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An Examination of the Physical and Technical Demands of the Competitive Season for NCAA
Division I Male Soccer Players

A dissertation

presented to

the faculty of the Department of Sport, Exercise, Recreation, and Kinesiology

East Tennessee State University

In partial fulfillment

of the requirements for the degree

Doctor of Philosophy in Sport Physiology and Performance

by

Emmanuel Espinoza

August 2024

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Keywords: GPS, collegiate soccer, technical-tactical, match demands, training load

ABSTRACT

An Examination of the Physical and Technical Demands of the Competitive Season for NCAA

Division I Male Soccer Players

by

Emmanuel Espinoza

The purposes of this dissertation were to examine the physical and technical demands of collegiate NCAA D-I male soccer players over the course of a competitive season. The following are the major findings of the dissertation:

Study 1 – GPS normative data was calculated by position using data from 5 seasons (2017, 2018, 2019, 2021, 2022). GPS data was compared by position for 5 different GPS-derived metrics. No statistically significant differences were found in any field or lab testing data by position.

Statistically significant relationships were found between physical match performance variables of TD and SPR with both YYIRT-1 and 20m sprint time, as well as between IMA-A and 20m sprint time. These results suggest that both the YYIRT-1 and the 20m sprint test is related to match performance in soccer players of this population.

Study 2 – Normative data was provided for technical-tactical variables retrieved via WyScout®, a video analysis software used to tag technical actions of soccer games. Normative technical-tactical data are presented as mean \pm SD. Statistically significant low to moderate negative correlations were found between total volume of technical actions and GPS variables. No statistically significant relationships were found between the strength-power lab tests measures and any of the total volume measures of technical actions. Statistically significant low to

moderate correlations were found between speed and endurance field tests and total volume of technical actions.

Study 3 – The relationship between training load and physical capabilities was examined by using appropriate testing. Bootstrapped ANOVA results showed statistically significant changes in pre and post testing for Static Jump Peak Power in the loaded condition. No other significant changes in lab testing results were found. Statistically significant changes in Yo-Yo Intermittent Recovery Test scores were found in pre- and post-testing. The relationship between GPS training load metrics and percentage of change in the administered test was found to be statistically significant between HSR distance and YYIRT distance, CMJ Peak Power and both TD and IMA-D.

Physical capacity of NCAA D-I male soccer players seems to deteriorate over the season, but not differ statistically from baseline measurements. Physical changes could be context-dependent and a consequence of the specific training plan. Overall, soccer performance at the NCAA D-I level is multi-factorial and an analysis of the in-season demands of this population of athletes appears to yield some counterintuitive results.

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DEDICATION

This dissertation is dedicated to my family. To my parents, Silvia and Artemio who have sacrificed more than I could ever know so my sisters and I could have the world at our disposal. To my beautiful fiancé, Danielle for always supporting me in my professional pursuits and pushing me to be great in all aspects of my life. To my sisters Sianya and Mireya, for helping me keep perspective and reminding me of what really matters in life. I love you all.

Esta tesis queda dedicada a mi familia. A mis padres, Silvia y Artemio quienes han sacrificado más de lo que yo me podría imaginar para que mis hermanas y yo pudiéramos tener el mundo a nuestra disposición. A mi hermosa futura esposa Danielle, por siempre apoyarme en mi carrera y motivarme a sobresalir en todos los aspectos de mi vida. A mis hermanas Siany y Mireya por ayudarme a mantener la perspectiva y recordarme de lo que realmente importa en esta vida. Los amo a todos.

Emmanuel

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Chapter 1. Introduction

Soccer is one of the most popular sports in the world with a large viewership across the world (FIFA, 2007). Due to its popularity, soccer has also been one of the most researched sports, particularly at the collegiate level (Jenkins et al., 2022). However, despite all this research, it appears that a very small percentage focuses on the match demands of collegiate soccer players and focuses on injury or other aspects of sports medicine. Match demands, particularly in team sports, are dependent on contextual factors that influence not only the result, but the physical outputs of the match (Paul et al., 2015; Romero-Rodriguez et al., 2024; Díez et al., 2021; Oliva-Lozano et al., 2022). Given the influence of these, it is important to note that soccer in the United States at the NCAA D-I level is vastly different from the majority of soccer played at the international level.

Because of the difference in match demands for this population of soccer players, it is important for the physical demands of a NCAA D-I season to be understood. Measures of external load tracking have developed over the last two decades that allow the quantification of match demands in team sports. In soccer, GPS has become widely adopted as standard practice of external load quantification and player tracking (Thoedoropoulos, Bettel, & Kosy, 2020). These days, the collection of microsensors inside a “GPS” unit include GNSS signal, accelerometers, gyroscopes, and magnetometers all operating at high frequencies that allow for collection of thousands of data points related to player physical performance (Hennessy & Jeffreys, 2018). Another layer for analysis that has come about with the rise of technological advances is the technical-tactical analysis of match performance that is now at the coaching staff’s disposal. Multi-camera tracking systems used in professional sports have not only made the tracking of physical outputs more available, but they have also been at the forefront of the

influx of technical-tactical data that is now commonplace in soccer performance departments. The rise of technical-tactical analysis has made this data indispensable in large-scale organizations and thus should be understood in relation to physical outputs in team sports.

In addition to GPS technology, the implementation of force plate testing has become more common place due to the increased commercial availability and reduced costs of purchasing such technology. Modern day force plate systems allow for easy implementation of various tests of physical outputs such as a variety of jump tests and isometric tests such as the Isometric Mid-Thigh Pull (IMTP). In addition to these tests of physical performance, there is a long history of field-testing performed in soccer and in team sports in general. Due to the easy implementation of field tests and their high degree of ecological validity, field-testing batteries have a long history of success and implementation in soccer and have been thoroughly researched. Bangsbo (1994) developed the Yo-Yo Intermittent Recovery Test (YYIRT-L1) which has been proven to have high degrees of correlation to match running performance in soccer players. Sprint testing has also been a consistent test performed in team sport. In soccer players, 20-meter sprints have been commonly used due to the frequency of this action in soccer (Faude et al., 2012).

Dissertation Purposes

1. To further investigate the physical match demands of NCAA D-I male soccer using a larger sample over a longer period of time
2. To further investigate the physical performance capabilities of NCAA D-I male soccer players assess through a battery of physical performance tests
3. To quantify the technical-tactical demand of NCAA D-I male soccer using multi-camera tracking system software

4. To examine the relationships between technical-tactical match performance variables, physical match performance, and physical capabilities examined during performance testing
5. To examine the relationship between changes in physical performance testing and training load over a single competitive season in NCAA D-I male soccer players

Chapter 2. Review of the Literature

The ultimate goal of sport science is to improve performance by affecting physiological changes in athletes based around researched and innovative interventions. In order to achieve this goal, one must first understand the demands of the sport in which one is attempting to have a positive effect. For this reason, a good deal of sport science research is based around an attempt to deeply understand the demands of sport, whether that's through careful observation, direct or indirect measurement of physical outputs, or collection of longitudinal data. In soccer specifically, the analysis of match demands goes back almost 50 years. Reilly & Thomas (1976) were among the first to examine the match demands of professional soccer players and the distances covered. Withers et al. (1982) analyzed the demands of professional soccer in Australian professional soccer. Mayhew and Wenger (1985) used video to analyze four professional players in-match during competitive games for the North American Soccer League (NASL). Each player was recorded for 7-minute intervals and the subsequent video was tagged using a specifically designed computer program to tag the physical activity taking place.

As technology evolves, the methods used to evaluate player performance have also evolved. Currently there are multiple methods of analyzing match demands in sport such as the use of High-Speed Video Cameras, Global Navigation Satellite System (GNSS), Accelerometers and Inertial Measurement Units (IMUs), and Local Positioning Systems (LPS) (Torres-Ronda, Beanland, Whitehead, Sweeting, & Clubb, 2022) these tools of evaluation are primarily based around physical outputs and use different methods to come to their conclusions. GNSS (colloquially known as GPS) has become the primary technology used to evaluate physical demands in sport over the course of the last decade. With its increase in both availability and affordability, the use of GPS at different levels of sport has brought about new research and new

insights into the specific demands of both practice and matches for different sports. Different metrics are used to evaluate physical demands based on velocities achieved, accelerometer variables, and even custom metrics provided by these GPS companies. The present review of the literature is an examination of the use of GPS in soccer across different levels of competition, the use of physical testing in soccer at different levels of competition, and the use of video to analyze technical and tactical demand in soccer at different levels, all of which will be compared to the present data available at the American Division-I level of competition.

GPS in Sport

The use of player tracking in sports using GPS has grown exponentially over the last decade or so. One of the goals of sport science is to understand the external load placed on athletes, which has brought about an increase in the use of technology that aims at quantifying external load. An increase in the availability of this technology – primarily GPS – has saturated the market and subsequently brought down the cost of using this technology. Torres-Ronda et al (2022) describe the three main purposes of this technology as Describing, Monitoring, and Planning, and give guidelines for best practice when it comes to the evaluation of the technology, its intended use, and the metrics used for player evaluation (Torres-Ronda et al., 2022). The use of GPS for tracking athletes has been in question since the late 1990s when Schutz and Chambaz put a commercially available GPS tracker on a recreationally trained runner and had them run at different speeds (Schutz & Chambaz, 1997). Edgecomb and Norton (2006) were some of the first to use GPS technology in team sports when they examined the validity and reliability of this technology to evaluate total distance covered by Australian Rules Football players (Edgecomb & Norton, 2006). The use of GPS units in sport-specific running patterns was examined by Jennings et al. (2010) by using a course involving changes of direction while subjects wore two

GPS units in a custom-made harness that placed the units between the scapulae. The GPS units sampled at both 1 Hz and 5 Hz, with the 5 Hz unit showing greater reliability during the sport-specific activity. Expanding on this research, Boyd et al. (2011) examined the reliability and validity of combined GPS/ Accelerometer units in Australian Rules Football players and concluded that the GPS unit could be used when examining the player outputs (Boyd et al., 2011). Aughey (2011) was one of the first to review the use of GPS technologies in team sports, with most of what he discovered being in the realm of Australian Rules Football or Cricket. Aughey (2011) highlighted the differences between using GPS units with different sampling rates, using GPS for different types of activities, and the speed at which these activities are conducted (Aughey, 2011). A review by Scott et al. (2016) also highlighted the improvements in the reliability of both distance and velocity measurements of portable GPS units based on sampling rates, with statistically significant improvements in the measures between 1 Hz and 5Hz and then again between 5Hz and 10Hz (Scott et al., 2016). All of these are factors to consider in the collection of data, particularly during the unpredictable tasks presented in team sports. As technology surrounding GPS systems has improved, so has the breadth and the depth of the research involving the use of this technology in sport. A steady increase in the availability and amount of research regarding GPS in team sports has been noted from 2001 to 2015 (Malone et al., 2017). Malone et al.'s review highlights the importance of understanding the method by which technology calculates the metrics it reports and how to account for variation and error within the measurements.

Catapult Optimeye S5

Catapult Sports (Catapult Sports, Melbourne, VIC, Australia) is perceived today as one of the main providers of GPS technology in sport, and has been one of the pioneers of player

tracking in sports. A recent review of the literature on GPS units by Principe et al. (2020) found that Catapult Sports was the listed GPS provider in at least 17 out of 21 of the studies included in the review (Principe et al., 2020). Additionally, approximately 42% of these studies were performed using the Catapult MinimaxX unit, which is no longer supported by Catapult Sports. The next generation of GPS units designed by Catapult Sports was the Optimeye S5 unit. The Optimeye S5 unit is a GNSS unit that contains a tri-axial accelerometer, a tri-axial gyroscope, and a tri-axial magnetometer, all of which sample at 100 Hz. According to Principe et al. (2020), the Optimeye S5 system from Catapult is the second most popular GPS system presented in the available research. The validity and reliability of this unit and its different capabilities has been tested in the research. For instance, Holme (2015) examined the reliability and validity of accelerometer-derived metrics from Catapult's Optimeye S5 unit, particularly the Inertial Movement Analysis or IMAs. An IMA is Catapult's way of quantifying data from the accelerometer by using an algorithm to quantify the magnitude and direction of an agility action (Holme, 2015). IMAs were proven to be both valid and reliable when measuring and quantifying change of direction activities. Nicolella et al. (2018) aimed to test the reliability of the Optimeye S5 by subjecting it to a number of tests in a controlled laboratory setting (Nicolella, Torres-Ronda, Saylor, Schelling, 2018). The results of this study were indicative of a high level of intraunit reliability for accelerometer-derived metrics (PlayerLoad).

GPS in Soccer

The use of GPS units to quantify external load in athletes has been a long process, but some sports were less reluctant to become early-adopters – soccer is one of these sports. The Fédération Internationale de Football Association (FIFA), the governing body of international soccer, approved the use of tracking technology in matches during the year 2015 (FIFA, 2015).

Previously, the use of GPS was only allowed in training and was not allowed in official competitive matches in the professional ranks, resulting in an abundance of literature on different levels of competition (amateur, amateur youth, elite youth, etc...). Hill-Hass et al. (2009) used GPS units on youth soccer players (U16) in order to examine the time-motion demands of small-sided games (SSG) in conjunction with their physiological outputs (Hill-Haas et al., 2009). This was one of the first studies using GPS in a soccer population, at the time of the study the technology was not as advanced as it is today, with the GPS unit sampling rate only being 1 Hz. In addition to the limited sampling rate of the GPS units, no accelerometer data was reported for this study. Similarly, Barbero-Alvarez et al. (2008) used GPS units with a 1 Hz sampling rate to examine the time-motion demands of locomotion as well as the subsequent heart rate response in youth female soccer players during a friendly 7v7 soccer game (Barbero-Alvarez et al., 2008). Harley et al. (2010) use Catapult MinimaxX units to assess the motion demands of over 100 youth soccer players from U12 to U16 involved in two professional English club academy systems. Data from competitive games was analyzed for the players who were involved in the study and were presented as both relative and absolute in terms of physical demand (Harley et al., 2010). In professional soccer, Dellal et al. (2012) used GPS to investigate the demand of SSGs during an international national camp (Dellal et al., 2013). The physical demands of professional soccer players during an 11v11 game were first evaluated by Mallo et al. (2015). Although the data was not published until 2015, this was the first study to examine the in-match physical demands of professional soccer players using GPS technology (Mallo et al., 2015). Authors of this study used GPS units sampling at 1 Hz during pre-season friendly matches before the start of the 2011 and 2012 La Liga seasons (Mallo et al., 2015). This was one of the first studies that used GPS technology to quantify physical outputs in professional soccer. Scott et al.

(2014) also examined the match demands of professional soccer players in the Australian professional league, but also examined the training data for the competitive season from which the match data that were collected. The results of this study revealed statistically significant differences between the high-intensity distance covered by players during matches compared to training sessions (Scott et al., 2014). Suarez-Arrones et al. were among the first to place GPS devices on professional soccer players in Europe during competitive matches. By using a combination of heart rate and GPS, the authors of the study were able to quantify physical and physiological demands of the professional soccer players involved in the study, however, only one half of match data was used in this examination. Torreño et al. (2016) expanded on the work of Suarez-Arrones et al (2014) by analyzing the physical and physiological outputs of both halves of competition in professional European soccer players using GPS and heart rate. Data was collected over two seasons using GPS that recorded at 5 Hz frequency, an improvement over some of the previous investigations done in professional soccer at the time (Torreño et al., 2016). GPS has also been used in order to quantify training load in professional soccer players across a season while accounting for different influential factors related to training load (Malone et al., 2017).

GPS Derived Key Performance Indicators (KPI)

The most commonly reported metric using GPS technology is total distance covered. Because the GPS units use an atomic clock to help calculate displacement, they can provide information about the velocity of the movements performed by the athletes as well as the time spent in certain velocity zones. The distance metrics that are calculated are based on the speed at which these distances are covered. These are termed “velocity bands” and are typically chosen by the sport scientist in charge of the GPS data collection (Hennessy & Jeffreys, 2018). The two

velocity bands of note are typically High-Speed Running (HSR) and Sprint Running (SPR), which are recorded when players achieve velocities greater than 19.8 and 25.2 km/h, respectively (Sæterbakken et al., 2019). Although the literature often states the designation of velocity bands in their methods, there seems to be no consensus on what the velocity thresholds for each band should be set at, due to the different rationales that are applied in the designation of said thresholds (Sweeting et al., 2017). Diaz-Soto et al. (2022) review the literature related to velocity and accelerometer thresholds using GPS technology and found that while the majority of velocity band designations that were individualized were related to a 40m maximal sprint test, there was no majority and no consensus with how the subsequent individualization of velocity thresholds should take place (Diaz-Soto et al., 2022). It is suggested that one of the reasons in the early inconsistencies in the data could be related to the decreased reliability of GPS units at higher velocities of movement and during sport specific activity (Johnston et al., 2014; Coutts et al., 2010). There is also a substantial difference in the core technology that some of these studies use for comparison. While GPS is a term that is used to referred to most external load tracking devices these days, there are fundamental differences between the old GPS units and newer GNSS units both in the method used to acquire the data and the quality of the data itself, therefore the data should not be compared as if the devices are interchangeable (Jackson et al., 2018). It is also important to note that some studies have shown better reliability and validity of measurements at higher velocities using newer GNSS units vs older GPS units and even newer Local Positioning Systems (Roe et al., 2016; Hoppe et al., 2018; Beato et al., 2018). Other GPS-derived metrics such as Metabolic Power, Explosive Distance, or High Metabolic Load Distance, which are measures of the metabolic exertion a player experiences above a certain threshold of Metabolic Power ($W \cdot kg^{-1}$) in addition to “over or under” a certain velocity of movement

(Hennessy & Jeffreys, 2018). It should be noted the formula used for Metabolic Power is a relative power formula ($N \cdot M \cdot s^{-1} \cdot kg \cdot^{-1}$). Metabolic power was proposed as a method of quantifying intensity in soccer by Osgnach et al. (2009). The authors of this study used video analysis and known calculations of energy costs to calculate power at different running speeds and use them as a measure of intensity in professional soccer players (Osgnach et al., 2009). However, Buccheit et al. (2015) attempted to validate the use of Metabolic Power as a measurement for metabolic demand, but found that GPS-derived metabolic power was markedly underestimated when compared to actual power at specific VO_2 gas exchange measurements (Buccheit et al., 2015). Furthermore, the metric used to estimate intensity of effort during training was found to be unreliable (Buccheit et al., 2015). Thus, what had previously been referred to as metabolic power (Osgnach et al., 2009), was erroneous terminology and largely unusable. Regardless, metrics involving GPS derived power measures have been consistently used to evaluate match demands, practice demands, and overall fitness for soccer players at different levels of competition (Manzi et al., 2014; Tierney et al. 2016; García-Calvo et al., 2022; Castagna et al., 2016).

Accelerometer-Derived Key Performance Indicators (KPI)

Not all movement in sport that requires high physical demand occurs at high velocities, therefore understanding the metrics derived from the other Micro-Electromechanical Sensors (MEMS) that are present in the devices has become crucial to getting a full picture of the external load experienced by the athlete. PlayerLoad is one of Catapult Sports® main proprietary metrics and has been used extensively to quantify external load in athletes. PlayerLoad is defined as “...the sum of the accelerations across all axes of the internal tri-axial accelerometer during movement. It takes into account instantaneous rate of change of

acceleration and divides it by a scaling factor (divided by 100).” (Catapult Sports). Boyd et al. (2011) used Catapult MinimaxX units to determine the reliability of PlayerLoad as a metric to report the external load placed on the athletes. A number of testing conditions (Machine, Lab, and Field) showed high inter-unit and intra-unit reliability for PlayerLoad at each condition (Boyd et al., 2011). Barret et al. (2014) Reaffirmed Boyd’s findings but highlighted the differences between the measurements taken at the Center of Mass (COM) and the measurements taken between the scapulae, noting that comparisons between players should be avoided due to the influence of running style on PlayerLoad (Barret et al., 2014). This finding was later reaffirmed by Akyildiz et al. (2022) who found similar differences in PlayerLoad during field tests in soccer players when the GPS units were placed between the scapulae versus on the COM (Akyildiz et al., 2022). The reliability for the Catapult Optimeye S5 unit’s calculation of PlayerLoad was assessed by Nicolella et al. (2018). The results of this examination showed excellent intraunit reliability, but high variability between units – especially when comparisons are made between individual axes (Nicolella et al., 2018). Additionally, the Authors of this study found large differences between the PlayerLoad given by Catapult’s software and the player load that resulted as a calculation of the equation given by Catapult Sports, suggesting additional data manipulation or filtering before the final values are exported to the user. Despite this, PlayerLoad has become a commonly reported metric for team sports. Barron et al. (2014) used PlayerLoad to investigate the acceleration and deceleration load placed on youth soccer players (Barron et al., 2014). Because measurements taken from accelerometers are not in need of a GPS, they are frequently used for indoor sports to quantify the physical demand of movement, often with metrics like PlayerLoad (Wik, 2015; Holme, 2015; Randsell et al., 2020).

A review by Gomez-Carmona et al. (2020) highlights the use of Inertial Movement Analysis (IMA) as another accelerometer-derived metric frequently used in the research by Catapult Sports technology users. IMAs have been used in research to report on the match demands of different athletes, particularly those of indoors sports such as handball and basketball (Wik, 2015; Holme, 2015; Meylan et al., 2016; Luteberget et al., 2017; Randsell et al., 2020; Fox et al., 2020) and can be described as “*Application of polynomial smoothing curves between the start and end point of identified accelerative events. The magnitudes of such events are subsequently calculated by summing the accelerations under the polynomial curves, measured in terms of delta-velocity*” (Gomez-Carmona et al., 2020). While some studies have shown a good reliability for these metrics, others highlight some of the shortcomings in the calculation of said metrics and warn against their use. For instance, Meylan et al. (2016) overlaid raw IMA traces from an accelerometer with video for change of direction tasks in female soccer players playing at a national team level. The authors found that the variability for high-intensity IMAs ranged between 13 and 21% and therefore IMAs depending on the task at hand, and therefore concluded that IMAs should not be used to assess acceleration, deceleration, or other change of direction activities. However, later research contradicts the findings of Meylan et al. (2016) when newer technology was used. Meylan et al. (2016) conducted their study using Catapult MinimaxX units, but Wik (2015) and Holme (2015) assessed the reliability of Catapult’s newer models, Optimeye S5, and found good reliability for IMA measurements. Similarly, Luterberget et al. (2017) found good reliability of IMA measurements from Optimeye S5 units when they were non-directional, in the higher bands (medium or high categories), or expressed as a count of total IMAs. Other studies have used IMAs as a way of quantifying physical load related to changes of direction in different sporting populations (Randsell et al., 2020; Konefal et al., 2022; Kupperman et al.,

2021). It is important to note that IMA research has been conducted by exploring or associating accelerometer-variables that have presumably not been well measured or well understood by those conducting the research. For instance, while IMA measurements derived from changes in the accelerometer, they don't actually report accelerations or decelerations from the accelerometer and thus should be reported as the delta velocity in units of meters per second ($m \cdot s^{-1}$) (Wik, 2015; Holme, 2015; Luterberget et al., 2015). This does not always appear to be the case in research that investigates IMAs, having instances of IMAs reported in meters per second squared ($m \cdot s^{-2}$) (Gomez-Carmona et al., 2020). Similar concerns with the algorithm for PlayerLoad have been stated and should be noted when reporting as a measure of comparison between players or between devices (Bredt et al., 2020; Nicolella et al., 2018).

GPS in Collegiate Soccer

Although soccer was one of the early adopters of GPS technology, the accessibility to GPS/GNSS technology was usually limited to organizations with a high level of economic investment, due to the associated costs. The increased developments of both the player technology and sports performance departments have led to an overall increase in the number of investigations using GPS in different athletic populations. At the American NCAA collegiate level, there is abundance of research that is centered around Division-I (D-I) female soccer players. Vevosci and Favero (2014) were some of the first to examine the physical demands of collegiate soccer players, focusing on female collegiate soccer players at the NCAA D-I level. Alexander (2014) followed up on this work by investigating the high-intensity demand of NCAA D-I female soccer players at different positions using Catapult MinimaxX units. A later investigation by Sausaman et al. (2019) also added to the research on women's college soccer by investigating the locomotor demands of women's college soccer players by examining four

seasons worth of data of a team participating at the NCAA D-I level (Sausaman, Sams, Mizuguchi, DeWeese, Stone, M.H., 2019). More recently, Isihida et al. (2022) examined the relationship between external and internal training load in female collegiate soccer players, with an emphasis on the differences between player position groups (Ishida, Travis, Draper, White, Stone, 2022). Although early research at the NCAA level started and has continued with the women's game, there are significant differences in the physical demand between male and female players, as highlighted by research in both professional soccer and NCAA D-I soccer (Krustrup et al., 2005; McFadden et al., 2020).

While the physical demands of soccer players as a whole have been thoroughly investigated, the physical demand of NCAA D-I male soccer players has not been as thoroughly investigated until recently. Sams et al. (2015) were some of the first to examine the physical demands of NCAA D-I male soccer players and examine the differences between different positions over two seasons (Sams et al., 2015). A few years later, Curtis et al. (2018) examined the physical demands of NCAA D-I soccer players across a competitive season using GPS and Heart Rate (Curtis et al. 2018). GPS data was collected using Catapult MinimaxX devices for a total of 235 match observations across 18 soccer players and 24 total matches of a single soccer team. Descriptive data for distances covered at different speeds as well as acceleration and deceleration data were provided for each position, with statistically significant differences between midfielders and all other positions. Slater et al. (2018) also examined the physical outputs of collegiate soccer players, examining the data by half, by position, and by proportion of total distance covered in a single longitudinal study following one NCAA D-I soccer team across a single season (Slater et al. 2018). Curtis et al (2020) later expanded on the research in this area by adding contextual factors to the physical demands of the season such as starter vs reserve

players, position groups, training day in relation to the next match (MD-1, MD-2, etc...), in-season vs post-season, and other factors specific to an NCAA D-I environment (Curtis et al., 2020). This time by examining 5 teams across 2 seasons, the authors were able to analyze substantially more data, with over 5,000 total data points to analyze, collected from 107 NCAA D-I male soccer players. The results of this study indicated statistically significant differences in match load between starters and reserves as well as differences between time-periods of the season, with pre-season having the highest physiological load in the shortest amount of time (Curtis et al., 2020). Training load throughout a season was also examined by Ryan et al. (2022) by investigating measures of internal load via heart rate and measures of external load via GPS. Statistically significant differences were found between different periods of the season and between position groups, with heart rate data showing larger differences (Ryan et al., 2022). Curtis et al. (2021) used heart rate and GPS data to highlight the differences in training load over a season in NCAA D-I soccer players. By examining 5 NCAA D-I teams across two competitive seasons, a substantial gap was found between the accumulated workloads of starters (over 60% of matches started) and reserves, particularly in the GPS variables examined (Curtis et al. 2021). Fields et al. (2021) examined these same differences in external load between starters and non-starters across a competitive season in NCAA D-I male soccer players and found no statistically significant differences in external practice load. This finding suggests that non-starters are chronically undertraining because they have the same external loading during training sessions, but do not receive the same game load as starters during the season (Fields et al. 2021).

Physical Testing in Soccer

With soccer being the most popular sport in the world, there has been expansive research carried out in order to understand the physical determinants of performance in soccer players.

Thomas & Reilly (1979) performed an extensive battery of physical tests on a population of professional soccer players throughout the course of a full season. Twenty-six tests were performed at three different time-points, including 17 anthropometric tests, 4 tests of muscular strength and power, as well as 5 measures of cardiac function (Reilly & Thomas, 1979). A review by Hoff (2005) found that the most common physical attributes that are tested in this population are aerobic power and muscular strength (Hoff, 2005). This review was also an examination of strategies to both test and train these physical characteristics in populations of soccer players. An earlier review by Tumilty (1993) was an examination of both aerobic and anaerobic capabilities of soccer players and touched on different anaerobic measurements related to soccer performance such as vertical jump, agility and change-of-direction testing, strength, and anaerobic power (Tumilty, 1993). Svensson & Drust (2005) reviewed the available literature on testing surrounding soccer players and highlighted the importance of using field tests rather than lab tests in order to get more valid results (Svensson & Drust, 2005). There have been a wide range of investigations in different populations describing the physiological profiles of soccer players at different levels (Sporis, et al., 2009; Slimani & Nikolaidis, 2017; Silva et al., 2021). In male collegiate soccer players, the research surrounding physical testing varies in terms of scope and sampled population. Samples of lower division NCAA soccer players (Division-III) have been performed by both Magal et al. (2009) and Miller et al. (2011).

Although each of these studies were performed at a different time of the competitive calendar (off-season vs in-season), both of these studies focused on indicators of aerobic and anaerobic physical performance, using tests such as the Wingate test, VO_{2max} testing, and agility testing (Magal et al., 2009; Miller et al. 2011). In NCAA D-I soccer players, physical performance testing has been performed more extensively. In male populations specifically,

Kraemer et al. (2004) examined changes in blood serum testosterone and cortisol, along with changes in physical performance testing, across the course of an NCAA season (Kraemer et al. 2004). Additional research on performance testing variables in male NCAA soccer players highlights some of the changes in physical performance across a competitive season, including statistically significant decreases in fitness and various performance testing variables (Silvestre et al. 2006; Sapp et al. 2017). This section will review the different tests that are included in the scope of this dissertation as well as their relevance to soccer performance.

Isometric Mid-Thigh Pull

The Isometric Mid-Thigh Pull (IMTP) was first developed by M.H. Stone, H.S. O'Bryant, and G. Haff (Stone et al. 2019) in the early 1990's to test force isometric production capabilities in various sports, particularly weightlifters, at specific positions and relate these measures to dynamic performances (Stone et al. 2019; Haff et al. 1997). While initially designed to assess strength-power sport performance, reviews by Brady et al. (2018), Giles et al. (2020), and Stone et al. (2019) demonstrated that the IMTP assessment is consistently used in different sports populations to assess different biomotor abilities related to sport performance (Brady et al., 2018; Giles et al., 2020 Stone et al., 2019). For instance, Stone et al. (2003) aimed to find relationships between IMTP-derived variables and different aspects of dynamic performance in NCAA collegiate track and field throwers (Stone et al., 2003). Both Beckham et al. (2013) and Stone et al. (2003) highlighted the importance of Rate of Force Development (RFD) and training that emphasizes high-RFD in order to improve physical performance (Stone et al., 2003; Beckham et al. 2013). Since its inception, the IMTP has been used to measure absolute and relative isometric strength in many different sport populations. McGuigan & Winchester (2008) were among the first to examine the role of IMTP-derived variables in the physical performance

of NCAA football players. Strong correlations between 1RM tests and Isometric Peak Force (IPF) were found, along with weak correlations between the same 1RM tests and RFD (McGuigan & Winchester, 2008). Nuzzo et al (2008) contributed to the research in NCAA athletes, specifically in American Football and Track & Field, finding that absolute isometric testing variables were not strongly correlated with countermovement jump (CMJ) variables, but both IMTP and CMJ results improved when body mass was taken into account (Nuzzo et al., 2008). More normative data in NCAA athletes was later provided by both Kraska et al (2009) and Beckham et al. (2014) who both examined the results of large numbers of NCAA athletes from different sports including sprint cycling, soccer, track and field, tennis, volleyball, and softball (Kraska et al., 2014, Stone et al., 2006, Stone et al., 2003).

Specifically in soccer players, Dos'Santos et al. (2017) were the first to publish the reliability of IMTP measures in a population exclusively made of soccer athletes. The authors administered IMTP tests to 13 professional youth soccer players after a 7-week preseason, finding a high within-session reliability for the IMTP kinetic variables being examined, with Peak Force showing the highest degree of reliability (Dos'Santos et al., 2017). In one of the first studies assessing the IMTP performance elite soccer players, Brownlee et al. (2018) recruited over 150 soccer players ranging from U9 to U21 age groups and compared the IMTP results of elite youth players to non-elite youth players that were matched for their maturity-offset based on Peak Height Velocity (PHV). Only small differences were observed between the Pre-PHV and Mid-PHV stages of development in this study, but a similar examination by Morris et al. found that while differences are highlighted between ages and stages of development, there were little to no differences when the results were normalized by body mass (Brownlee et al., 2018; Morris et al., 2018). In professional soccer players, the relationship between IMTP and sprint

performance was examined by Mason et al. (2020). Negative correlations of varying degrees were found between sprint performance variables and measures of performance in IMTP at different timepoints (F50, F100, etc...), with stronger negative correlations occurring with the later timepoints of IMTP force variables (Mason et al., 2020). Abbott & Clifford (2021) examined Peak Force from IMTP and its relationship to recovery in professional soccer players, finding that stronger players had a tendency to recover faster. In collegiate soccer players, both Thomas et al. (2015) and Kuki et al. (2017) examined the relationship between variables derived from IMTP and the results of other physical performance tests (i.e. sprint testing, CMJ testing, etc). The results of both of these studies indicated that there is indeed a relationship between sprint testing and IMTP variables at specific timepoints (Thomas et al., 2015; Kuki et al., 2017). While these studies were carried out on “collegiate soccer players”, the studies do not specify which population of collegiate soccer players the samples were pulled from and thus the results of these studies are difficult to extrapolate to NCAA D-I athletes. In NCAA D-I male soccer players specifically, Ishida et al. (2021) used IMTP along with other physical performance tests to establish a relationship between strength and power characteristics and physical performance related to sport (Ishida et al., 2021).

Jump Testing

Jump testing has been a part of athlete monitoring for decades. Bosco & Komi were some of the first to use the countermovement (CMJ) and static jump (SJ) for profiling purposes, using the two jumps to determine the relationship between skeletal muscle fiber composition and jump performance (Bosco & Komi, 1979). Since the development of these two tests, different tools have been used to assess both the static and countermovement jumps, such as potentiometers, switch mats, accelerometers, LED light systems, and force platforms operating at different

frequencies (Hatze, 1998; Cronin et al., 2004; Castagna et al., 2013; Chouko et al., 2014; Loturco et al., 2017). Force plate assessments of jumping ability have become more prominent in the research and have been used to assess different physical abilities related to jumping. In soccer players, the countermovement jump has typically been used to assess physical performance or to measure neuromuscular fatigue after games. Due to the accessibility of tools used to measure jump performance, as well as the extensive amount of research on the subject, a variety of methods for collecting data on jump performance exist in the literature.

