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ASSOCIATION BETWEEN BASELINE FIELD TEST PERFORMANCE AND MATCH PHYSICAL PERFORMANCE IN D1 FEMALE SOCCER PLAYERS

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ABSTRACT
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Title: Association Between Baseline Field Test Performance and Match Physical Performance in D1 Female Soccer Players

Chairperson: Shane Murphy

Background: Fitness testing is utilized by numerous soccer programs as a means for evaluation of player physical capacity. Previous literature has shown Yo-Yo Intermittent Recovery Test Level 1 (YYIR1) performance is associated with match physical performance in elite adult and youth soccer players. Until now, these relationships have not been investigated in the collegiate soccer setting, despite the YYIR1 being regularly utilized at the collegiate level to determine eligibility for competition, influence playing time, and to assess adaptation to training programs. For these reasons the association between the YYIR1 and match physical performance was investigated in women's collegiate soccer.
Aims: 1) To investigate the association between the YYIR1 and match physical performance in collegiate female soccer players. 2) To expand on existing YYIR1 performance and match physical performance data in this population.
Methods: Baseline YYIR1 performance scores, GPS match data, and confounding factors data were collected for two competitive seasons. A linear mixed model was used to assess the relationship between baseline YYIR1 performance and match total distance (TD), high-intensity running distance (HIRD), and sprint distance (SD) metrics, while adjusting for potential confounding factors.
Hypothesis: Increased YYIR1 performance is associated with increased match TD, HIRD, and SD when confounding factors are adjusted for.
Results: The mean YYIR1 baseline score was 33.1 ± 5.3 levels (1323 ± 211m). Mean match physical performance values for TD, HIRD, and SD were 107.7±12, 7.84±3.34, and 1.63±1.1 m/min, respectively. Linear mixed model results demonstrated that an increase in YYIR1 performance by one level is associated with increases in match physical performance of 0.95 (0.257 - 1.651) m/min, 0.27 (0.138 - 0.405) m/min, and 0.05 (0.002 - 0.095) m/min for TD, HIRD, and SD, respectively.
Discussion: Increased performance in the YYIR1 is associated with an increase in match physical performances in collegiate female soccer players. This extends similar previous findings from other populations and provides evidence that the YYIR1 is a valuable tool for strength and conditioning when assessing physical preparation for competition in collegiate female soccer players. This study also expands existing data describing YYIR1 performance and match physical performance in D1 female soccer players.

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Chapter 1: Introduction

Soccer requires intermittent bouts of high intensity physical activity followed by periods of low intensity movement (Stolen et al., 2005). The physical demands of elite men's soccer matches have been quantified utilizing various techniques (Bradley et al., 2013; Di Salvo et al., 2009; Rampinini, Bishop, et al., 2007; Randers et al., 2010). The implementation of global positioning systems (GPS) to monitor athlete movement has allowed for match analysis to be done at a greater scale and with greater consistency (Scott et al., 2016). These wearable devices allow for the quantification of match physical performance through the tracking of running distances within various speed zones (Bradley & Vescovi, 2015). Compared with elite men, a limited number of studies have analyzed match physical performance of elite women's soccer players using GPS or other tracking methods, though the literature is growing (H. A. Andersson et al., 2010; Gabbett & Mulvey, 2008; Hewitt et al., 2014; Krustrup et al., 2005; Mohr et al., 2008). Even fewer studies have utilized GPS to investigate the unique match demands found in collegiate women's soccer (McCormack et al., 2014; Vescovi & Favero, 2014; Wells et al., 2015).

Sex-based differences in match physical performance have been demonstrated at both the elite and collegiate levels of soccer (Bradley et al., 2014; McFadden et al., 2020; Iñigo Mujika et al., 2009). Additionally, sex-based differences in the physical capacities of soccer players seem to be present (Datson et al., 2014; Stolen et al., 2005). Different competitive levels also appear to influence match physical performance, with international female matches (Datson et al., 2017) requiring players to cover more total distance and perform more high intensity running when compared to collegiate female match data (McCormack et al., 2014). These differences between sexes and competitive level, when taking into consideration with the paucity of research in female collegiate soccer, provide a strong rationale for further investigation into the physical capacity and match physical performance of this population.

Decrements in physical performance over the course of competitive matches has also been investigated due to the role these decreases may play in determining match success (Mohr et al., 2005). Indeed, decreases in match running performance have been seen during elite male and elite women's soccer competitions. Mohr et al. observed a temporary decrease in physical performance in the 5 minutes following the most intense 5-minute period of a half (Mohr et al., 2003). Additionally, decreases in total distance, high intensity running (>3.89m/s) and very high intensity running (>5.28m/s) have been seen between first and second half of Italian series A men's soccer matches (E. Rampinini et al., 2009). Similarly, a study analyzing elite women's soccer matches found decreases in cumulative jogging, running, and sprinting distance (>1.67m/s) between the first 15 minutes of play and latter periods of the second half. This study found 22.4% and 26.1% decreases in running distances during minutes 60 to 75 and 75 to 90, respectively (Hewitt et al., 2014). To the best of the author's knowledge, decrements in physical performance during collegiate soccer matches have not been investigated in either male or female players.

It has been suggested that physical performance over the course of a soccer match is influenced by factors separate from the athletes' physical capacity to meet match demands (Bradley & Noakes, 2013). Accounting for these confounding influences when analyzing match performance is recommended to provide contextual meaning to the metrics in question (Carling, 2013; Mackenzie & Cushion, 2013). One such factor that has been proposed in previous literature is strength of the opponent, with higher strength opponents resulting in increased running distances for the reference team (H. A. Andersson et al., 2010; Castellano et al., 2011; Hewitt et al., 2014; Lago et al., 2010; Rampinini, Coutts, et al., 2007). Additionally, playing position has been shown to influence match physical performance in female soccer players, with midfielders covering greater total distances (H. A. Andersson et al., 2010; Datson et al., 2017; Gabbett & Mulvey, 2008; Hewitt et al., 2014), defenders performing less high intensity activity (H. A. Andersson et al., 2010; Datson et al., 2017; Mohr et al., 2008), and forwards performing more sprinting (Mohr et al., 2008). In addition to a player's position, their status as a starter should be considered as a confounding factor, as starting players have a greater relative rank to their teammates. The influence of starter status on match physical performance has not been investigated in female collegiate soccer; however, it has been shown that NCAA D1 female soccer starters experience greater training loads and muscle soreness throughout the competitive season when compared to non-starters (McLean et al., 2012). This suggests the differing physical demands placed on starters when compared to non-starters, and potential for those demands and resulting fatigue to affect match physical performance. These potentially confounding factors should be considered when assessing match physical performance.

