000	.000		.000
	N	233	1735	1735	1735	1735
Number of sprints performed	Pearson Correlation	.130*	.777**	.818**	.748**	1
	Sig. (2-tailed)	.047	.000	.000	.000	
	N	233	1735	1735	1735	1735

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Figure 1 - Scatterplot Between InStat and Training Load Score

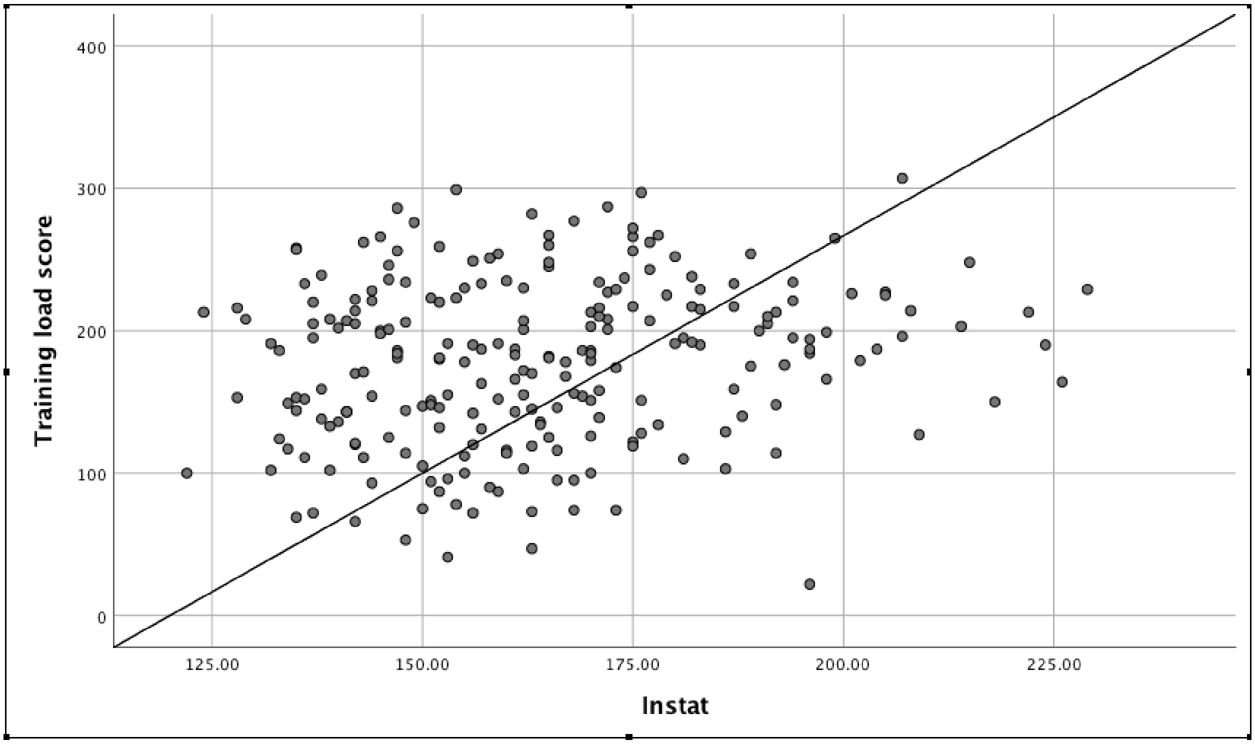


Figure 2 - Scatterplot Between InStat and Total Distance

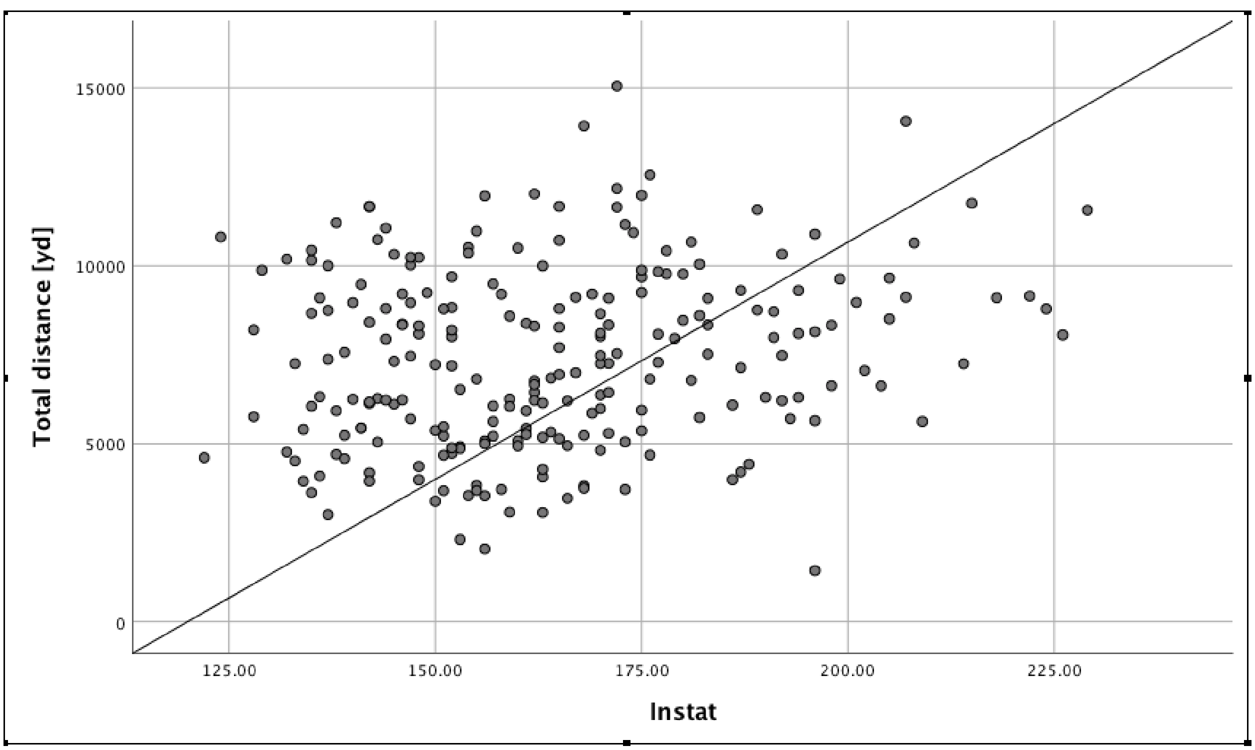


Figure 3 - Scatterplot Between InStat and Sprints

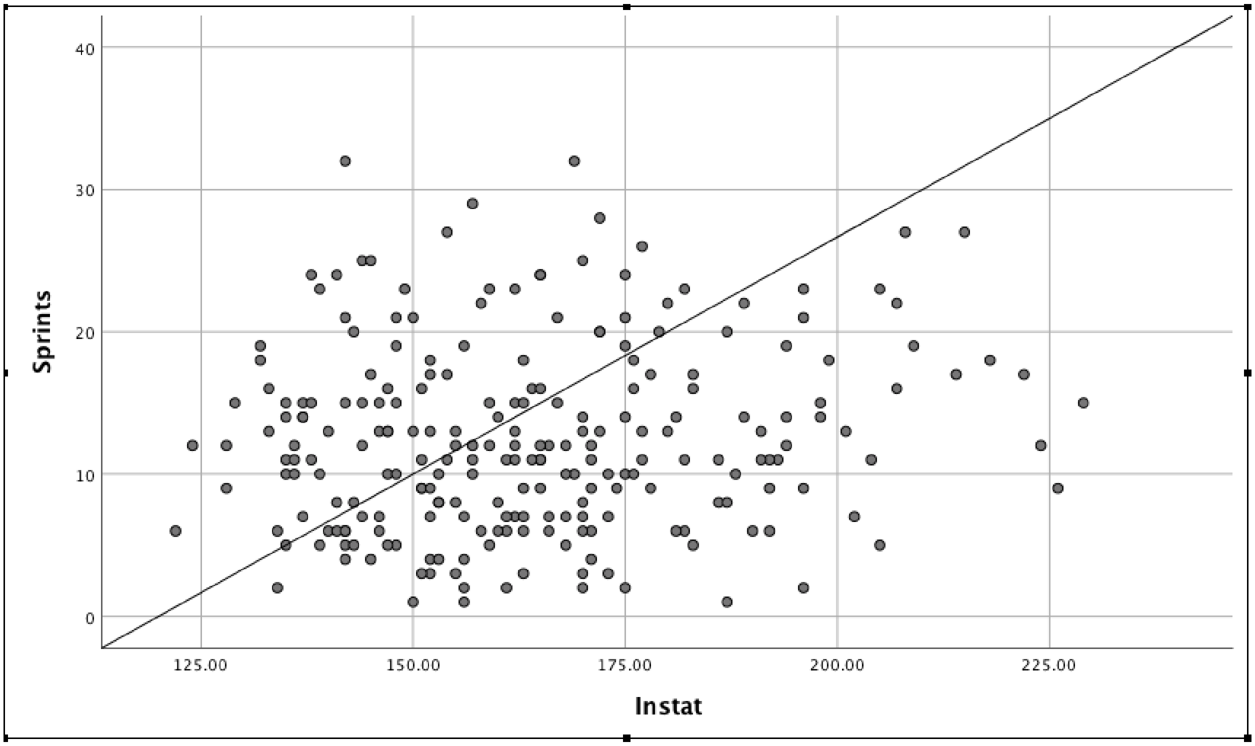


Figure 4 - Scatterplot Between InStat and Time at or Above 70% Maximum Heart Rate