A review by Petrigna et al. (2019) showed a wide range of methods used in the assessment of jump performance in adolescents. The authors provided sample Standard Operating Procedures based on the most common practices found in their meta-analysis (Petrigna et al., 2019). In soccer players specifically, there has been a wide range of jump testing performed at different ages and levels of competition and for various assessments of performance. Castagna & Castellini (2013) tested the jump performance of elite male and female performers at the national team level of different ages using an Optojump. The authors did not find any statistically significant differences between male age groups, but found large differences in jump performance both between male and female soccer players and between age groups of female soccer players (Castagna & Castellini, 2013). Chelly et al (2010) applied a plyometric-based strength training program to a cohort of adolescent, recreational soccer players. The program resulted in statistically significant changes in markers of lower limb performance, but notably SJ and CMJ (Chelly et al., 2010). Kotzamanidis et al. (2005) performed a similar examination with youth soccer players, analyzing the differences in jump performance after a period of strength training alone, strength training and sprint training, or a control condition. Statistically significant improvement was found from pre- to post-test results for subjects that

participated in the combined training (Kotzamanidis et al., 2005). Quagliarella et al. (2011) used force-plate derived metrics to evaluate the differences in neuromuscular performance, finding significant differences between competitive and recreationally trained youth soccer players (Quagliarella et al., 2011).

Both the countermovement jump (CMJ) and the static or squat jump (SJ) have been used extensively for monitoring purposes in competitive athletes (Petrigna et al., 2019), and while both are considered excellent assessments of physical neuromuscular performance, there are marked differences in the mechanisms behind both and their underlying performances (Van Hooren & Zolotarjova, 2017). Nedelec et al. (2014) studied the effect of soccer actions during a match and the recovery kinetics at different timepoints after the match, finding that changes in CMJ performance were statistically significantly correlated with the number of high intensity changes of direction at 24 hours post-match (Nedelec et al., 2014). In general, jump testing has been used to assess a number of different characteristics, including recovery after matches. Andersson & colleagues (2008) studied the changes in neuromuscular performance in female soccer players at different timepoints post-match. The repeated measures analysis indicated that the performance in jump testing was markedly lower for all post-match timepoints, indicating the negative effects of match play on neuromuscular performance (Andersson et al., 2008).

At the collegiate level, many studies examining the different elements of physical performance of women soccer players have been completed. Vescovi et al. (2007) used a switch mat to assess the positional differences in jump height of female NCAA D-I lacrosse players (Vescovi et al., 2007). Lombard et al (2020) monitored changes in the recovery of amateur male soccer players after simulated matches. A field test designed to simulate a soccer match was performed by athletes and followed up by self-reported wellness questionnaires and

countermovement jumps performed on force platforms (Lombard et al., 2020). In this same vein, other research has been performed in order to assess the performance of both male and female NCAA soccer players at different levels. Hoffman et al. (2003) used a linear position transducer attached to the athletes' centers of mass in order to assess jump height in NCAA D-III female soccer players after matches (Hoffman et al., 2003). Ishida et al. (2021) evaluated the acute effects of match play on neuromuscular performance in NCAA D-I female soccer players. The authors discovered that there was a statistically significant decrease in neuromuscular performance in weighted and unweighted CMJ performance from pre-match jumps to 12 hours post-match jumps (Ishida et al., 2021). The relationship between weekly training load and jump height was examined by Polly da Costa Valladão et al. (2023) by comparing the sum of weekly training load in GPS variables and the jump performance on a switch mat in NCAA D-I female soccer players (Polly da Costa Valladão et al., 2023).

In male collegiate soccer players, the relationship between training load and measures of physical performance has been studied by few authors. Kai et al. (2020) used the CMJ test on switch mats as part of a battery of tests used in order to evaluate the effect of preseason training on physical performance in male collegiate soccer players (Kai et al., 2020). A small increase in CMJ jump height with a small effect size was found across after the preseason period. The authors of this study, however, provided no further information about the subjects' level of competition or previous training, making it hard to extrapolate from their results. McFarland et al. (2016) examined the relationship between jump performance and sprinting performance in male and female soccer players at the NCAA Division-II level. While the jump tests were found to be correlated to some degree with the sprint tests, jump height was the only variable used to compare to sprint time leaving other CMJ related variables open to further examination

(McFarland et al., 2016). Sams et al. (2018) studied the effect of an athlete monitoring program on measures of fatigue using SJ derived variables, specifically in NCAA D-I soccer players. Loaded SJ (20 kg) were measured on a switch mat every week and were then assessed in relation to the weekly training load. No statistically significant decreases in SJ jump height were found throughout the course of the season suggesting the effectiveness of the monitoring program being evaluated (Sams et al., 2018).

Yo-Yo Intermittent Recovery Test – Level 1

Stølen et al. (2005) reviewed the literature on the physiological demands of soccer and remained steadfast in the importance of the aerobic system in soccer performance (Stølen et al., 2005). The Yo-Yo Intermittent Recovery Test-Level 1 (YYIRT-L1) was developed by Bangsbo (Bangsbo, 1994) in order to assess the fitness level of soccer players in a more specific manner. The YYIRT-L1 consists of bouts of 2 x 20m shuttles performed at increasing speeds followed immediately by 2 x 5m jogs as active rest (Bangsbo et al., 2008). Krstrup et al. (2003) examined the physiological and physical responses to the YYIRT-L1 test in semi-professional Danish soccer players, finding that there were clear relationships between the YYIRT-L1 test and measures of blood lactate, blood markers of fatigue, and VO_{2max} (Krstrup et al., 2003). Krstrup et al. (2003) also examined the reliability of the YYIRT-L1 and found no statistically significant differences between tests performed one week apart with an intra-individual Coefficient of Variation (CV) of 4.9%. Different levels of the YYIR Tests are available and have different formats, with the level one being a longer test and thus challenges more aerobic processes. The YYIRT-L2 starts the test at a higher speed and has more efforts at higher speeds, and is therefore believed to be a better measure of the anaerobic energy contribution of an athlete (Schmitz et al., 2018).

The YYIRT-L1 has been commonly used in different populations as part of field test batteries commonly used to assess physical performance. In particular, the YYIRT-L1 has become common practice in youth soccer players. The YYIRT-L1 has been used to assess the aerobic performance of youth soccer players at different levels and is the most commonly reported YYIR test used in players over 16 years of age (Schmitz et al., 2018). Castagna et al. (2010) examined the relationship between YYIRT-L1 scores and physical match performance in elite-level youth soccer players. The study showed statistically significant correlations between final score in the YYIRT-L1 and the total distance covered throughout the match, highlighting the importance of aerobic fitness in soccer match performance (Castagna et al., 2010). This is also in line with findings from Krustup et al. (2003). Bujnovsky et al. (2019) also examined the physical performance of the YYIRT-L1 in youth soccer players, but highlighted the differences in positional demands between players (Bujnovsky et al., 2019). The previously mentioned study gave way to similar results as similar studies performed on male youth soccer players and elite male soccer players.

Sprint Testing

Soccer has long been thought of as a sport that requires substantial endurance, competition mean heart rates of up to 85% of maximal values and average oxygen uptake of approximately 70% of maximum oxygen consumption (VO_{2max}) (Bangsbo et al., 2006; Bangsbo et al., 2007). Despite the relevance of the aerobic system for performance, recent research in the sport of soccer has revealed anaerobic energy system outputs to be fundamental for success (Dolci et al., 2020). In fact, an in-depth examination of the physical demands of official matches contested in the English Premier League have revealed statistically significant changes in both the total demand placed on soccer players and the number of high-intensity actions in a match

over the last few years (Bush et al., 2015). Furthermore, researchers believe that the demands of soccer a decade from now will be even greater with respect to the anaerobic energy system (Nassis et al., 2020). Not only is the development of the anaerobic energy system relevant for coping with game demands but it is essential for success. Faude, Koch, and Meyer (2012) concluded that straight line sprint actions are the most frequent physical actions that happen before goals are scored in elite-level soccer (Faude et al., 2012). Given the importance of the anaerobic system, specifically sprinting speed, in determining success in soccer, protocols have been developed to test soccer players' sprints at various distances.

Mirkov et al. (2008) examined the reliability of different field tests in professional soccer players and found that there was a high degree of reliability for 20m sprint tests, as well as among other field performance tests (Mirkov et al., 2008). Little & Williams (2005) investigated the relationship between anaerobic tests of speed and power in 106 professional soccer players across 2 different levels of competition. They used an agility test, a 10m sprint from a static start, and a 20m flying sprint with a 30m run-up (Little & Williams, 2005). While this testing battery did include a large sample size from a homogenous population, it is difficult to draw any immediate conclusions from the 20m sprint, as it is different from the majority of the research, which uses a static start instead of a flying sprint. Haugen et al. (2013) examined the anaerobic performance of soccer players of different levels and ages across multiple decades using a large sample of national level athletes. Marked differences were found in 0-20m sprint times between soccer players of different ages and of different levels, highlighting the importance of developing the anaerobic qualities of soccer as an athlete progresses through level of competition and age groups (Haugen et al., 2013).

In youth soccer players, the relationship between strength and sprint training was further examined by Comfort et al. (2014). The authors of this study found statistically significant negative correlations between 5m sprint time and SJ and CMJ, however, no statistically significant relationships between sprint times and back squat were found in this particular study. In a similar study, Styles et al. (2016) showed contrasting results to Comfort et al. (2014). Styles et al. examined the relationship between Squat 1RM and sprint times at different distances, finding statistically significant negative correlations between increases in squat 1RM and decreases in sprint times (Styles et al., 2015). The relationship between sprints, repeated sprint ability (RSA) and aerobic performance was investigated by Meckel et al. (2009). A 20m shuttle test and a 20m repeated sprint test protocol were used to investigate the relationship between aerobic performance and repeated sprint ability, with a statistically significant negative correlation between estimated VO_{2max} and performance in the 20m RSA protocol (Meckel et al., 2009). A 40m RSA test was also used in this study, but no statistically significant relationships were found between VO_{2max} and 40m RS performance, highlighting the importance of 20m sprints in soccer players. Mendez-Villanueva et al. (2011) used a 40m sprint test to determine differences in acceleration and maximum speed capacity between different age groups and different maturity statuses (Mendez-Villanueva et al., 2011). Statistically significant differences were found in both 10m sprint time and 20m fly time when results were split up by both age group and maturity status, reflecting the effect of maturation on anaerobic abilities related to performance.

Assessments of speed and endurance are also important at the NCAA D-I level (Sayers et al., 2008). In collegiate soccer players, Bellon et al. (2019) used a 20m sprint protocol to identify the different phases of early acceleration (Drive, Mid-STANCE, Transition, etc.). The authors of the

study used intercollegiate soccer players at the NCAA D-I level as subjects and used LED light transmitting devices to gain insights into the kinematics of soccer players during a 20m sprint (Bellon et al., 2019). Nagahara et al., (2016) also examined the kinematics and kinetics of collegiate soccer players, although the level of competition is unclear. The authors' study included a 35m sprint protocol after the first and second half of friendly matches in order to compare the performance between the two and determine the effect of playing a soccer game on the kinetics of a straight-line sprint (Nagahara et al., 2016). The results demonstrated a clear performance decrement from pre-match to post-match testing, but no decrement from pre-match to after the first half. While the protocol used in this study used a longer distance in the sprint, it is clear from the results that the ability to maintain sprint kinetics in the presence of fatigue is correlated with the high-speed distance covered during the game. Lockie et al. (2017) used a 30m sprint test along with a 30m RSA test to examine the relationships between sprint times at 10m and 30m and performance in an RSA test. A clear relationship between the 10m and 30m times and the RSA performance decrement was established in the results of the study, highlighting in the importance of improving straight line sprinting qualities in order to improve anaerobic performance (Lockie et al., 2017).

Video Tracking/WyScout

Since Thomas & Reilly (1979) first used video to assess the physical demands of soccer, this method of determining physical demands has evolved substantially towards evaluating both physical and technical demands of the sport. As technology has evolved, the use of different video analyses methods has been used to assess the physical demands of different levels of professional soccer in different leagues. The use of post-match video analysis and semi-automatic camera systems (i.e., ProZone ®, AMISCO Pro ®, SICS ®, WyScout ®, etc...) have

been used to assess physical match demands in professional soccer at different levels (Di Salvo et al., 2007; Rampinini et al., 2007; Di Salvo et al., 2009; Bradley et al., 2009; Randers et al., 2010; Bradley et al., 2013). More recently, this technology has been used to assess physical performance with relation to the contextual factors around the match, such as playing position, opponent level, first vs second half match performance, substitutions, different phases of the game etc... (Di Salvo et al., 2007; Carling, 2010; Castellano, Blanco-Villaseñor, & Alvarez, 2011; Bradley et al., 2011; Bush et al., 2015; Arjol-Serrano, Lampre, Díez, Castillo, Sanz-López, & Lozano, 2021). While AMISCO Pro and ProZone were the most common video-analysis providers in the early research published, more research has been done using newer video analysis providers such as WyScout and OPTA (Otero-Saborido, et al., 2021).

WyScout is a video analysis company based in Chivari, Italy that uses their video platform to provide analysis of soccer matches at different levels of competition. The reliability of WyScout has been previously examined by Pappalardo et al. (2019) before using WyScout event data in an algorithm for ranking player performances (Pappalardo et al., 2019). The reliability of the system was tested in accordance with previously used optical tracking validation methods (Liu et al., 2017). While camera-based player tracking systems have become common at the higher levels of competition in professional soccer, WyScout and other similar platforms, such as Statsbomb or Whoscored, have been used to gain insights about the technical-tactical indicators of soccer performance in professional soccer (Plakias et al., 2023). Mitrotasios et al. (2019) used video taken from WyScout's platform to determine the most common methods of creating goal-scoring opportunities in different professional European soccer leagues (Mitrotasios et al., 2019). Because of its video dissection capabilities, WyScout has also been used to analyze specific phases of matches. Mitrotasios et al. (2021) used WyScout to analyze the

success rate of corner kicks in the professional Spanish League, finding a very low overall success rate that was dependent on the zone where the kick landed (Mitrotasios et al., 2021). Díez et al. (2021) used WyScout to examine the physical outputs of soccer players in relation to the technical-tactical demands for each position in a professional soccer team. Physical outputs were measured for each player using 18 Hz GPS units and technical-tactical variables were analyzed by WyScout and then further analyzed by the authors of the study. This study analyzed 30 official matches of a Spanish professional team in the second division and broke down both physical and technical-tactical indicators by position for the matches analyzed (Díez et al., 2021). While there has been research relating technical tactical factors to physical outputs (Arjol-Serrano et al., 2021; Brito de Souza et al., 2019; Bush et al., 2015), Díez et al (2021) are the only group to publish these metrics, to this author's knowledge, that uses WyScout specifically for the analysis of technical-tactical variables.

Summary

In summary, there are many different facets of performance that can be examined at the NCAA D-I level of soccer that remain rich in information but, more than likely, untapped sources of information. Several new technologies that are used in higher levels of elite soccer can provide further information about the demands of NCAA D-I male soccer and help practitioners and coaches prepare the athletes in this population in a more effective manner. GPS measures are commonly used in elite levels of sport in order to understand the physical demand of matches on players. Micro electromechanical systems allow for deeper insights into the physical load by measuring outputs via accelerometers, gyroscopes, and magnetometers, giving a clearer picture of the physical demands of sport. Other tracking technologies in elite soccer have given insight into other aspects related to the match demands of soccer players such as technical-tactical

variables, effects of formation, quality of opposition and other important factors that influence performance. Additionally, there are a number of studies that have been carried out in recent years that examine the physical capabilities of soccer players that are related to performance. Tests of explosive power, maximum strength, aerobic endurance, and sprint speed have been carried out in these populations to varying degrees. The main theme in the literature for NCAA male soccer as a whole is the lack of depth in the literature available for this population in any of the facets of performance listed above. The lack of available literature on this population shows a need for better understanding in order to maximize the potential of these athletes who operate within a unique set of constraints as well as unique demands of competition.

**Chapter 3. The Physical Performance of Male Collegiate Soccer Players: A Retrospective
Analysis**

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Abstract

The purpose of this study was to add to the existing data specific to NCAA D-I male soccer players related to both physical match performance and physical capacity examined through a battery of performance tests. Data from 73 eligible male soccer players from a Division-I Southeastern mid-major institution was used for a retrospective analysis. Athletes were subjected to a battery of physical performance tests in order to assess a range of physical capabilities. GPS data from matches was used to assess match physical performance. Linear mixed models were used to examine the relationship between GPS match physical outputs and field tests and lab tests administered in the testing battery. Generalized Least Squares models were used to assess the positional differences for the GPS match outputs. Statistically significant relationships were found between GPS match outputs and field tests. No statistically significant relationships were found between GPS match outputs and lab tests. Statistically significant differences were found between position groups, with the FWD group being different than the MID or DEF group. Statistical significance was set a $p \leq .05$. The results uncovered suggest that field tests could be better predictors of match physical performance than lab tests. Additionally, the positional differences found in this study differ from most of the literature examining positional differences at different levels. This deviation suggests that the match demands for FWD differ statistically significantly than FWD at other levels of competition.

Keywords: GPS, NCAA soccer, match demands, physical testing, positional differences

Introduction

Soccer is one of the most popular and most widely played sports in the world, with approximate 3.5 billion viewers annually and over 270 million participants globally (FIFA, 2007). Popularity in the United States has also grown in both the men's and women's game with franchise purchases and sales hitting new records of investment (Mendola, 2023; Gutierrez, 2024). The growth in popularity in the United States has brought about the need to understand the ecosystem of elite amateur soccer that feeds into the professional ranks. One of the branches of soccer increasing in popularity in the United States is at the NCAA D-I level with 202 member institutions and over 5,900 participating athletes in the 2020-2021 season (NCAA, 2021). With increased levels of participation at this level of soccer – from a sports science perspective – it is important to understand the physical demands of soccer players that could potentially reach the professional ranks.

The analysis of the physical outputs of soccer players is rooted in video analysis of matches individually coded by dedicated researchers (Reilly, 1976). Technological advances have made the evaluation of physical workloads vastly simpler and more readily available for analysis with the emergence of GPS tracking systems (Aughey et al., 2011; Hennessy & Jeffreys, 2018). The increased use of GPS technology in soccer has brought about an enormous amount of data and a subsequent increase in the research surrounding physical match demands of the sport. Soccer physical match performance has been widely examined at different levels of competition from elite professional levels to amateur and recreational levels (Abbott et al., 2018; Bangsbo et al., 2006; Curtis et al., 2018; Mallo et al., 2015; Scott et al., 2014). Despite its increased popularity in the last few years, NCAA D-I soccer has not seen a lot of representation in the research. Recently, more research has come about that examines the physical demands placed on

this specific population of athletes (Curtis et al., 2018; Curtis et al., 2020; Aziz et al., 2023; Anderson et al., 2021). Curtis et al. (2018) focused on examining the match outputs of this population across an entire competitive season for NCAA D-I soccer players by using GPS. Basic Descriptive statistics and positional differences were given by the authors, who found trends in this population that are in agreement with research in more elite populations, mainly that central midfielders (CM), covered the most ground during matches. Anderson et al. (2021) examined two seasons worth of internal and external load data of a NCAA D-I soccer team, comparing both absolute and relative outputs for matches and training throughout the competitive season, finding marked differences between training load and competition load. Ryan et al. (2020) examined the positional demands of training load, speed, heart rate, and recovery in a cohort of 21 NCAA D-I male collegiate soccer players over the course of a 14-week season, observing statistically significant differences between positions for measures of internal and external load throughout the season.

In addition to physical match demands on the field, the physical demand of soccer players is often examined using a variety of tests of different physical capacities (i.e. cardiovascular endurance, strength, power, etc.). One of the more popular tests of physical ability is the countermovement jump (CMJ). The CMJ has been used in varying populations using different modalities such as jump mats, LED light systems, and force platforms (Rago et al. 2018; Haugen, Tønnessen, & Seiler, 2012). Because jump performance and jump-derived variables are associated with various characteristics of athleticism, jump tests are often used with soccer player to assess potential sport-specific physical capabilities. Another test that has been widely used in the population is the Isometric Mid-Thigh Pull. Abott & Clifford (2022) used the IMTP Peak Force (IPF) as an indicator of strength in professional soccer players in order to

assess the effect of strength on recovery and its association to match physical performance. Testing batteries for soccer players have also included a field-testing component to measure aerobic and anaerobic outputs. Chamari et al. (2004) performed field and lab tests in elite adolescent soccer players, including 20- and 30-meter sprint tests as well as aerobic performance field tests. Although there is a large quantity of research examining physical performance in soccer, there is scarce research in the specific population of NCAA D-I male soccer players.

In populations of NCAA D-I male soccer players specifically, there has been some research using both dynamic and isometric performance tests. Silvestre et al. (2006) examined the relationship between body composition and performance in physical tests in a population of NCAA D-I male soccer players, finding that players with higher lean mass and less fat mass performed better in these tests. Similarly, Ishida et al. (2021) examined the relationships between body composition and physical testing performance, adding more depth to the previous research by studying short sprints, SJ and CMJ jumps on force platforms, and IMTP on force platforms. Similar relationships were found between the isometric strength variables, body composition, and sprinting performance were all found to varying degrees. More specific to jump testing Sole et al. (2018) used a large cohort of male and female NCAA D-I soccer players to assess the RSI qualities of these two specific populations and provide normative data. Similarly, Harry et al. (2017) looked at the differences in Ground Reaction forces (GRFs) between two different jump tasks measured via force platforms. Ishida et al. (2020) examined the changes in physical performance tests (CMJ, IMTP, sprint) in relation to a partial block periodization strength training program. The current state of the research is growing, but given the amount of research performed in soccer at other levels of competition, there is a need for more in-depth research in larger populations of NCAA D-I male soccer players. Thus, the purposes of the study were: to

provide additional normative data on GPS match outputs for male collegiate soccer players at the NCAA D-I level, to provide additional normative data on physical performance testing outputs of male collegiate soccer players at the NCAA D-I level, and to examine the relationships between match GPS outputs and physical performance testing outputs.

Methods

Experimental Approach to the Problem

The design of this study was a retrospective analysis using previously collected data collected for athlete monitoring purposes. The study was designed in order to examine the match demand of NCAA D-I men's collegiate soccer. Data used in the study were collected as part of a comprehensive athlete monitoring program for the soccer team. The data included GPS data matches and results from a number of physical performance tests including, countermovement and static jump testing on force platforms, and isometric mid-thigh pull testing on force platforms. Data were collected before the start of the season as part of a battery of pre-season physical performance testing. Athletes who did not consent for their data to be included in the ETSU Sport Science Research Repository were excluded from the analysis ($n = 2$).

Subjects

Data from an eligible 73 NCAA D-I male collegiate soccer players (height = 178.0 ± 5.9 cm; body mass = 75.4 ± 13.3 kg; age = 20.79 ± 1.68 years) was retrieved from the ETSU Sport Science Research Repository. Retrospective analysis of the performance data was approved by the East Tennessee State Institutional Review Board (ETSU IRB # c0623.17sw).

Procedures

GPS Training Load Data. GPS training load data from matches and training sessions was retrieved from the University Sport Science Research Repository. Data was collected over

the span of five competitive Fall seasons for the sample of NCAA D-I soccer players (2017-2022). The Fall season was chosen for analysis because this is the designated “in-season” period for men’s soccer by the NCAA. Data was collected by a qualified sports scientist that was present at every game and training session. All competitive non-conference matches and conferences championships took place during the Fall seasons. The 2020 Fall season was excluded due to the restrictions placed around competition and practice due to the global COVID-19 pandemic. A total of 97 matches were played across five seasons, including exhibition games, non-conference games, conference games, and conference tournament games. 290 training sessions were collected across the same time span. A training session was designated as practice that was led by the soccer coaching staff, included a majority of the players in it, and a session in which the nature of the exercise was not purely conditioning. Each player was assigned a playing positions out of three major categories based on the position designated in the original data. If no assigned position was available in the data, then the position group that was assigned on the ETSU athletics website was assigned to that athlete.

Testing Procedures. Testing was conducted at the beginning of every season. Lab protocols and field-testing protocols were performed on the same day. Prior to testing, Players performed a standardized warm up before the start of testing that included 25 jumping jacks, 1 x 5 repetitions @ 20 kg and 3 x 5 repetitions @ 60 kg of a mid-thigh pull (MTP).

Jump Testing Data. Lab testing data was retrieved from the Sport Science Research Repository. Lab data included data collected from two different types of jump tests – Static Jumps (SJ) and Countermovement Jumps (CMJ). All jumps were performed on dual force platforms sampling at 1000 Hz (91.0 cm × 91.0 cm; Rice Lake Weighing Systems, Rice Lake, WI, USA). The tests were done in loaded and unloaded conditions. The unloaded condition

consisted of the athletes jumping with a PVC pipe on their back with the loaded condition consisting of athletes jumping with a 20 kg barbell on their back. Each athlete who was included performed at least one instance of every jump condition (SJ-0, SJ-20, CMJ-0, CMJ-20). SJ included 1 warm up repetition at 50% and 75% self-perceived effort for the SJ-0 and 1 warm up repetition at 75% self-perceived effort for the SJ-20 condition. CMJ warm-up included on repetition of CMJ-0 at 75% self-perceived effort. During SJ testing, the athletes were instructed to stand still on the force platforms and maintain a squat position with the load on their back at a knee angle of 90° measured via goniometer. Athletes jumped from the bottom position on the command of “3-2-1, Jump!” given by the tester. A minimum of two trials were performed for each condition, with additional trials taking place if the difference in jump height exceeded 2.0 cm. The average values of the two best jumps, determined by jump height, were taken and used in the final analysis. A total of 535 observations were used in the final analysis, consisting 46 different athletes, 133 unweighted static jumps (SJ-0), 131 weighted static jumps (SJ-20), 138 unweighted countermovement jumps (CMJ-0) and 133 weighted countermovement jumps (CMJ-20) across the seasons included. The average of the top two jumps for each condition was used in the final analysis. The variables derived from the jumps that were used in the analysis included jump height (cm), peak power (W), and net impulse (NI). The reliability of these metrics at specific epochs of 200 msec have been examined and validated in previous research (Merrigan et al., 2020; Haff et al., 2015). Raw data was analyzed using a custom Labview software (National instruments, Austin, Tx) using a 4th order Butterworth low pass filter. JH, PP, and NI were all automatically calculated by the software. The jump offset and zero were all determined by an assigned sports scientist.

Isometric Mid-Thigh Pull Data. Isometric Mid-Thigh Pull (IMTP) testing was performed after Jump Testing on dual force plates (91.0 cm × 91.0 cm; Rice Lake Weighing Systems, Rice Lake, WI, USA; 1000Hz sampling rate). Athletes were strapped into a custom-built rack that included a fixed steel bar with an adjustable height. Each athlete was instructed to grab onto the bar and flex their ankle, knee, and hip joints until a knee angle measured via goniometer of $125 \pm 5^\circ$ was achieved. The IMTP warm up consisted of two submaximal trials at 50% and 75% of perceived maximal effort. Once the athletes were strapped in, they were instructed to pull upward as fast and as hard as possible on the command of “3-2-1, Pull!” A minimum of two trials were used for assessment, with additional trials being performed if there was a difference greater than 200 N between trials, or if there was a countermovement greater than 200 N at the start of the test. The average values of the two best trials, determined by isometric peak force, were taken and used in the final analysis. A total of 170 observations were used in the analysis from 53 different athletes. The average of the top two trials were used in the final analysis. The two best pulls were determined by sorting the pulls by peak force. PF, RFD, and IMP were all derived from the Force-Time Curve. Raw data was analyzed using a custom Labview software (National instruments, Austin, Tx) using a 4th order Butterworth low pass filter. PF was determined by the highest point in the Force-Time curve. RFD was calculated using a 0-200 millisecond window. Impulse was calculated using a 0-200 millisecond window, using the summation of area under the curve. The start of the pull was manually calculated by an assigned sports scientist.

20 m Sprint Test. A 20 m sprint test was used to evaluate the athletes' anaerobic capabilities. Times were calculated using timing gates (Witty, Microgate, Bolzano, Italy) at 0-10- and 20m intervals. Distances were calculated using a tape measure and were performed by a

certified strength and conditioning coach. Athletes performed a maximum of two trials from a static start, with the start line 30cm behind the first timing gate (Bellon et al., 2019). All trials were performed on a soccer field in soccer shoes. ICCs were calculated for the data utilized in the study (ICC = 0.95). The average time of the two trials was computed and used in the analysis.

Yo-Yo Intermittent Recovery Test Level I. A Yo-Yo Intermittent Recovery Test- Level 1 (YYIRT-1) was performed to assess the athletes' soccer-related fitness performance. The YYIRT-1 consists of 20m shuttle runs that increase speed incrementally, along with a 10m recovery run. The starting speed of the test is 10 km•h⁻¹. Beeps at different time intervals dictate the average running velocity. Players were given one warning if they failed to reach the start line before the second beep in the repetition. The total distance covered during the YYIRT-1 was used in the analysis. Distances were measured with a tape measure by a certified strength & conditioning coach. All trials were performed on a soccer field in soccer shoes. ICC was not calculated for this particular set of data but previous examinations of the YYIRT-L1 have shown it to be a reliable test with reported ICCs between 0.87–0.95 for youth players U15, U17, and U19 (Deprez et al. 2015) and ICCs ranging from 78-90% for different populations, with the majority of the ICCs higher than 90% specifically for the YYIRT-L1 (Grgic et al. 2019).

Statistical Analyses

The statistical software R (version 4.2.1) and the packages nlme, car, tidyverse, emmeans, performance, and AICcmodavg were used to perform the different analyses on the relevant data. The positional differences in GPS outputs were determined using an Analysis of Variance (ANOVA). ANOVAs were fit using a Generalized Least Squares model instead of a General Linear model for the relevant GPS variables, due to the combination of violation of

assumptions in a linear model fit as well as missing data points. GPS variables were taken from match data and were scaled by dividing the sum of all of game data by the number of game minutes played. Significance was set a $p < .05$. To describe the magnitude of the differences, Cohen's d effect sizes (ES) with 95% confidence intervals (CI) were calculated from the resultant t ratios. Descriptions of effect size magnitudes follow Hopkins (Hopkins, 2002): $<0.2 =$ trivial, $0.2 - 0.6 =$ small, and $0.6 - 1.2 =$ moderate.

The relationships between GPS variables and field-testing variables were examined using various Linear Mixed Models (LMM) built with the `lme()` function from the `nlme` package. Linear mixed modeling was chosen because LMM are able to cope with unbalanced designs and missing data (Cnaan et al., 1997) — due to the nature of the data and multiple missing data points in the given repository data sets, this was deemed to be an appropriate approach. A random effect was set either for the individual athlete, for their position group, or the coach during that season, or for a combination of these depending on how the fit of the model was affected. The random intercept that improved model fit was used in the final model. GPS variables were set as dependent variables with the interaction between the field tests set as independent variables. For the IMA variables, the only model that was used for post-hoc test was the High-Intensity Decelerations model. High-Intensity Acceleration model was not included in the post-hoc analysis because there was no difference between positions when examining the marginal means. The positional differences between groups that achieved statistical significance were only between DEF and MID, with the mean difference showing the DEF group showing higher levels of high-intensity IMAs per minute played. Generalized Least Squares models were fitted when violations of homoscedasticity or autocorrelation were found in the General Linear Models.

Results

Descriptive statistics for all relevant GPS variables and performance testing are provided in the Tables 1-5:

Table 1

GPS Data Mean \pm SD (Data from 2017-2022 matches)

| Total Distance (m) | HSR Distance (m) | Sprint Distance (m) | High-Int IMA Accelerations | High-Int IMA Decelerations |
|--|---------------------|------------------------|-------------------------------|-------------------------------|
| 7445.5 \pm 2805.8 | 291.9 \pm 126.4 | 65.7 \pm 34.7 | 7.0 \pm 3.7 | 6.2 \pm 2.7 |
| <i>n</i> games = 97 Means are taken from LMMs built in order to account for missing values and imbalanced sample sizes. | | | | |

Table 2*Positional GPS Data Mean \pm SD (Data from 2017-2022 matches)*

| Position Group | Total Distance (m) | HSR Distance (m) | Sprint Distance (m) | High-Int IMA Accelerations | High-Int IMA Decelerations |
|---------------------|------------------------|----------------------|---------------------|----------------------------|----------------------------|
| DEF (n = 23) | 7405.9 \pm 4256.4 | 266.4 \pm 196.4 | 65.4 \pm 70.1 | 6.5 \pm 4.9 | 6.6 \pm 5.6 |
| MID (n = 28) | 7387.5 \pm 4249.4 | 279.6 \pm 204.6 | 52.1 \pm 61.2 | 5.7 \pm 4.7 | 6.9 \pm 5.7 |
| FWD (n = 12) | 8956.1 \pm 3644 | 432.7 \pm 208 | 112.1 \pm 75.6 | 7.0 \pm 4.5 | 9.2 \pm 6.4 |
| <i>n Games = 97</i> | | | | | |

Table 3*Jump Testing Data Mean ± SD (Data from 2017-2022 Pre-season)*

| Position Group | Jump Type | Bar Weight (kg) | Jump Height (cm) | Net Impulse (N•s) | Peak Power (W) |
|-----------------|-----------------|-----------------|------------------|-------------------|----------------|
| DEF (n = 60) | CMJ (n = 15) | 0 | 35.8 ± 6.5 | 216.9 ± 25.7 | 4443.7 ± 619.9 |
| | CMJ (n = 15) | 20 | 27.0 ± 5.6 | 238.8 ± 38.1 | 4458.3 ± 816.1 |
| | SJ (n = 15) | 0 | 32.3 ± 5.9 | 210.1 ± 25.1 | 4423.7 ± 768.7 |
| | SJ (n = 15) | 20 | 25.0 ± 4.9 | 233.2 ± 27.6 | 4410.7 ± 714.2 |
| | CMJ (n = 21) | 0 | 35.6 ± 4.9 | 202.6 ± 21.9 | 4102.4 ± 524.8 |
| | CMJ (n = 21) | 20 | 25.8 ± 4.0 | 213.0 ± 21.0 | 3902.5 ± 486.4 |
| MID (n = 84) | SJ (n = 21) | 0 | 31.8 ± 4.6 | 186.4 ± 22.7 | 3847.4 ± 576.7 |
| | SJ (n = 21) | 20 | 24.0 ± 4.0 | 207.8 ± 24.5 | 3838.4 ± 558.7 |
| | CMJ (n = 10) | 0 | 34.3 ± 3.4 | 187.2 ± 34.4 | 3856.9 ± 669.9 |

| | | | | | |
|----------|----------|----|------------|--------------|----------------|
| FWD | CMJ | 20 | 25.5 ± 2.4 | 201.0 ± 33.4 | 3748.9 ± 627.9 |
| (n = 40) | (n = 10) | | | | |
| | SJ | 0 | 31.0 ± 3.5 | 178.6 ± 37.6 | 3805.8 ± 810.5 |
| | (n = 10) | | | | |
| | SJ | 20 | 23.9 ± 2.5 | 199.0 ± 38.9 | 3764.7 ± 773.3 |
| | (n = 10) | | | | |

Jump Types:

CMJ: Countermovement Jump

SJ: Static Jump

Player Positions:

DEF: Defender

MID: Midfielder

FWD: Forward

Table 4

Isometric Mid-Thigh Pull Testing Data Mean ± SD (Data from 2017-2022)

| Position Group | Peak Force (n) | RFD @ 200 msec (n/s) | Impulse @ 200 msec (n•s) |
|----------------|----------------|----------------------|--------------------------|
| DEF | 3451.5 ± 639.4 | 5251.9 ± 2798.3 | 343.2 ± 90.1 |
| (n = 29) | | | |
| MID | 3524.8 ± 522.2 | 6046.4 ± 2773.0 | 331.7 ± 88.4 |
| (n = 36) | | | |
| FWD | 3698.5 ± 519.5 | 6300.0 ± 2561.5 | 335.0 ± 106.2 |
| (n = 29) | | | |

Player Positions:

DEF: Defender

MID: Midfielder

FWD: Forward

Table 5

Field-testing Data Mean ± SD (Data from 2017-2022 Pre-season)

| Position Group | YYIRT1 Distance (m) | 20m Sprint Time (s) |
|-----------------|---------------------|---------------------|
| DEF (n = 30) | 1953.3 ± 465.1 | 3.024 ± 0.089 |
| MID (n = 40) | 2042.0 ± 379.9 | 3.032 ± 0.112 |
| FWD (n = 20) | 2132.0 ± 350.7 | 2.981 ± 0.089 |

Player Positions:
DEF: Defender
MID: Midfielder
FWD: Forward

Field Tests & GPS Variables

The results for the LMM created for the field tests and GPS match outputs are found in the Table 5. Match TD was statistically related to both YYIRT-L1 distance and 20m sprint time; Match SPR was statistically significant related to 20m sprint time; Match IMA-D were statistically significantly related to 20m sprint time; Match IMA-A were statistically significantly related to the interaction between YYIRT-L1 distance and 20m sprint time. No other relationships between match GPS variables and field tests achieved statistical significance.