A major aim of collegiate soccer programs is to physically prepare athletes for the demands of competition, allowing them to achieve optimal physical performance and reduce fatigue during competition. A variety of fitness testing protocols can be employed to assess the physical capacity of soccer athletes (Svensson & Drust, 2005). Testing protocols are utilized to assess an athlete's response to training programs and physical preparation for competition. Major determinants of testing protocol selection by soccer programs often include the ability to test large groups in a time efficient manner and the cost of the test. These influence test selection due to the need to avoid excessively burdening a team's training schedule or financial resources. For this reason, field tests are often selected over laboratory testing to gauge team fitness.

Aerobic capacity has been identified as a key determinant in a soccer athlete's physical preparation for competition (Datson et al., 2014; Stolen et al., 2005). A strong positive correlation ($r = 0.81$, $P = <.001$) has been demonstrated between VO2max and the amount of high intensity running (>4.17m/s) performed during an elite women's soccer match (Krustrup et al., 2005). Similar relationships between match physical performance and VO2max have been seen in NCAA D1 female soccer players during an intrasquad match, where physical performance was analyzed using GPS technology

(McCormack et al., 2014). These researchers found correlations between VO2max and total running distance ($r = 0.831$, $p = 0.003$) and high intensity running (>3.61m/s) distance ($r = 0.755$, $p = 0.012$) (McCormack et al., 2014). Furthermore, a review of the literature on female soccer athletes suggests aerobic capacity can discriminate between levels of competition, with elite players having higher aerobic capacities than sub-elite (Datson et al., 2014). These findings suggest the importance of aerobic fitness due to its association with physical performance during match play.

The intermittent nature of soccer, its high intensity running demands, and frequent changes of direction has led to the development of several sport specific field tests to assess aerobic capabilities with these demands in mind. The Yo-Yo intermittent recovery test level 1 (YYIR1) has been utilized to assess intermittent high intensity running capabilities in collegiate female soccer players (Lockie et al., 2018). This test involves an incremental protocol to exhaustion that includes intermittent bouts of high intensity running interrupted by a change of direction, with brief periods of rest between bouts (Krustrup et al., 2003). Several studies have demonstrated significant strong correlations between YYIR1 performance and maximal aerobic capacity (Krustrup et al., 2003; Ermanno Rampinini et al., 2009).

Previous research has shown that the YYIR1 is related to several key measures of match physical performance in both men's and women's elite soccer (Krustrup et al., 2003; Krustrup et al., 2005). These studies demonstrated correlations with high intensity running distance (>4.17m/s) and total distance during a match. Similar relationships have also been demonstrated between YYIR1 performance and match physical performance in male youth soccer players (Castagna et al., 2009; Castagna et al., 2010; Rebelo et al., 2014). The relationship between YYIR1 performance and match physical performance has not been investigated in the collegiate soccer setting, despite it commonly being employed by NCAA soccer teams during baseline testing.

In many NCAA collegiate soccer programs results from testing protocols such as the YYIR1 often influence eligibility to compete, starter status and playing time determinations. Furthermore, the YYIR1 is regularly used to assess an athlete's fitness, based on the assumption that improvements in test results will correlate to improvements in match performance. Often this assessment takes place prior to the start of the competitive season, following an off-season period. Despite its regular implementation in collegiate soccer programs, the relationship between a collegiate women soccer athlete's performance in the YYIR1 and match physical performance has not been investigated. Furthermore, the physical performances during women collegiate soccer matches have been investigated sparingly. Therefore, our aims for this study were 1) quantify the physical capacity of D1 collegiate female soccer players and their physical performance during competitive matches, and 2) assess the relationship between a baseline YYIR1 and match-related performance metrics in the same season.

Statement of problem

The yo-yo intermittent fitness test level 1 (YYIR1) is regularly used to assess collegiate soccer players' physical capacity under the assumption that test results will relate to match physical performance and game success. Results of this field-based fitness test often influence eligibility to compete, playing time determinations, and assessments of response to training. A protocol's inclusion in a baseline testing battery must be justified due to the scarcity of time available for such testing and the need for true indicators of physical preparation. Collegiate athletic performance, and sports medicine professionals can benefit from research investigating if, and to what extent, the YYIR1 relates to match physical performance.

Scientific Aims

1) Quantify the physical capacity of D1 collegiate female soccer players and their physical performance during competitive matches.

2) Assess the relationship between a baseline YYIR1 and match-related physical performance metrics in the same season.

Research hypotheses

1) No statistical hypothesis for SA #1 (Descriptive Aim)

2) Increased YYIR1 performance is associated with increased match total distance, high intensity running distance, and sprint distance when confounding factors are accounted for.

Significance of the study

We aim to provide insight to athletic performance and sport medicine professionals about the value of utilizing the YYIR1 when determining a collegiate soccer athlete's physical preparation for competition, with the goal of optimizing soccer match performance and mitigating injury.

Rationale of the study

Fitness testing is utilized by numerous soccer programs as a means for evaluation of player physical readiness and adaptation to training programs. Previous literature has shown YYIR1 performance is associated with match physical performance in elite adult and youth soccer players (Castagna et al., 2009; Castagna et al., 2010; Krustrup et al., 2003; Krustrup et al., 2005; Rebelo et al., 2014). These associations demonstrate the ecological and logical validity of the YYIR1 as a baseline measure. Until now, these relationships have not been investigated in the women's collegiate soccer setting, despite the YYIR1 being regularly utilized at the collegiate level to determine eligibility for competition, influence playing time, and to assess adaptation to training programs. For these reasons the association between the YYIR1 and match physical performance was investigated in women's collegiate soccer.