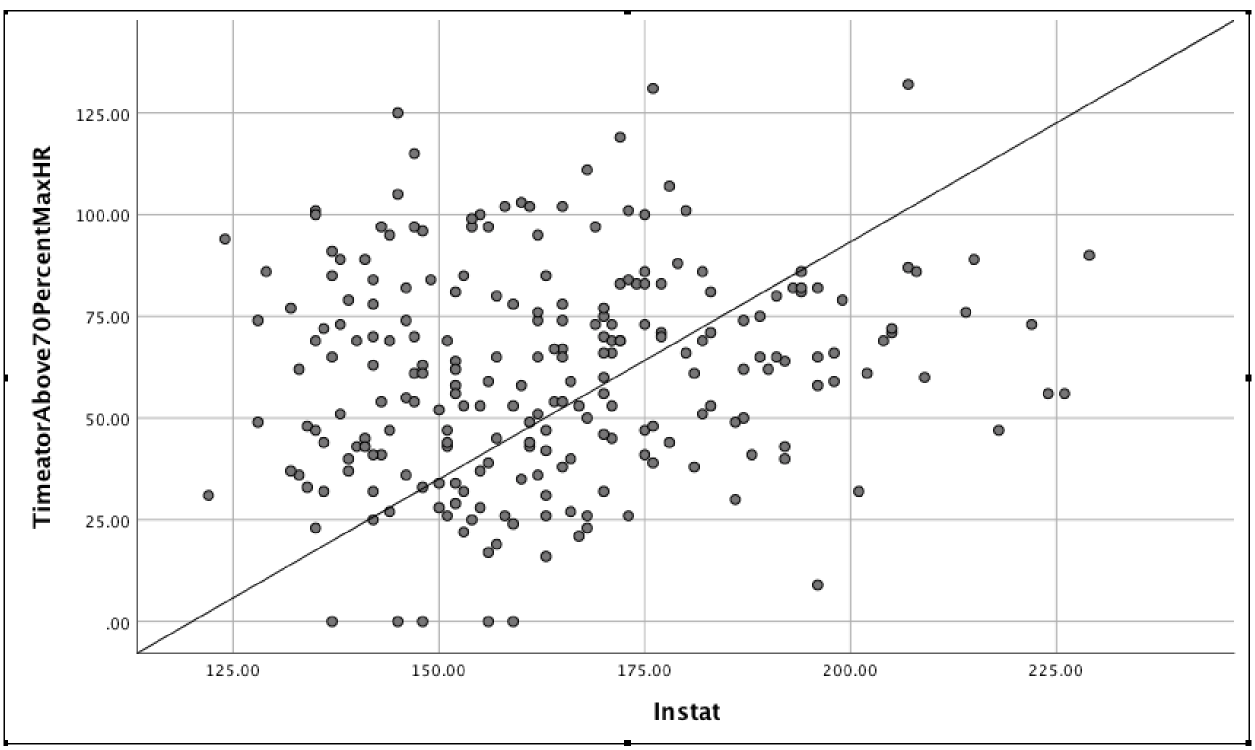


Figure 5 - Scatterplot Between Training Load Score and Total Distance

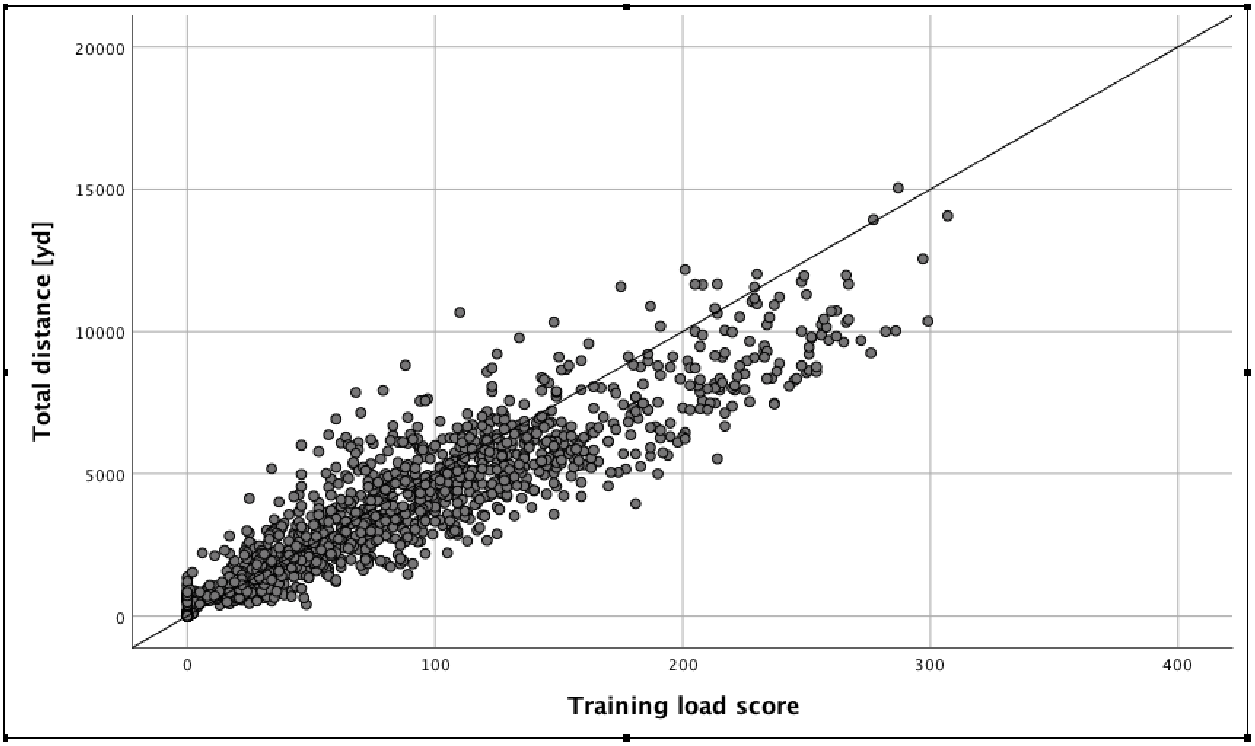


Figure 6 - Scatterplot Between Training Load Score and Sprints

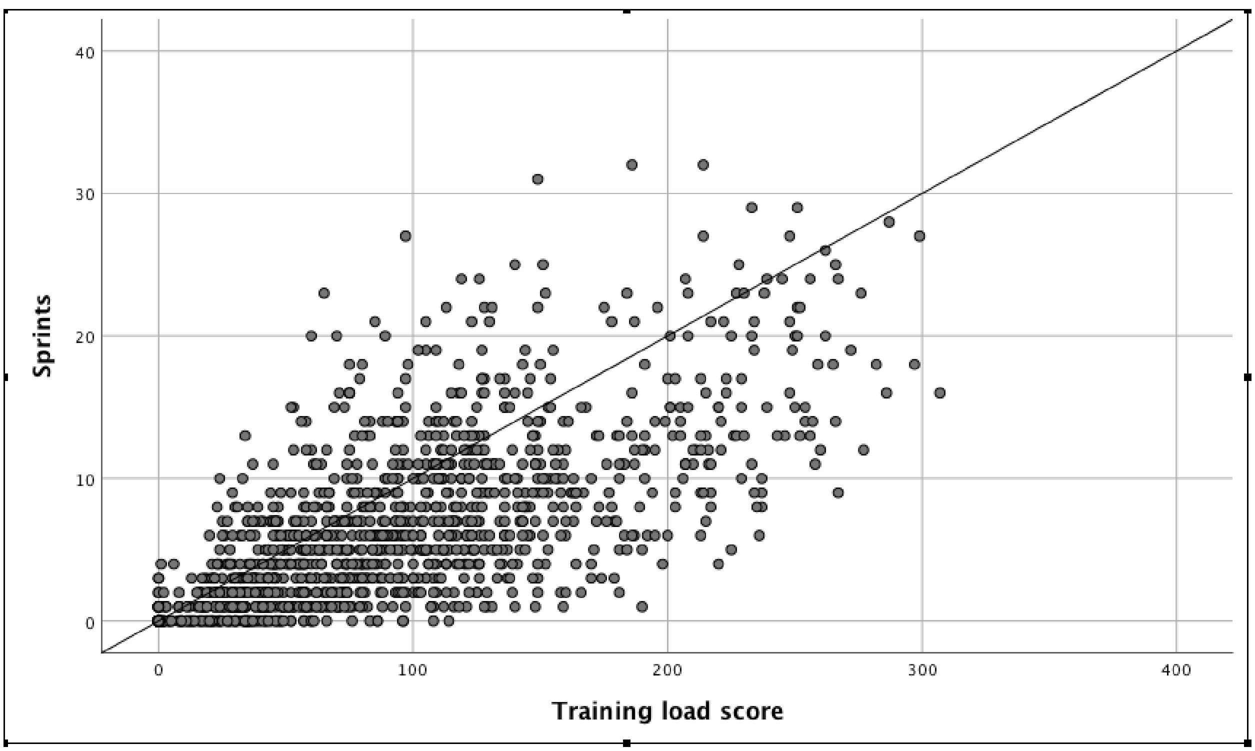
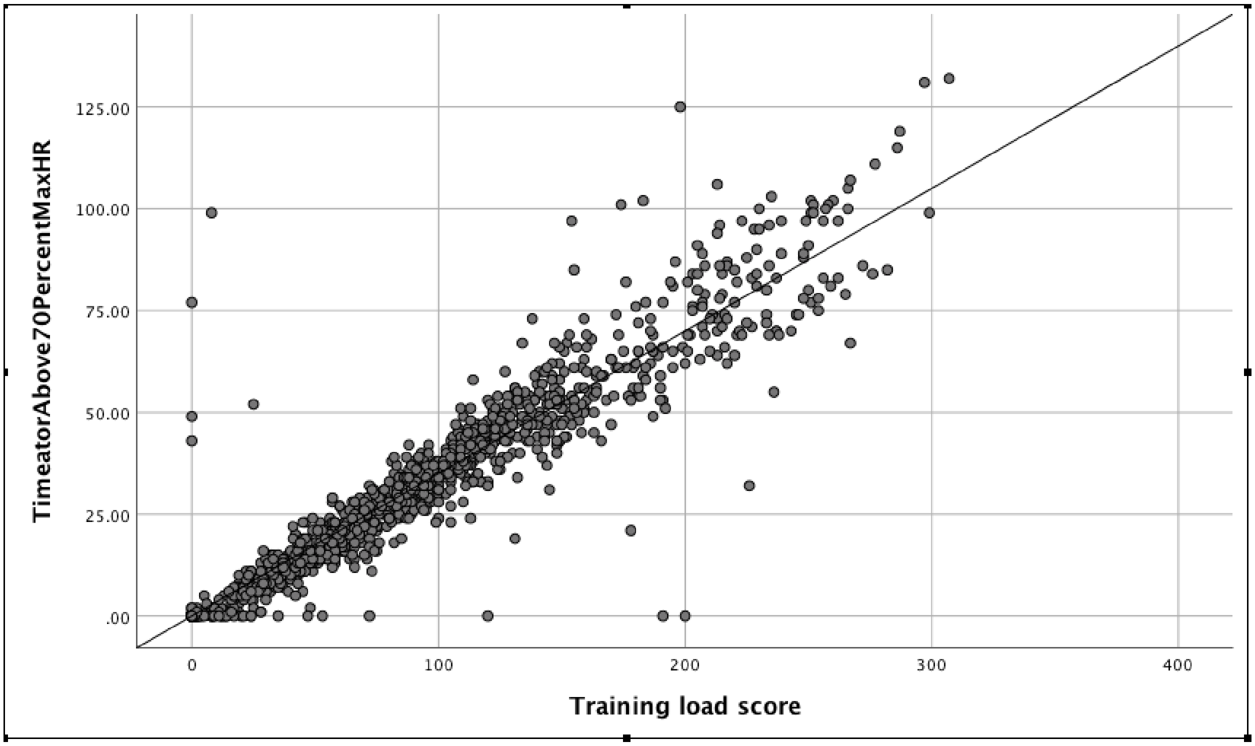


Figure 7 - Scatterplot Between Training Load Score and Time at or Above 70% Maximum Heart Rate



BIOGRAPHY OF THE AUTHOR

Finn was born in Manchester, England where he lived for six years before moving permanently to Maine, United States of America. Here he lived in Winslow and attended Winslow Senior High school and then the University of New England for his Bachelors of Science in Applied Exercise Science. Finn graduated from The University of New England in May of 2016 before going on to work in New York City as an Elite Level Personal Trainer for Crunch Fitness, then as a Sports Performance Coach for Parisi Speed School Colorado. During this time Finn maintained his Certified Strength and Conditioning Specialist certification and professional membership with the National Strength and Conditioning Association by attending various conferences and other continuing education opportunities. Additionally he is CPR/First Aid certified through the American Heart Association. Finn is a candidate for the Master of Science degree in Kinesiology and Physical Education from the University of Maine in May 2021.