Table 6*Linear Mixed Models for field test and match-related GPS metrics*

| Dependent Variable | Random Effects | Fixed Effects | Marginal R ² | 95% CI | P-value |
|--------------------|---------------------------------|--|-------------------------|---------------------|----------------|
| Match TD | Random Intercept for Athlete | YYIRT-L1 Distance | 0.021 | [0.006, 0.020] | $p = 0.002^*$ |
| | | 20m Sprint Time | | [7.188, 75.878] | $p = 0.022^*$ |
| | | Interaction Effect of YYIRT * 20m Sprint | | [-0.101, 0.055] | $p = 0.530$ |
| | | YYIRT-L1 Distance | | [-0.0003, 3.623] | $p = 0.490$ |
| Match HSR | Random Intercept for Athlete | 20m Sprint Time | 0.007 | [-4.761, 0.888] | $p = 0.161$ |
| | | Interaction Effect of YYIRT * 20m Sprint | | [-0.003, 0.010] | $p = 0.268$ |
| | | YYIRT-L1 Distance | | [4.179e-05, 0.0004] | $p = 0.0179^*$ |
| | | 20m Sprint Time | | [-2.934, -0.330] | $p = 0.0182^*$ |
| Match SPR | Random Intercept for Athlete | Interaction Effect of YYIRT * 20m Sprint | 0.223 | [-9.345e-04, 0.002] | $p = 0.470$ |

| | | | | | |
|-------------|-------------------------------|--|----------|--------------|--------|
| Match IMA-D | Random | YYIRT-L1 Distance | | [-9.769e-06, | $p =$ |
| | | | | 1.583e-05] | 0.615 |
| | Athlete | Intercept for 20m Sprint Time | 0.000 | [0.020, | $p =$ |
| | | | | 0.123] | 0.011* |
| Match IMA-A | Random | Interaction Effect of YYIRT * 20m Sprint | | [-5.537e-05, | $p =$ |
| | | | | 1.867e-04] | 0.260 |
| | Athlete | YYIRT-L1 Distance | | [-8.878e-06, | $p =$ |
| | | | | 1.928e-05] | 0.437 |
| Athlete | Intercept for 20m Sprint Time | 0.001 | [-0.087, | $p =$ | |
| | | | 0.0487] | 0.548 | |
| | | Interaction Effect of YYIRT * 20m Sprint | | [-3.533e-04, | $p =$ |
| | | | | -9.272e-05] | 0.003* |

Note: Alpha level was set a $p \leq 0.05$

† Indicates there may still be an issue with the modeling

Lab Tests & GPS Variables

The results for the LMMs created to assess the relationships between Lab Tests and GPS outputs are in Table 6. The relationships examined between lab test outputs and match performance were related.

Table 7*Relationship between Lab Testing and GPS Data*

| Dependent Variable | Random Effects | Fixed Effects | Marginal R ² | Estimate 95% CI | P-value |
|-----------------------|--|---------------|-------------------------|-----------------------|-------------|
| Match HSR | Random Effect of Athlete & Random Effect of Position Group | PP CMJ-0 | 0.032 | [-0.002, 0.001] | $p = 0.988$ |
| | | PP CMJ-20 | | [-0.001, 0.002] | $p = 0.572$ |
| | | PP SJ-0 | | [-0.001,0.002] | $p = 0.447$ |
| | | PP SJ -0 | | [-0.002,0.001] | $p = 0.373$ |
| | | PF | | [-0.0001, 0.126e-05] | $p = 0.077$ |
| Match IMA-A | Random Effect of Athlete & Random Effect of Coach | PF-Allo | 1.000 † | [-0.0002, 2.06e-03] | $p = 0.067$ |
| | | PF | | [-4.53e-05, 4.67e-05] | $p = 0.955$ |
| Match IMA-D | Random Effect of Athlete & Random Effect of Coach | PF-Allo | 0.001 | [-9.13e-04, 7.55e-04] | $p = 0.724$ |
| | | PF | | | |
| Match Sprint Distance | Random Effect of Athlete & Random Effect of Coach | JH CMJ-0 | 0.007 | [-0.014, 0.025] | $p = 0.576$ |

| | | | |
|-----------|---------|-------------------|----------------|
| NI CMJ-0 | 0.013 | [-0.001, 0.003] | $p =$ 0.409 |
| PP CMJ-0 | 0.000 † | [-0.0002, 0.0002] | $p =$ 0.992 |
| JH CMJ-20 | 0.001 | [-0.023, 0.029] | $p =$ 0.814 |
| NI CMJ-20 | 0.005 | [-0.006, 0.004] | $p =$ 0.620 |
| PP CMJ-20 | 0.000 † | [-0.0002, 0.0002] | $p =$ 0.996 |
| JH SJ-0 | 0.002 | [-0.021, 0.028] | $p =$ 0.757 |
| NI SJ-0 | 0.000 † | [-0.005, 0.005] | $p =$ 0.902 |
| PP SJ-0 | 0.015 | [-0.0001, 0.0002] | $p =$ 0.490 |
| JH SJ-20 | 0.003 | [-0.023, 0.032] | $p =$ 0.733 |
| NI SJ-20 | 0.002 | [-0.005, 0.004] | $p =$ 0.771 |
| PP SJ-20 | 0.001 | [-0.0002, 0.0002] | $p =$ 0.852 |

Note: Alpha level was set a $p \leq 0.05$

PP: Jump Peak Power
 JH: Jump Height
 NI: Jump Net Impulse
 SJ: Static Jump
 CMJ: Countermovement Jump
 PF: Peak Force
 PF-Allo: Peak Force, allometrically scaled ($PF/BM^{0.67}$)

† Indicates there may still be an issue with the modeling

The results above show that none of the relationships examined between lab test outputs and match performance were related.

Positional Differences

The results for the GLS models used to assess positional differences in match outputs are found below:

Table 8

Game-related GPS metrics differences between playing positions

| Dependent Variable | Contrast | P-value | Cohen's d [95% CI] |
|--------------------|-----------|-----------|-------------------------|
| Match TD | DEF - FWD | 0.022* | -0.789 [-1.382, -0.197] |
| | DEF - MID | 0.920 | -0.093 [-0.567, 0.382] |
| | FWD - MID | 0.042* | 0.697 [0.124, 1.271] |
| Match HSR | DEF - FWD | < 0.0001* | -1.591 [-2.218, -0.965] |
| | DEF - MID | 0.616 | -0.224 [-0.699, 0.251] |
| | FWD - MID | < 0.0001* | 1.367 [0.769, 1.966] |
| Match SPR | DEF - FWD | 0.0001* | -1.255 [-1.859, -0.652] |
| | DEF - MID | 0.4681 | 0.281 [-0.194, 0.756] |
| | FWD - MID | < 0.0001* | 1.536 [-0.951, 2.122] |

| | | | |
|-------------|-----------|--------|-----------------------|
| | DEF - FWD | 0.215 | 0.072 [-0.014, 0.159] |
| Match IMA-D | DEF - MID | 0.043* | 0.084 [0.014, 0.153] |
| | FWD - MID | 0.960 | 0.011 [-0.073, 0.096] |

Note: Alpha level was set a $p \leq 0.05$

DEF: Defender

MID: Midfielder

FWD: Forward

The results above suggest that the only statistically significant differences between position DEF and FWD players were in Match TD and Match HSR. The comparisons between MID players and FWD & DEF players yielded several statistically significant differences for match GPS variables, specifically, Match TD (MID vs FWD), Match HSR (MID vs FWD), Match SPR (MID vs FWD), and Match IMA-D (MID vs DEF). Positional differences were examined using pairwise contrasts using the Tukey method. Differences in Total Distance covered during a match were found to be statistically significant between DEF and FWD ($p = .0221^*$) and between FWD and MID ($p = .0416^*$). The direction of the mean difference suggests that FWD covered more total distance than both DEF and MID. Differences in High-Speed Running Distance were found to have a statistically significant differences between DEF and FWD as well as between FWD and MID ($p < .0001^*$ for both), with the mean difference suggesting that FWD covered more HSR per game minute than DEF and FWD. The differences between groups for sprint distance followed a similar pattern with differences between DEF and FWD being statistically significant ($p = .0001^*$) as well as FWD and MID ($p < .0001^*$).

Discussion

The purpose of this study was to examine the physical demands and physical performance of male NCAA D-I soccer. A secondary purpose of this study was to highlight positional differences in both match outputs and physical performance tests. One of the main findings of this study was the relationship between the GPS match performance variables and the field tests. The LMMs used to assess these relationships showed statistically significant relationships between TD and both field tests, SPR and both field tests, IMA-D and 20m sprint time, and IMA-A and the interaction between both of the tests. The relationship with TD and field-testing variables can be explained by previous research. Bangsbo et al. (2008) highlight the importance of both the aerobic and anaerobic system in match physical performance in soccer players, so it stands to reason that the results of these tests are related to match physical outputs. Likewise, the relationship between the field tests and SPR match outputs follow the same logic. Because repeated anaerobic outputs require both efficient aerobic and anaerobic processes, and changes in the ratio of SPR per minute played could be explained by the performance in these tests.

The most surprising finding of this study in regards to positional differences was that there were statistically significant differences in match physical performance outputs between FWD and the other two position groups when examining TD, HSR, and SPR. These findings suggest that forwards covered more TD, HSR, and SPR compared to defenders and midfielders. The positional differences in this study go against some of the literature based in professional soccer, where the MID position is the one that typically covers more ground during match and training activities (Owen et al., 2016; Owen et al., 2017). This result is also in conflict with the results in previous literature in NCAA populations (Curtis et al., 2018; Aziz et al., 2023) It is

important to note that there are multiple factors potentially influencing these results – the main factor being the rotation of the players during the match. The competition format NCAA D-I allows for re-entry of substitutions during the match, that is, players can rest for a period of time and come back on in the same half. This allows match outputs to stay high relative to minutes played, particularly with players who play less minutes. It is also important to note that the nature of the study does not allow for further classification of player positions (e.g. outside defender vs central defender, wide midfielder vs central midfielder, etc.) which can also be affected by contextual factors associated with the match, such as the given formation, coaching staff, coaching tactics, personnel, and others (Curtis et al., 2020; Diez et al., 2021; Romero et al., 2024). The preliminary LMMs accounted for the random effect of different coaches throughout the given period of analysis, but model changes proved to not be statistically significant so the effect of coach was removed in order to simplify the models. The limitations of the data are mostly in the nature of the collection. Because the data was extracted from a data repository, there is no way to control for different collection methods, especially over a period of 5 years. Additionally, the changes in coaching staff over that time span could alter some of the player classifications, as different coaches typically change team tactics according to their preference and thus affect the physical outputs of some players (playing time, position changes, etc.). Additionally, players were not divided into central and wide players due to a lack of knowledge on player position assignment beyond what was provided. This lack of classification could be the reason why some of the results presented differ from the majority of the previous research presented on these populations.

Practical Applications

The practitioner can examine the results of this study and ascertain there is a difference in the demand of NCAA D-I male soccer players compared to the populations which there were numerous studies on match demands. Positional demand may need to be re-evaluated for this population due to differences between FWD and the other positions available. Additionally, norms have been provided for benchmarking for physical capabilities in a number of different relevant tests. These tests of physical capability encompass the different areas of physical outputs that are required for collegiate soccer (strength, speed, aerobic endurance, etc.). These results can be used for comparison for coaches who work with these populations to varying degrees depending on available resources at a given institution.

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References

1. Abbott, W., Brickley, G., & Smeeton, N. J. (2018). Physical demands of playing position within English Premier League academy soccer. <https://doi.org/10.14198/jhse.2018.132.04>
2. Abbott, W., & Clifford, T. (2022). The influence of muscle strength and aerobic fitness on functional recovery in professional soccer players. *J Sports Med Phys Fitness*, 62(12), 1623-1629. <https://doi.org/10.23736/S0022-4707.21.13401-2>
3. Anderson, T., Adams, W. M., Martin, K. J., & Wideman, L. (2021). Examining internal and external physical workloads between training and competitive matches within collegiate Division I men's soccer. *J Strength Cond Res*, 35(12), 3440-3447. <https://doi.org/10.1519/JSC.0000000000004149>
4. Bangsbo, J., Mohr, M., & Krstrup, P. (2006). Physical and metabolic demands of training and match-play in the elite football player. *J Sports Sci*, 24(7), 665-674. <https://doi.org/10.1080/02640410500482529>
5. Bujnovky, D., Maly, T., Ford, K. R., Sugimoto, D., Kunzmann, E., Hank, M., & Zahalka, F. (2019). Physical fitness characteristics of high-level youth football players: Influence of playing position. *Sports (Basel)*, 7(2). <https://doi.org/10.3390/sports7020046>
6. Chamari, K., Hachana, Y., Ahmed, Y. B., Galy, O., Sghaier, F., Chatard, J. C., Hue, O., & Wisloff, U. (2004). Field and laboratory testing in young elite soccer players. *Br J Sports Med*, 38(2), 191-196. <https://doi.org/10.1136/bjism.2002.004374>
7. Cnaan, A., Laird, N. M., & Slasor, P. (1997). Using the general linear mixed model to analyse unbalanced repeated measures and longitudinal data. *Stat Med*, 16(20), 2349-2380. [https://doi.org/10.1002/\(sici\)1097-0258\(19971030\)16:20<2349::aid-sim667>3.0.co;2-e](https://doi.org/10.1002/(sici)1097-0258(19971030)16:20<2349::aid-sim667>3.0.co;2-e)

8. Curtis, R. M., Huggins, R. A., Benjamin, C. L., Sekiguchi, Y., Adams, W. M., Arent, S. M., Jain, R., Miller, S. J., Walker, A. J., & Casa, D. J. (2020). Contextual factors influencing external and internal training loads in collegiate men's soccer. *J Strength Cond Res*, *34*(2), 374-381. <https://doi.org/10.1519/JSC.0000000000003361>
9. Curtis, R. M., Huggins, R. A., Looney, D. P., West, C. A., Fortunati, A., Fontaine, G. J., & Casa, D. J. (2018). Match demands of National Collegiate Athletic Association Division I men's soccer. *J Strength Cond Res*, *32*(10), 2907-2917. <https://doi.org/10.1519/JSC.0000000000002719>
10. Deprez, D., Fransen, J., Lenoir, M., Philippaerts, R., & Vaeyens, R. (2015). The Yo-Yo intermittent recovery test level 1 is reliable in young high-level soccer players. *Biol Sport*, *32*(1), 65-70. <https://doi.org/10.5604/20831862.1127284>
11. Diez, A., Lozano, D., Arjol-Serrano, J. L., Mainer-Pardos, E., Castillo, D., Torrontegui-Duarte, M., Nobari, H., Jaen-Carrillo, D., & Lampre, M. (2021). Influence of contextual factors on physical demands and technical-tactical actions regarding playing position in professional soccer players. *BMC Sports Sci Med Rehabil*, *13*(1), 157. <https://doi.org/10.1186/s13102-021-00386-x>
12. FIFA. (2007). *FIFA Big Count*. IFA Communications Division, Information Services. Retrieved May 18, 2024 from <https://www.yumpu.com/en/document/view/7282907/fifa-big-count-2006-270-million-people-active-in-football-fifacom>
13. Gutierrez, J. (2024). *Ron Burkle Sells NWSL's San Diego Wave FC At Record-Breaking Price*. Retrieved May 18, 2024 from <https://www.forbes.com/sites/jackiegutierrez/2024/03/14/ron-burkle-sells-san-diego-wave-fc-at-record-breaking-price/?sh=52912e6c505d>

14. Grgic, J., Oppici, L., Mikulic, P., Bangsbo, J., Krstrup, P., & Pedisic, Z. (2019). Test–Retest Reliability of the Yo-Yo Test: A Systematic Review. *Sports Medicine*, *49*(10), 1547-1557. <https://doi.org/10.1007/s40279-019-01143-4>
15. Harry, J. R., Barker, L. A., Mercer, J. A., & Dufek, J. S. (2017). Vertical and horizontal impact force comparison during jump landings with and without rotation in NCAA Division I male soccer players. *J Strength Cond Res*, *31*(7), 1780-1786. <https://doi.org/10.1519/JSC.0000000000001650>
16. Hopkins, W. G. (2002). *A New View of Statistics*. Retrieved Accessed May 13 from <http://www.sportsci.org/resource/stats/effectmag.html>
17. Krstrup, P., Mohr, M., Ellingsgaard, H., & Bangsbo, J. (2005). Physical demands during an elite female soccer game: importance of training status. *Med Sci Sports Exerc*, *37*(7), 1242-1248. <https://doi.org/10.1249/01.mss.0000170062.73981.94>
18. Lockie, R. G., Moreno, M. R., Orjalo, A. J., Stage, A. A., Liu, T. M., Birmingham-Babauta, S. A., Hurley, J. M., Torne, I. A., Beiley, M. D., Risso, F. G., Davis, D. L., Lazar, A., Stokes, J. J., & Giuliano, D. V. (2019). Repeated-Sprint Ability in Division I collegiate male soccer players: Positional differences and relationships with performance tests. *J Strength Cond Res*, *33*(5), 1362-1370. <https://doi.org/10.1519/JSC.0000000000001948>
19. Mallo, J., Mena, E., Nevado, F., & Paredes, V. (2015). Physical demands of top-class soccer friendly matches in relation to a playing position using Global Positioning System technology. *J Hum Kinet*, *47*, 179-188. <https://doi.org/10.1515/hukin-2015-0073>
20. Mendola, N. (2023). *San Diego awarded MLS franchise after reported \$500 million fee*. Retrieved May 18, 2024 from <https://www.nbcsports.com/soccer/news/san-diego-awarded-mls-franchise-after-reported-500-million-fee>

21. NCAA. (2021). *NCAA Sports Sponsorship and Participation Rates Report*. Retrieved May 18, 2024 from https://ncaaorg.s3.amazonaws.com/research/sportpart/2021RES_SportsSponsorshipParticipationRatesReport.pdf
22. Owen, A. L., Dunlop, G., Rouissi, M., Haddad, M., Mendes, B., & Chamari, K. (2016). Analysis of positional training loads (ratings of perceived exertion) during various-sided games in European professional soccer players. *International Journal of Sports Science & Coaching*, 11(3), 374-381. <https://doi.org/10.1177/1747954116644064>
23. Owen, A. L., Lago-Peñas, C., Gómez, M.-Á., Mendes, B., & Dellal, A. (2017). Analysis of a training mesocycle and positional quantification in elite European soccer players. *International Journal of Sports Science & Coaching*, 12(5), 665-676. <https://doi.org/10.1177/1747954117727851>
24. R.L., R. R. R. (1991). *Essentials of behavioral research: Methods and data analysis*. McGraw Hill.
25. Romero-Rodríguez, R. C., Pérez-Chao, E.A., Ribas, C., Memmert, D., Gómez-Ruano, M.A. (2024). Influence of contextual factors on most demanding scenarios in under-19 professional soccer players. *Biology of Sport*, 41(4), 51-60. <https://doi.org/10.5114/biolsport.2024.136087>
26. Schmitz, B., Pfeifer, C., Kreitz, K., Borowski, M., Faldum, A., & Brand, S.-M. (2018). The Yo-Yo Intermittent Tests: A Systematic Review and Structured Compendium of Test Results [Systematic Review]. *Frontiers in Physiology*, 9. <https://doi.org/10.3389/fphys.2018.00870>

27. Scott, B., Lockie, R., Davies, S., Clark, A., Lynch, D., & Janse de Jonge, X. (2014). The physical demands of professional soccer players during in-season field-based training and match-play. *Journal of Australian Strength and Conditioning*.
28. Silvestre, R., West, C., Maresh, C. M., & Kraemer, W. J. (2006). Body composition and physical performance in men's soccer: a study of a National Collegiate Athletic Association Division I team. *J Strength Cond Res*, 20(1), 177-183. <https://doi.org/10.1519/R-17715.1>
29. Sole, C. J., Suchomel, T. J., & Stone, M. H. (2018). Preliminary scale of reference values for evaluating Reactive Strength Index-Modified in male and female NCAA Division I athletes. *Sports (Basel)*, 6(4). <https://doi.org/10.3390/sports6040133>

**Chapter 4. The Relationship Between Physical Performance and Technical-Tactical
Performance in Male Collegiate Soccer Players**

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Abstract

The purpose of this study was to examine the technical-tactical match demands of NCAA D-I male soccer players as well as examine the relationship of the technical-tactical variables with physical capability and physical match outputs. Data from an eligible 23 NCAA D-I male soccer players playing at a mid-major Southeastern university were used in the retrospective analysis. Technical-tactical data was pulled from WyScout® for analysis. GPS data from matches where WyScout® data was available were also used in the analysis. Physical performance data was collected from pre-testing values. Correlation analysis was performed between technical-tactical variables and all the variables relating to physical capabilities. Match technical-tactical and physical outputs were scaled by player based on the number of total minutes played in a given match. Linear models were fit to the data to examine the relationships between the volume of technical actions and the physical outputs. Statistically significant relationships were found between technical-tactical variables and high-intensity GPS variables. No statistically significant relationships were found between technical-tactical variables and the lab performance testing variables. Positional differences were examined when a statistically significant interaction effect for position was found in the models constructed. Statistical significance was set at $p \leq 0.05$. The results suggest that there are no statistically significant relationships between technical-tactical performance and physical match performance. Additionally, there was no evidence in the results to suggest that performance tests were indicative of match technical-tactical performance.

Keywords: WyScout®, technical-tactical, match demands, physical capabilities

Introduction

The evolution of technology in sports has led to an influx of data related to sport-specific performance (Adam, 2022). The first published video analysis of soccer players was done by Reilly (1976), using video analysis to quantify the physical demands in professional English soccer. Recent developments in video tracking technology have made it possible to quantify the physical demands of elite-level soccer, with companies such as Prozone® being able to track individual physical outputs based on video tracking (Rampinini et al., 2007; DiSalvo & Modonutti, 2009). This and other multi-camera systems have been validated for use in soccer (Di Salvo et al., 2006; Castellano et al., 2014; Redwood-Brown et al., 2012).

Technical-tactical performance variables are the sport-specific measures that are indicative of individual and team performance. These variables have been previously studied in the context of professional soccer at different levels and to different extents. Rampinini et al. (2009) using Italian Serie A professional players, showed that there is a statistically significant relationship between the amount of physical work performed during a match and the final performance of the team over the season, with more successful teams performing less physical work, but having higher technical-tactical outputs. Bush et al. (2015) examined the effect of contextual factors on physical performance markers in the English Premier League over the course of a season. Data from this study showed a much higher variability in the technical-tactical performance markers examined in comparison to the physical performance markers examined. Yi et al. (2020) examined the changes in technical variables in matches of the UEFA Champions League competition, showing differences between knockout stage and group stage matches. A longitudinal analysis of Spanish professional football by González-Rodenas et al. (2024) showed a decreasing trend in the number of offensive team sequences from the 2008

season to the 2021 season, but an increase in team-associated variables such as total passes, passing accuracy, and passing per offensive sequence.

In professional soccer, technical-tactical variables have been analyzed with respect to performance in various contexts. Forcher et al. (2023) conducted a systematic review on the available literature related to physical performance assessed using multi-camera tracking systems. Analysis of technical-tactical and contextual variables in soccer using multi-camera technology dates back to the early 2010s when Bradley et al. (2011) examined a variety of different factors on the physical in-match performance of Premier League soccer. Multi-camera systems have been previously used to examine physical match demands in different contexts, including opponent level, final score, and match location (i.e. home vs away matches) (Castellano et al., 2011; Gonzalez-Rodenas et al., 2019; Fernandez-Navarro et al., 2018). Previous analyses have been conducted in the Spanish professional soccer league with a different camera tracking system (OPTA) investigating similar technical-tactical and match contextual variables (Brito de Souza et al., 2019a; Brito de Souza et al., 2019b). Russell et al. (2013) examined the changes in outputs of technical variables at different stages of the match, finding decrements in technical-tactical performance in the second half and at different 15-minute intervals.

In recent years, analysis of technical variables has expanded in the professional ranks with data providers such as StatsBomb® and WyScout®. WyScout® is a multi-camera tracking system that analyzes soccer data specifically at different levels of competition. This instrument has been validated by previous research (Pappalardo et al., 2019). WyScout® data has been used in previous research in evaluations of the quality technical-tactical actions of soccer players (Sanchez-Lopez, Echezarra, & Castellano, 2023; Izzo et al., 2020). Related specifically to WyScout®, Diez et al. (2021) analyzed the physical and technical-tactical outputs of Spanish

professional soccer players using GPS and the WyScout® camera tracking system software. Normative values for both technical-tactical variables as well as physical outputs were provided in different contexts, such as positional differences, Home/Away matches, Wins/Losses, etc. Gonzalez-Rodenas et al. (2020) used WyScout® to analyze the effects of technical and contextual variables on goal-scoring effectiveness.

The amateur levels of competition. Contextual variables, such as location, opponent quality, end result, half of play, etc. have been analyzed by previous studies in populations of NCAA D-I and NCAA D-III soccer players (Curtis et al., 2018; Curtis et al., 2020; Aziz et al., 2023). Despite the analyses of contextual factors in this specific population, there is limited research on the technical-tactical demands of playing at the level of NCAA D-I male soccer. WyScout® makes NCAA information available, but to the authors' knowledge there is very limited published data on this specific population. Examinations of technical variables have been done in NCAA D-I female populations previously, but the insights provided cannot be extrapolated to male populations (Alexander, 2014; Spalding, 2017). Recent studies have attempted to draw connections between technical-tactical performance variables obtained via WyScout® and cognitive performance (Phillips et al., 2023), although this examination was also performed on a female population of NCAA D-I soccer players.

Although more expansive, there also appears to be insufficient amounts of research in this population with regards to physical capabilities and physical performance. Ishida et al. (2021a) examined the physical capabilities of NCAA D-I male soccer players in relation to a strength training intervention, with a testing battery that included Static Jumps (SJ) Isometric Mid-Thigh Pulls (IMTP) and a 20-meter sprint test. Another examination by Ishida et al. (2021b)

examined the relationships between lean body mass and physical performance in the Countermovement Jump (CMJ), SJ, IMTP, 20-meter sprint, and Yo-Yo Intermittent Recovery Tests.

There is a clear lack of depth in the research evaluating the technical demands for this population and their relationship with the physical outputs in a match. Therefore, the purpose of this study is two-fold: to address the lack of literature on technical-tactical performance in male collegiate soccer players as well as to examine the possible relationships between technical-tactical variables found in the soccer literature and the players' physical capabilities.

Methods

Experimental Approach to the Problem

The design of this study was a retrospective analysis using previously collected data that was collected for athlete monitoring purposes. The study was designed to provide normative data for technical-tactical variables in a population of male collegiate soccer players, as well as examining the relationship between technical-tactical performance and physical outputs.

Subjects

Data from a single competitive season was used for this study, resulting in 30 NCAA D-I soccer players at a mid-major university in the Southeastern United States. ($n = 30$, height = 179.0 ± 5.2 cm; weight = 79.2 ± 6.7 kg; age = 20.7 ± 1.6 years). Players with missing testing data or a total of less than 90 cumulative minutes played across the matches analyzed were excluded from the analysis, resulting in a final sample of 12 players. The data was retrieved from two sources, the Institutional Sport Science Research Repository, and WyScout®. WyScout® is a video analysis service that holds publicly available technical-tactical data on various soccer matches and provides it to its subscribers. Positions were assigned by the head coach based on

the tactical 3-4-3 formation implemented by the coaching staff. Previous research has shown that tactical formation has a statistically significant effect on physical output during soccer matches (Arjol-Serrano et al., 2021; Forcher et al., 2023). Subjects were placed into one of the following positional categories: Center Back (CB), Wide Back (WB), Central Midfielder (CM), Wide Forward (WF), Central Forward (CF). If multiple positions were played during a single match, players were assigned the position where they spent the most match time. Goalkeepers were excluded from the analysis due to the statistically significant differences in match demands compared to field players. A retrospective analysis of the physical performance data and the technical-tactical data was approved by the University Institutional Review Board (Protocol number c0623.17sw).

Procedures

Technical-Tactical Data. WyScout® data is publicly available to its subscribers and stored in their Application Programming Interface (API). Access to the API is provided to subscribers and available for extraction. The data was Event data from 4 conferences matches was available for extraction, so all 4 were used in the analysis. Because the event data provided by WyScout® is extremely expansive, previous literature on technical-tactical analysis in soccer was used to inform the final selection of variables used in the final analysis. The technical-tactical variables chosen for analysis mirror those used in Diez et al (2021). The variables chosen were as follows divided into offensive and defensive indicators:

General Volume: sum of offensive and defensive indicators

Offensive Indicators: Offensive Volume (OV), Total Passes (TP), Total Pass Success (TPS), Total Forward Pass (FP), Total Forward Pass Success (FPS), Total Forward Passes in Attacking Half (AZP), Total Forward Passes in Attacking Half Success (AZPS), Total Shots

(GS), Shot on Target (GST), Dribbles (DR), Turnovers (TO), Total Crosses (CR), Total Cross Success (CRS),

Defensive Indicators: Defensive Volume (DV), Total Interceptions (IN), Interceptions in Opponent Half (OPIN), Total Clearances (CL), Total Aerial Duels (AD), Total Aerial duels won (ADW).

GPS Training Load Data. GPS Training Load data from matches were retrieved from the University Sport Science Research Repository for the 2022 Fall season. The Fall season is characterized by competitive non-conference and conference matches and provides an opportunity for top-performers to compete for the NCAA national championship. The soccer team used for examination participated in a total of 19 matches over that span, with 2 Exhibition matches, 5 Conference matches, and 1 Conference Tournament game. Although GPS data was available for all these matches, only the matches that had available WyScout data were used in the final analysis for a total of 3 conference games and one conference tournament game.

Jump Testing Data. Lab testing data was collected from the ETSU Sport Science Research Repository. Lab data included data collected for Countermovement Jumps (CMJ) at two different weight conditions, 0-kg and 20-kg (CMJ-0, CMJ-20). All jumps were performed on dual force platforms sampling at 1000 Hz (91.0 cm × 91.0 cm; Rice Lake Weighing Systems, Rice Lake, WI, USA). The tests were done in loaded and unloaded conditions. The unloaded condition consisted of the athletes jumping with a PVC pipe on their back with the loaded condition consisting of athletes jumping with a 20 kg barbell on their back. Each athlete who was included performed at least one instance of every jump condition (CMJ-0, CMJ-20). Players performed a standardized warm up before the start of testing that included 25 jumping jacks, 1 x 5 repetitions @ 20 kg and 3 x 5 repetitions @ 60 kg of a mid-thigh pull (MTP). CMJ warm-up

included on repetition of CMJ-0 at 75% self-perceived effort. Athletes were instructed to jump by starting from a standing position and performing a countermovement to approximately 90° of knee bend and then jumping as high as possible. All jumps were performed on the command of “3-2-1, Jump!” given by the tester. A minimum of two trials were performed for each condition, with additional trials taking place if the difference in jump height exceeded 2.0 cm. The average values of the two best jumps, determined by jump height, were taken and used in the final analysis. The variables derived from the jumps that were used in the analysis included jump height (cm), peak power (W), and net impulse (NI). The reliability of these metrics at specific epochs of 200 msec have been examined and validated in previous research (Merrigan et al., 2020; Haff et al., 2015). Raw data was analyzed using a custom Labview software (National Instruments, Austin, Tx) using a 4th order Butterworth low pass filter. JH, PP, and NI were all automatically calculated by the software. The jump offset and zero were all determined by an assigned sports scientist.

Isometric Mid-Thigh Pull. Isometric Mid-Thigh Pull (IMTP) testing was performed after Jump Testing on dual force plates (91.0 cm × 91.0 cm; Rice Lake Weighing Systems, Rice Lake, WI, USA; 1000Hz sampling rate). Athletes were strapped into a custom-built rack that included a fixed steel bar with an adjustable height. Each athlete was instructed to grab onto the bar and flex their ankle, knee, and hip joints until a knee angle measured via goniometer of 125 ± 5° was achieved. The IMTP warm up consisted of two submaximal trials at 50% and 75% of perceived maximal effort. Once the athletes were strapped in, they were instructed to pull upward as fast and as hard as possible on the command of “3-2-1, Pull!” A minimum of two trials were used for assessment, with additional trials being performed if there was a difference greater than 200N between trials, or if there was a countermovement greater than 200N at the start of the test.