Delimitations

1. Included only soccer athletes. All athletes are part of the University of Montana soccer team.

2. Conducted baseline fitness assessment using a field test procedure common in collegiate soccer (Yo-Yo Intermittent Recovery Test Level 1)

3. Competitive matches were be used for match physical performance data collection

4. GPS units were utilized to assess match physical performance

Limitations

1. Excluded other field sport athletes and soccer athletes of different competitive levels.

2. Did not obtain direct physiological measures of baseline physical capacity.

3. Conducted a quasi-experimental design without the ability to control for some confounding factors such as: athlete pacing, mental fatigue, tactical strategies, or environmental factors.

4. Reliance on GPS units utilizing proprietary software for calculation of match physical performance measures

Assumptions

1. Match physical running performance in collegiate soccer players at the University of Montana is representative of other collegiate soccer athletes.

2. Field testing protocols are the predominant methods utilized by collegiate soccer programs for baseline fitness assessments.

3. Data collected during matches is representative of the physical performances and demands of competition. All physical movements performed by athletes during competitive matches are done so with the goal of winning the match.

4. The performance measurements measured and calculated by the GPS units and proprietary software are valid and reliable.

Chapter 2: Review of Related Literature

Match Analysis Methods

A competitive soccer match places a variety of demands on participants, with success dependent on appropriate technical, tactical, mental, and physical performance relative to the opponent. Specifically, understanding the match physical performance demands is an essential prerequisite for the design and implementation of training and testing programs with the intention to prepare soccer athletes for competition (Reilly, 2005). Physical preparation is completed to increase the athlete's ability to meet competitive match demands, improving performance and possibly reducing the risk for injury. With these goals in mind, creating a deeper understanding of the requirements of match play is the first step.

To better understand match demands, a methodological approach of match analysis must be taken. The analysis of in-match running demands in team sports has evolved over the past several decades from time consuming retrospective video analysis to semi-automatic video systems, and most recently real-time instantaneous tracking of athlete movements utilizing wearable technology (Datson et al., 2017; Gabbett & Mulvey, 2008; Panduro et al., 2022). With the development of these technologies has come increases in the amount and types of performance data that can be collected.

Early soccer time-motion analysis studies on match physical demands were initially collected utilizing real time hand notation, publicly available game films, or specialized recordings (Reilly, 1976; Stolen et al., 2005). A standardized procedure for video motion analysis of match demands was developed which involved the classification of movement demands based on designated locomotor categories and movement speeds (Bangsbo et al., 1991). This method involves the placement of a video camera at midfield and slightly elevated from the playing area to allow for the recording of an individual player throughout the match. These videos are then used to retroactively code the movement activities of that player by a trained observer. The locomotor categories utilized, as described in Bangsbo et al. (1991), are as follows: Standing (0 km/hr), Walking (6 km/hr), Jogging (8 km/hr), low-speed running (12 km/hr), moderate speed running (15 km/hr), high-speed running (18km/hr), sprinting (25 km/hr), and backward running (10 km/hr) (Bangsbo et al., 1991). The reproducibility of these methods was investigated, with intra-individual coefficient of variances for total distance and distance of locomotor categories being less than 5% (Krustrup & Bangsbo, 2001). Additionally, inter-individual variance of this analysis method was observed to be less than 4% (Bangsbo et al., 1991). These general procedures have been utilized in many studies involving the analysis of player activity during matches (H. A. Andersson et al., 2010; Krustrup et al., 2005; M. Mohr et al., 2003; Rampinini, Bishop, et al., 2007). Although the development of this match analysis methodology provided valuable information on the match demands of elite soccer players, it is time consuming in set-up and implementation, while only allowing for retrospective analysis of player activity. These limitations often reduced the possible sample sizes in studies and prevented the method's use outside of academia. Some of these barriers to use began to be removed with the development of systems that allowed for simultaneous and near automatic analysis of matches.

One such match analysis methodology is video based semi-automatic computerized tracking systems. These devices utilize fixed multi-camera systems to simultaneously record the movements of all objects on the playing field (Carling et al., 2008). Utilizing proprietary analysis processes, the systems can identify and track the movements of individuals on the field and the ball. Depending on the system manufacturer, this process may be semi-automatic, with human assistance required in certain instances (Barris & Button, 2008). These computerized tracking systems greatly increase the number of athletes that may be analyzed, while also providing information about periods of ball contact. These prove to be advantages for the analysis of physical and technical activities of players for both academic research and practical application by coaches. Many important and insightful studies have been conducted in elite soccer utilizing such systems, furthering the understanding of match demands (Bradley et al., 2013;

Bradley et al., 2014; Datson et al., 2017; Di Salvo et al., 2009; Mara et al., 2017b; Rampinini, Bishop, et al., 2007; E. Rampinini et al., 2009).The reliability and validity of such systems has been investigated, with results showing them to be adequate for research purposes (Di Salvo et al., 2006; Di Salvo et al., 2009; Randers et al., 2010). Despite the advantages of simultaneous tracking of multiple players, these systems still possess several drawbacks. Analysis is still limited to after the completion of a match, and therefore real time feedback is unable to be viewed. Additionally, such systems are usually permanently affixed in stadiums, which may limit its use to the elite level teams that play at such venues. Lastly, while greatly decreasing the time demands for analysis, active user input is still required during the movement coding process. The above limitations may reduce the practicality of these systems for analysis by researchers or practitioners who are challenged by facility access or time availability.

Match analysis has been influenced most recently by the increasing development of wearable technology integrating global positioning systems (GPS) and inertial motion units (IMU) (Chambers et al., 2015). GPS devices can be utilized to track athlete physical performance during training and competitions and have increasingly been utilized by researchers and practitioners (Scott et al., 2016). GPS devices will be covered in greater detail later in this review. IMUs have also been utilized as either standalone devices or in concert with devices such as GPS units to augment measurement accuracy (Chambers et al., 2015). These technologies can provide instantaneous, real-time movement feedback for multiple athletes (Cummins et al., 2013). Additionally, most wearable technology companies provide software platforms through which processed data can be organized and displayed for practitioners. This increases the potential of these tools to be used by coaches without the skills or time necessary to process the raw data collected by the devices. However, with this ease of use comes a greater number of unpublished calculations used to calculate performance metrics, which may lead to a loss in data transparency and trust. It should be noted these drawbacks are present in semi-automatic automatic computerized tracking systems as well.

Demands of Female Soccer Matches

Physiological Demands

Heart rate monitoring during competitive soccer matches has been shown to be an accurate assessment of soccer match intensity and appropriate for the assessment of aerobic demands of the game (Alexandre et al., 2012; Ali & Farrally, 1991; Esposito et al., 2004). The heart rate response of field players during elite female soccer matches has been well investigated, with mean and peak values ranging from 85-89% and 97-99% of maximum heart rate (HRmax), respectively (H. A. Andersson et al., 2010; Krustrup et al., 2005; Panduro et al., 2022). It has been demonstrated that field players spent more than a quarter of playing time above a heart rate of 180bpm, and approximately half of total playing time between 160-180bpm. The same researchers found that heart rate responses did not differ between playing positions (Panduro et al., 2022). Individualized HR-VO2 relationships have been utilized to estimate oxygen uptake during elite female competitive matches, with average values being between 77-80% VO2max and peak values at 96% VO2max (Krustrup et al., 2005; M Mohr et al., 2003).

Collegiate female soccer players have demonstrated similar heart rate responses to competitive matches. They achieve average heart rates approximating 172bpm, (Paulsen et al., 2018), spending more than an hour of total playing time at or above 80% HRmax (McFadden et al., 2020). Similarly, it has been demonstrated collegiate female soccer athletes spend more than 42% and 38% of total playing time between 80-89% HRmax and 90-100% HRmax, respectively (Bozzini et al., 2020). These findings suggest the important role the aerobic system plays in meeting the energy demands of competitive female soccer matches at both the elite and collegiate level.

While the importance of the aerobic system for soccer performance is apparent based on heart rate responses, it is important to remember soccer is an intermittent sport consisting of periods of high intensity anaerobic activity followed by periods of active recovery (Stolen et al., 2005). During a soccer match, some of the most pivotal moments occur while players are exerting at intensities requiring anerobic energy production, such as sprinting (Faude et al., 2012). Given these demands, it is prudent to understand the utilization or depletion of substrates important to anaerobic energy production.

Glycogen depletion after a soccer match has been seen as a marker of the anaerobic demands on soccer athletes and a probable contributor to fatigue (Bangsbo et al., 2007; Mohr et al., 2005; Mohr et al., 2022). Limited information exists on the utilization of glycogen by female soccer players during competitive matches, with a greater body of evidence in male players. However, it appears that both male and female elite soccer players experience significant reductions in muscle glycogen at the end of a soccer match (Mohr et al., 2022). In male players, muscle glycogen levels have been shown to be reduced in response to both friendly and competitive matches, but complete depletion is not always the case (Bangsbo et al., 2007). Reductions in glycogen levels have been seen in elite female players during and following a friendly match (Krustrup et al., 2022). In this study a match-induced reduction of 42% was seen in muscle glycogen stores. There was also a complete or nearly complete depletion of 80% of Type 1 muscle fibers and 69% of analyzed type 2 muscle fibers after the match (Krustrup et al., 2022).

Soccer athletes are often required to perform maximal or near maximal sprints with short durations of active rest between them. Phosphocreatine (PCr) is extremely important for explosive, short duration activities requiring a high rate of ATP utilization. During maximal short sprint activities lasting less than 6s PCr will account for approximately 50% of the ATP demands (Gaitanos et al., 1993; Hargreaves & Spriet, 2006). Dawson et al. demonstrated PCr stores may decrease up to 55% following a 6s maximal short sprint (Dawson et al., 1997). Therefore, PCr is critical to short sprint performance, especially at the onset of the maximal effort and provides for a large proportion of the energy demands without being fully depleted. Limited information exists on the utilization of PCr by female soccer players during competitive matches. However, one study did observe decrements in PCr during an experimental match following an intense period of play when compared to a measurement before the match. Decrements of 15 mmol/kg (18%) and 10 mmol/kg (12%) were observed following intense periods of play in the first and second halves, respectively (Krustrup et al., 2022). These decrement measurements are likely underestimated due to the delay between the high intensity activity and the muscle biopsy collection (~30s). Based on PCr resynthesis rates, the authors suggested the actual PCr concentration immediately following the intense periods were 30-35 mmol/kg (37-43%) lower than the baseline measure (Krustrup et al., 2022).

Physical Performance Demands

A modest but growing number of studies have analyzed match physical performance of elite women's soccer players (H. A. Andersson et al., 2010; Datson et al., 2017; Gabbett & Mulvey, 2008; Hewitt et al., 2014; Krustrup et al., 2005; Mohr et al., 2008; Panduro et al., 2022). Less research has been conducted on the match demands in collegiate women's soccer (McCormack et al., 2014; Vescovi & Favero, 2014; Wells et al., 2015).

Total distances covered in elite female soccer matches are usually around 10km when analyzed using either video-based methods (H. A. Andersson et al., 2010; Datson et al., 2017; Gabbett & Mulvey, 2008; Mohr et al., 2008) or GPS (Hewitt et al., 2014; Panduro et al., 2022). This appears to indicate an increase in the total distance physical demands of the game when compared to historically reported data (Davis & Brewer, 1993). Female collegiate players appear to cover slightly less total distance when compared to elite female players, with values ranging from 8-10km (McCormack et al., 2014; McFadden et al., 2020; Vescovi & Favero, 2014; Wells et al., 2015).

It has been suggested that high intensity running (HIR) performance is critical to soccer match success and is occurs during the most important moments for the determination of match success (Mohr et al., 2008; Stolen et al., 2005). Sprinting has also been highlighted as important during goal scoring situations (Faude et al., 2012). Differences in velocity thresholds for HIR and sprinting make a general summary of studies challenging. In elite female studies, general HIR minimum thresholds have been placed as low as 1.67 m/s (Hewitt et al., 2014) and as high as 4.47 m/s (Vescovi & Falenchuk, 2019). Despite this apparent wide range, most studies appear to set elite female HIR thresholds within a range of 4 m/s and 4.17 m/s, with accumulated HIR distances over the course of the game ranging from 1.3 to 2.5km (H. A. Andersson et al., 2010; Datson et al., 2017; Krustrup et al., 2005; Mohr et al., 2008). Designated sprint thresholds in elite female soccer have generally been reported at 6.94 m/s (H. A. Andersson et al., 2010; Datson et al., 2017; Krustrup et al., 2005; Mohr et al., 2008), though this threshold has been suggested to be too high for the analysis of most female soccer players (Bradley & Vescovi, 2015). Nevertheless, using thresholds around 6.94 m/s elite female players have been reported to cover between 0.16 to 0.46 km above this intensity level during competitive matches (H. A. Andersson et al., 2010; Datson et al., 2017; Krustrup et al., 2005; Mohr et al., 2008).