The average values of the two best trials, determined by isometric peak force, were taken and used in the final analysis. IMTP variables assessed for the IMTP were Isometric Peak Force (IPF), RFD @ 200 msec (RFD200) and Impulse @ 200 msec (IMP200). Raw data was analyzed using a custom Labview software (National instruments, Austin, Tx) using a 4th order Butterworth low pass filter. PF was determined by the highest point in the Force-Time curve. RFD was calculated using a 0-200 msec window. Impulse was calculated using a 0-200 msec window, using the summation of area under the curve. The start of the pull was manually calculated by an assigned sports scientist.

20 m Sprint Test. A 20 m sprint test was used to evaluate the athletes' anaerobic capabilities. Times were calculated using timing gates (Witty, Microgate, Bolzano, Italy) at 0-10- and 20m intervals. Athletes performed a maximum of two trials from a static start, with the start line 30cm behind the first timing gate so the laser would not be set off by the athlete's knee (Bellon et al., 2019). The height of the first gate was placed about 75cm off the ground in order to avoid being set off by the athlete's knee. The rest of the timing gates were placed approximately 1.0 meter off the ground in order to be close to the height of the athletes' hips. Distances for the test were calculated using a tape measure by a certified strength and conditioning coach. All trials were performed on a soccer field in soccer shoes. ICCs were calculated for the data utilized in the study (ICC = 0.95). The average time of the two trials was computed and used in the analysis.

Yo-Yo Intermittent Recovery Test Level I. A Yo-Yo Intermittent Recovery Test- Level 1 (YYIRT-1) was performed to assess the athletes' soccer-related fitness performance. The YYIRT-1 consists of 20m shuttle runs that increase speed incrementally, along with a 10m recovery run. The starting speed of the test is 10 km•h⁻¹. Beeps at different time intervals dictate the average

running velocity. Players were given one warning if they failed to reach the start line before the second beep in the repetition. The total distance covered during the YYIRT-1 was used in the analysis. Distances for the test were calculated using a tape measure by a certified strength and conditioning coach. All trials were performed on a soccer field in soccer shoes. ICC was not calculated for this particular set of data but previous examinations of the YYIRT-L1 have shown it to be a reliable test with reported ICCs between 0.87–0.95 for youth players U15, U17, and U19 (Deprez et al. 2015) and ICCs ranging from 78-90% for different populations, with the majority of the ICCs higher than 90% specifically for the YYIRT-L1 (Grgic et al. 2019).

Statistical Analysis

Normative data are presented as mean \pm standard deviation. Players who played under 10 minutes during those 4 games were excluded ($n = 3$). Due to the small sample of games and lack of players who played a complete 90-minute game, data were summed for each game in the sample and the summed data was used in the final analysis. Descriptive data was reported by taking the per-minute values for the technical variables and multiplying those by 90 in order to get a per-90-minute value. Means and standard deviations were calculated with this transformed data. Due to the issues with Linear modeling, Poisson Regression Models were used, specifically from the Quasi-Poisson family. Field times were log transformed to have the data be relative to the time played for each player. The models built were used in order to assess the relationships between physical GPS outputs, lab tests, field tests, and the technical variables chosen for the analysis when examining the differences by position group. Assumptions for these models were assessed and violation of statistical assumptions were corrected for in the modeling. WyScout® variables were set as the dependent variables with the player position and its interaction with the physical output or physical capability variable set as the independent variable. If statistically

significant interaction effects were found in a given model, then those relationships were assessed and reported. If no statistically significant interaction effects were found in the models constructed, then position was removed from the model and the model was re-assessed with the physical performance or physical capability variable used as the independent variable.

Correlations between physical performance and physical capability variables and technical-tactical variables were also assessed using Pearson's r . Subsequent r -values and p -values were reported for each of the relationships. Defensive, Offensive, as well as General volume were used in the final statistics because they encompassed the totality of the actions performed by a player.

Results

Descriptive data are presented below as mean and standard deviation in Tables 1-4. Pearson correlation values are presented in Table 5 for WyScout® variables and the match GPS outputs as well as the physical performance tests. Pearson's r correlation values are provided along with corresponding p -values for each relationship examined. Descriptive statistics are provided in Tables 1-4 below:

Table 9*Average Projected Technical Outputs per 90 Minutes*

| Variable | Abbreviated | Mean \pm SD |
|-----------------------------|-------------|------------------|
| General Volume | GV | 245.2 \pm 78.3 |
| Offensive Volume | OV | 229.3 \pm 74 |
| Defensive Volume | DV | 15.9 \pm 9.6 |
| Total Pass | TP | 101.7 \pm 32 |
| Total Pass Success | TPS | 78.5 \pm 30.7 |
| Forward Pass | FP | 12.3 \pm 7.1 |
| Forward Pass Success | FPS | 8.7 \pm 6.4 |
| Attacking Zone Pass | AZP | 5.5 \pm 3.8 |
| Attack Zone Pass Success | AZPS | 3.9 \pm 3.5 |
| Shots | TS | 0.7 \pm 0.9 |
| Shots on Goal | GST | 0.8 \pm 1.1 |
| Dribbles | DR | 2.3 \pm 2.3 |
| Dribbles Success | DRS | 1 \pm 1.2 |
| Turnovers | TO | 12.8 \pm 3.9 |
| Crosses | CR | 1 \pm 1.3 |
| Crosses Success | CRS | 0.1 \pm 0.2 |
| Interceptions | IN | 4.4 \pm 3.2 |
| Opposing Half Interceptions | OPIN | 1.5 \pm 2.1 |
| Clearance | CL | 0.2 \pm 0.4 |
| Aerial Duels | AD | 6.5 \pm 4.3 |
| Aerial Duels Won | ADW | 3.4 \pm 3.3 |

Table 10*Estimated Technical Output per 90 Minutes by Position Group*

| Metric | Position | | | | |
|--------|--------------|--------------|--------------|--------------|--------------|
| | CB | WB | CM | WF | CF |
| | (n = 6) | (n = 4) | (n = 6) | (n = 4) | (n = 2) |
| GV | 308.9 ± 27.2 | 220.8 ± 62.7 | 302.9 ± 48.6 | 152.2 ± 24.4 | 167.8 ± 45.8 |
| OV | 295.2 ± 30.4 | 207.1 ± 57.1 | 279.4 ± 42.9 | 143.3 ± 23.4 | 152.7 ± 55.6 |
| DV | 13.7 ± 4.8 | 13.7 ± 7.4 | 23.5 ± 12.6 | 8.9 ± 2.5 | 15.1 ± 9.8 |
| TP | 135.1 ± 8.8 | 91.6 ± 20.3 | 121.8 ± 15.1 | 63.2 ± 11.7 | 67 ± 19.4 |
| TPS | 106.1 ± 10.1 | 59.7 ± 13.4 | 103.3 ± 14.5 | 44 ± 12.3 | 45.8 ± 10.1 |
| FP | 19.8 ± 3.7 | 13.2 ± 8.1 | 14.2 ± 5 | 4.7 ± 2 | 5.1 ± 5 |
| FPS | 14.8 ± 4.4 | 8.7 ± 7 | 10.6 ± 5.8 | 2.6 ± 0.9 | 2.5 ± 3.5 |
| AZP | 4 ± 2.9 | 5.7 ± 2.5 | 8.6 ± 4.4 | 3.3 ± 1.2 | 3.3 ± 4.7 |
| AZPS | 2.9 ± 2.3 | 4.5 ± 3.3 | 6.4 ± 4.4 | 1.8 ± 1.6 | 1.6 ± 2.2 |
| TS | 0.6 ± 0.5 | 0.7 ± 0.9 | 0.2 ± 0.5 | 1.2 ± 1.2 | 2.4 ± 1.9 |
| GST | 0.6 ± 0.5 | 0.4 ± 0.5 | 0.2 ± 0.5 | 1.2 ± 1.2 | 2 ± 1.3 |
| DR | 0.7 ± 0.4 | 3.4 ± 1.5 | 1.1 ± 1.4 | 4.3 ± 2.1 | 3.3 ± 4.7 |
| DRS | 0.5 ± 0.3 | 0.6 ± 0.6 | 0.6 ± 1.3 | 1.9 ± 0.9 | 2 ± 2.9 |
| TO | 9.7 ± 0.9 | 15.5 ± 5.8 | 12.2 ± 4.5 | 13.3 ± 2.6 | 16 ± 1.2 |
| CR | 0.3 ± 0.3 | 2.7 ± 1.8 | 0 ± 0.1 | 1.5 ± 1.1 | 1.4 ± 0.6 |
| CRS | 0.1 ± 0.2 | 0.2 ± 0.1 | 0 ± 0.1 | 0.2 ± 0.2 | 0.3 ± 0.4 |
| IN | 4.3 ± 1.5 | 6.5 ± 5.6 | 6 ± 2.8 | 1.5 ± 1.2 | 2.1 ± 1.5 |

| | | | | | |
|------|-----------|-----------|-----------|-----------|-----------|
| OPIN | 0.3 ± 0.4 | 2 ± 2.4 | 3.1 ± 2.8 | 0.4 ± 0.5 | 0.2 ± 0.2 |
| CL | 0.7 ± 0.8 | 0.2 ± 0.3 | 0.1 ± 0.2 | 0 ± 0 | 0 ± 0 |
| AD | 5.2 ± 2.5 | 4 ± 0.7 | 8.7 ± 6.2 | 5.6 ± 3.4 | 8.2 ± 4.6 |
| ADW | 3.2 ± 1.6 | 1 ± 0.9 | 5.6 ± 4.4 | 1.4 ± 0.9 | 4.6 ± 3.8 |

Technical Variable Definitions:

GV = General Volume, OV = Offensive Volume, DV = Defensive Volume, TP = Total Passes, TPS = Total Pass Success, FP = Forward Passes, FPS = Forward Pass Success, AZP = Attacking Zone Pass, TS = Total Shots, GST = Goal Shots on Target, DR = Dribbles, DRS = Dribble Success, TO = Turnovers, CR = Total Crosses, CRS = Total Cross Success, IN = Interceptions, OPIN = Interceptions in Opponent Half, CL = Clearances, AD = Aerial Duels, ADW = Aerial Duels Won

Positional Definitions:

CB = Center Back, WB = Wide Back, CM = Center Midfielder, WF = Wide Forward, CF = Central Forward

Table 11

Average GPS Outputs per 90 Minutes

| GPS Metric | Abbreviation | Mean ± SD |
|----------------------------------|--------------|-----------------|
| Total Distance (m) | TD | 10756.2 ± 948.3 |
| HSR Distance (m) | HSR | 451.9 ± 188.4 |
| Sprint Distance (m) | SPR | 92.6 ± 80.3 |
| High-Intensity IMA Accelerations | IMA-A | 11.7 ± 6.3 |
| High-Intensity IMA Decelerations | IMA-D | 5.9 ± 3.8 |

Table 12*Average GPS Outputs per 90 Minutes by Position*

| Metric | Position | | | | |
|--------|----------------|---------------|---------------|---------------|---------------|
| | CB (n = 4) | WB (n = 3) | CM (n = 6) | WF (n = 4) | CF (n = 2) |
| TD | 9928.9 ± 276.7 | 11071 ± 765.8 | 10380.7 ± 879 | 11199 ± 702.6 | 12179.7 ± 851 |
| HSR | 292 ± 50.3 | 491.8 ± 192.9 | 362.6 ± 152.6 | 605.5 ± 124.2 | 672.4 ± 217.8 |
| SPR | 57.3 ± 42.5 | 106 ± 55.4 | 21.7 ± 24.6 | 182.7 ± 80 | 175.5 ± 21.6 |
| IMA-A | 6 ± 2.9 | 10.1 ± 0.9 | 16.9 ± 8.5 | 11.1 ± 2 | 12.41 ± 6.9 |
| IMA-D | 5.7 ± 2.7 | 5.6 ± 1.5 | 7.2 ± 5.9 | 4.1 ± 3.3 | 6 ± 0.3 |

Metric Definitions:

TD = Total Distance, HSR = High Speed Running Distance, SPR = Sprint Distance,
 IMA-A = High-Intensity IMA Accelerations, IMA-D = High-Intensity IMA Decelerations

Correlations were calculated between the WyScout® variables and each of the match GPS metrics, lab performance tests, and field performance test values. The *r* values and corresponding p-values for each of those relationships are found in Tables 5-7 below:

Table 13*Correlations – WyScout® and Match GPS Outputs*

| WyScout® Metric | GPS Metric | | | | |
|--------------------|----------------|---------------|-----------------|-------------|-------------|
| | Total Distance | HSR Distance | Sprint Distance | IMA-Accel | IMA-Decel |
| GV | $r = -0.667$ | $r = -0.656$ | $r = -0.774$ | $r = 0.205$ | $r = 0.140$ |
| | $p = 0.002^*$ | $p = 0.002^*$ | $p = 0.0001^*$ | $p = 0.400$ | $p = 0.569$ |
| OV | $r = -0.672$ | $r = -0.679$ | $r = -0.763$ | $r = 0.208$ | $r = 0.093$ |
| | $p = 0.001^*$ | $p = 0.001^*$ | $p = 0.0001^*$ | $p = 0.392$ | $p = 0.706$ |
| DV | $r = -0.267$ | $r = -0.114$ | $r = -0.438$ | $r = 0.066$ | $r = 0.423$ |
| | $p = 0.268$ | $p = 0.641$ | $p = 0.060$ | $p = 0.790$ | $p = 0.071$ |

GV = General Volume,
OV = Offensive Volume,
DV = Defensive Volume

Table 14*Correlations – WyScout® and Lab Testing Results*

| WyScout® Metric | Lab Tests Results | | | | | | | | |
|--------------------|-------------------|--------------|--------------|---------------|---------------|---------------|------------|----------------|----------------|
| | CMJ- 0 JH | CMJ- 0 PP | CMJ- 0 NI | CMJ- 20 JH | CMJ- 20 PP | CMJ- 20 NI | IMTP PF | IMTP RFD200 | IMTP IMP200 |
| | GV | $r =$ | $r =$ | $r =$ | $r =$ | $r =$ | $r =$ | $r =$ | $r =$ |
| - | | - | - | -0.075 | -0.225 | -0.094 | 0.083 | - | -0.211 |
| 0.287 | | 0.348 | 0.181 | $p =$ | $p =$ | $p =$ | $p =$ | $p =$ | $p =$ |
| | | | | 0.782 | 0.402 | 0.728 | 0.770 | 0.278 | 0.450 |

| | | | | | | | | | |
|----|------------|------------|------------|------------|------------|------------|------------|------------------|------------|
| | <i>p</i> = | <i>p</i> = | <i>p</i> = | | | | | | |
| | 0.282 | 0.187 | 0.501 | | | | | | |
| | <i>r</i> = | <i>r</i> = | <i>r</i> = | <i>r</i> = | <i>r</i> = | <i>r</i> = | <i>r</i> = | <i>r</i> = | <i>r</i> = |
| | - | - | - | -0.105 | -0.235 | -0.116 | - | <i>r</i> = - | -0.198 |
| OV | 0.141 | 0.350 | 0.213 | | | | 0.093 | 0.278 | |
| | <i>p</i> = | <i>p</i> = | <i>p</i> = | <i>p</i> = | <i>p</i> = | <i>p</i> = | <i>p</i> = | <i>p</i> = 0.317 | <i>p</i> = |
| | 0.603 | 0.183 | 0.428 | 0.700 | 0.381 | 0.668 | 0.742 | | 0.479 |
| | <i>r</i> = | <i>r</i> = | <i>r</i> = | <i>r</i> = | <i>r</i> = | <i>r</i> = | <i>r</i> = | <i>r</i> = | <i>r</i> = |
| | 0.094 | - | 0.144 | 0.179 | -0.040 | 0.115 | 0.020 | <i>r</i> = - | -0.213 |
| DV | | 0.148 | | | | | | 0.167 | |
| | <i>p</i> = | <i>p</i> = | <i>p</i> = | <i>p</i> = | <i>p</i> = | <i>p</i> = | <i>p</i> = | <i>p</i> = 0.553 | <i>p</i> = |
| | 0.730 | 0.583 | 0.115 | 0.508 | 0.896 | 0.671 | 0.943 | | 0.447 |

Technical Variables:

GV = General Volume, OV = Offensive Volume, DV = Defensive Volume

Lab Testing Variables:

- CMJ-0 JH = Countermovement Jump Jump Height – 0 Kg External Load
 - CMJ-0 PP = Countermovement Jump Peak Power – 0 Kg External Load
 - CMJ-0 NI = Countermovement Jump Net Impulse – 0 Kg External Load
 - CMJ-20 JH = Countermovement Jump Jump Height – 20 Kg External Load
 - CMJ-20 PP = Countermovement Jump Peak Power – 20 Kg External Load
 - CMJ-20 NI = Countermovement Jump Net Impulse – 20 Kg External Load
 - IMTP PF = Isometric Mid-Thigh Pull Peak Force
 - IMTP RFD200 = Isometric Mid-Thigh Pull RFD @ 200 msec
 - IMTP IMP200 = Isometric Mid-Thigh Pull Impulse @ 200 msec
-

Table 15*Correlations – WyScout® and Field-testing Results*

| WyScout® metric | Field Test | |
|--------------------|-----------------------|----------------------|
| | YYIRT-L1 Distance (m) | Mean 20m Sprint Time |
| GV | $r = -0.525$ | $r = 0.507$ |
| | $p = 0.037^*$ | $p = 0.045^*$ |
| OV | $r = -0.524$ | $r = 0.519$ |
| | $p = 0.037^*$ | $p = 0.040^*$ |
| DV | $r = -0.262$ | $r = 0.161$ |
| | $p = 0.328$ | $p = 0.552$ |

GV = General Volume,
OV = Offensive Volume,
DV = Defensive Volume

Results for the statistical models built per position are below in Tables 8-13. Only models that displayed statistically significant interaction effects for position are shown. The CF position was excluded from this analysis because the number of subjects for that group was less than three after accounting for missing testing data points.

Table 16*Poisson Regression Results – General Volume & GPS Metrics*

| Model Dep Var | Predictor | Estimate | Pseudo R ² (Efron) | IRR | IRR 95% CI | P-value |
|----------------|-----------|-------------|----------------------------------|--------|----------------|---------|
| General Volume | TD | -0.00000399 | 0.961 | 0.9999 | [0.999, 1.000] | 0.532 |
| | HSR | -0.000255 | 0.962 | 0.9997 | [0.999, 1.000] | 0.0436* |
| | SPR | -0.000793 | 0.970 | 0.9992 | [0.998, 0.999] | 0.0350* |
| | IMA-A | 0.00118 | 0.982 | 0.9958 | [0.981, 0.997] | 0.0140* |
| | IMA-D | 0.00175 | 0.969 | 0.9891 | [0.990, 1.020] | 0.511 |

Table 17*Poisson Regression Results – Offensive Volume & GPS Metrics*

| Model Dep Var | Predictor | Estimate | Pseudo R ² (Efron) | IRR | IRR 95% CI | P-value |
|------------------|-----------|-------------|----------------------------------|--------|----------------|---------|
| Offensive Volume | TD | -0.00000310 | 0.954 | 0.9999 | [0.999, 1.000] | 0.640 |
| | HSR | -0.000241 | 0.956 | 0.9997 | [0.999, 1.000] | 0.066 |
| | SPR | -0.000584 | 0.967 | 0.9993 | [0.999, 1.000] | 0.053 |
| | IMA-A | -0.0107 | 0.980 | 0.9964 | [0.981, 0.997] | 0.0194* |
| | IMA-D | 0.00505 | 0.964 | 0.9890 | [0.990, 1.021] | 0.530 |

Table 18*Poisson Regression Results – Defensive Volume & GPS Metrics*

| Model | Dep | Dar | Predictor | Estimate | Pseudo R ² (Efron) | IRR | IRR 95% CI | P-value |
|------------------|-----|-----|-----------|------------|----------------------------------|--------|----------------|----------|
| | | | TD | -0.0000180 | 0.868 | 0.9999 | [0.999, 1.000] | 0.0171* |
| | | | HSR | -0.000501 | 0.849 | .9995 | [0.999, 1.000] | 0.0243* |
| Defensive Volume | | | SPR | -0.00120 | 0.934 | 0.9976 | [0.998, 0.999] | 0.00452* |
| | | | IMA-A | -0.0139 | 0.952 | 0.9878 | [0.974, 0.998] | 0.0381* |
| | | | IMA-D | 0.00664 | 0.821 | 0.9905 | [0.983, 1.031] | 0.588 |

Table 19*Poisson Regression Results – Technical Variables & CMJ Variables*

| Model Dep Var | Predictor | Estimate | Psuedo R ² (Efron) | IRR | IRR 95% CI | P-value |
|---------------------|-------------------------|-------------|-------------------------------------|--------|--------------------|------------|
| General Volume | CMJ-20 JH:PositionWB | -0.155 | 0.970 | 0.8562 | [0.765, .961] | 0.0372* |
| | CMJ-0 PP:PositionWB | -0.00152 | 0.994 | 0.9985 | [0.997, 0.999] | 0.0107* |
| | CMJ-0 PP | 0.00122 | 0.994 | 1.0012 | [1.0004, 1.002] | 0.0245* |
| | CMJ-0 JH | -0.0265 | 0.822 | 0.9738 | [0.947, 1.001] | 0.0827 |
| | CMJ-20 PP | -0.00000344 | 0.743 | 0.9999 | [0.999, 1.000] | 0.983 |
| | CMJ-0 NI | 0.00111 | 0.746 | 1.0011 | [0.991, 1.011] | 0.827 |
| | CMJ-20 NI | 0.00304 | 0.759 | 1.0030 | [0.995, 1.011] | 0.468 |
| Offensive Volume | CMJ-0 JH | 0.0292 | 0.973 | 1.0296 | [1.015, 1.044] | 0.0000493* |

| | | | | | |
|---------------|-----------|-------|--------|----------|------------|
| CMJ-0 | | | | [0.8889, | |
| JH:PositionWB | -0.0958 | | 0.9087 | 0.929] | 6.40e-17* |
| CMJ-0 | | | | [0.954, | |
| JH:PositionWF | -0.0282 | | 0.9722 | 0.991] | 0.00353* |
| CMJ-0 | | | | [1.033, | |
| JH:PositionCB | 0.0604 | | 1.0622 | 1.092] | 0.0000188* |
| CMJ-0 | | | | [0.781, | |
| JH:PositionCF | -0.164 | | 0.8484 | 0.918] | 0.0000615* |
| CMJ-20 JH | | | | [1.033, | |
| | 0.0513 | | 1.0527 | 1.073] | 9.26e- 8* |
| CMJ-20 | | | | [0.831, | |
| JH:PositionWB | -0.154 | | 0.8572 | 0.884] | 1.64e-22* |
| | | 0.960 | | | |
| CMJ-20 | | | | [0.925, | |
| JH:PositionWF | -0.0499 | | 0.9513 | 0.978] | 4.46e- 4* |
| CMJ-20 | | | | [0.775, | |
| JH:PositionCF | -0.177 | | 0.8375 | 0.902] | 5.00e- 6* |
| CMJ-0 PP | | | | [1.001, | |
| | 0.00118 | | 1.0012 | 1.002] | 3.50e- 9* |
| CMJ-0 | | | | [0.998, | |
| PP:PositionWB | -0.00149 | 0.991 | 0.9985 | 0.999] | 2.27e-13* |
| CMJ-0 | | | | [0.999, | |
| PP:PositionWF | -0.000802 | | 0.9992 | 0.999] | 0.000153* |

| | | | | | | |
|---------------------|---------------|-----------|-------|--------|---------|-----------|
| | CMJ-0 | -0.000693 | | 0.9993 | [0.999, | 0.000952* |
| | PP:PositionCB | | | | 1.000] | |
| | CMJ-0 | -0.00156 | | 0.9984 | [0.998, | 1.13e-11* |
| | PP:PositionCF | | | | 0.999] | |
| | CMJ-20 | -0.000724 | | 0.9993 | [0.999, | 0.00154* |
| | PP:PositionWB | | 0.989 | | 1.000] | |
| | CMJ-20 | -0.000702 | | 0.9993 | [0.999, | 0.00510* |
| | PP:PositionCF | | | | 1.000] | |
| | CMJ-0 | -0.00483 | | 0.9951 | [0.990, | 0.00495* |
| | NI:PositionWB | | | | 0.999] | |
| | CMJ-0 | 0.0236 | 0.989 | 1.0239 | [1.016, | 9.91e-10* |
| | NI:PositionWF | | | | 1.032] | |
| | CMJ-0 | 0.0210 | | 1.0212 | [1.015, | 4.75e-12* |
| | NI:PositionCB | | | | 1.027] | |
| | CMJ-20 | -0.00610 | | 0.9939 | [0.988, | 0.0347* |
| | NI:PositionWB | | | | 0.999] | |
| | CMJ-20 | 0.0119 | 0.990 | 1.0120 | [1.006, | 4.46e-5* |
| | NI:PositionWF | | | | 1.018] | |
| | CMJ-20 | 0.0180 | | 1.0181 | [1.012, | 8.04e-9* |
| | NI:PositionCB | | | | 1.024] | |
| Defensive Volume | CMJ-0 JH | 0.0932 | 0.890 | 1.0977 | [1.041, | 0.0006* |
| | | | | | 1.157] | |

| | | | | | |
|---------------|----------|-------|--------|-------------------|---------|
| CMJ-20 JH | 0.0870 | | 1.0909 | [1.016, 1.167] | 0.0134* |
| CMJ-20 | -0.167 | | 0.8459 | [0.748, 0.959] | 0.0081* |
| JH:PositionWB | | 0.815 | | | |
| CMJ-20 | -0.124 | | 0.8833 | [0.788, 0.990] | 0.0327* |
| JH:PositionWF | | | | | |
| CMJ-20 | 0.223 | | 1.2492 | [0.996, 1.557] | 0.0490* |
| JH:PositionCF | | | | | |
| CMJ-0 PP | 0.00179 | | 1.0018 | [1.000, 1.003] | 0.0130* |
| CMJ-0 | -0.00191 | | 0.9981 | [0.997, 0.999] | 0.0098* |
| PP:PositionWB | | 0.835 | | | |
| CMJ-0 | -0.00183 | | 0.9982 | [0.997, 0.999] | 0.0192* |
| PP:PositionWF | | | | | |
| CMJ-0 | -0.00216 | | 0.9978 | [0.996, 0.999] | 0.0057* |
| PP:PositionCB | | | | | |
| CMJ-20 PP | 0.00221 | | 1.0022 | [1.000, 1.004] | 0.0400* |
| CMJ-20 | -0.00236 | 0.843 | 0.9976 | [0.995, 0.999] | 0.0314* |
| PP:PositionWB | | | | | |
| CMJ-20 | -0.00224 | | 0.9978 | [0.995, 0.999] | 0.0412* |
| PP:PositionWF | | | | | |
| CMJ-20 | -0.00261 | | 0.9974 | [0.995, 0.999] | 0.0186* |
| PP:PositionCB | | | | | |
| CMJ-0 NI | 0.0327 | 0.874 | 1.0332 | [1.012, 1.058] | 0.0036* |

| | | | | | |
|---------------|---------|-------|--------|-------------------|---------|
| CMJ-0 | | | | | |
| NI:PositionWB | -0.0348 | | 0.9658 | [0.942, 0.988] | 0.0045* |
| CMJ-0 | | | | | |
| NI:PositionCB | -0.0462 | | 0.9548 | [0.926, 0.983] | 0.0020* |
| CMJ-20 | | | | | |
| NI:PositionCB | -0.0385 | 0.832 | 0.9623 | [0.930, 0.991] | 0.0167* |

Note: The ‘.’ notation denotes an interaction effect between the dependent variable and the player position. For example, CMJ-0 JH:PositionWB would refer to the interaction effect between the CMJ-0 JH and the WB position for the given information. See below for more details.

Jump variables:

CMJ-0: Countermovement Jump – 0 kg external load

CMJ-20: Countermovement Jump – 20 kg external load

JH: Jump Height

PP: Peak Power

NI: Net Impulse

Player Positions:

CB: Center Back

WB: Wide Back

CM: Central Midfielder

WF: Wide Forward

CF: Central Forward

Table 20*Poisson Regression Results – Technical Variables & IMTP Variables*

| Model Dep Var | Predictor | Estimate | Pseudo R ² (Efron) | IRR | IRR 95% CI | P-value |
|---------------------|-----------------------|------------|-------------------------------------|--------|-------------------|---------|
| General Volume | IMTP PF | 0.0000695 | 0.735 | 1.0001 | [0.999, 1.000] | 0.729 |
| | IMTP RFD200 | -0.0000488 | 0.755 | 0.9999 | [0.999, 1.000] | 0.185 |
| | IMTP IMP200 | -0.00149 | 0.738 | 0.9985 | [0.995, 1.001] | 0.311 |
| Offensive Volume | IMTP PF | 0.0000746 | 0.727 | 1.0001 | [0.999, 1.000] | 0.715 |
| | IMTP RFD200 | -0.0000491 | 0.746 | 0.9999 | [0.999, 1.000] | 0.191 |
| | IMTP IMP200 | -0.00146 | 0.728 | 0.9985 | [0.996, 1.001] | 0.328 |
| Defensive Volume | IMTP PF:PositionWB | -0.00288 | 0.9971 | .9971 | [0.995, 0.999] | 0.0206* |
| | IMTP PF:PositionCB | -0.00213 | 0.9971 | 0.9979 | [0.997, 0.999] | 0.0201* |

| | | | | | |
|-------------|------------|-------|--------|-------------------|-------|
| IMTP RFD200 | -0.0000346 | 0.956 | 0.9999 | [0.999, 1.000] | 0.624 |
| IMTP IMP200 | -0.00162 | 0.867 | 0.9983 | [0.993, 1.004] | 0.585 |

Note: The ‘.’ notation denotes an interaction effect between the dependent variable and the player position. For example, CMJ-0 JH:PositionWB would refer to the interaction effect between the CMJ-0 JH and the WB position for the given information. See below for more details.

IMTP variables:

PF: Peak Force

RFD200: RFD @ 200 msec epoch

IMP200: Impulse @ 200 msec epoch

Player Positions:

CB: Center Back

WB: Wide Back

CM: Central Midfielder

WF: Wide Forward

CF: Central Forward

Table 21*Poisson Regression Results – Technical Variables & Field-testing Variables*

| Model Dep Var | Predictor | Estimate | Pseudo | | | |
|------------------|------------|-----------|---------------------------|---------|------------------|---------|
| | | | R ² (Efron) | IRR | IRR 95% CI | P-value |
| General Volume | YYIRT | -0.000601 | 0.816 | 0.9994 | [0.999, 1.000] | 0.0201* |
| | 20m Sprint | 2.03 | 0.866 | 7.5825 | [2.099, 27.217] | 0.0078* |
| Offensive Volume | YYIRT | -0.000590 | 0.802 | 0.9994 | [0.999, 1.000] | 0.0274* |
| | 20m Sprint | 1.99 | 0.848 | 7.3282 | [1.905, 27.983] | 0.0115* |
| Defensive Volume | YYIRT | -0.000789 | 0.708 | 0.9992 | [0.998, 0.999] | 0.0611 |
| | 20m Sprint | 2.62 | 0.803 | 13.7188 | [1.355, 136.939] | 0.0429* |

Note: No significant interaction effects were found in the initial models, so a single predictor was used.

The correlation analysis performed between the technical-tactical volumes and the match-related GPS variables revealed statistically significant correlations between GV and TD ($r = -0.667, p = 0.002$), GV and HSR Distance ($r = -0.656, p = 0.002$), GV and SPR Distance ($r = -0.774, p = 0.0001$), OV and TD ($r = -0.672, p = 0.001$), OV and HSR Distance ($r = -0.679, p = 0.001$), OV and SPR Distance ($r = -0.763, p = 0.0001$). Similarly, statistically significant relationships were found between the field test results and the volume of technical actions performed. Specifically, statistically significant correlations were found between GV and YYIRT-L1 distance ($r = -0.525,$

$p = 0.037$), GV and 20m sprint time ($r = 0.507, p = 0.045$), OV and YYIRT-L1 distance ($r = -0.524, p = 0.037$), and OV and 20m sprint time ($r = 0.519, p = 0.040$). No statistically significant correlations were found between the physical capabilities related to lab testing and any of the technical tactical variables. The Poisson regression models yielded statistically significant results for a number of different variables. HSR, SPR, and IMA-A were found to have positive effects on the amount of general volume performed in games. Positive effects were found between offensive and IMA-A only. Positive effects on defensive volume were found for all GPS metrics. P-values and model statistics are found in Tables 8-10.

The relationships between the jump variables and the technical variables proved to be a bit more complex. The jump variables that were found to have positive effects on the amount of GV were CMJ-0 PP, and the interactions between CMJ-0 PP & the WB position, as well as the interaction between CMJ-20 and the WB position. A number of statistically significant positive effects were found between OV and CMJ-derived variables. This was also the case between DV and the CMJ-derived variables. Both of these dependent variables saw multiple statistically significant interaction effects between different positions, with the most frequent position effect being WF and WB. Further details can be found in Table 11.

Isometric Mid-Thigh Pull variables showed no statistically significant effects on the independent variables of GV and OV. DV was found to be statistically significantly affected by the interaction between both IMTP-PF and the positions of WB and CB. Both GV and OV were positively affected by YYIRT-L1 and 20m sprint test results. DV only saw a positive effect from 20m sprint times. Parameter estimates, p-values, and 95% CIs for effect sizes can be found in the corresponding tables.

Discussion

To the authors' knowledge, this study is the first of its kind in the given population. A technical-tactical analysis using video software performed in this population. The first novel finding in this study is that the in-match GPS variables that had statistically significant correlations had negative r values in relation to all of GV, and OV suggesting that a greater amount of running was a result of negative technical performance. All of the relationships between GPS and WyScout® metrics had negative r -values, suggesting that the relationship between the variables is inverse. In practical terms, this is suggestive of the fact that players who performed more physical work during matches performed fewer technical actions. Positional differences could also play a factor in the magnitude of the correlation. The normative data provided shows a large difference between the amount of general and offensive volume. This could be in part because the volume of TP was higher in the CB group, which in turn is typically the position group that has the least amount of physical demand (Di Salvo et al. 2007). The correlations of the field-testing and both GV and OV also showed negative relationships with the YYIRT-L1 distance covered. Again, positional differences specific to a 3-4-3 tactical system could be the main cause of these inverse relationships. Players who played in the center of the field were more likely to have contact with the ball and thus accumulate more of both OV and GV. While fitness is important for all players, players whose positions are more on the width of the field naturally have a higher physical demand due to the greater distances covered at high intensities (Mohr et al. 2003; Ingebrigtsen et al. 2015), but seemingly at the expense of the total volume of technical actions performed per minute of match time. Similarly, the correlations between GV, OV and 20m sprint time were positive, an indication that the fastest players were not the ones that performed the highest number of both general and offensive volume actions.

The Poisson regression models yielded curvilinear relationships between the technical variables examined and the physical performance and physical capability metrics. Most of the statistically significant relationships between the technical variables and the performance variables are suggestive of a positive effect of physical performance in a curvilinear fashion, meaning that the effect of the relationship sees a certain plateau at a certain point in the relationship between the variables. It is also important to note that most of the statistically significant results came from models that designated an interaction effect for position. The majority of the statistically significant effects for position were wide positions, mainly the WF and the WB. The field tests only showed statistical significance when examining the main effects.

The novelty in this examination result in many areas of improvement with regards to future research. First of all, the sample size for this study is very small, and while it is the nature of sport that every team is its own unique population the number of data points does not suffice in order to make more broad generalizations with regards to the global population of NCAA D-I soccer players. Only 4 games were available for technical-tactical analysis, and thus more than likely resulted in some skew in the end results. Secondly, the third-party software that is being used for the research is subject to potential errors in collection and subsequent tagging/analysis of a given game. Because of software errors, some of the data examined was not able to be tagged appropriately and thus excluded from the final analysis. From a context perspective, it is important to understand that the technical-tactical factors are subject to influence by a variety of external factors that affect performance, but were not examined here (i.e. Game location, quality of opponent, halftime score, final score, etc...). All of these factors have been previously examined at different levels of competition and have been found to have statistically significant effects on both physical and technical KPIs. More data is needed in order to make more global

inferences about this specific population, but the results presented in this study are a starting point for future examinations. Future research should focus on using a larger sample size and accounting for other related contextual elements that affect technical performance such as location (i.e. Home vs Away), quality of opponent, final result (i.e Win, Loss, Draw), etc.

Practical Applications

For practitioners considering using this data in an applied setting, it is important to note that both the physical and technical outputs presented are specific to the formation being proposed by the coaching staff for this team during this single season. This explorative data included provides a starting point for coaches to physically prepare their soccer athletes at this level. Technical outputs should be used cautiously in athlete preparation due to the dynamic nature of soccer. Every game provides different challenges from a technical-tactical perspective and no game in isolation should be used as a benchmark for performance preparation.

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References

1. Adam, D. (2022). Science and the World Cup: how big data is transforming football. *Nature*, 611(7936), 444-446. <https://doi.org/10.1038/d41586-022-03698-1>
2. Alexander, R. P. (2014). *Physical and technical demands of women's collegiate soccer* [East Tennessee State University].
3. Arjol-Serrano, J. L., Lampre, M., Díez, A., Castillo, D., Sanz-López, F., & Lozano, D. (2021). The Influence of playing formation on physical demands and technical-tactical actions according to playing positions in an elite soccer team. *International Journal of Environmental Research and Public Health*, 18(8), 4148. <https://www.mdpi.com/1660-4601/18/8/4148>
4. Brito de Souza, D., Lopez-Del Campo, R., Blanco-Pita, H., Resta, R., & Del Coso, J. (2019). An extensive comparative analysis of successful and unsuccessful football teams in LaLiga. *Front Psychol*, 10, 2566. <https://doi.org/10.3389/fpsyg.2019.02566>
5. Brito Souza, D., López-Del Campo, R., Blanco-Pita, H., Resta, R., & Del Coso, J. (2019). A new paradigm to understand success in professional football: analysis of match statistics in LaLiga for 8 complete seasons. *International Journal of Performance Analysis in Sport*, 19(4), 543-555. <https://doi.org/10.1080/24748668.2019.1632580>
6. Bush, M. D., Archer, D. T., Hogg, R., & Bradley, P. S. (2015). Factors influencing physical and technical variability in the English Premier League. *Int J Sports Physiol Perform*, 10(7), 865-872. <https://doi.org/10.1123/ijsp.2014-0484>
7. Castellano, J., Alvarez-Pastor, D., & Bradley, P. S. (2014). Evaluation of research using computerised tracking systems (Amisco® and Prozone®) to analyse physical

- performance in elite soccer: A systematic review. *Sports Medicine*, 44(5), 701-712.
<https://doi.org/10.1007/s40279-014-0144-3>
8. Deprez, D., Franssen, J., Lenoir, M., Philippaerts, R., & Vaeyens, R. (2015). The Yo-Yo intermittent recovery test level 1 is reliable in young high-level soccer players. *Biol Sport*, 32(1), 65-70. <https://doi.org/10.5604/20831862.1127284>
 9. Di Salvo, V., Adam, C., Barry, M., & Cardinale, M. (2006). Validation of Prozone ®: A new video-based performance analysis system. *International Journal of Performance Analysis in Sport*, 6, 108-119. <https://doi.org/10.1080/24748668.2006.11868359>
 10. Di Salvo, V., Baron, R., Tschan, H., Calderon Montero, F. J., Bachl, N., & Pigozzi, F. (2007). Performance characteristics according to playing position in elite soccer. *Int J Sports Med*, 28(03), 222-227. <https://doi.org/10.1055/s-2006-924294>
 11. Di Salvo, V., & Modonutti, M. (2009). Integration of different technology systems for the development of football training. *J Sports Sci Med*, 11, 3.
 12. Fernandez-Navarro, J., Fradua, L., Zubillaga, A., & McRobert, A. P. (2018). Influence of contextual variables on styles of play in soccer. *International Journal of Performance Analysis in Sport*, 18(3), 423-436. <https://doi.org/10.1080/24748668.2018.1479925>
 13. Forcher, L., Forcher, L., Wäsche, H., Jekauc, D., Woll, A., & Altmann, S. (2023). The influence of tactical formation on physical and technical match performance in male soccer: A systematic review. *International Journal of Sports Science & Coaching*, 18(5), 1820-1849. <https://doi.org/10.1177/17479541221101363>
 14. Gonzalez-Rodenas, J., Aranda-Malaves, R., Tudela-Desantes, A., Nieto, F., Uso, F., & Aranda, R. (2020). Playing tactics, contextual variables and offensive effectiveness in

- English Premier League soccer matches. A multilevel analysis. *PLoS One*, *15*(2), e0226978. <https://doi.org/10.1371/journal.pone.0226978>
15. Gonzalez-Rodenas, J., Mitrotasios, M., Aranda, R., & Armatas, V. (2020). Combined effects of tactical, technical and contextual factors on shooting effectiveness in European professional soccer. *International Journal of Performance Analysis in Sport*, *20*(2), 280-293. <https://doi.org/10.1080/24748668.2020.1743163>
 16. Gonzalez-Rodenas, J., Moreno-Perez, V., Campo, R. L., Resta, R., & Coso, J. D. (2024). Technical and tactical evolution of the offensive team sequences in LaLiga between 2008 and 2021. Is Spanish football now a more associative game? *Biol Sport*, *41*(2), 105-113. <https://doi.org/10.5114/biol sport.2024.131818>
 17. Grgic, J., Oppici, L., Mikulic, P., Bangsbo, J., Krstrup, P., & Pedisic, Z. (2019). Test-Retest Reliability of the Yo-Yo Test: A Systematic Review. *Sports Medicine*, *49*(10), 1547-1557. <https://doi.org/10.1007/s40279-019-01143-4>
 18. Haff, G. G., Ruben, R. P., Lider, J., Twine, C., & Cormie, P. (2015). A comparison of methods for determining the rate of force development during isometric midhigh clean pulls. *J Strength Cond Res*, *29*(2), 386-395. <https://doi.org/10.1519/JSC.0000000000000705>
 19. Ishida, A., Travis, S. K., & Stone, M. H. (2021). Short-term periodized programming may improve strength, power, jump kinetics, and sprint efficiency in soccer. *J Funct Morphol Kinesiol*, *6*(2). <https://doi.org/10.3390/jfmk6020045>
 20. Ishida, A., Travis, S. K., & Stone, M. H. (2021). Associations of body composition, maximum strength, power characteristics with sprinting, jumping, and intermittent

- endurance performance in male intercollegiate soccer players. *J Funct Morphol Kinesiol*, 6(1). <https://doi.org/10.3390/jfmk6010007>
21. Izzo, R., Rossini, U., Raiola, G., Cejudo, P. A., & Hosseini, V. I. C. (2020). Insurgence of fatigue and its implications in the selection and accuracy of passes in football. A case study. *Journal of Physical Education & Sport*, 20(4).
22. Merrigan, J. J., Stone, J. D., Hornsby, W. G., & Hagen, J. A. (2020). Identifying reliable and relatable force-time metrics in athletes-considerations for the isometric mid-thigh pull and countermovement jump. *Sports (Basel)*, 9(1).
<https://doi.org/10.3390/sports9010004>
23. Pappalardo, L., Cintia, P., Ferragina, P., Massucco, E., Pedreschi, D., Giannotti, F., & . (2019). PlayeRank: Data-driven performance evaluation and player ranking in soccer via a machine learning approach. *ACM Transactions on Intelligent Systems and Technology*, 10(5), 1–27. <https://doi.org/https://doi.org/10.1145/3343172>
24. Phillips, J., Dusseault, M., da Costa Valladão, S. P., Nelson, H., & Andre, T. (2023). Test transferability of 3D-MOT training on soccer specific parameters. *Research Directs in Strength and Performance*, 3(1).
25. Rampinini, E., Coutts, A. J., Castagna, C., Sassi, R., & Impellizzeri, F. M. (2007). Variation in top level soccer match performance. *Int J Sports Med*, 28(12), 1018-1024.
<https://doi.org/10.1055/s-2007-965158>
26. Rampinini, E., Impellizzeri, F. M., Castagna, C., Coutts, A. J., & Wisloff, U. (2009). Technical performance during soccer matches of the Italian Serie A league: effect of fatigue and competitive level. *J Sci Med Sport*, 12(1), 227-233.
<https://doi.org/10.1016/j.jsams.2007.10.002>

27. Redwood-Brown, A., Cranton, W., & Sunderland, C. (2012). Validation of a real-time video analysis system for soccer. *Int J Sports Med*, 33(8), 635-640.
<https://doi.org/10.1055/s-0032-1306326>
28. Reilly, T. (1976). A motion analysis of work-rate in different positional roles in professional football match-play. *Journal of Human Movement Studies*, 2, 87-97.
29. Russell, M., Rees, G., & Kingsley, M. I. (2013). Technical demands of soccer match play in the English Championship. *J Strength Cond Res*, 27(10), 2869-2873.
<https://doi.org/10.1519/JSC.0b013e318280cc13>
30. Sánchez-López, R., Etxeazarra, I., & Castellano, J. (2023). Validation of an instrument to qualify Football Competence via WyScout. 83-94. [https://doi.org/10.5672/apunts.2014-0983.es.\(2023/4\).154.08](https://doi.org/10.5672/apunts.2014-0983.es.(2023/4).154.08)
31. Schmitz, B., Pfeifer, C., Kreitz, K., Borowski, M., Faldum, A., & Brand, S.-M. (2018). The Yo-Yo Intermittent Tests: A Systematic Review and Structured Compendium of Test Results [Systematic Review]. *Frontiers in Physiology*, 9.
<https://doi.org/10.3389/fphys.2018.00870>
32. Spalding, J. (2017). *Technical and physical match demands of a NCAA Division I soccer goalkeeper* (Publication Number 10609047) [M.A., East Tennessee State University]. Dissertations & Theses @ East Tennessee State University; ProQuest One Academic. United States -- Tennessee. <https://www.proquest.com/dissertations-theses/technical-physical-match-demands-ncaa-division-i/docview/1906670106/se-2?accountid=10771>
33. https://libs.etsu.edu/primo/resolver.php?url_ver=Z39.88-2004&rft_val_fmt=info:ofi/fmt:kev:mtx:dissertation&genre=dissertations&sid=ProQ:ProQuest+Dissertations+%26+Theses+Global&atitle=&title=Technical+and+Physical+Matc

h+Demands+of+a+NCAA+Division+I+Soccer+Goalkeeper&issn=&date=2017-01-01&volume=&issue=&spage=&au=Spalding%2C+Joanne&isbn=978-1-369-80179-8&jtitle=&bttitle=&rft_id=info:eric/&rft_id=info:doi/

34. Thomas, V., & Reilly, T. (1979). Fitness assessment of English league soccer players through the competitive season. *Br J Sports Med, 13*(3), 103-109.
<https://doi.org/10.1136/bjism.13.3.103>
35. Yi, Q., Gomez-Ruano, M. A., Liu, H., Zhang, S., Gao, B., Wunderlich, F., & Memmert, D. (2020). Evaluation of the technical performance of football players in the UEFA Champions League. *Int J Environ Res Public Health, 17*(2).
<https://doi.org/10.3390/ijerph17020604>

**Chapter 5. The Relationship Between Training Load and Physical Performance Testing in
Male Collegiate Soccer Players**

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Abstract

The purpose of this study was to examine the relationship between training load and physical performance changes in NCAA D-I male soccer players over the course of a competitive season. Data from an eligible 30 NCAA D-I male soccer players from a Southeastern university were used in the retrospectively analysis. GPS data from matches and training sessions for a single season were analyzed. Pre- and Post-tests for a number of different physical capability tests were used in the analysis in order to assess the effect of accumulated training load on changes in physical capabilities. Repeated measures ANOVA were run on the relevant physical performance variables for Static Jumps (SJ), Countermovement Jumps (CMJ), Isometric Mid-Thigh Pull (IMTP), Yo-Yo Intermittent Recovery Test – Level 1 (YYIRT-L1), and 20m sprint tests. Statistical significant was set at $p \leq 0.05$. ANOVA results showed no statistically significant changes in any of the physical capabilities except for YYIRT-L1, showing significant decreases from pre-testing to post-testing values. Linear models were used to assess the relationship between the percent of change from pre-testing to post-testing and the amount of total training volume accumulated of the course of the season. The relationships between CMJ-0 Peak Power and Total Distance, YYIRT-L1 and High-Speed Running, and IMA-Decelerations and CMJ-0 PP were the only relationships examined that showed statistical significance. The results suggest that the physical demands of training and playing games does not significantly negatively affect the physical capabilities of the athlete from one timepoint to another, however, the amount of decrement could be affected by other factors not thoroughly examined in this study.

Keywords: Physical capabilities, pre-season testing, post-season testing, training load

Introduction

While the research on soccer players is already expansive, there is a growing need to understand specific populations of soccer players and how they perform physically over a season. Training load and its effects on athletic performance have also been examined more in-depth over the last few years. Gabbett et al. (2016) established the relationship between large fluctuations in training load and increased risk of injury. A brief review by Jiang et al. (2022) of the available literature on training load and schedule congestion in soccer also seems to support the notion that there is an increase in the risk of injury when training load is high, and periods of congested schedules are present.

Collegiate soccer in the United States is characterized by a short preseason and a condensed competitive schedule. More recently, research has come about examining male collegiate populations and the physical demands of collegiate soccer. In collegiate soccer, the density of the competitive schedule makes long-term performance planning a challenge (Curtis et al., 2021). The influence of contextual factors in soccer matches has been well-established in previous literature (Díez et al., 2020; Guerrero-Calderon et al., 2021), therefore it is important to note that there are contextual factors surrounding NCAA D-I soccer that influence the physical match demands of the athletes (Curtis et al., 2021).

Performance testing in soccer has also been carried out for a long time in various populations (Siegler, Robergs, & Weingart, 2006; Haugen, Tønnessen, & Seiler, 2013) but while normative data has been collected for many tests, there is still a need to examine the effects of competitive play on physical performance testing, particularly in under-researched populations, such as collegiate soccer. Clark et al. (2003) tracked measures of aerobic performance and CMJ performance over a three-year period. Thomas et al. (2017) examined the Dynamic Strength

Index in team sport athletes, including soccer players, by taking CMJ and Isometric Mid-Thigh Pull (IMTP) results and observing trends across different sports.

Training strategies often change over the course of a season to maximize athlete potential during the competitive season and place an increased emphasis on competition performance rather than training (Plisk & Stone, 2003; Stone et al., 2021). Because of this, there is often a decrease in markers of physical performance taken in the beginning stages of the competitive calendar. In soccer players, the Yo-Yo Intermittent Recovery Level I Test has been used as a measure of physical fitness (Bangsbo, 2008). This test has also been used to determine the level of fitness changes in soccer players after a competitive season (Haugen, 2018). Various examinations of measures of aerobic performance have yielded conflicting results, but a review by Jaspers et al. (2017) found that most of the literature examined which tracked seasonal cardiovascular changes in soccer players showed little to no changes in anaerobic and aerobic markers of performance. Similarly, Silva (2022) found that the results of aerobic performance tests varied according to the time of the season in which the tests were conducted. Younesi et al. (2021) examined the relationship between training load and various physical performance tests in professional soccer players, using measures of cardiovascular fitness as well as CMJ and 20m sprint tests. Although the battery of tests was expansive, the effects of training load were examined in the context of a preseason period and not in the context of a full competitive season. Similarly, a review by Jaspers et al. (2017) found increases in anaerobic performance outputs in relation to match time over a season.

To the author's knowledge, there has only been one study that examined changes in performance testing in relation to training load in the population of NCAA D-I soccer players (Huggins et al., 2019) though the only performance tests administered measured cardiovascular

power. Other examinations of training load and physical performance have focused mainly on different populations with different constraints or have not examined the effect of said training load on physical performance outputs.

Therefore, the purpose of this study is two-fold: To examine the changes in physical performance testing values from pre-testing to post-testing for maximal strength, power, speed and cardiovascular power as well as to determine the effect of total accumulated training load on the change in physical capacity

Methods

Experimental Approach to the Problem

The design of this study was a retrospective analysis using previously collected data collected for athlete monitoring purposes. The study was designed in order to examine the changes in physical performance testing for NCAA D-I male soccer athletes from pre-testing to post-testing. There was a period of 3 months between pre-testing and pos-testing. Additionally, the impact of the training load accumulated over the course of the season on the performance testing results was examined.

Subjects

Data from a single competitive season was used for this study, resulting in 30 NCAA D-I soccer players at a mid-major university in the Southeast United States to be eligible ($n = 30$, height = 179.0 ± 5.2 cm; weight = 79.2 ± 6.7 kg; age = 20.7 ± 1.6 years). The data was retrieved from the ETSU Sport Science Research Repository. Athletes participated in an average of 1.5 games per week, 4.3 training sessions per week, and 2 resistance training sessions per week. A retrospective analysis of the physical performance testing data was approved by the East Tennessee State Institutional Review Board (Protocol number c0623.17sw).

Athletes were excluded from the analysis for the following criteria: 1) Athlete's primary position was a Goalkeeper. 2) Athletes were excluded from the analysis of any test for which they did not complete either pre-test or post-test.

Procedures

GPS Training Load Data. GPS training load data from matches and training sessions were retrieved from the ETSU Sport Science Research Repository for the 2022 Fall season. The Fall season was chosen because this is the designated "In-Season" period for soccer at the NCAA level, running from early August to anywhere from late October to late November, depending on the success of a team's season. The soccer team used for examination participated in a total of 19 matches over that span, with 2 Exhibition matches, 5 Conference matches, and 1 Conference Tournament game. A total of 60 team training sessions took place in that time span. A qualified sports scientist was in charge of data collection for the team during this period. Data was collected by the sports scientist at every game and team training session. Player positions were assigned by the coach at the beginning of the season into one of 3 major categories: Forward (FWD), Midfielder (MID), Defender (DEF). Goalkeepers were excluded from the analysis due to the major positional differences in match demands. The GPS variables examined were as follows: Total Distance (TD), High Speed Running Distance – distance covered above $5.5 \text{ m}\cdot\text{sec}^{-1}$ and below $7.0 \text{ m}\cdot\text{sec}^{-1}$ (HSR), Sprint Distance – distance covered above $7.0 \text{ m}\cdot\text{sec}^{-1}$, High-Intensity IMA Decelerations (IMA-D) and High-Intensity IMA Accelerations (IMD-A). IMAs are proprietary to Catapult software and are derived using a combination of accelerometer and gyroscope data in order to determine the magnitude and direction of a movement.

Jump Testing Data. Lab testing data was collected from the ETSU Sport Science Research Repository. Lab data included data collected from two different types of jump tests – Static Jumps (SJ) and Countermovement Jumps (CMJ). All jumps were performed on dual force platforms sampling at 1000 Hz (91.0 cm × 91.0 cm; Rice Lake Weighing Systems, Rice Lake, WI, USA). The tests were done in loaded and unloaded conditions. The unloaded condition consisted of the athletes jumping with a PVC pipe on their back with the loaded condition consisting of athletes jumping with a 20 kg barbell on their back. Each athlete who was included performed at least one instance of every jump condition (SJ-0, SJ-20, CMJ-0, CMJ-20). Players performed a standardized warm up before the start of testing that included 25 jumping jacks, 1 x 5 repetitions @ 20 kg and 3 x 5 repetitions @ 60 kg of a mid-thigh pull (MTP). SJ included 1 warm up repetition at 50% and 75% self-perceived effort for the SJ-0 and 1 warm up repetition at 75% self-perceived effort for the SJ-20 condition. CMJ warm-up included one repetition of CMJ-0 at 75% self-perceived effort. During SJ testing, the athletes were instructed to stand still on the force platforms and maintain a squat position with the load on their back at a knee angle of 90° measured via goniometer. Athletes jumped from the bottom position on the command of “3-2-1, Jump!” given by the tester. A minimum of two trials were performed for each condition, with additional trials taking place if the difference in jump height exceeded 2.0 cm. The average values of the two best jumps, determined by jump height, were taken and used in the final analysis. The variables derived from the jumps that were used in the analysis included jump height (JH; cm), peak power (PP; W), and net impulse (NI; N•s). Thomas et al. (2021) previously examined the differences in CMJ variables between male and female soccer players, using JH, PP, and Relative Propulsion Impulse. Petridis et al. (2019) provided normative data in CMJ and SJ performance for 3 different age groups of youth soccer players from U16 to U18 in an elite

Hungarian league using maximum and relative values for JH, NI, and PP. The variables derived from the jumps that were used in the analysis included jump height (cm), peak power (W), and net impulse (NI). The reliability of these metrics at specific epochs of 200 msec have been examined and validated in previous research (Merrigan et al., 2020; Haff et al., 2015). Raw data was analyzed using a custom Labview software (National instruments, Austin, Tx) using a 4th order Butterworth low pass filter. JH, PP, and NI were all automatically calculated by the software. The jump offset and zero were all determined by an assigned sports scientist.

Isometric Mid-Thigh Pull. Isometric Mid-Thigh Pull (IMTP) testing was performed after Jump Testing on dual force plates (91.0 cm × 91.0 cm; Rice Lake Weighing Systems, Rice Lake, WI, USA; 1000Hz sampling rate). Athletes were strapped into a custom-built rack that included a fixed steel bar with an adjustable height. Each athlete was instructed to grab onto the bar and flex their ankle, knee, and hip joints until a knee angle measured via goniometer of $125 \pm 5^\circ$ was achieved. The IMTP warm up consisted of two submaximal trials at 50% and 75% of perceived maximal effort. Once the athletes were strapped I, they were instructed to pull upward as fast and as hard as possible on the command of “3-2-1, Pull!” A minimum of two trials were used for assessment, with additional trials being performed if there was a difference greater than 200N between trials, or if there was a countermovement greater than 200N at the start of the test. The average values of the two best trials, determined by isometric peak force, were taken and used in the final analysis. IMTP variables assessed for the IMTP were Isometric Peak Force (IPF), RFD @ 200 msec (RFD200) and Impulse @ 200 msec (IMP200). Raw data was analyzed using a custom Labview software (National instruments, Austin, Tx) using a 4th order Butterworth low pass filter. PF was determined by the highest point in the Force-Time curve. RFD was calculated using a 0-200 msec window. Impulse was calculated using a 0-200 msec

window, using the summation of area under the curve. The start of the pull was manually calculated by an assigned sports scientist. RFD, and IMP with no time epochs have previously been examined in competitive weightlifters to examine changes in performance in relation to training load across a competition calendar (Hornsby et al., 2017). The reliability of these metrics at different time epochs was investigated by Merrigan et al. (2020). In this study, the authors tested the reliability of CMJ and IMTP metrics derived from force platforms, finding that absolute impulse and instantaneous force readings had a high degree of reliability, but reliability did not meet acceptable standards in all RFD metrics examined. However, Haff et al. (2015) showed more reliable ICC in RFD windows at higher epochs, specifically in RFD200 and RFD 250.

20 m Sprint Test. A 20 m sprint test was used to evaluate the athletes' anaerobic capabilities. Times were calculated using timing gates (Witty, Microgate, Bolzano, Italy) at 0-10- and 20m intervals. Athletes performed a maximum of two trials from a static start, with the start line 30cm behind the first timing gate so the laser would not be set off by the athlete's knee (Bellon et al. 2019). The height of the first gate was placed about 75cm off the ground in order to avoid being set off by the athlete's knee. The rest of the timing gates were placed approximately 1.0 meter off the ground in order to be close to the height of the athletes' hips. Distances were measured using a tape measure by a certified strength and conditioning coach. All trials were conducted on a soccer field in soccer shoes. The average time of the two trials was computed and used in the analysis. ICCs were calculated for the data utilized in the study (ICC = 0.95).

Yo-Yo Intermittent Recovery Test Level I. A Yo-Yo Intermittent Recovery Test- Level 1 (YYIRT-1) was performed to assess the athletes' soccer-related fitness performance. The YYIRT-1 consists of 20m shuttle runs that increase speed incrementally, along with a 10m recovery run.

The starting speed of the test is $10 \text{ km}\cdot\text{h}^{-1}$. Beeps at different time intervals dictate the average running velocity. Players were given one warning if they failed to reach the start line before the second beep in the repetition. The total distance covered during the YYIRT-1 was used in the analysis. Distances were measured using a tape measure by a certified strength and conditioning coach. All trials were conducted on a soccer field in soccer shoes. ICC was not calculated for this particular set of data but previous examinations of the YYIRT-L1 have shown it to be a reliable test with reported ICCs between 0.87–0.95 for youth players U15, U17, and U19 (Deprez et al. 2015) and ICCs ranging from 78-90% for different populations, with the majority of the ICCs higher than 90% specifically for the YYIRT-L1 (Grgic et al. 2019).

Statistical Analysis

Data is presented as mean \pm standard deviation, The data were analyzed in two different ways. In the first analysis, a Repeated Measures Analysis of Variance (RM ANOVA) was used to determine if there were any statistically significant differences between testing timepoints. The size of the effect was determined using Hedges' g values for effect size. Effect sizes were interpreted in accordance to Cohen (1998): $< 0.2 =$ trivial, $0.2 - 0.5 =$ small, $0.5 - 0.8 =$ medium, $> 0.8 =$ large. In cases where there were there was violation of the statistical assumption of normality of residuals, the results were bootstrapped and the subsequent confidence intervals were reported. No measures of effect size could be computed for bootstrapped results. To measure the effect of training load on performance testing changes, a series of linear models were developed to determine the size, direction, and statistical significance of each relationship. For this analysis, the total training load was calculated by dividing the physical outputs by the total time for each session (training or game) in which the player was involved. The ratios for each event the player participated in were then added up for the season, giving a cumulative load

that was scaled by participation level. The cumulative load of 5 GPS-derived variables were used in the final analysis. A General Linear Model was used in order to examine the relationship between these cumulative load scores and the various physical performance variables that were derived from the lab tests. The percentage change for each variable from pre-test to post-test was used as the dependent variable in the model while the GPS variables were designated as the independent variables either as main effects or interaction effects. The 95% confidence interval was provided along with the subsequent p-value for each relationship, Significance was set at $p < .05$.

Results

Weekly Load

The average weekly GPS load is in the table below:

Table 22

Average Cumulative GPS Load

| | TD | HSR | SPR | IMA-A | IMA-D |
|---------------------|-------------|------------|-----------|-------|-------|
| Average Season Load | 352,088 (m) | 12,384 (m) | 3,195 (m) | 362 | 247 |
| Average Weekly Load | 27,033 (m) | 951 (m) | 240 (m) | 28 | 19 |

ANOVA Analysis

Due to violations of the assumption of normality of residuals, a permutation ANOVA was performed and the posthoc tests were bootstrapped. The results for the bootstrapping are in Table 3.

Table 23*ANOVA Results for Jump Tests*

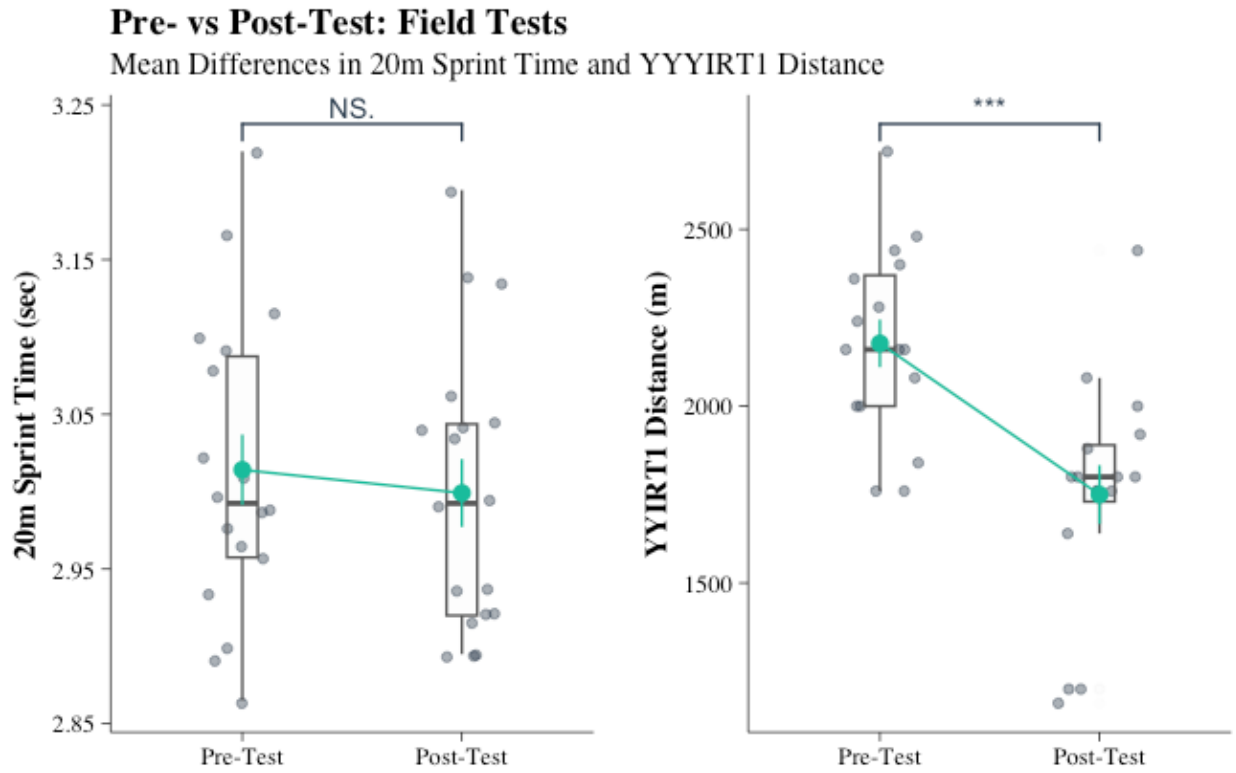
| Dependent Variable | Independent Variables | Original | Boot Bias | Estimate 95% CI |
|---------------------|--|----------|-----------|-----------------|
| CMJ-0: Jump Height | Interaction of Time, Jump Type, and Bar Weight | 1.121 | 0.002 | [-0.247, 2.645] |
| CMJ-20: Jump Height | Interaction of Time, Jump Type, and Bar Weight | 0.603 | 0.003 | [-0.616, 1.837] |
| SJ-0: Jump Height | Interaction of Time, Jump Type, and Bar Weight | 0.850 | 0.008 | [-0.067, 2.062] |
| SJ-20: Jump Height | Interaction of Time, Jump Type, and Bar Weight | 0.453 | 0.006 | [-0.285, 1.235] |
| CMJ-0: Peak Power | Interaction of Time, Jump Type, and Bar Weight | 1.121 | 0.003 | [-0.076, 2.024] |
| CMJ-20: Peak Power | Interaction of Time, Jump Type, and Bar Weight | .603 | 0.007 | [-0.615, 1.850] |
| SJ-0: Peak Power | Interaction of Time, Jump Type, and Bar Weight | 0.850 | 0.003 | [-0.076, 2.023] |
| SJ-20: Peak Power | Interaction of Time, Jump Type, and Bar Weight | 00.603 | 0.007* | [0.303, 1.241] |
| CMJ-0: Net Impulse | Interaction of Time, Jump Type, and Bar Weight | 1.121 | 0.009 | [-0.241, 2.038] |

| | | | | |
|---------------------|--|-------|-------|-----------------|
| CMJ-20: Net Impulse | Interaction of Time, Jump Type, and Bar Weight | 0.615 | 0.006 | [-0.626, 1.869] |
| SJ-0: Net Impulse | Interaction of Time, Jump Type, and Bar Weight | 0.850 | 0.009 | [-0.088, 2.038] |
| SJ-20: Net Impulse | Interaction of Time, Jump Type, and Bar Weight | 0.453 | 0.004 | [-0.276, 1.265] |

After bootstrapping the post hoc tests, the only mean difference that reached statistical significance was the mean difference in PP in SJ-20 (Original: 0.603; Boot Bias: 0.007*; 95% CI [0.303 -- 1.241]). The 95% confidence interval for all other bootstrapped post hoc tests crossed 0, therefore we can infer that they are not statistically significant differences. Of the examined IMTP variables examined, there were no statistically significant differences between testing timepoints for any of variables that were chosen for analysis. The analysis for PF yielded a non-significant p-value ($p = .563$). Additionally, there were no statistically significant differences found between testing timepoints for RFD200 ($p = .253$) or for IMP200 ($p = .645$, respectively). The 20m sprint test also yielded no statistically significant changes between testing timepoints ($p = 0.209$). The only ANOVA that yielded statistically significant changes was the YYIRT-1. A statistically significant p-value for the difference between testing timepoints was observed and the Cohen's d effect size was calculated ($p = .0001^*$, $d = 1.318$ [.618 – 1.995], large). The size and direction of the Cohen's d value suggests that there was a large decrease in YYIRT-1 distance covered from pre-testing values to post-testing values (Table 2).