The ability to perform sequences of maximal or near maximal sprints with short durations of active rest between them is critical for many team-sport athletes, including soccer players. This key determinant of competitive performance has been termed repeated-sprint ability (RSA) (Spencer et al., 2008). Soccer players have been the target population for many of the currently published research studies on RSA. This interest in RSA as a performance indicator in soccer is well warranted with elite female soccer athletes as well. Professional female soccer competitions involve intermittent bouts of high and low intensity exercise, some of which would qualify as repeated-sprint sequences (RSS) (Gabbett & Mulvey, 2008; Mohr et al., 2008). RSS vary depending on the specific sport, but generally consist of 3-6 short (<10s) sprints interspersed with brief (<60s) recovery periods (Buchheit et al., 2010; Girard et al., 2011; Nakamura et al., 2017). In addition to the presence of these high intensity bouts and RSS, a single instance of sprinting is associated with key plays within soccer matches such as ball possession, assists and goal scoring opportunities in professional male players (Faude et al., 2012). Buchheit et al. analyzed RSS over the course of a competitive season in elite male youth soccer players, revealing that RSA demands differ depending on age, playing position, and playing time (Buchheit et al., 2010). Therefore, RSA may be a critical for performance in female soccer players and the requirements of RSA may be different depending on individual factors.

In addition to the low and high intensity running and sprinting demands of soccer, the sport also requires athletes to perform short high intensity actions pertaining to changes in velocity and direction. Some of these actions have been deemed to be high intensity accelerations and decelerations and may impose a significant mechanical and metabolic load on the athletes that cannot be assessed through regular two-dimensional time-motion analysis (Dalen et al., 2016). There is limited literature on the acceleration and deceleration demands in soccer match play. Most published studies utilizing accelerometers have been conducted in male soccer but may provide some insights into this aspect of the sport's physical demands. Based on playing position in elite male matches, high intensity (>2.5m/s^2) accelerations are performed at frequencies ranging from 27 occurrences per minute for central defenders up to 114 occurrences per minute for midfielders. High intensity (<-2.5m/s^2) decelerations are performed at frequencies ranging from 45 to 136 occurrences per minute for central defenders and all midfielders, respectively (Harper et al., 2019). One study has investigated to acceleration and deceleration demands in elite female soccer using video recordings and an optical player tracking system (Mara et al., 2017a). The authors found players performed a total of 423 moderate to high intensity accelerations (>2.0m/s^2) and 430 decelerations (<-2.0m/s^2). Differences between playing positions were seen for the demands of both accelerations and decelerations during competition (Mara et al., 2017a)

Contextual Influences on Match Physical Performance

Strength of Opponent

One factor that has been proposed to influence match physical performance in previous literature is strength of the opponent. It has been demonstrated that higher strength opponents resulting in increased running distances for the reference team (H. A. Andersson et al., 2010; Castellano et al., 2011; Hewitt et al., 2014; Lago et al., 2010; Rampinini, Coutts, et al., 2007)

Playing Position

Playing position has been shown to influence match physical performance in female soccer players, with midfielders covering greater total distances (H. A. Andersson et al., 2010; Datson et al., 2017; Gabbett & Mulvey, 2008; Hewitt et al., 2014), defenders performing less high intensity activity (H. A. Andersson et al., 2010; Datson et al., 2017; Mohr et al., 2008), and forwards performing more sprinting (Mohr et al., 2008).

Environmental

Trewin et al. 2018 investigated the effects of the venue elevation and air temperature on physical performance, measured using 10hz GPS monitors, during 47 elite female matches. The investigators found that lower total running distances were seen when competing above 500m of elevation. Additionally, they observed an overall decrease in match physical performance with an increase in air temperature above 21 degrees Celsius (Trewin et al., 2018). Similarly, another study in D1 female soccer players observed significant decreases in high intensity physical performance metrics with increasing wet-bulb globe temperatures (Trewin et al., 2018). It has also been demonstrated that playing surface may impact match physical performance, with artificial turf increasing the moderate and high intensity physical performances (Vescovi & Falenchuk, 2019).

GPS Monitors

The analysis of team-sport activities has evolved from a simple real time visual analysis with note taking to the real-time tracking of player movements using GPS technology. GPS time-motion analysis has proved to be valuable in the tracking of player movements, speeds, and overall activity demands. With the integration of several other micro technologies these devices are becoming more sophisticated and able to more accurately measure and report player movements with greater detail (Lutz et al., 2019). These devices have been shown to be valid and reliable when tracking distance covered, running speeds, and overall workload performed. However, caution should be taken when utilizing GPS technology for the analysis of short sprint activities or change of direction (Aughey, 2011). It seems that the validity and reliability of these devices when tracking short sprints and change of direction is mainly associated with the sampling rate at which the device can capture geospatial data. A device with a sampling rate of at least 10HZ is recommended to increase confidence in the information collected on these movement types (Scott et al., 2016)

Physical Capacity of Female Soccer Players

Elite Female Soccer Players

Aerobic capacity has been identified as a key determinant in a soccer athlete's physical preparation for competition (Datson et al., 2014; Stolen et al., 2005). The aerobic capabilities of elite female soccer players have been assessed using a variety of methodologies, including measurement of maximal oxygen uptake (VO2max) and the conduction of aerobic field testing. Direct VO2max measurements in elite female soccer players have been reported to range from 49.4– 57.6 mL/kg/min (H. Andersson et al., 2010; Datson et al., 2014; T. A. Haugen et al., 2014; Ingebrigtsen et al., 2011; Krustrup et al., 2005). In a study by Haugen et al. the VO2max of approximately 200 Norwegian female soccer players were analyzed over a period of 18 years. An analysis of these results showed that national team players had 5% and 13% higher VO2max than 1st-division and 2nd-division players, respectively. This demonstrates the variance of VO2max across professional levels of play.

In addition to laboratory measurements, field-based testing has also been utilized to assess the aerobic capacity of elite female soccer players. The YYIR1 has been widely used for this purpose in both male and female elite players. In elite female players YYIR1 performances range from 1224m – 1379m

(Krustrup et al., 2005; I. Mujika et al., 2009), with a compendium of YYIR1 results reporting a global mean and standard deviation of 1197±502m for sub elite/elite female soccer players.

As discussed previously, in addition to soccer's aerobic demands, there is also a large anerobic component to match play, especially during key moments of goals and assists (Faude et al., 2012; Stolen et al., 2005). A variety of anaerobic tests have been implemented with elite female soccer players, with timed linear sprints and vertical jump testing being the most common. Additionally, several repeated sprint ability (RSA) tests have been developed and implemented to assess this physical trait. Due to variances in testing protocols, direct comparison between results is challenging and should be conducted with caution.

As explained by Haugen et al. there are a variety of factors that can influence linear speed testing, all of which make comparisons between results challenging (T. Haugen et al., 2014). 20 meters is a common distanced used for timed linear sprints in soccer players. 20m sprint times in elite female players have been reported to range between 3.17s – 3.39s (Andersson et al., 2008; Vescovi, 2012). Vertical jump testing has been used in soccer players as an assessment of power (Stolen et al., 2005). A countermovement jump CMJ without the use of arms has been commonly used to assess jump performance in elite female soccer players, with values ranging from 30.5cm – 42cm (Andersson et al., 2008; Iñigo Mujika et al., 2009; Vescovi et al., 2011).

Collegiate Female Soccer Players

Fewer published studies include data describing the physical capacities of female collegiate soccer players compared to the literature on elite male and female players. However, the number of studies on this population have been increasing in recent years.

Maximal oxygen uptakes for female collegiate players have been shown to be between 40.69 – 51.7 ml/kg/min (McCormack et al., 2014; McFadden et al., 2020; Miller et al., 2007; Peart et al., 2018; Sanders et al., 2017). Miller et al. demonstrated a significant decrease in VO2max of approximately 8.8% from august to December, a timeframe that spans the collegiate season, in Division 1 female soccer players (Miller et al., 2007). However, these findings did not appear to be reproduced in Division 2 female soccer players in a study by Peart et al., as no such decrease in VO2max was seen over the course of the season (Peart et al., 2018).

YYIR1 performances for this population have been reported to range between 1628m – 1700m, which is considerably higher than reported values for elite female soccer players (Lockie et al., 2018; Risso et al., 2017). However, these differences in performance may be due to variation in the implementation of YYIR1 testing procedures. These studies reported ending the test after a participant received two *successive* warnings, as opposed to ending the test after two total warnings. This alteration is contrary to original testing procedure and may have resulted in elevated YYIR1 performance values (Bangsbo et al., 2008; Krustrup et al., 2003; Krustrup et al., 2005). Another study in collegiate female soccer players using the original testing procedures reported minimum and maximum YYIR1 performance values, ranging from 1000m - 1720m (Benjamin et al., 2020).

Little data has been published about the linear speed capabilities of collegiate female players. However, Lockie et al. published data of 5m, 10m, and 30m linear sprint times with median times of 1.144s, 1.974s, and 4.719s, respectively (Lockie et al., 2018). Athletes in this population have shown to produce CMJ results ranging from 43.57cm – 53.64cm with the use of arms (Lockie et al., 2018; McFadden et al., 2021; Peart et al., 2018) and 41.9cm without the use of arms (Vescovi et al., 2006). Published Wingate anaerobic test data has shown collegiate female soccer player peak power outputs ranging from 11.05 – 16.66 W/kg and mean power outputs ranging from 6.04 – 7.70 W/kg.

Fatigue and Match Physical Performance

Running performance indicators of fatigue

Decrements in physical performance during competitive matches has been investigated due to the role these decreases may play in determining match success (Mohr et al., 2005). Decreases in match running performance have been seen during elite male and elite women's soccer competitions. Mohr et al. observed a temporary decrease in high intensity running (>4.17m/s) in the 5 minutes following the most intense 5-minute period of a half, with a statistically significant decrease of 12% occurring (Mohr et al., 2003). Additionally, decreases in total distance, high intensity running (>3.89m/s) and very high intensity running (>5.28m/s) of 2%, 7%, and 7%, respectively, have been seen between first and second half of Italian series A men's soccer matches (E. Rampinini et al., 2009). In the same study, decreases of 5% and 9% in total distance with the ball and high intensity running with the ball were seen between halves, respectively. Similarly, a study analyzing elite women's soccer matches found decreases in cumulative jogging, running, and sprinting distance (>1.67m/s) between the first 15 minutes of play and latter periods of the second half. This study found 22.4% and 26.1% decreases in running distances during minutes 60 to 75 and 75 to 90, respectively (Hewitt et al., 2014).

Physical Capacity and Match Physical Performance

Aerobic Capacity and Match Physical Performance

A strong positive correlation (r = 0.81, P = <.001) has been demonstrated between VO2max and the amount of high intensity running (>4.17m/s) performed during an elite women's soccer match (Krustrup et al., 2005). Similar relationships between match physical performance and VO2max have been seen in NCAA D1 female soccer players during an intrasquad match, where physical performance was analyzed using GPS technology. These researchers found correlations between VO2max and total running distance (r = 0.831, p = 0.003) and high intensity running (>3.61m/s) distance (r = 0.755, p = 0.012) (McCormack et al., 2014). In addition to its correlations with match physical performance, aerobic capacity, a review of the literature on female soccer athletes suggests it can discriminate between levels of competition, with elite players having higher aerobic capacities than sub-elite (Datson et al., 2014). These findings suggest the importance of aerobic fitness in the prediction of physical performance during match play.