Figure 1

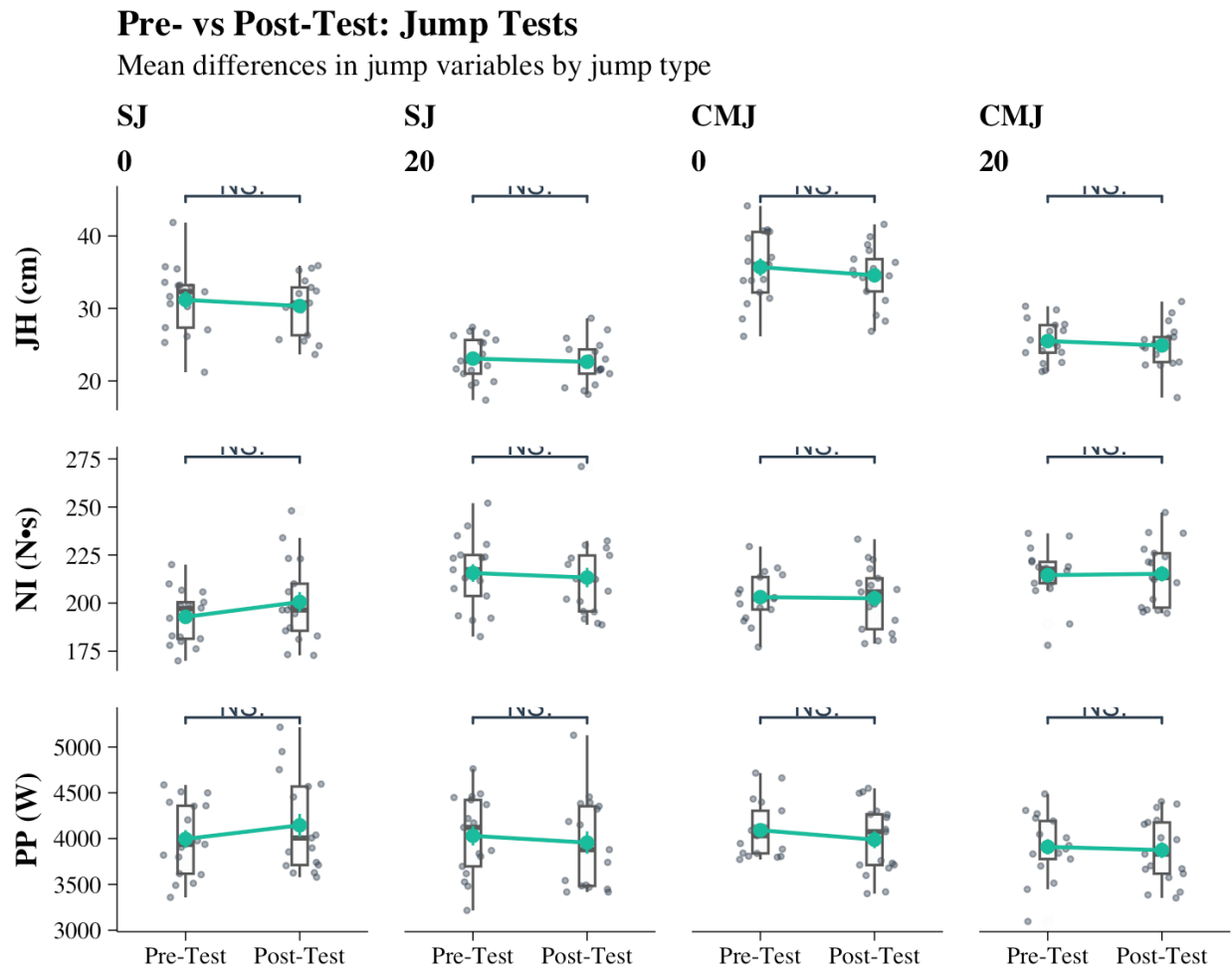
Mean Differences in YYIRT-L1 Distance



Points represent individual tests for that group.
Green points represent the group mean

Figure 2

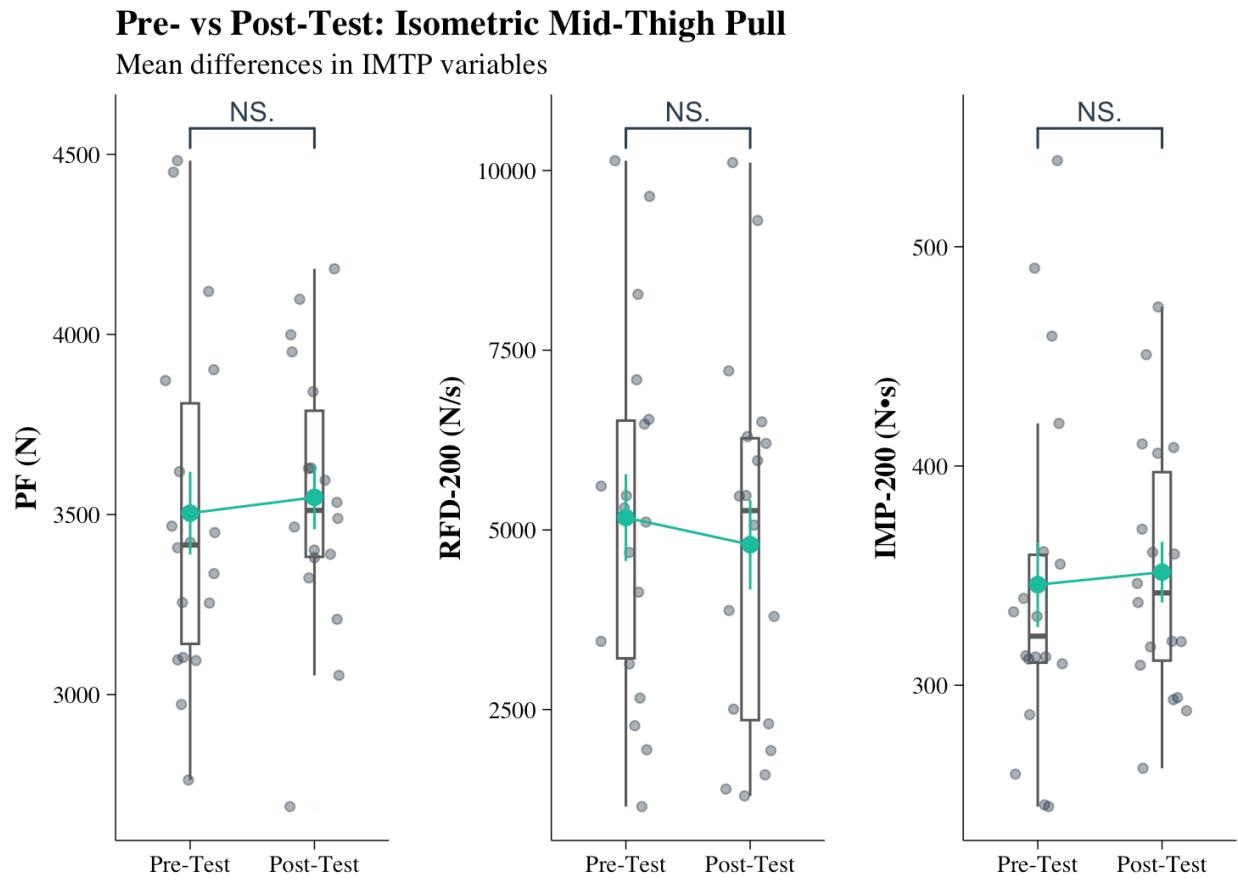
Mean Differences in Jump Variables per Condition



Points represent individual tests for that group.
Green points represent the group mean

Figure 3

Mean Differences in IMTP Variables



Points represent individual tests for that group.
Green points represent the group mean

Table 24*ANOVA Results for IMTP, Yo-Yo IR 1, and 20 m Sprints*

| Independent Variable | Dependent Variable | Timepoint | Estimated | Hedges g | Hedges | P-VALUE |
|----------------------|----------------------|-----------|---------------|-------------|---------------|--------------------|
| | | | Marginal Mean | Effect Size | g | |
| IMTP | Isometric Peak | Pre-Test | 3504 | -0.10 | [-0.74, 0.54] | <i>p</i> = 0.563 |
| | Force (N) | Post-Test | 3548 | | | |
| IMTP | RFD @ | Pre-Test | 5171 | 0.14 | [-0.50, 0.78] | <i>p</i> = 0.253 |
| | 200ms (N/sec) | Post-Test | 4795 | | | |
| IMTP | Impulse @ | Pre-Test | 346 | -0.08 | [-0.72, 0.56] | <i>p</i> = 0.645 |
| | 200ms (N*sec) | Post-Test | 352 | | | |
| YYIRT-1 | Yo-Yo | Pre-Test | 2178 | 1.37 † | [.62, 2.12] | <i>p</i> = 0.0001* |
| | Distance Covered (m) | Post-Test | 1750 | | | |
| 20m Sprint | Time (sec) | Pre-Test | 3.01 | 0.15 | [-.49, 0.79] | <i>p</i> = 0.209 |
| | | Post-Test | 3.00 | | | |

Note: † Represents a statistically significant large effect

Linear Models

The 95% CIs for effect sizes and the subsequent p-values for each of the linear models are in the Table 5.

Table 25

Linear Models: Percent Change ~ GPS Training Load

| Performance Test | Dependent Variable | Independent Variable | Relative Importance (Normalized lmg) | Standardized Coefficient | Standardized Coefficients 95% CI | p-value |
|--------------------------|--------------------|-----------------------------|--------------------------------------|--------------------------|----------------------------------|-------------|
| 20m Sprint | % Change | Ratio HSR | 0.374 | 0.98 | [-0.09, 2.06] | $p = 0.066$ |
| | | Ratio SPR | 0.377 | -0.84 | [-1.90, 0.22] | $p = 0.129$ |
| | | Interaction HSR * SPR | 0.248 | -0.36 | [-1.10, 0.37] | $p = 0.308$ |
| YYIRT-1 | % Change YYIRT-1 | Ratio HSR | 0.667 | 0.45 | [-0.27, 1.17] | $p = 0.059$ |
| | | Ratio IMA Decel | 0.103 | -0.19 | [-0.82, 0.44] | $p = 0.603$ |
| | | Interaction HSR * IMA Decel | 0.230 | 0.56 | [-0.27, 1.39] | $p = 0.166$ |
| Isometric Mid-Thigh Pull | % Change ISO PF | Ratio Total Distance | 0.316 | -0.12 | [-2.53, 2.29] | $p = 0.915$ |
| | | Ratio HSR | 0.332 | 0.33 | [-1.87, 2.53] | $p = 0.750$ |

| | | | | | | |
|-----------|--------------|-------------|-------|-------|---------------|-------|
| | | Ratio IMA | 0.352 | 0.21 | [-0.58, 1.00] | $p =$ |
| | | Decel | | | | 0.571 |
| | | Ratio Total | 0.342 | 0.36 | [-1.88, 2.61] | $p =$ |
| | | Distance | | | | 0.731 |
| Isometric | % Change | | | | | |
| Mid-Thigh | ISO RFD | Ratio HSR | 0.393 | 0.28 | [-1.76, 2.33] | $p =$ |
| | | | | | | 0.769 |
| | Pull @ 200ms | Ratio IMA | 0.264 | -0.43 | [-1.16, 0.30] | $p =$ |
| | | Decel | | | | 0.227 |
| | | Ratio Total | 0.435 | -1.06 | [-3.56, 1.44] | $p =$ |
| | % Change | Distance | | | | 0.375 |
| Isometric | | | | | | |
| | ISO | Ratio HSR | 0.528 | 1.04 | [-1.25, 3.32] | $p =$ |
| Mid-Thigh | | | | | | 0.344 |
| | Impulse @ | Ratio IMA | 0.036 | 0.10 | [-0.72, 0.91] | $p =$ |
| | | Decel | | | | 0.801 |
| | 200ms | Ratio Total | 0.406 | 1.07 | [-1.11, 3.25] | $p =$ |
| | | Distance | | | | 0.306 |
| | % Change | | | | | |
| | Peak | Ratio HSR | 0.383 | -1.25 | [-3.37, 0.86] | $p =$ |
| | | | | | | 0.221 |
| | Power | Ratio IMA | 0.211 | 0.21 | [-0.42, 0.84] | $p =$ |
| | | Decel | | | | 0.485 |
| | | Ratio Total | 0.272 | 1.46 | [-0.63, 3.54] | $p =$ |
| SJ-0 | | Distance | | | | 0.155 |

| | | | | | | |
|-------|----------|-------------|-------|-------|---------------|----------------|
| | % Change | Ratio HSR | 0.308 | -1.60 | [-3.51, 0.31] | $p =$ 0.094 |
| | Net | Ratio IMA | | | | $p =$ |
| | Impulse | Decel | 0.419 | 0.37 | [-0.32, 1.05] | 0.266 |
| | | Ratio Total | | | | $p =$ |
| | % Change | Distance | 0.418 | 1.52 | [-0.36, 3.40] | 0.102 |
| SJ-0 | Jump | Ratio HSR | 0.247 | -1.14 | [-2.86, 0.57] | $p =$ 0.173 |
| | Height | Ratio IMA | | | | $p =$ |
| | | Decel | 0.335 | 0.24 | [-0.38, 0.85] | 0.419 |
| | | Ratio Total | | | | $p =$ |
| | % Change | Distance | 0.374 | 0.80 | [-1.63, 3.24] | 0.485 |
| SJ-20 | Peak | Ratio HSR | 0.224 | -0.64 | [-2.86, 1.59] | $p =$ 0.543 |
| | Power | Ratio IMA | | | | $p =$ |
| | | Decel | 0.402 | 0.18 | [-0.62, 0.98] | 0.630 |
| | | Ratio Total | | | | $p =$ |
| | % Change | Distance | 0.464 | 1.39 | [-0.87, 3.65] | 0.205 |
| SJ-20 | Net | Ratio HSR | 0.276 | -1.09 | [-3.15, 0.98] | $p =$ 0.275 |
| | Impulse | Ratio IMA | | | | $p =$ |
| | | Decel | 0.260 | 0.10 | [-0.65, 0.84] | 0.781 |

| | | | | | | |
|-------|----------|-------------|-------|-------|----------------|---------|
| | | Ratio Total | | | | $p =$ |
| | | Distance | 0.356 | -0.18 | [-2.25, 1.88] | 0.850 |
| | % Change | | | | | |
| | | Ratio HSR | | | | $p =$ |
| SJ-20 | Jump | Ratio HSR | 0.400 | 0.64 | [-1.25, 2.53] | 0.475 |
| | Height | | | | | |
| | | Ratio IMA | | | | $p =$ |
| | | Decel | 0.244 | 0.25 | [-0.43, 0.93] | 0.439 |
| | | Ratio Total | | | | $p =$ |
| | | Distance | 0.408 | 2.15 | [0.88, 3.42] | 0.003** |
| | % Change | | | | | |
| | | Ratio HSR | | | | $p =$ |
| CMJ-0 | Net | Ratio HSR | 0.251 | -1.78 | [-2.94, -0.62] | 0.006** |
| | Impulse | | | | | |
| | | Ratio IMA | | | | $p =$ |
| | | Decel | 0.341 | 0.30 | [-0.11, 0.72] | 0.137 |
| | | Ratio Total | | | | $p =$ |
| | | Distance | 0.244 | 1.15 | [-0.24, 2.53] | 0.096 |
| | % Change | | | | | |
| | | Ratio HSR | | | | $p =$ |
| CMJ-0 | Peak | Ratio HSR | 0.154 | -1.08 | [-2.35, 0.18] | 0.087 |
| | Power | | | | | |
| | | Ratio IMA | | | | $p =$ |
| | | Decel | 0.602 | 0.66 | [0.21, 1.12] | 0.008** |
| | | Ratio Total | | | | $p =$ |
| | % Change | Distance | 0.336 | 0.80 | [-1.03, 2.63] | 0.360 |
| | Jump | | | | | |
| | Height | Ratio HSR | 0.219 | -0.46 | [-2.13, 1.22] | 0.562 |

| | | | | | | |
|--------|----------|-------------|-------|-------|---------------|-------|
| | | Ratio IMA | 0.446 | 0.41 | [-0.19, 1.01] | $p =$ |
| | | Decel | | | | 0.166 |
| | | Ratio Total | 0.312 | 0.89 | [-1.20, 2.98] | $p =$ |
| | % Change | Distance | | | | 0.373 |
| CMJ-20 | Net | Ratio HSR | 0.188 | -0.69 | [-2.60, 1.22] | $p =$ |
| | | | | | | 0.447 |
| | Impulse | Ratio IMA | 0.500 | 0.38 | [-0.30, 1.07] | $p =$ |
| | | Decel | | | | 0.248 |
| | | Ratio Total | 0.143 | 0.17 | [-1.96, 2.30] | $p =$ |
| | % Change | Distance | | | | 0.863 |
| CMJ-20 | Peak | Ratio HSR | 0.088 | -0.27 | [-2.22, 1.68] | $p =$ |
| | | | | | | 0.769 |
| | Power | Ratio IMA | 0.769 | 0.62 | [-0.08, 1.32] | $p =$ |
| | | Decel | | | | 0.076 |
| | | Ratio Total | 0.391 | 0.04 | [-2.12, 2.19] | $p =$ |
| | % Change | Distance | | | | 0.969 |
| CMJ-20 | Jump | Ratio HSR | 0.412 | 0.45 | [-1.52, 2.42] | $p =$ |
| | | | | | | 0.629 |
| | Height | Ratio IMA | 0.198 | 0.15 | [-0.56, 0.86] | $p =$ |
| | | Decel | | | | 0.647 |

The variables that showed statistically significant relationships with the ratio of GPS variables were CMJ-0 NI with TD ($p = 0.003$) and HSR ($p = 0.006$); CMJ0-PP and IMA-D ($p =$

008). All other relationships did not reach statistical significance at an alpha level of .05 (Table 5).

Discussion

The results of the RM ANOVA suggest that there were no significant performance changes in any of the tests administered, except for the YYIRT-1 and PP in the SJ-20. The lack of changes in the strength, power and speed tests, corroborated by *trivial* effect sizes, could be indicative of the effectiveness of the training program that took place during the season. Without access to the prescribed training program, it is impossible to say if there was an effect of strength training in maintaining strength levels across the competitive season. As for the YYIRT-1 results, this could be explained by a lack of soccer-specific fitness maintained over the course of the season. Mohr & Krustup (2014) examined seasonal changes in YYIRT-1 and YYIRT-2 values across a season in semi-professional soccer players and found that positive changes were present in the mid-season testing values, but followed by decreases in the end-of-season values. A consideration for these results is how much carry over “specific” training has to fitness-related tasks or tests. Although Bangsbo et al. (2008) showed a high degree of agreement between YYIRT scores and match-related fitness outcomes, it is important to consider the differences between tasks. For example, Thomakos et al. (2023) compared the effects of a preseason program that was focused on soccer-ball related fitness vs H.I.I.T. protocols on the results of a YYIRT-L1 test in elite U19 soccer players. Although both groups showed improvements after 4 weeks, the degree of improvement in the YYIRT-L1 was statistically significantly greater for the group that did not use the ball in their fitness protocols. Similar to the findings of the previous study, work done by Howard & Stavrianeas (2017) found that High School aged boys improved fitness when they took part to a training program that included High-Intensity Interval Training

(HIIT). Elloumi et al. (2012) examined the relationship between total training load and changes in performance testing after a high-intensity training period of 6 weeks. The authors showed decreases in all performance testing results that were correlated with the training load accumulated over that time.

Another interesting finding of this study is that measures of physical performance that were derived from the tests did not realize statistically significant changes, notably, no statistically significant decreases were found in the groups. One explanation for this lack of change could be the strength training program. Suchomel et al. (2018) highlight the need for in season training in order to maintain the physical qualities that are important for sports performance (RFD, impulse, strength, etc.). The lack of changes in the measures of physical strength could speak to a properly structured strength training intervention across the season. The importance of maintaining fitness characteristics while minimizing fatigue during a Competition Phase has been highlighted by DeWeese et al. (2015), therefore a lack of changes in performance testing could speak to a properly structured training. Although the only statistically significant change from pre-testing to post-testing was a *large* ($ES = 1.37$) decrease in YYIRT-L1 distance covered, these results appear to be in direct contradiction with Haugen (2018) who performed a long-term study examining performance changes in soccer players across a multitude of tests. Haugen observed a statistically significant increase in most performance measures over the course of a year of observation in a population of professional Norwegian soccer players (Haugen, 2018), but it is important to note that the period of adaptations for this population of NCAA D-I athletes was much shorter. Interestingly, the lack of increases in CMJ performance measures are in concert with what was published by Jaspers et al. (2017). Jaspers et al. (2017) reviewed the literature that examined the relationship between CMJ testing performance and

indicators of soccer match volume over the course of a competitive season. Various populations of soccer players were included in the review and the authors came to the conclusion that in most populations, markers of cardiovascular performance had a tendency to increase from pre-test to post-test. Perhaps the results are conflicting due to the characteristics of populations sampled in each individual study and the limitations associated with each population.

The relationships between the magnitude of change and the training load accumulated also showed limited statistically significant relationships based on the relationships examined. The most substantial relationships were found between CMJ-0 NI and the ratio of TD and Ratio of HSR as well as CMJ-0 PP and the Ratio of IMA-D. Although most of the linear models assessed did not achieve statistical significance, the relative importance and standardized coefficients are indicative of relationships that could be of importance in the dependent variables being assessed. Of note, the change in YYIRT-L1 scores and the ratio of HSR performed over a course of a season did not achieve statistical significance, but the standardized coefficients suggest a moderate relationship between the amount of HSR and IMA-D performed with the percentage of change seen in the YYIRT-L1. Poulson (2017) found similar relationships between IMA-Decelerations at different magnitudes and decreases in CMJ performance in soccer players, indicating a relationship between deceleration and fatigue. The relationships between the GPS variables examined and CMJ performance could be an indication of changes in force production capabilities across a competitive season. The results, however, are contrasting when examining the effect of TD and HSR on CMJ-0 NI. TD was associated with an increase in CMJ-0 NI while HSR was associated with a decrease in CMJ-0 NI. This could potentially be explained by the differences in match demand by position. Wide players tend to see elevated HSR distances compared to central positions, making it likely that the accumulation of distances

at these velocities are associated with negative changes in CMJ-0 NI performance, as previously discussed in Chapter III.

This study is not without its limitations. For one, the paucity of the data collected made it hard to build statistical models that would be free of any statistical violations, thus a lot of the models built had to be reconstructed with more data. It is also important to note that the study design was retrospective and thus the data collection was not a controlled aspect of this study. Data cleaning issues such as missing values and small sample sizes definitely contributed to the final analysis and influenced the results. From a statistical perspective, the relatively small sample sizes and data exclusions resulted in some violations of key statistical assumptions, which could have influenced the final results. Future investigations should provide larger sample sizes in order to draw better conclusions from the resulting data. Another limitation of the study is the lack of information regarding the training program. Because of the nature of the analysis, no information on the training plan was provided, where it seems that the training program could have had an effect on the results. Future investigations should account for volume load of any strength training programs that take place during the time period examined and any other modalities used as part of the training program.

Practical Applications

One of the practical applications that can be taken from this study is the importance of providing adequate stimulus to maintain aerobic fitness throughout the competitive season. Sharp decreases in aerobic fitness over the season could be explained by a few different factors. Aerobic fitness specific to the YYIRT-L1 could have decreased due to a lack of specific conditioning carried out over the course of the season, therefore an additional adequate aerobic

stimulus may be appropriate in this population in order to maintain soccer-specific fitness over the course of a season.

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References

1. Bellon, C. R., DeWeese, B. H., Sato, K., Clark, K. P., & Stone, M. H. (2019). Defining the early, mid, and late subsections of sprint acceleration in Division I men's soccer players. *J Strength Cond Res*, 33(4), 1001-1006. <https://doi.org/10.1519/JSC.0000000000003088>
2. Clark, N. A., Edwards, A.M., Morton, R.H., Butterly, R. J. (2008). Season-to-season variations of physiological fitness within a squad of professional male soccer players. *Journal of Sports Science and Medicine*, 07, 157-165.
3. Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences* (2nd ed.). Routledge. <https://doi.org/10.4324/9780203771587>
4. Curtis, R. M., Huggins, R. A., Benjamin, C. L., Sekiguchi, Y., Adams, W. M., Arent, S. M., Jain, R., Miller, S. J., Walker, A. J., & Casa, D. J. (2020). Contextual factors influencing external and internal training loads in collegiate men's soccer. *J Strength Cond Res*, 34(2), 374-381. <https://doi.org/10.1519/JSC.0000000000003361>
5. Curtis, R. M., Huggins, R. A., Benjamin, C. L., Sekiguchi, Y., S, M. A., B, C. A., Pullara, J. M., West, C. A., & Casa, D. J. (2021). Seasonal accumulated workloads in collegiate men's soccer: A comparison of starters and reserves. *J Strength Cond Res*, 35(11), 3184-3189. <https://doi.org/10.1519/JSC.0000000000003257>
6. Curtis, R. M., Huggins, R. A., Looney, D. P., West, C. A., Fortunati, A., Fontaine, G. J., & Casa, D. J. (2018). Match demands of National Collegiate Athletic Association Division I men's soccer. *J Strength Cond Res*, 32(10), 2907-2917. <https://doi.org/10.1519/JSC.0000000000002719>

7. Deprez, D., Fransen, J., Lenoir, M., Philippaerts, R., & Vaeyens, R. (2015). The Yo-Yo intermittent recovery test level 1 is reliable in young high-level soccer players. *Biol Sport*, 32(1), 65-70. <https://doi.org/10.5604/20831862.1127284>
8. DeWeese, B. H., Hornsby, G., Stone, M., Stone, M.H. (2015). The training process: Planning for strength–power training in track and field. Part 1: Theoretical aspects. *Journal of Sport and Health Science*, 4(4), 308-317. <https://doi.org/https://doi.org/10.1016/j.jshs.2015.07.003>
9. Diez, A., Lozano, D., Arjol-Serrano, J. L., Mainer-Pardos, E., Castillo, D., Torrontegui-Duarte, M., Nobari, H., Jaen-Carrillo, D., & Lampre, M. (2021). Influence of contextual factors on physical demands and technical-tactical actions regarding playing position in professional soccer players. *BMC Sports Sci Med Rehabil*, 13(1), 157. <https://doi.org/10.1186/s13102-021-00386-x>
10. Elloumi, M., Makni, E., Moalla, W., Bouaziz, T., Tabka, Z., Lac, G., & Chamari, K. (2012). Monitoring training load and fatigue in rugby sevens players. *Asian J Sports Med*, 3(3), 175-184. <https://doi.org/10.5812/asjasm.34688>
11. Gabbett, T. J. (2016). The training-injury prevention paradox: should athletes be training smarter and harder? *Br J Sports Med*, 50(5), 273-280. <https://doi.org/10.1136/bjsports-2015-095788>
12. Guerrero-Calderon, B., Klemp, M., Castillo-Rodriguez, A., Morcillo, J. A., & Memmert, D. (2021). A new approach for training-load quantification in elite-level soccer: Contextual factors. *Int J Sports Med*, 42(8), 716-723. <https://doi.org/10.1055/a-1289-9059>
13. Grgic, J., Oppici, L., Mikulic, P., Bangsbo, J., Krstrup, P., & Pedisic, Z. (2019). Test–Retest Reliability of the Yo-Yo Test: A Systematic Review. *Sports Medicine*, 49(10), 1547-1557. <https://doi.org/10.1007/s40279-019-01143-4>

14. Haff, G. G., Ruben, R. P., Lider, J., Twine, C., & Cormie, P. (2015). A comparison of methods for determining the rate of force development during isometric midhigh clean pulls. *J Strength Cond Res*, 29(2), 386-395. <https://doi.org/10.1519/JSC.0000000000000705>
15. Haugen, T. A. (2018). Soccer seasonal variations in sprint mechanical properties and vertical jump performance. *Kinesiology*, 50(1).
16. Hopkins, W. G. (2002). *A New View of Statistics*. Retrieved Accessed May 13 from <http://www.sportsci.org/resource/stats/effectmag.html>
17. Hornsby, W. G., Gentles, J. A., MacDonald, C. J., Mizuguchi, S., Ramsey, M. W., & Stone, M. H. (2017). Maximum strength, Rate of force development, jump height, and peak power alterations in weightlifters across five months of training. *Sports (Basel)*, 5(4). <https://doi.org/10.3390/sports5040078>
18. Howard, N., & Stavrianeas, S. (2017). In-season high-intensity interval training improves conditioning In high school soccer players. *Int J Exerc Sci*, 10(5), 713-720. <https://www.ncbi.nlm.nih.gov/pubmed/28966710>
19. Jaspers, A., Brink, M. S., Probst, S. G., Frencken, W. G., & Helsen, W. F. (2017). Relationships Between Training Load Indicators and Training Outcomes in Professional Soccer. *Sports Med*, 47(3), 533-544. <https://doi.org/10.1007/s40279-016-0591-0>
20. Jiang, Z., Hao, Y., Jin, N., & Li, Y. (2022). A systematic review of the relationship between workload and injury risk of professional male soccer players. *Int J Environ Res Public Health*, 19(20). <https://doi.org/10.3390/ijerph192013237>
21. McFadden, B. A., Walker, A. J., Arent, M. A., Bozzini, B. N., Sanders, D. J., Cintineo, H. P., Bello, M. L., & Arent, S. M. (2020). Biomarkers correlate with body composition and

- performance changes throughout the season in women's Division I collegiate soccer players. *Front Sports Act Living*, 2, 74. <https://doi.org/10.3389/fspor.2020.00074>
22. Merrigan, J. J., Stone, J. D., Hornsby, W. G., & Hagen, J. A. (2020). Identifying reliable and reliable force-time metrics in athletes—considerations for the isometric mid-thigh pull and countermovement jump. *Sports (Basel)*, 9(1). <https://doi.org/10.3390/sports9010004>
23. Mohr, M., & Krustup, P. (2014). Yo-Yo intermittent recovery test performances within an entire football league during a full season. *J Sports Sci*, 32(4), 315-327. <https://doi.org/10.1080/02640414.2013.824598>
24. Newans, T., Bellinger, P., Drovandi, C., Buxton, S., & Minahan, C. (2022). The utility of Mixed Models in sport science: A call for further adoption in longitudinal data sets. *Int J Sports Physiol Perform*, 17(8), 1289-1295. <https://doi.org/10.1123/ijsp.2021-0496>
25. Plisk, S. S., Stone, M.H. (2020). Periodization strategies. *Strength & Conditioning Journal*, 25(6), 19-37. [https://doi.org/https://doi.org/10.1519/00126548-200312000-00005](https://doi.org/10.1519/00126548-200312000-00005).
26. Poulson, J. (2017). Impact of match performance on countermovement jumps when analysing post-match recovery status in elite soccer players. In S. M. s. University (Ed.). Twickenham.
27. Schmitz, B., Pfeifer, C., Kreitz, K., Borowski, M., Faldum, A., & Brand, S.-M. (2018). The Yo-Yo Intermittent Tests: A Systematic Review and Structured Compendium of Test Results [Systematic Review]. *Frontiers in Physiology*, 9. <https://doi.org/10.3389/fphys.2018.00870>
28. Siegler, J., Robergs, R., & Weingart, H. (2006). The application of soccer performance testing protocols to the non-elite player. *J Sports Med Phys Fitness*, 46(1), 44-51. <https://www.ncbi.nlm.nih.gov/pubmed/16596098>

29. Silva, J. R. (2022). The soccer season: performance variations and evolutionary trends. *PeerJ*, *10*, e14082. <https://doi.org/10.7717/peerj.14082>
30. Silva, J. R., Magalhaes, J. F., Ascensao, A. A., Oliveira, E. M., Seabra, A. F., & Rebelo, A. N. (2011). Individual match playing time during the season affects fitness-related parameters of male professional soccer players. *J Strength Cond Res*, *25*(10), 2729-2739. <https://doi.org/10.1519/JSC.0b013e31820da078>
31. Silva, J. R., Rebelo, A., Marques, F., Pereira, L., Seabra, A., Ascensao, A., & Magalhaes, J. (2014). Biochemical impact of soccer: an analysis of hormonal, muscle damage, and redox markers during the season. *Appl Physiol Nutr Metab*, *39*(4), 432-438. <https://doi.org/10.1139/apnm-2013-0180>
32. Stone, M. H., Hornsby, W. G., Haff, G. G., Fry, A. C., Suarez, D. G., Liu, J., Gonzalez-Rave, J. M., & Pierce, K. C. (2021). Periodization and Block Periodization in sports: Emphasis on strength-power training-a provocative and challenging narrative. *J Strength Cond Res*, *35*(8), 2351-2371. <https://doi.org/10.1519/JSC.0000000000004050>
33. Taylor, J. M., Madden, J. L., Cunningham, L. P., Wright, M. (2022). Fitness testing in soccer revisited. *Strength & Conditioning Journal*, *44*(5). <https://doi.org/https://doi.org/10.1519/ssc.0000000000000702>.
34. Thomakos, P., Spyrou, K., Katsikas, C., Geladas, N. D., & Bogdanis, G. C. (2023). Effects of concurrent high-intensity and strength training on muscle power and aerobic performance in young soccer players during the pre-season. *Sports (Basel)*, *11*(3). <https://doi.org/10.3390/sports11030059>
35. Thomas, C., Dos'Santos, T., & Jones, P. A. (2017). A comparison of dynamic strength index between team-sport athletes. *Sports (Basel)*, *5*(3). <https://doi.org/10.3390/sports5030071>

36. Thomas, C., Jones, P. A., & Dos'Santos, T. (2022). Countermovement jump force-time curve analysis between strength-matched male and female soccer players. *Int J Environ Res Public Health*, 19(6). <https://doi.org/10.3390/ijerph19063352>

Chapter 6. Summary and Directions of Future Research

The purpose of this dissertation was to provide insights into the physical and technical demands placed on NCAA D-I male soccer players. Access to a range of varying data was used to investigate different facets related to the performance of this specific population of soccer athletes. The following individual research projects were conducted in an attempt to fulfill the purposes of this dissertation: 1) a retrospective analysis with five years of performance data to assess physical match demands and outputs in physical performance testing, 2) A new type of investigation involving video analysis software used to assess technical-tactical performance of soccer players and the relationships of those technical-tactical variables to physical performance, and 3) an investigation into the relationship of physical performance tests to the training load accumulated over a season.