Field Test Performance and Match Physical Performance

Previous research has shown that the YYIR1 is related to several key measures of match physical performance in both men's and women's elite soccer (Krustrup et al., 2003; Krustrup et al., 2005). These studies demonstrated correlations with high intensity running distance (>4.17m/s) and total distance during a match. Similar relationships have also been demonstrated between YYIR1 performance and match physical performance in male youth soccer players (Castagna et al., 2009; Castagna et al., 2010; Rebelo et al., 2014). The relationship between YYIR1 performance and match physical performance has not been investigated in the collegiate soccer setting, despite it commonly being employed by NCAA soccer teams during baseline testing.

Chapter 3: Methodology

Experimental Approach to the Problem

To investigate if and to what extent the Yo-Yo Intermittent Recovery Test Level 1 (YYIR1) is associated with match physical performance, baseline measures were analyzed along with GPS match data and potential confounding factors. An archive of baseline, match performance, and confounding factor data were utilized for the team of interest's 2021 competitive collegiate soccer season. The YYIR1 was completed by members of the same team prior to the start of their 2022 competitive season. Match physical performance was analyzed throughout the 2022 competitive season utilizing wearable GPS monitoring devices. Potential confounding factors were measured at the start of the competitive season, during matches or at the end of the competitive season, depending on the nature of the variable. A linear mixed model was used to assess the relationship between baseline YYIR1 performance and match total distance (TD), high intensity running distance (HIRD), and sprint distance (SD) metrics. This model assessed these relationships while accounting for the confounding factors of playing position, player starting status, match location, game number, season year, and season period.

Definition of terms

- High Speed Running – Running between a speed of 4.3m/s and 5.6m/s

- Sprinting – Running above a speed of 5.6m/s

- High Intensity Running Distance (HIRD) – Sum of both high-speed running distance and sprinting distance. Sum of all running distance above 4.3m/s.

- Sprinting Distance (SD) – Sum of running distance above 5.6m/s

Procedures

Participants

A total of 55 participants were considered for inclusion in the preliminary analysis.

Baseline YYIR1 results and match physical performance metrics of 29 NCAA Division 1 soccer athletes were considered for our analysis of the 2021 competitive season. 1 athlete did not complete the baseline YYIR1 test and was excluded from the study. 3 goalkeepers were excluded from the study due to the significantly altered running demands of their position group during matches. The 2021 season data archive included GPS data and confounding factor information for 18 competitive matches.

For the 2022 competitive season, a convenience sample of 26 NCAA Division 1 soccer athletes was recruited. For our analysis, athletes participating in both seasons were considered as separate participants for each season. All athletes were medically cleared for sport participation by a physician through the University of Montana's athletic training department. 4 goalkeepers were excluded from the study. We collected GPS analysis and confounding factor data for 19 matches over the course of the 2022 competitive season. An overview of the 2022 competitive season can be found in figure 1, which represents the general timeline of the 2021 season as well.

AUG 2022				SEPT 2022					OCT 2022				NOV 2022		
Pre-Season		Out of Conference (OC)					In Conference (IC)					Post Conference (PC)			
W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11	W12	W13	W14	W15	W16
YYIR1		G1	G4	G6	G8	G10	G12	G14	G16	G17	G18		G20		
		G2	G5	G7	G9	G11	G13	G15			G19				
		G3													

Figure 1: Overview of 2022 competitive season timeline. ("W" = Week, "G" = Game)

After removing excluded athletes, a total of 47 athletes were involved in the preliminary analysis. Descriptive statistics for all participants can be found in Table 1. Categories were used to aid in the descriptive representation of baseline characteristics (Datson et al., 2022), however, for the main analysis YYIR1 Score was utilized.

Table 1: Baseline characteristics for all subjects by YYIR1 performance (n=47)

Baseline Characteristics for All Subjects*

		YYIR1 Performance**		
	All	Low	Moderate	High
	(N= 47)	(N= 17)	(N= 20)	(N= 10)
Age				
Mean (SD)	19.6 (1.36)	19.9 (1.32)	19.4 (1.31)	19.5 (1.58)
Height (cm)				
Mean (SD)	168 (5.86)	167 (6.21)	169 (6.18)	169 (4.80)
Position				
Forward	13 (27.7%)	4 (23.5%)	7 (35.0%)	2 (20.0%)
Midfielder	15 (31.9%)	7 (41.2%)	5 (25.0%)	3 (30.0%)
Defender	19 (40.4%)	6 (35.3%)	8 (40.0%)	5 (50.0%)
Season Year				
2021	25 (53.2%)	9 (52.9%)	10 (50.0%)	6 (60.0%)
2022	22 (46.8%)	8 (47.1%)	10 (50.0%)	4 (40.0%)
Matches Started				
Mean (SD)	5.85 (6.78)	5.29 (7.35)	6.15 (6.39)	6.20 (7.19)

Note:

*All subject baseline data provided, regardless of match playing time

**YYIR1 Performance Categories for <20 years old: Low <28, Moderate = 28-34, High >34

**YYIR1 Performance Categories for 20+ years old: Low <31, Moderate = 31-37, High >37

General Assessment

Approval of the utilization of the 2021 season data for research purposes was obtained from the University of Montana Institutional Review Board. All 2021 season data was deidentified and stored securely.

Data collection for the 2022 competitive season began in August 2022. Procedures were approved by the University of Montana Institutional Review Board. All participants were informed of the benefits and risks of this study, as well as provided written consent. At the onset of data collection, participants completed a demographic survey detailing player age, specific playing position, years of collegiate playing experience at the time of the baseline data collection.

Baseline Fitness Test

The Yo-Yo Intermittent Recovery Test Level 1 (YYIR1) was used as a baseline fitness assessment. The YYIR1 is an incremental running exercise protocol to exhaustion that involves bouts of high-speed running interrupted by a change of direction, with brief periods of active recovery between bouts. (Krustrup et al., 2003) The high-speed running bouts of the test progressively increase in speed, until the participant can no longer complete the bout at the prescribed speed and the test is terminated. The test quickly progresses in speed from 10 km/hr to 14.5 km/hr over the course of the first eleven test levels. Upon reaching level twelve the speed increases by 0.5 km/hr every eight levels. Each running bout of the YYIR1 consists of 2 x 20-meter runs. The first 20-meter run is down from the start/finish line to the turning line, immediately followed by a 20-meter run back to the start/finish line. At the conclusion of each bout a 10 second active recovery period composed of a 2 x 5-meter jog is performed. (Figure 2.)