The results of study one provided more in-depth normative data related to physical performance. Interestingly, the physical outputs of the FWD position were the highest in terms of match demand, which contradicts the bulk of the available research on elite soccer players. Another possible reason for the differences between the studied carried out here and the previous research done could be related to the system of play or the management of player rotations throughout a single match and an entire season. This paper adds to the scarce amount of research on match demands that exists for soccer players at this level of competition. Similarly, normative data was provided for tests related to physical capabilities, including tests of maximal force, explosive power, and aerobic endurance. These data were then related to the physical match performance data previously mentioned and their relationship to physical match performance was determined. Statistically significant relationships were found between field-testing variables and match outputs calculated using GPS, suggesting that these field tests are an important tool

that can be used to project performance in this population of athletes. Study 2 was novel in that an examination of this kind had not been performed in this population. The limited amount of data made it difficult to extrapolate the findings to a large population, but this study does provide new insights on the technical demands of soccer players in at this level of competition. The technical variables were then related to physical performance and physical capabilities, finding a few statistically significant relationships between these two kinds of variables. The first two studies differ from Study 3, as this study was focused on the relationships between training load and the decrements or improvements found between pre- and post-testing of physical capabilities. The lack of statistically significant decrements could be related to the effects of a strength training program carried out throughout the competitive season (or the relative level of the athlete), though this was not related to the primary aim of the study. Overall, the findings of study 3 suggest that training load can have an effect of end-of-season physical capabilities and these should be accounted for in the implementation of the training program during the competitive season. Additionally, due to the issues found in the data examined, the results of these three studies should be taken lightly in terms of broader applications. Having data that has more depth and is more consistently collected would improve these studies and make inferences about the broader population of NCAA D-I soccer players much more applicable.

This dissertation was successful in raising new questions about a scarcely studied segment of elite-level soccer, as well as in providing new data to add to the existing literature that examines match demands. Although new insights have been provided, further research needs to focus on multiple cohorts within the same population when examining both the physical demands and the technical-tactical demands of the players. Additionally, information relevant to the in-season training demands and the effect of these training/match demands on physical

capabilities appears to be novel in this specific population. Understanding the demands of training and competition across a season will help coaches and sports performance practitioners prepare the athletes for the demands of a competitive season.

References

- Abbott, W., Brickley, G., & Smeeton, N. J. (2018). Physical demands of playing position within English Premier League academy soccer. <https://doi.org/10.14198/jhse.2018.132.04>
- Abbott, W., & Clifford, T. (2022). The influence of muscle strength and aerobic fitness on functional recovery in professional soccer players. *J Sports Med Phys Fitness*, 62(12), 1623-1629. <https://doi.org/10.23736/S0022-4707.21.13401-2>
- Adam, D. (2022). Science and the World Cup: how big data is transforming football. *Nature*, 611(7936), 444-446. <https://doi.org/10.1038/d41586-022-03698-1>
- Akyildiz, Z., Clemente, F. M., Şentürk, D., Gürol, B., Yildiz, M., Ocak, Y., & Günay, M. (2022). Investigation of the convergent validity and reliability of unit position differences of Catapult S5 GPS units in field conditions. *Journal of Sports Engineering and Technology*. <https://doi.org/https://doi.org/10.1177/17543371221100592>
- Alexander, R. (2014). Physical and technical demands of women's collegiate soccer [East Tennessee State University]. Johnson City, TN.
- Anderson, T., Adams, W. M., Martin, K. J., & Wideman, L. (2021). Examining internal and external physical workloads between training and competitive matches within collegiate Division I men's soccer. *J Strength Cond Res*, 35(12), 3440-3447. <https://doi.org/10.1519/JSC.0000000000004149>
- Andersson, H., Raastad, T., Nilsson, J., Paulsen, G., Garthe, I., & Kadi, F. (2008). Neuromuscular fatigue and recovery in elite female soccer: effects of active recovery. *Med Sci Sports Exerc*, 40(2), 372-380. <https://doi.org/10.1249/mss.0b013e31815b8497>
- Arjol-Serrano, J. L., Lampre, M., Diez, A., Castillo, D., Sanz-Lopez, F., & Lozano, D. (2021). The Influence of Playing Formation on Physical Demands and Technical-Tactical Actions

- According to Playing Positions in an Elite Soccer Team. *Int J Environ Res Public Health*, 18(8). <https://doi.org/10.3390/ijerph18084148>
- Aughey, R. J. (2011). Applications of GPS technologies to field sports. *Int J Sports Physiol Perform*, 6(3), 295-310. <https://doi.org/10.1123/ijsp.6.3.295>
- Bangsbo, J., & . (1994). *Fitness Training in Football: A Scientific Approach*. August Krogh Institute, University Of Copenhagen.
- Bangsbo, J., Iaia, F. M., & Krstrup, P. (2007). Metabolic response and fatigue in soccer. *Int J Sports Physiol Perform*, 2(2), 111-127. <https://doi.org/10.1123/ijsp.2.2.111>
- Bangsbo, J., Iaia, F. M., & Krstrup, P. (2008). The Yo-Yo intermittent recovery test: a useful tool for evaluation of physical performance in intermittent sports. *Sports Med*, 38(1), 3751. <https://doi.org/10.2165/00007256-200838010-00004>
- Bangsbo, J., Mohr, M., & Krstrup, P. (2006). Physical and metabolic demands of training and match-play in the elite football player. *J Sports Sci*, 24(7), 665-674. <https://doi.org/10.1080/02640410500482529>
- Barbero Álvarez, J. C., Gómez López, M., Barbero Álvarez, V., Granda, J., Castagna, C., & . (2008). Heart rate and activity profile for young female soccer players. *Journal of Human Sport and Exercise*, 3(2), 1-11. <https://doi.org/https://doi.org/10.4100/jhse.2008.32.01>
- Barrett, S., Midgley, A., & Lovell, R. (2014). PlayerLoad: reliability, convergent validity, and influence of unit position during treadmill running. *Int J Sports Physiol Perform*, 9(6), 945-952. <https://doi.org/10.1123/ijsp.2013-0418>
- Barron, D. J., Atkins, S., Edmundson, C., & Fewtrell, D. (2014). Accelerometer derived load according to playing position in competitive youth soccer. *International Journal of Performance Analysis in Sport*, 14(3), 734–743.

<https://doi.org/https://doi.org/10.1080/24748668.2014.11868754>

- Beato, M., Devereux, G., & Stiff, A. (2018). Validity and reliability of Global Positioning System units (STATSports Viper) for measuring distance and peak speed in sports. *J Strength Cond Res*, 32(10), 2831-2837. <https://doi.org/10.1519/JSC.0000000000002778>
- Beckham, G., Mizuguchi, S., Carter, C., Sato, K., Ramsey, M., Lamont, H., Hornsby, G., Haff, G., & Stone, M. (2013). Relationships of isometric mid-thigh pull variables to weightlifting performance. *J Sports Med Phys Fitness*, 53(5), 573-581. <https://www.ncbi.nlm.nih.gov/pubmed/23903539>
- Beckham, G. K., Suchomel, T. J., Bailey, C. A., Sole, C. J., & Grazer, J. L. (2014). The relationship of the Reactive Strength Index-Modified and measures of force development in the Isometric Mid-Thigh Pull.
- Bellon, C. R., DeWeese, B. H., Sato, K., Clark, K. P., & Stone, M. H. (2019). Defining the early, mid, and late subsections of sprint acceleration in Division I men's soccer players. *J Strength Cond Res*, 33(4), 1001-1006. <https://doi.org/10.1519/JSC.0000000000003088>
- Bosco, C., & Komi, P. V. (1979). Mechanical characteristics and fiber composition of human leg extensor muscles. *Eur J Appl Physiol Occup Physiol*, 41(4), 275-284. <https://doi.org/10.1007/BF00429744>
- Boyd, L. J., Ball, K., & Aughey, R. J. (2011). The reliability of MinimaxX accelerometers for measuring physical activity in Australian football. *Int J Sports Physiol Perform*, 6(3), 311-321. <https://doi.org/10.1123/ijsp.6.3.311>
- Bradley, P. S., Carling, C., Archer, D., Roberts, J., Dodds, A., Di Mascio, M., Paul, D., Diaz, A. G., Peart, D., & Krustup, P. (2011). The effect of playing formation on high-intensity running and technical profiles in English FA Premier League soccer matches. *J Sports*

- Sci*, 29(8), 821-830. <https://doi.org/10.1080/02640414.2011.561868>
- Bradley, P. S., Carling, C., Gomez Diaz, A., Hood, P., Barnes, C., Ade, J., Boddy, M., Krstrup, P., & Mohr, M. (2013). Match performance and physical capacity of players in the top three competitive standards of English professional soccer. *Hum Mov Sci*, 32(4), 808-821. <https://doi.org/10.1016/j.humov.2013.06.002>
- Bradley, P. S., Sheldon, W., Wooster, B., Olsen, P., Boanas, P., & Krstrup, P. (2009). High-intensity running in English FA Premier League soccer matches. *J Sports Sci*, 27(2), 159-168. <https://doi.org/10.1080/02640410802512775>
- Brady, C. J., Harrison, A. J., & Comyns, T. M. (2020). A review of the reliability of biomechanical variables produced during the isometric mid-thigh pull and isometric squat and the reporting of normative data. *Sports Biomech*, 19(1), 1-25. <https://doi.org/10.1080/14763141.2018.1452968>
- Bredt, S., Chagas, M. H., Peixoto, G. H., Menzel, H. J., & de Andrade, A. G. P. (2020). Understanding Player Load: Meanings and limitations. *J Hum Kinet*, 71, 5-9. <https://doi.org/10.2478/hukin-2019-0072>
- Brito de Souza, D., Lopez-Del Campo, R., Blanco-Pita, H., Resta, R., & Del Coso, J. (2019a). An extensive comparative analysis of successful and unsuccessful football teams in LaLiga. *Front Psychol*, 10, 2566. <https://doi.org/10.3389/fpsyg.2019.02566>
- Brito de Souza, D., Lopez-Del Campo, R., Blanco-Pita, H., Resta, R., & Del Coso, J. (2019b). An extensive comparative analysis of successful and unsuccessful football teams in LaLiga. *Front Psychol*, 10, 2566. <https://doi.org/10.3389/fpsyg.2019.02566>
- Brito Souza, D., López-Del Campo, R., Blanco-Pita, H., Resta, R., & Del Coso, J. (2019c). A new paradigm to understand success in professional football: analysis of match statistics

- in LaLiga for 8 complete seasons. *International Journal of Performance Analysis in Sport*, 19(4), 543-555. <https://doi.org/10.1080/24748668.2019.1632580>
- Brownlee, T. E., Murtagh, C. F., Naughton, R. J., Whitworth-Turner, C. M., O'Boyle, A., Morgans, R., Morton, J. P., Erskine, R. M., & Drust, B. (2018). Isometric maximal voluntary force evaluated using an isometric mid-thigh pull differentiates English Premier League youth soccer players from a maturity-matched control group. *Science and Medicine in Football*, 2(3), 209–215. <https://doi.org/https://doi.org/10.1080/24733938.2018.1432886>
- Buchheit, M., Manouvrier, C., Cassirame, J., & Morin, J. B. (2015). Monitoring locomotor load in soccer: Is metabolic power, powerful? *Int J Sports Med*, 36(14), 1149-1155. <https://doi.org/10.1055/s-0035-1555927>
- Bujnovky, D., Maly, T., Ford, K. R., Sugimoto, D., Kunzmann, E., Hank, M., & Zahalka, F. (2019). Physical fitness characteristics of high-level youth football players: Influence of playing position. *Sports (Basel)*, 7(2). <https://doi.org/10.3390/sports7020046>
- Bush, M., Barnes, C., Archer, D. T., Hogg, B., & Bradley, P. S. (2015). Evolution of match performance parameters for various playing positions in the English Premier League. *Hum Mov Sci*, 39, 1-11. <https://doi.org/10.1016/j.humov.2014.10.003>
- Bush, M. D., Archer, D. T., Hogg, R., & Bradley, P. S. (2015). Factors influencing physical and technical variability in the English Premier League. *Int J Sports Physiol Perform*, 10(7), 865-872. <https://doi.org/10.1123/ijsp.2014-0484>
- Carling, C. (2010). Analysis of physical activity profiles when running with the ball in a professional soccer team. *J Sports Sci*, 28(3), 319-326. <https://doi.org/10.1080/02640410903473851>

- Castagna, C., & Castellini, E. (2013a). Vertical jump performance in Italian male and female national team soccer players. *J Strength Cond Res*, 27(4), 1156-1161.
<https://doi.org/10.1519/JSC.0b013e3182610999>
- Castagna, C., Ganzetti, M., Ditroilo, M., Giovannelli, M., Rocchetti, A., & Manzi, V. (2013b). Concurrent validity of vertical jump performance assessment systems. *J Strength Cond Res*, 27(3), 761-768. <https://doi.org/10.1519/JSC.0b013e31825dbcc5>
- Castagna, C., Manzi, V., Impellizzeri, F., Weston, M., & Barbero Alvarez, J. C. (2010). Relationship between endurance field tests and match performance in young soccer players. *J Strength Cond Res*, 24(12), 3227-3233.
<https://doi.org/10.1519/JSC.0b013e3181e72709>
- Castagna, C., Varley, M., Povoas, S. C. A., & D'Ottavio, S. (2017). Evaluation of the match external load in soccer: Methods comparison. *Int J Sports Physiol Perform*, 12(4), 490-495. <https://doi.org/10.1123/ijsp.2016-0160>
- Castellano, J., Alvarez-Pastor, D., & Bradley, P. S. (2014). Evaluation of research using computerised tracking systems (Amisco® and Prozone®) to analyse physical performance in elite soccer: A systematic review. *Sports Medicine*, 44(5), 701-712.
<https://doi.org/10.1007/s40279-014-0144-3>
- Castellano, J., Blanco-Villasenor, A., & Alvarez, D. (2011). Contextual variables and time-motion analysis in soccer. *Int J Sports Med*, 32(6), 415-421.
<https://doi.org/10.1055/s-0031-1271771>
- Chamari, K., Hachana, Y., Ahmed, Y. B., Galy, O., Sghaier, F., Chatard, J. C., Hue, O., & Wisloff, U. (2004). Field and laboratory testing in young elite soccer players. *Br J Sports Med*, 38(2), 191-196. <https://doi.org/10.1136/bjism.2002.004374>

- Chelly, M. S., Ghenem, M. A., Abid, K., Hermassi, S., Tabka, Z., & Shephard, R. J. (2010). Effects of in-season short-term plyometric training program on leg power, jump- and sprint performance of soccer players. *J Strength Cond Res*, *24*(10), 2670-2676.
<https://doi.org/10.1519/JSC.0b013e3181e2728f>
- Choukou, M. A., Laffaye, G., & Taiar, R. (2014). Reliability and validity of an accelerometric system for assessing vertical jumping performance. *Biol Sport*, *31*(1), 55-62.
<https://doi.org/10.5604/20831862.1086733>
- Clark, N. A., Edwards, A.M., Morton, R.H., Butterly, R. J. (2008). Season-to-season variations of physiological fitness within a squad of professional male soccer players. *Journal of Sports Science and Medicine*, *07*, 157-165.
- Cnaan, A., Laird, N. M., & Slasor, P. (1997). Using the general linear mixed model to analyse unbalanced repeated measures and longitudinal data. *Stat Med*, *16*(20), 2349-2380.
[https://doi.org/10.1002/\(sici\)1097-0258\(19971030\)16:20<2349::aid-sim667>3.0.co;2-e](https://doi.org/10.1002/(sici)1097-0258(19971030)16:20<2349::aid-sim667>3.0.co;2-e)
- Comfort, P., Stewart, A., Bloom, L., & Clarkson, B. (2014). Relationships between strength, sprint, and jump performance in well-trained youth soccer players. *J Strength Cond Res*, *28*(1), 173-177. <https://doi.org/10.1519/JSC.0b013e318291b8c7>
- Coutts, A. J., Quinn, J., Hocking, J., Castagna, C., & Rampinini, E. (2010). Match running performance in elite Australian Rules Football. *Journal of Science and Medicine in Sport*, *13*(5), 543-548. <https://doi.org/https://doi.org/10.1016/j.jsams.2009.09.004>
- Cronin, J. B., Hing, R. D., & McNair, P. J. (2004). Reliability and validity of a linear position transducer for measuring jump performance. *J Strength Cond Res*, *18*(3), 590-593.
[https://doi.org/10.1519/1533-4287\(2004\)18<590:RAVOAL>2.0.CO;2](https://doi.org/10.1519/1533-4287(2004)18<590:RAVOAL>2.0.CO;2)
- Curtis, R. M., Huggins, R. A., Benjamin, C. L., Sekiguchi, Y., Adams, W. M., Arent, S. M., Jain,

- R., Miller, S. J., Walker, A. J., & Casa, D. J. (2020). Contextual factors influencing external and internal training loads in collegiate men's soccer. *J Strength Cond Res*, 34(2), 374-381. <https://doi.org/10.1519/JSC.0000000000003361>
- Curtis, R. M., Huggins, R. A., Benjamin, C. L., Sekiguchi, Y., S, M. A., B, C. A., Pullara, J. M., West, C. A., & Casa, D. J. (2021). Seasonal accumulated workloads in collegiate men's soccer: A comparison of starters and reserves. *J Strength Cond Res*, 35(11), 3184-3189. <https://doi.org/10.1519/JSC.0000000000003257>
- Curtis, R. M., Huggins, R. A., Looney, D. P., West, C. A., Fortunati, A., Fontaine, G. J., & Casa, D. J. (2018). Match demands of National Collegiate Athletic Association Division I men's soccer. *J Strength Cond Res*, 32(10), 2907-2917. <https://doi.org/10.1519/JSC.0000000000002719>
- Dellal, A., Owen, A., Wong, D. P., Krustup, P., van Exsel, M., & Mallo, J. (2012). Technical and physical demands of small vs. large sided games in relation to playing position in elite soccer. *Hum Mov Sci*, 31(4), 957-969. <https://doi.org/10.1016/j.humov.2011.08.013>
- DeWeese, B. H., Hornsby, G., Stone, M., Stone, M.H. (2015). The training process: Planning for strength–power training in track and field. Part 1: Theoretical aspects. *Journal of Sport and Health Science*, 4(4), 308-317. <https://doi.org/https://doi.org/10.1016/j.jshs.2015.07.003>
- Di Salvo, V., Adam, C., Barry, M., & Cardinale, M. (2006). Validation of Prozone ®: A new video-based performance analysis system. *International Journal of Performance Analysis in Sport*, 6, 108-119. <https://doi.org/10.1080/24748668.2006.11868359>
- Di Salvo, V., Baron, R., Tschann, H., Calderon Montero, F. J., Bachl, N., & Pigozzi, F. (2007). Performance characteristics according to playing position in elite soccer. *Int J Sports*

- Med*, 28(3), 222-227. <https://doi.org/10.1055/s-2006-924294>
- Di Salvo, V., Gregson, W., Atkinson, G., Tordoff, P., & Drust, B. (2009). Analysis of high intensity activity in Premier League soccer. *Int J Sports Med*, 30(3), 205-212. <https://doi.org/10.1055/s-0028-1105950>
- Di Salvo, V., & Modonutti, M. (2009). Integration of different technology systems for the development of football training. *J Sports Sci Med*, 11, 3.
- Díaz-Soto, F. J., Rico-González, M., Palucci Vieira, L. H., Clemente, F. M., Nobari, H., & Pino-Ortega, J. (2022). A systematic review of velocity and accelerometer thresholds in soccer. *International Journal of Sports Science & Coaching*. <https://doi.org/10.1177/17479541221143346>
- Diez, A., Lozano, D., Arjol-Serrano, J. L., Mainer-Pardos, E., Castillo, D., Torrontegui-Duarte, M., Nobari, H., Jaen-Carrillo, D., & Lampre, M. (2021). Influence of contextual factors on physical demands and technical-tactical actions regarding playing position in professional soccer players. *BMC Sports Sci Med Rehabil*, 13(1), 157. <https://doi.org/10.1186/s13102-021-00386-x>
- Dolci, F., Hart, N. H., Kilding, A. E., Chivers, P., Piggott, B., & Spiteri, T. (2020). Physical and energetic demand of soccer. *Strength and Conditioning Journal*, 42(3), 70–77. <https://doi.org/10.1519/ssc.0000000000000533>
- Dos'Santos, T., Thomas, C., Comfort, P., McMahon, J. J., Jones, P. A., Oakley, N. P., & Young, A. L. (2018). Between-session reliability of isometric midhigh pull kinetics and maximal power clean performance in male youth soccer players. *J Strength Cond Res*, 32(12), 3364-3372. <https://doi.org/10.1519/JSC.0000000000001830>
- Edgecomb, S. J., & Norton, K. I. (2006). Comparison of global positioning and computer-based

- tracking systems for measuring player movement distance during Australian football. *J Sci Med Sport*, 9(1-2), 25-32. <https://doi.org/10.1016/j.jsams.2006.01.003>
- Elloumi, M., Makni, E., Moalla, W., Bouaziz, T., Tabka, Z., Lac, G., & Chamari, K. (2012). Monitoring training load and fatigue in rugby sevens players. *Asian J Sports Med*, 3(3), 175-184. <https://doi.org/10.5812/asjasm.34688>
- Faude, O., Koch, T., & Meyer, T. (2012). Straight sprinting is the most frequent action in goal situations in professional football. *J Sports Sci*, 30(7), 625-631. <https://doi.org/10.1080/02640414.2012.665940>
- Fernandez-Navarro, J., Fradua, L., Zubillaga, A., & McRobert, A. P. (2018). Influence of contextual variables on styles of play in soccer. *International Journal of Performance Analysis in Sport*, 18(3), 423-436. <https://doi.org/10.1080/24748668.2018.1479925>
- Fields, J., Merrigan, J., Feit, M. K., & Jones, M. (2021). Practice versus game external load measures in starters and non-starters of a men's collegiate soccer team. *International Journal of Strength and Conditioning*, 1(1). <https://doi.org/10.47206/ijsc.v1i1.76>
- FIFA. (2007). *FIFA Big Count*. IFA Communications Division, Information Services. Retrieved Mar 18, 2024 from <https://www.yumpu.com/en/document/view/7282907/fifa-big-count-2006-270-million-people-active-in-football-fifacom>
- Fox, J. L., O'Grady, C. J., & Scanlan, A. T. (2020). The relationships between external and internal workloads during basketball training and games. *Int J Sports Physiol Perform*, 15(8), 1081-1086. <https://doi.org/10.1123/ijsp.2019-0722>
- Gabbett, T. J. (2016). The training-injury prevention paradox: should athletes be training smarter and harder? *Br J Sports Med*, 50(5), 273-280. <https://doi.org/10.1136/bjsports-2015-095788>

- Garcia-Calvo, T., Ponce-Bordon, J. C., Pons, E., Lopez Del Campo, R., Resta, R., & Raya-Gonzalez, J. (2022). High metabolic load distance in professional soccer according to competitive level and playing positions. *PeerJ*, *10*, e13318.
<https://doi.org/10.7717/peerj.13318>
- Giles, G., Lutton, G., & Martin, J. (2022). Scoping review of the isometric mid-thigh pull performance relationship to dynamic sport performance assessments. *J Funct Morphol Kinesiol*, *7*(4). <https://doi.org/10.3390/jfmk7040114>
- Gómez-Carmona, C. D., Bastida-Castillo, A., Ibáñez, S. J., & Pino-Ortega, J. (2020). Accelerometry as a method for external workload monitoring in invasion team sports. A systematic review. *PLoS One*, *15*(8). <https://doi.org/10.1371/journal.pone.0236643>
- Gonzalez-Rodenas, J., Aranda-Malaves, R., Tudela-Desantes, A., Nieto, F., Uso, F., & Aranda, R. (2020). Playing tactics, contextual variables and offensive effectiveness in English Premier League soccer matches. A multilevel analysis. *PLoS One*, *15*(2), e0226978.
<https://doi.org/10.1371/journal.pone.0226978>
- Gonzalez-Rodenas, J., Mitrotasios, M., Aranda, R., & Armatas, V. (2020). Combined effects of tactical, technical and contextual factors on shooting effectiveness in European professional soccer. *International Journal of Performance Analysis in Sport*, *20*(2), 280-293. <https://doi.org/10.1080/24748668.2020.1743163>
<https://doi.org/10.1080/24748668.2020.1743163>
- Gonzalez-Rodenas, J., Moreno-Perez, V., Campo, R. L., Resta, R., & Coso, J. D. (2024). Technical and tactical evolution of the offensive team sequences in LaLiga between 2008 and 2021. Is Spanish football now a more associative game? *Biol Sport*, *41*(2), 105-113.
<https://doi.org/10.5114/biolport.2024.131818>

- Guerrero-Calderon, B., Klemp, M., Castillo-Rodriguez, A., Morcillo, J. A., & Memmert, D. (2021). A new approach for training-load quantification in elite-level soccer: Contextual factors. *Int J Sports Med*, 42(8), 716-723. <https://doi.org/10.1055/a-1289-9059>
- Gutierrez, J. (2024). Ron Burkle Sells NWSL's San Diego Wave FC At Record-Breaking Price. Retrieved May 18, 2024 from <https://www.forbes.com/sites/jackiegutierrez/2024/03/14/ron-burkle-sells-san-diego-wave-fc-at-record-breaking-price/?sh=52912e6c505d>
- Haff, G. G., Ruben, R. P., Lider, J., Twine, C., & Cormie, P. (2015). A comparison of methods for determining the rate of force development during isometric midthigh clean pulls. *J Strength Cond Res*, 29(2), 386-395. <https://doi.org/10.1519/JSC.0000000000000705>
- Haff, G. G., Stone, M. H., O'Bryant, H. S., Harman, E., Dinan, C., Johnson, R., & Han, K. H. (1997). Force-time dependent characteristics of dynamic and isometric muscle actions. *The Journal of Strength and Conditioning Research*, 11(4), 269. [https://doi.org/https://doi.org/10.1519/1533-4287\(1997\)011%3C0269:ftdcod%3E2.3.co;2](https://doi.org/https://doi.org/10.1519/1533-4287(1997)011%3C0269:ftdcod%3E2.3.co;2)
- Harley, J. A., Barnes, C. A., Portas, M., Lovell, R., Barrett, S., Paul, D., & Weston, M. (2010). Motion analysis of match-play in elite U12 to U16 age-group soccer players. *J Sports Sci*, 28(13), 1391-1397. <https://doi.org/10.1080/02640414.2010.510142>
- Harry, J. R., Barker, L. A., Mercer, J. A., & Dufek, J. S. (2017). Vertical and horizontal impact force comparison during jump landings with and without rotation in NCAA Division I male soccer players. *J Strength Cond Res*, 31(7), 1780-1786. <https://doi.org/10.1519/JSC.0000000000001650>
- Hatze, H. (1998). Validity and reliability of methods for testing vertical jumping performance. *Journal of Applied Biomechanics*, 14(2), 127-140. <https://doi.org/10.1123/jab.14.2.127>

- Haugen, T. A. (2018). Soccer seasonal variations in sprint mechanical properties and vertical jump performance. *Kinesiology, 50*(1).
- Haugen, T. A., Tonnessen, E., & Seiler, S. (2013). Anaerobic performance testing of professional soccer players 1995-2010. *Int J Sports Physiol Perform, 8*(2), 148-156.
<https://doi.org/10.1123/ijsp.8.2.148>
- Hennessy, L., & Jeffreys, I. (2018). The current use of GPS, its potential, and limitations in soccer. *Strength and Conditioning Journal, 40*(3), 83-94.
<https://doi.org/10.1519/ssc.0000000000000386>
- Hill-Haas, S. V., Dawson, B. T., Coutts, A. J., & Rowsell, G. J. (2009). Physiological responses and time-motion characteristics of various small-sided soccer games in youth players. *J Sports Sci, 27*(1), 1-8. <https://doi.org/10.1080/02640410902761199>
- Hoff, J. (2005). Training and testing physical capacities for elite soccer players. *J Sports Sci, 23*(6), 573-582. <https://doi.org/10.1080/02640410400021252>
- Hoffman, J. R., Nusse, V., & Kang, J. (2003). The effect of an intercollegiate soccer game on maximal power performance. *Can J Appl Physiol, 28*(6), 807-817.
<https://doi.org/10.1139/h03-060>
- Holme, B. R. (2015). Wearable microsensor technology to measure physical activity demands in *handball* [Norwegian School of Sport Sciences]. Norway.
- Hopkins, W. G. (2002). *A New View of Statistics*. Retrieved Accessed May 13 from <http://www.sportsci.org/resource/stats/effectmag.html>
- Hoppe, M. W., Baumgart, C., Polglaze, T., & Freiwald, J. (2018). Validity and reliability of GPS and LPS for measuring distances covered and sprint mechanical properties in team sports. *PLoS One, 13*(2), e0192708. <https://doi.org/10.1371/journal.pone.0192708>

- Hornsby, W. G., Gentles, J. A., MacDonald, C. J., Mizuguchi, S., Ramsey, M. W., & Stone, M. H. (2017). Maximum strength, Rate of force development, jump height, and peak power alterations in weightlifters across five months of training. *Sports (Basel)*, 5(4).
<https://doi.org/10.3390/sports5040078>
- Howard, N., & Stavrianeas, S. (2017). In-season high-intensity interval training improves conditioning In high school soccer players. *Int J Exerc Sci*, 10(5), 713-720.
<https://www.ncbi.nlm.nih.gov/pubmed/28966710>
- Ishida, A., Bazylar, C. D., Sayers, A. L., Mizuguchi, S., & Gentles, J. A. (2021). Acute effects of match-play on neuromuscular and subjective recovery and stress state in division I collegiate female soccer players. *J Strength Cond Res*, 35(4), 976-982.
<https://doi.org/10.1519/JSC.0000000000003981>
- Ishida, A., Travis, S. K., Draper, G., White, J. B., & Stone, M. H. (2022). Player position affects relationship between internal and external training loads during Division I collegiate female soccer season. *J Strength Cond Res*, 36(2), 513-517.
<https://doi.org/10.1519/JSC.0000000000004188>
- Ishida, A., Travis, S. K., & Stone, M. H. (2021). Associations of body composition, maximum strength, power characteristics with sprinting, jumping, and intermittent endurance performance in male intercollegiate soccer players. *J Funct Morphol Kinesiol*, 6(1).
<https://doi.org/10.3390/jfmk6010007>
- Ishida, A., Travis, S. K., & Stone, M. H. (2021). Short-term periodized programming may improve strength, power, jump kinetics, and sprint efficiency in soccer. *J Funct Morphol Kinesiol*, 6(2). <https://doi.org/10.3390/jfmk6020045>
- Ishida, A., Travis, S. K., & Stone, M. H. (2021). Associations of body composition, maximum

- strength, power characteristics with sprinting, jumping, and intermittent endurance performance in male intercollegiate soccer players. *J Funct Morphol Kinesiol*, 6(1). <https://doi.org/10.3390/jfmk6010007>
- Izzo, R., Rossini, U., Raiola, G., Cejudo, P. A., & Hosseini, V. I. C. (2020). Insurgence of fatigue and its implications in the selection and accuracy of passes in football. A case study. *Journal of Physical Education & Sport*, 20(4).
- Jackson, B. M., Polglaze, T., Dawson, B., King, T., & Peeling, P. (2018). Comparing global positioning system and Global Navigation Satellite System measures of team-sport movements. *Int J Sports Physiol Perform*, 13(8), 1005-1010. <https://doi.org/10.1123/ijsp.2017-0529>
- Jaspers, A., Brink, M. S., Probst, S. G., Frencken, W. G., & Helsen, W. F. (2017). Relationships between training load indicators and training outcomes in professional soccer. *Sports Med*, 47(3), 533-544. <https://doi.org/10.1007/s40279-016-0591-0>
- Jenkins, A. S., Pollock, J. R., Moore, M. L., Makovicka, J. L., Brinkman, J. C., & Chhabra, A. (2022). The 100 most-cited and influential articles in collegiate athletics. *Orthop J Sports Med*, 10(7), 23259671221108401. <https://doi.org/10.1177/23259671221108401>
- Jennings, D., Cormack, S., Coutts, A. J., Boyd, L., & Aughey, R. J. (2010). The validity and reliability of GPS units for measuring distance in team sport specific running patterns. *Int J Sports Physiol Perform*, 5(3), 328-341. <https://doi.org/10.1123/ijsp.5.3.328>
- Jiang, Z., Hao, Y., Jin, N., & Li, Y. (2022). A systematic review of the relationship between workload and injury risk of professional male soccer players. *Int J Environ Res Public Health*, 19(20). <https://doi.org/10.3390/ijerph192013237>
- Johnston, R. J., Watsford, M. L., Kelly, S. J., Pine, M. J., & Spurrs, R. W. (2014). Validity and

interunit reliability of 10 Hz and 15 Hz GPS units for assessing athlete movement demands. *J Strength Cond Res*, 28(6), 1649-1655.

<https://doi.org/10.1519/JSC.0000000000000323>

Kai, T., Anbe, Y., Morinaga, H., Shiokawa, K., Akamine, T., & Takai, Y. (2020). Association of training load with body composition and physical fitness during preseason in collegiate male soccer players. *Football Science*, 17, 98-107.

https://doi.org/10.57547/jssfenfs.17.1_98

Konefal, M., Chmura, J., Zacharko, M., Zajac, T., & Chmura, P. (2022). The relationship among acceleration, deceleration and changes of direction in repeated small sided games. *J Hum Kinet*, 85, 96-103. <https://doi.org/10.2478/hukin-2022-0113>

Kotzamanidis, C., Chatzopoulos, D., Michailidis, C., Papaiaikovou, G., & Patikas, D. (2005). The effect of a combined high-intensity strength and speed training program on the running and jumping ability of soccer players. *J Strength Cond Res*, 19(2), 369-375.

<https://doi.org/10.1519/R-14944.1>

Kraemer, W. J., French, D. N., Paxton, N. J., Hakkinen, K., Volek, J. S., Sebastianelli, W. J., Putukian, M., Newton, R. U., Rubin, M. R., Gomez, A. L., Vescovi, J. D., Ratamess, N. A., Fleck, S. J., Lynch, J. M., & Knuttgen, H. G. (2004). Changes in exercise performance and hormonal concentrations over a big ten soccer season in starters and nonstarters. *J Strength Cond Res*, 18(1), 121-128.

[https://doi.org/10.1519/1533-4287\(2004\)018<0121:ciepah>2.0.co;2](https://doi.org/10.1519/1533-4287(2004)018<0121:ciepah>2.0.co;2)

Kraska, J. M., Ramsey, M. W., Haff, G. G., Fethke, N., Sands, W. A., Stone, M. E., & Stone, M. H. (2009). Relationship between strength characteristics and unweighted and weighted vertical jump height. *Int J Sports Physiol Perform*, 4(4), 461-473.

<https://doi.org/10.1123/ijsp.4.4.461>

Krustrup, P., Mohr, M., Amstrup, T., Rysgaard, T., Johansen, J., Steensberg, A., Pedersen, P. K., & Bangsbo, J. (2003). The yo-yo intermittent recovery test: physiological response, reliability, and validity. *Med Sci Sports Exerc*, 35(4), 697-705.

<https://doi.org/10.1249/01.MSS.0000058441.94520.32>

Krustrup, P., Mohr, M., Ellingsgaard, H., & Bangsbo, J. (2005). Physical demands during an elite female soccer game: importance of training status. *Med Sci Sports Exerc*, 37(7), 1242-1248. <https://doi.org/10.1249/01.mss.0000170062.73981.94>

Kuki, S., Sato, K., Stone, M. H., Okano, K., Yoshida, T., & Tanigawa, S. (2017). The relationship between isometric mid-thigh pull variables, jump variables and sprint performance in collegiate soccer players. *Journal of Trainology*, 6(2), 42-46.

https://doi.org/10.17338/trainology.6.2_42

Kupperman, N., Curtis, M. A., Saliba, S. A., & Hertel, J. (2021). Quantification of workload and wellness measures in a women's collegiate volleyball season. *Front Sports Act Living*, 3, 702419. <https://doi.org/10.3389/fspor.2021.702419>

Little, T., & Williams, A. G. (2005). Specificity of acceleration, maximum speed, and agility in professional soccer players. *J Strength Cond Res*, 19(1), 76-78.

<https://doi.org/10.1519/14253.1>

Liu, H., Hopkins, W., Gómez, A. M., & Molinuevo, S. J. (2013). Inter-operator reliability of live football match statistics from OPTA Sportsdata. *International Journal of Performance Analysis in Sport*, 13(3), 803–821. <https://doi.org/10.1080/24748668.2013.11868690>

Lockie, R. G., Moreno, M. R., Orjalo, A. J., Stage, A. A., Liu, T. M., Birmingham-Babauta, S. A., Hurley, J. M., Torne, I. A., Beiley, M. D., Risso, F. G., Davis, D. L., Lazar, A., Stokes, J.

- J., & Giuliano, D. V. (2019). Repeated-sprint ability in Division I Collegiate Male soccer players: Positional differences and relationships with performance tests. *J Strength Cond Res*, 33(5), 1362-1370. <https://doi.org/10.1519/JSC.0000000000001948>
- Lombard, W., Starling, L., Wewege, L., & Lambert, M. (2021). Changes in countermovement jump performance and subjective readiness-to-train scores following a simulated soccer match. *Eur J Sport Sci*, 21(5), 647-655. <https://doi.org/10.1080/17461391.2020.1757764>
- Loturco, I., Pereira, L. A., Kobal, R., Kitamura, K., Cal Abad, C. C., Marques, G., Guerriero, A., Moraes, J. E., & Nakamura, F. Y. (2017). Validity and usability of a new system for measuring and monitoring variations in vertical jump performance. *J Strength Cond Res*, 31(9), 2579-2585. <https://doi.org/10.1519/JSC.0000000000002086>
- Luteberget, L. S., Holme, B. R., & Spencer, M. (2018). Reliability of wearable inertial measurement units to measure physical activity in team handball. *Int J Sports Physiol Perform*, 13(4), 467-473. <https://doi.org/10.1123/ijsp.2017-0036>
- Magal, M., Smith, R. T., Dyer, J. J., & Hoffman, J. R. (2009). Seasonal variation in physical performance-related variables in male NCAA Division III soccer players. *J Strength Cond Res*, 23(9), 2555-2559. <https://doi.org/10.1519/JSC.0b013e3181b3ddbdf>
- Mallo, J., Mena, E., Nevado, F., & Paredes, V. (2015). Physical demands of top-class soccer friendly matches in relation to a playing position using Global Positioning System technology. *J Hum Kinet*, 47, 179-188. <https://doi.org/10.1515/hukin-2015-0073>
- Malone, J. J., Di Michele, R., Morgans, R., Burgess, D., Morton, J. P., & Drust, B. (2015). Seasonal training-load quantification in elite English premier league soccer players. *Int J Sports Physiol Perform*, 10(4), 489-497. <https://doi.org/10.1123/ijsp.2014-0352>
- Malone, J. J., Lovell, R., Varley, M. C., & Coutts, A. J. (2017). Unpacking the black box:

- Applications and considerations for using GPS devices in sport. *Int J Sports Physiol Perform*, 12(Suppl 2), S218-S226. <https://doi.org/10.1123/ijsp.2016-0236>
- Manzi, V., Impellizzeri, F., & Castagna, C. (2014). Aerobic fitness ecological validity in elite soccer players: a metabolic power approach. *J Strength Cond Res*, 28(4), 914-919. <https://doi.org/10.1519/JSC.0000000000000239>
- Mason, L., Kirkland, A., Steele, J., & Wright, J. (2021). The relationship between isometric mid-thigh pull variables and athletic performance measures: empirical study of English professional soccer players and meta-analysis of extant literature. *J Sports Med Phys Fitness*, 61(5), 645-655. <https://doi.org/10.23736/S0022-4707.20.11205-2>
- Mayhew, S. R., & Wenger, H. A. (1985). Time-motion analysis of professional soccer. *Journal of Human Movement Studies*, 11(1), 49-52.
- McFadden, B. A., Walker, A. J., Arent, M. A., Bozzini, B. N., Sanders, D. J., Cintineo, H. P., Bello, M. L., & Arent, S. M. (2020). Biomarkers correlate with body composition and performance changes throughout the season in women's Division I collegiate soccer players. *Front Sports Act Living*, 2, 74. <https://doi.org/10.3389/fspor.2020.00074>
- McFadden, B. A., Walker, A. J., Bozzini, B. N., Sanders, D. J., & Arent, S. M. (2020). Comparison of internal and external training loads in male and female collegiate soccer players during practices vs. games. *J Strength Cond Res*, 34(4), 969-974. <https://doi.org/10.1519/JSC.00000000000003485>
- McFarland, I. T., Dawes, J. J., Elder, C. L., & Lockie, R. G. (2016). Relationship of two vertical jumping tests to sprint and change of direction speed among male and female collegiate soccer players. *Sports (Basel)*, 4(1). <https://doi.org/10.3390/sports4010011>
- McGuigan, M. R., & Winchester, J. B. (2008). The relationship between isometric and dynamic

- strength in college football players. *J Sports Sci Med*, 7(1), 101-105.
<https://www.ncbi.nlm.nih.gov/pubmed/24150141>
- Meckel, Y., Machnai, O., & Eliakim, A. (2009). Relationship among repeated sprint tests, aerobic fitness, and anaerobic fitness in elite adolescent soccer players. *J Strength Cond Res*, 23(1), 163-169. <https://doi.org/10.1519/JSC.0b013e31818b9651>
- Mendez-Villanueva, A., Buchheit, M., Kuitunen, S., Douglas, A., Peltola, E., & Bourdon, P. (2011). Age-related differences in acceleration, maximum running speed, and repeated-sprint performance in young soccer players. *J Sports Sci*, 29(5), 477-484.
<https://doi.org/10.1080/02640414.2010.536248>
- Mendola, N. (2023). San Diego awarded MLS franchise after reported \$500 million fee. Retrieved May 18, 2024 from <https://www.nbcsports.com/soccer/news/san-diego-awarded-mls-franchise-after-reported-500-million-fee>
- Merrigan, J. J., Stone, J. D., Hornsby, W. G., & Hagen, J. A. (2020). Identifying reliable and reliable force-time metrics in athletes—considerations for the isometric mid-thigh pull and countermovement jump. *Sports (Basel)*, 9(1). <https://doi.org/10.3390/sports9010004>
- Meylan, C., Trewin, J., & McKean, K. (2017). Quantifying explosive actions in international women's soccer. *Int J Sports Physiol Perform*, 12(3), 310-315.
<https://doi.org/10.1123/ijsp.2015-0520>
- Miller, D. K., Kieffer, H. S., Kemp, H. E., & Torres, S. E. (2011). Off-season physiological profiles of elite National Collegiate Athletic Association Division III male soccer players. *J Strength Cond Res*, 25(6), 1508-1513. <https://doi.org/10.1519/JSC.0b013e3181dba3df>
- Mirkov, D., Nedeljkovic, A., Kukolj, M., Ugarkovic, D., & Jaric, S. (2008). Evaluation of the reliability of soccer-specific field tests. *J Strength Cond Res*, 22(4), 1046-1050.

<https://doi.org/10.1519/JSC.0b013e31816eb4af>

Mitrotasios, M., Casal, C., Armatas, V., Losada, J., & Maneiro, R. (2021). Analysis of corner kick success in La Liga Santander 2019/2020. *European Journal of Human Movement*, 47, 8–22. <https://doi.org/https://doi.org/10.21134/eurjhm.2021.47.2>

Mitrotasios, M., Gonzalez-Rodenas, J., Armatas, V., & Aranda, R. (2019). The creation of goal scoring opportunities in professional soccer. Tactical differences between Spanish La Liga, English Premier League, German Bundesliga and Italian Serie A. *International Journal of Performance Analysis in Sport*, 19(3), 452–465. <https://doi.org/https://doi.org/10.1080/24748668.2019.1618568>

Mohr, M., & Krstrup, P. (2014). Yo-Yo intermittent recovery test performances within an entire football league during a full season. *J Sports Sci*, 32(4), 315-327. <https://doi.org/10.1080/02640414.2013.824598>

Morris, R., Emmonds, S., Jones, B., Myers, T. D., Clarke, N. D., Lake, J., Ellis, M., Singleton, D., Roe, G., & Till, K. (2018). Seasonal changes in physical qualities of elite youth soccer players according to maturity status: comparisons with aged matched controls. *Science and Medicine in Football*, 2(4), 272-280. <https://doi.org/10.1080/24733938.2018.1454599>

Nagahara, R., Morin, J. B., & Koido, M. (2016). Impairment of sprint mechanical properties in an actual soccer match: A pilot study. *Int J Sports Physiol Perform*, 11(7), 893-898. <https://doi.org/10.1123/ijsp.2015-0567>

Nassis, G. P., Massey, A., Jacobsen, P., Brito, J., Randers, M. B., Castagna, C., Mohr, M., & Krstrup, P. (2020). Elite football of 2030 will not be the same as that of 2020: Preparing players, coaches, and support staff for the evolution. *Scand J Med Sci Sports*, 30(6), 962-

964. <https://doi.org/10.1111/sms.13681>

NCAA. (2021). NCAA Sports Sponsorship and Participation Rates Report. Retrieved May 18, 2024 from https://ncaaorg.s3.amazonaws.com/research/sportpart/2021RES_SportsSponsorshipParticipationRatesReport.pdf

Nedelec, M., McCall, A., Carling, C., Legall, F., Berthoin, S., & Dupont, G. (2014). The influence of soccer playing actions on the recovery kinetics after a soccer match. *J Strength Cond Res*, 28(6), 1517-1523. <https://doi.org/10.1519/JSC.0000000000000293>

Nelson, A. G., McGuigan, M. R., & Winchester, J. B. (2008). The relationship between isometric and dynamic strength in college football players. *Medicine & Science in Sports & Exercise*, 40(5). <https://doi.org/10.1249/01.mss.0000322664.81874.75>

Newans, T., Bellinger, P., Drovandi, C., Buxton, S., & Minahan, C. (2022). The utility of Mixed Models in sport science: A call for further adoption in longitudinal data sets. *Int J Sports Physiol Perform*, 17(8), 1289-1295. <https://doi.org/10.1123/ijsp.2021-0496>

Nicolella, D. P., Torres-Ronda, L., Saylor, K. J., & Schelling, X. (2018). Validity and reliability of an accelerometer-based player tracking device. *PLoS One*, 13(2), e0191823. <https://doi.org/10.1371/journal.pone.0191823>

Nuzzo, J. L., McBride, J. M., Cormie, P., & McCaulley, G. O. (2008). Relationship between countermovement jump performance and multijoint isometric and dynamic tests of strength. *J Strength Cond Res*, 22(3), 699-707. <https://doi.org/10.1519/JSC.0b013e31816d5eda>

Oliva Lozano, J. M., Rago, V., Fortes, V., & Muyor, J. M. (2022). Impact of match-related contextual variables on weekly training load in a professional soccer team: a full season

- study. *Biol Sport*, 39(1), 125-134. <https://doi.org/10.5114/biolSport.2021.102927>
- Osgnach, C., Poser, S., Bernardini, R., Rinaldo, R., & di Prampero, P. E. (2010). Energy cost and metabolic power in elite soccer: a new match analysis approach. *Med Sci Sports Exerc*, 42(1), 170-178. <https://doi.org/10.1249/MSS.0b013e3181ae5cfd>
- Otero-Saborido, F. M., Aguado-Méndez, R. D., Torreblanca-Martínez, V. M., & González-Jurado, J. A. (2021). Technical-tactical performance from data providers: A systematic review in regular football leagues. *Sustainability*, 13(18), 10167. <https://doi.org/https://doi.org/10.3390/su131810167>
- Owen, A. L., Djaoui, L., Newton, M., Malone, S., & Mendes, B. (2017). A contemporary multi-modal mechanical approach to training monitoring in elite professional soccer. *Science and Medicine in Football*, 1(3), 216-22. <https://doi.org/10.1080/24733938.2017.1334958>
- Owen, A. L., Dunlop, G., Rouissi, M., Haddad, M., Mendes, B., & Chamari, K. (2016). Analysis of positional training loads (ratings of perceived exertion) during various-sided games in European professional soccer players. *International Journal of Sports Science & Coaching*, 11(3), 374-381. <https://doi.org/10.1177/1747954116644064>
- Owen, A. L., Lago-Peñas, C., Gómez, M.-Á., Mendes, B., & Dellal, A. (2017). Analysis of a training mesocycle and positional quantification in elite European soccer players. *International Journal of Sports Science & Coaching*, 12(5), 665-676. <https://doi.org/10.1177/1747954117727851>
- Pappalardo, L., Cintia, P., Ferragina, P., Massucco, E., Pedreschi, D., Giannotti, F., & . (2019). PlayeRank: Data-driven performance evaluation and player ranking in soccer via a machine learning approach. *ACM Transactions on Intelligent Systems and Technology*, 10(5), 1–27. <https://doi.org/https://doi.org/10.1145/3343172>

- Paul, D. J., Bradley, P. S., & Nassis, G. P. (2015). Factors affecting match running performance of elite soccer players: shedding some light on the complexity. *Int J Sports Physiol Perform*, *10*(4), 516-519. <https://doi.org/10.1123/IJSPP.2015-0029>
- Petrigna, L., Karsten, B., Marcolin, G., Paoli, A., D'Antona, G., Palma, A., & Bianco, A. (2019). A review of countermovement and squat jump testing methods in the context of public health examination in adolescence: Reliability and feasibility of current testing procedures. *Front Physiol*, *10*, 1384. <https://doi.org/10.3389/fphys.2019.01384>
- Phillips, J., Dusseault, M., da Costa Valladão, S. P., Nelson, H., & Andre, T. (2023). Test transferability of 3D-MOT training on soccer specific parameters. *Research Directs in Strength and Performance*, *3*(1).
- Plakias, S., Moustakidis, S., Kokkotis, C., Papalexi, M., Tsatalas, T., Giakas, G., & Tsaopoulos, D. (2023). Identifying soccer players' playing styles: A systematic review. *J Funct Morphol Kinesiol*, *8*(3). <https://doi.org/10.3390/jfmk8030104>
- Plisk, S. S., Stone, M.H. (2020). Periodization strategies. *Strength & Conditioning Journal*, *25*(6), 19-37. <https://doi.org/https://doi.org/10.1519/00126548-200312000-00005>.
- Polly da Costa Valladao, S., Phillips, J., Logan, A., & Andre, T. (2023). Relationships between pre-match training load variables and matchday Countermovement jump height in NCAA DI women's soccer. *Research Directs in Strength and Performance*, *3*(1). <https://doi.org/https://doi.org/10.53520/rdsp2023.10555>
- Poulson, J. (2017). Impact of match performance on countermovement jumps when analysing post-match recovery status in elite soccer players. In S. M. s. University (Ed.). Twickenham.
- Principe, V. A., Vale, R. G. d. S., & Nunes, R. d. A. M. (2020). A systematic review of load

- control in football using a Global Navigation Satellite System (GNSS). *Motriz: Revista de Educação Física*, 26(4). <https://doi.org/10.1590/s1980-65742020000400059>
- Quagliarella, L., Sasanelli, N., Belgiovine, G., Accettura, D., Notarnicola, A., & Moretti, B. (2011). Evaluation of counter movement jump parameters in young male soccer players. *J Appl Biomater Biomech*, 9(1), 40-46. <https://doi.org/10.5301/JABB.2011.7732>
- R.L., R. R. R. (1991). *Essentials of behavioral research: Methods and data analysis*. McGraw Hill.
- Rampinini, E., Coutts, A. J., Castagna, C., Sassi, R., & Impellizzeri, F. M. (2007). Variation in top level soccer match performance. *Int J Sports Med*, 28(12), 1018-1024. <https://doi.org/10.1055/s-2007-965158>
- Rampinini, E., Impellizzeri, F. M., Castagna, C., Coutts, A. J., & Wisloff, U. (2009). Technical performance during soccer matches of the Italian Serie A league: effect of fatigue and competitive level. *J Sci Med Sport*, 12(1), 227-233. <https://doi.org/10.1016/j.jsams.2007.10.002>
- Randers, M. B., Mujika, I., Hewitt, A., Santisteban, J., Bischoff, R., Solano, R., Zubillaga, A., Peltola, E., Krstrup, P., & Mohr, M. (2010). Application of four different football match analysis systems: a comparative study. *J Sports Sci*, 28(2), 171-182. <https://doi.org/10.1080/02640410903428525>
- Ransdell, L. B., Murray, T., Gao, Y., Jones, P., & Bycura, D. (2020). A 4-Year profile of game demands in elite women's Division I college basketball. *J Strength Cond Res*, 34(3), 632-638. <https://doi.org/10.1519/JSC.0000000000003425>
- Redwood-Brown, A., Cranton, W., & Sunderland, C. (2012). Validation of a real-time video analysis system for soccer. *Int J Sports Med*, 33(8), 635-640.

<https://doi.org/10.1055/s-0032-1306326>

Reilly, T. (1976). A motion analysis of work-rate in different positional roles in professional football match-play. *Journal of Human Movement Studies*, 2, 87-97.

Roe, G., Darrall-Jones, J., Black, C., Shaw, W., Till, K., & Jones, B. (2017). Validity of 10-HZ GPS and timing gates for assessing maximum velocity in professional Rugby Union players. *Int J Sports Physiol Perform*, 12(6), 836-839.

<https://doi.org/10.1123/ijsp.2016-0256>

Romero-Rodríguez, R. C., Pérez-Chao, E.A., Ribas, C., Memmert, D., Gómez-Ruano, M.A. (2024). Influence of contextual factors on most demanding scenarios in under-19 professional soccer players. *Biology of Sport*, 41(4), 51-60.

<https://doi.org/10.5114/biolport.2024.136087>

Russell, M., Rees, G., & Kingsley, M. I. (2013). Technical demands of soccer match play in the English Championship. *J Strength Cond Res*, 27(10), 2869-2873.

<https://doi.org/10.1519/JSC.0b013e318280cc13>

Ryan, G. A., Snarr, R. L., Eisenman, M. L., & Rossi, S. J. (2022). Seasonal training load quantification and comparison in college male soccer players. *J Strength Cond Res*, 36(4), 1038-1045. <https://doi.org/10.1519/JSC.0000000000003589>

Saeterbakken, A., Haug, V., Fransson, D., Grendstad, H. N., Gundersen, H. S., Moe, V. F., Ylvisaker, E., Shaw, M., Riiser, A., & Andersen, V. (2019). Match running performance on three different competitive standards in Norwegian soccer. *Sports Med Int Open*, 3(3), E82-E88. <https://doi.org/10.1055/a-0943-3682>

Sams, M. L., Pustina, A., Liu, J., Smith, J., Grazer, J., & Mizuguchi, S. (2015, December, 2015). The effect of position and team formation on the physical activity profiles of a division I

- men's soccer team 10th Annual Coaching and Sport Science College, Johnson City, TN.
- Sams, M. L., Sato, K., DeWeese, B. H., Sayers, A. L., & Stone, M. H. (2018). Quantifying changes in squat jump height across a season of men's collegiate soccer. *J Strength Cond Res*, 32(8), 2324-2330. <https://doi.org/10.1519/JSC.0000000000002118>
- Sánchez-López, R., Etxezarra, I., & Castellano, J. (2023). Validation of an instrument to qualify Football Competence via WyScout. 83-94. [https://doi.org/10.5672/apunts.2014-0983.es.\(2023/4\).154.08](https://doi.org/10.5672/apunts.2014-0983.es.(2023/4).154.08)
- Sapp, R. M., Aronhalt, L., Landers-Ramos, R. Q., Spangenburg, E. E., Wang, M. Q., & Hagberg, J. M. (2017). Laboratory and match physiological data from an elite male collegiate soccer athlete. *J Strength Cond Res*, 31(10), 2645-2651. <https://doi.org/10.1519/JSC.0000000000002063>
- Sausaman, R. W., Sams, M. L., Mizuguchi, S., DeWeese, B. H., & Stone, M. H. (2019). The physical demands of NCAA Division I women's college soccer. *J Funct Morphol Kinesiol*, 4(4). <https://doi.org/10.3390/jfmk4040073>
- Sayers, A., Sayers, B. E., & Binkley, H. (2008). Preseason fitness testing in National Collegiate Athletic Association soccer. *Strength and Conditioning Journal*, 30(2), 70–75. <https://doi.org/https://doi.org/10.1519/ssc.0b013e31816a8849>
- Schmitz, B., Pfeifer, C., Kreitz, K., Borowski, M., Faldum, A., & Brand, S. M. (2018). The Yo-Yo intermittent tests: A systematic review and structured compendium of test results. *Front Physiol*, 9, 870. <https://doi.org/10.3389/fphys.2018.00870>
- Schutz, Y., & Chambaz, A. (1997). Could a satellite-based navigation system (GPS) be used to assess the physical activity of individuals on earth? *Eur J Clin Nutr*, 51(5), 338-339.

<https://doi.org/10.1038/sj.ejcn.1600403>

Scott, B., Lockie, R., Davies, S., Clark, A., Lynch, D., & Janse de Jonge, X. (2014). The physical demands of professional soccer players during in-season field-based training and match-play. *Journal of Australian Strength and Conditioning*.

Scott, M. T., Scott, T. J., & Kelly, V. G. (2016). The validity and reliability of Global Positioning Systems in team sport: A brief review. *J Strength Cond Res*, 30(5), 1470-1490.

<https://doi.org/10.1519/JSC.0000000000001221>

Siegler, J., Robergs, R., & Weingart, H. (2006). The application of soccer performance testing protocols to the non-elite player. *J Sports Med Phys Fitness*, 46(1), 44-51.

<https://www.ncbi.nlm.nih.gov/pubmed/16596098>

Silva, J. R. (2022). The soccer season: performance variations and evolutionary trends. *PeerJ*, 10, e14082. <https://doi.org/10.7717/peerj.14082>

Silva, J. R., Magalhaes, J. F., Ascensao, A. A., Oliveira, E. M., Seabra, A. F., & Rebelo, A. N. (2011). Individual match playing time during the season affects fitness-related parameters of male professional soccer players. *J Strength Cond Res*, 25(10), 2729-2739.

<https://doi.org/10.1519/JSC.0b013e31820da078>

Silva, J. R., Rebelo, A., Marques, F., Pereira, L., Seabra, A., Ascensao, A., & Magalhaes, J. (2014). Biochemical impact of soccer: an analysis of hormonal, muscle damage, and redox markers during the season. *Appl Physiol Nutr Metab*, 39(4), 432-438.

<https://doi.org/10.1139/apnm-2013-0180>

Silva, R., Lima, R., Camões, M., Leão, C., Matos, S., Pereira, J., Bezerra, P., & Clemente, F. M. (2021). Physical fitness changes among amateur soccer players: Effects of the pre-season period. *Biomedical Human Kinetics*, 13(1), 63-72. <https://doi.org/10.2478/bhk-2021-0009>

- Silvestre, R., Kraemer, W. J., West, C., Judelson, D. A., Spiering, B. A., Vingren, J. L., Hatfield, D. L., Anderson, J. M., & Maresh, C. M. (2006). Body composition and physical performance during a National Collegiate Athletic Association Division I men's soccer season. *J Strength Cond Res*, *20*(4), 962-970. <https://doi.org/10.1519/R-18165.1>
- Silvestre, R., West, C., Maresh, C. M., & Kraemer, W. J. (2006). Body composition and physical performance in men's soccer: a study of a National Collegiate Athletic Association Division I team. *J Strength Cond Res*, *20*(1), 177-183. <https://doi.org/10.1519/R-17715.1>
- Slater, L. V., Baker, R., Weltman, A. L., Hertel, J., Saliba, S. A., & Hart, J. M. (2018). Activity monitoring in men's college soccer: a single season longitudinal study. *Res Sports Med*, *26*(2), 178-190. <https://doi.org/10.1080/15438627.2018.1431535>
- Slimani, M., & Nikolaidis, P. T. (2019). Anthropometric and physiological characteristics of male soccer players according to their competitive level, playing position and age group: a systematic review. *J Sports Med Phys Fitness*, *59*(1), 141-163. <https://doi.org/10.23736/S0022-4707.17.07950-6>
- Sole, C. J., Suchomel, T. J., & Stone, M. H. (2018). Preliminary scale of reference values for evaluating Reactive Strength Index-Modified in male and female NCAA Division I athletes. *Sports (Basel)*, *6*(4). <https://doi.org/10.3390/sports6040133>
- Spalding, J. (2017). Technical and physical match demands of a NCAA Division I soccer goalkeeper (Publication Number 10609047) [M.A., East Tennessee State University]. Dissertations & Theses @ East Tennessee State University; ProQuest One Academic. United States -- Tennessee.

<https://www.proquest.com/dissertations-theses/technical-physical-match-demands-ncaa-division-i/docview/1906670106/se-2?accountid=10771>

https://libs.etsu.edu/primo/resolver.php?url_ver=Z39.88-2004&rft_val_fmt=info:ofi/fmt:kev:mtx:dissertation&genre=dissertations&sid=ProQ:ProQuest+Dissertations+%26+Theses+Global&atitle=&title=Technical+and+Physical+Match+Demands+of+a+NCAA+Division+I+Soccer+Goalkeeper&issn=&date=2017-01-01&volume=&issue=&spage=&au=Spalding%2C+Joanne&isbn=978-1-369-80179-8&jtitle=&btittle=&rft_id=info:eric/&rft_id=info:doi/

Sporis, G., Jukic, I., Ostojic, S. M., & Milanovic, D. (2009). Fitness profiling in soccer: physical and physiologic characteristics of elite players. *J Strength Cond Res*, 23(7), 1947-1953. <https://doi.org/10.1519/JSC.0b013e3181b3e141>

Stolen, T., Chamari, K., Castagna, C., & Wisloff, U. (2005). Physiology of soccer: an update. *Sports Med*, 35(6), 501-536. <https://doi.org/10.2165/00007256-200535060-00004>

Stone, M. H., Hornsby, W. G., Haff, G. G., Fry, A. C., Suarez, D. G., Liu, J., Gonzalez-Rave, J. M., & Pierce, K. C. (2021). Periodization and Block Periodization in sports: Emphasis on strength-power training-a provocative and challenging narrative. *J Strength Cond Res*, 35(8), 2351-2371. <https://doi.org/10.1519/JSC.0000000000004050>

Stone M.H., O'Bryant H.S., Hornsby G., Cunanan A., Mizuguchi S., Suarez D.G., South M., Marsh D.J., Haff G.G., Ramsey M.W., Beckham G.K., Santana H.A.P, Wagle J.P., Stone M.E., and Pierce K.P. The Use of the Isometric Mid-thigh Pull in the Monitoring of Weightlifters: 25+ Years of Experience. *UKSCA Journal: Professional Strength and Conditioning*. 54:10-26, 2019.

Stone, M. H., Sanborn, K., O'Bryant, H. S., Hartman, M., Stone, M. E., Proulx, C., Ward, B., &

- Hruby, J. (2003). Maximum strength-power-performance relationships in collegiate throwers. *J Strength Cond Res*, 17(4), 739-745.
[https://doi.org/10.1519/1533-4287\(2003\)017<0739:msrict>2.0.co;2](https://doi.org/10.1519/1533-4287(2003)017<0739:msrict>2.0.co;2)
- Stone, M.H., Sands, W.A., Carlock, J.O.N., Callan, S.A.M., Dickie, D.E.S., Daigle, K., Cotton, J., Smith, S.L. and Hartman, M., 2004. The importance of isometric maximum strength and peak rate-of-force development in sprint cycling. *The Journal of Strength & Conditioning Research*, 18(4), pp.878-884.
- Styles, W. J., Matthews, M. J., & Comfort, P. (2016). Effects of strength training on squat and sprint performance in soccer players. *J Strength Cond Res*, 30(6), 1534-1539.
<https://doi.org/10.1519/JSC.0000000000001243>
- Suarez-Arrones, L., Torreno, N., Requena, B., Saez De Villarreal, E., Casamichana, D., Barbero-Alvarez, J. C., & Munguia-Izquierdo, D. (2015). Match-play activity profile in professional soccer players during official games and the relationship between external and internal load. *J Sports Med Phys Fitness*, 55(12), 1417-1422.
<https://www.ncbi.nlm.nih.gov/pubmed/25289717>
- Suchomel, T. J., Bailey, C. A., Sole, C. J., Grazer, J. L., & Beckham, G. K. (2015). Using reactive strength index-modified as an explosive performance measurement tool in Division I athletes. *J Strength Cond Res*, 29(4), 899-904.
<https://doi.org/10.1519/JSC.0000000000000743>
- Svensson, M., & Drust, B. (2005). Testing soccer players. *J Sports Sci*, 23(6), 601-618.
<https://doi.org/10.1080/02640410400021294>
- Sweeting, A. J., Cormack, S. J., Morgan, S., & Aughey, R. J. (2017). When is a sprint a sprint? A review of the analysis of team-sport athlete activity profile. *Front Physiol*, 8, 432.

<https://doi.org/10.3389/fphys.2017.00432>

Taylor, J. M., Madden, J. L., Cunningham, L. P., Wright, M. (2022). Fitness testing in soccer revisited. *Strength & Conditioning Journal*, 44(5).

<https://doi.org/10.1519/ssc.0000000000000702>.

Theodoropoulos, J. S., Bettle, J., & Kosy, J. D. (2020). The use of GPS and inertial devices for player monitoring in team sports: A review of current and future applications. *Orthop Rev (Pavia)*, 12(1), 7863. <https://doi.org/10.4081/or.2020.7863>

Thomakos, P., Spyrou, K., Katsikas, C., Geladas, N. D., & Bogdanis, G. C. (2023). Effects of concurrent high-intensity and strength training on muscle power and aerobic performance in young soccer players during the pre-season. *Sports (Basel)*, 11(3).

<https://doi.org/10.3390/sports11030059>

Thomas, C., Dos'Santos, T., & Jones, P. A. (2017). A comparison of dynamic strength index between team-sport athletes. *Sports (Basel)*, 5(3). <https://doi.org/10.3390/sports5030071>

Thomas, C., Jones, P. A., & Dos'Santos, T. (2022). Countermovement jump force-time curve analysis between strength-matched male and female soccer players. *Int J Environ Res Public Health*, 19(6). <https://doi.org/10.3390/ijerph19063352>

Thomas, C., Jones, P. A., Rothwell, J., Chiang, C. Y., & Comfort, P. (2015). An investigation into the relationship between maximum isometric strength and vertical jump performance. *Journal of Strength and Conditioning Research*, 29(8), 2176-2185.

<https://doi.org/10.1519/JSC.0000000000000866>

Thomas, V., & Reilly, T. (1979). Fitness assessment of English league soccer players through the competitive season. *Br J Sports Med*, 13(3), 103-109.

<https://doi.org/10.1136/bjism.13.3.103>

- Tierney, P. J., Young, A., Clarke, N. D., & Duncan, M. J. (2016). Match play demands of 11 versus 11 professional football using Global Positioning System tracking: Variations across common playing formations. *Hum Mov Sci*, *49*, 1-8.
<https://doi.org/10.1016/j.humov.2016.05.007>
- Torreno, N., Munguia-Izquierdo, D., Coutts, A., de Villarreal, E. S., Asian-Clemente, J., & Suarez-Arrones, L. (2016). Relationship between external and internal loads of professional soccer players during full matches in official games using Global Positioning Systems and heart-rate technology. *Int J Sports Physiol Perform*, *11*(7), 940-946. <https://doi.org/10.1123/ijsp.2015-0252>
- Torres-Ronda, L., Beanland, E., Whitehead, S., Sweeting, A., & Clubb, J. (2022). Tracking systems in team sports: A narrative review of applications of the data and sport specific analysis. *Sports Med Open*, *8*(1), 15. <https://doi.org/10.1186/s40798-022-00408-z>
- Tumilty, D. (1993). Physiological characteristics of elite soccer players. *Sports Med*, *16*(2), 80-96. <https://doi.org/10.2165/00007256-199316020-00002>
- Van Hooren, B., & Zolotarjova, J. (2017). The difference between countermovement and squat jump performances: A review of underlying mechanisms with practical applications. *J Strength Cond Res*, *31*(7), 2011-2020. <https://doi.org/10.1519/JSC.0000000000001913>
- Vescovi, J. D., Brown, T. D., & Murray, T. M. (2007). Descriptive characteristics of NCAA Division I women lacrosse players. *J Sci Med Sport*, *10*(5), 334-340.
<https://doi.org/10.1016/j.jsams.2006.07.010>
- Vescovi, J. D., & Favero, T. G. (2014). Motion characteristics of women's college soccer matches: Female Athletes in Motion (FAiM) study. *Int J Sports Physiol Perform*, *9*(3), 405-414. <https://doi.org/10.1123/IJSP.2013-0526>

- Wik, E. H. (2015). Activity profiles and fatigue in elite female and male team handball: *Individual and team characteristics* [Norwegian School of Sport Sciences]. Norway.
- Withers, R. T. (1982). Match analyses of Australian professional soccer players. *Journal of Human Movement Studies*, 8, 159-176.
- Yi, Q., Gomez-Ruano, M. A., Liu, H., Zhang, S., Gao, B., Wunderlich, F., & Memmert, D. (2020). Evaluation of the technical performance of football players in the UEFA Champions League. *Int J Environ Res Public Health*, 17(2).
<https://doi.org/10.3390/ijerph17020604>

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