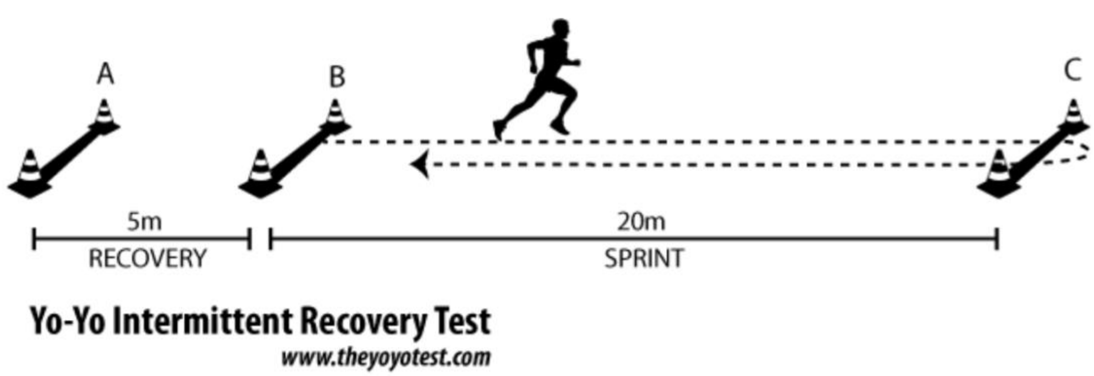


Figure 2: Diagram of YYIR1 equipment setup and running procedure

The speed of each test level is controlled by a standardized audio recording. During each bout there are three audible beeps emitted from the recording signifying: 1) initiation of the running bout and departure from the start/finish line 2) arrival at the turning line, confirmed by placement of a foot on or beyond the line 3) return to the start/finish line, confirmed by placement of a foot on or beyond the line. The speed of the running bout is regulated by decreasing the time between the first and third beeps, with the second beep always occurring at the halfway point of that time. Failure to return to the start/finish line by the third beep results in a “miss” for the participant. Upon the participant receiving two misses the test is terminated, with the final level recorded. This final level achieved represents the score the participant receives. The test speed protocol can be found in Table 2.

All participants completed the YYIR1 testing protocol on the same day. Up to twelve participants completed the protocol simultaneously. Successful completion of each running bout was monitored by observers familiar with the testing protocol. At least four observers were present during testing and were responsible for determining if an athlete successfully completed a bout or received a “miss” for that level. Each observer was responsible for watching no more than 4 participants to facilitate accurate simultaneous judgement.

YYIR1 score (level achieved) was used as the explanatory/predictor variable for linear mixed modeling when assessing the relationship between YYIR1 performance and match physical performance.

Table 2: Yo-Yo Intermittent Recovery Test Level 1 - Speed Protocol up to Level 51 (Krustrup et al., 2003)

Test Level	Speed Level	Speed (km/hr)	Accumulated Distance
1	1	10	40
2	2	11.5	80
3	3	13	120
4	3	13	160
5	4	13.5	200
6	4	13.5	240
7	4	13.5	280
8	5	14	320
9	5	14	360
10	5	14	400
11	5	14	440
12	6	14.5	480
13	6	14.5	520
14	6	14.5	560
15	6	14.5	600
16	6	14.5	640
17	6	14.5	680
18	6	14.5	720
19	6	14.5	760
20	7	15	800
21	7	15	840
22	7	15	880
23	7	15	920
24	7	15	960
25	7	15	1000
26	7	15	1040
27	7	15	1080
28	8	15.5	1120
29	8	15.5	1160
30	8	15.5	1200
31	8	15.5	1240
32	8	15.5	1280
33	8	15.5	1320
34	8	15.5	1360
35	8	15.5	1400
36	9	16	1440
37	9	16	1480
38	9	16	1520
39	9	16	1560
40	9	16	1600
41	9	16	1640
42	9	16	1680
43	9	16	1720
44	10	16.5	1760
45	10	16.5	1800
46	10	16.5	1840
47	10	16.5	1880
48	10	16.5	1920
49	10	16.5	1960
50	10	16.5	2000
51	10	16.5	2040

Match Physical Performance Metrics

Match physical performance was analyzed using a 10hz wearable GPS monitor system (Sports Performance Tracking Pty. Ltd, Cremorne, Victoria, Australia). Each GPS unit was assigned to a specific athlete and used by that athlete for every match. The GPS monitors were turned on at least 30 minutes prior to the start of each match to allow for optimal satellite signal acquisition. Monitors were worn by all study participants for the duration of the match, including when they are on the sideline.

To ensure an appropriate representation of overall match demands, only match data from participants who accumulate at least 60 minutes (≥60 min) of playing time was included in the final analysis. This is in alignment with previous research in NCAA D1 women soccer players analyzing match physical demands utilizing 10hz GPS monitors (Benjamin et al., 2020). This threshold for inclusion allows for a more accurate representation of overall match demands, limiting the potential confounding influences a brief period of play may have on match physical performance.

Match physical performance metrics of total distance covered (TD), total high intensity running distance covered (HIRD), and total sprint distance covered (SD) were extracted from the collected GPS data. All metrics were normalized to the number of minutes played by the athlete to facilitate comparisons between individuals with different playing time in a match.

TD is the total distance covered by the athlete over the course of the competitive match. This included walking, running and sprinting distances. The total distance covered in meters was divided by total minutes played to calculate TD.

TD (m/min) = Total Distance Covered (m) ÷ Total Minutes Played (min)

A high-speed running velocity threshold was placed at 4.3 m/s (15.48 km/hr) based on previous sex-specific recommendations (Bradley & Vescovi, 2015). This threshold is also in near alignment with the threshold used in previous GPS match analysis research in NCAA women soccer players (Vescovi & Favero, 2014). HIRD is the total distance covered above the high-speed running velocity threshold divided by the total minutes played in the match. This metric encapsulates both high-speed running distance and sprinting distance.

HIRD (m/min) = Distance covered above 4.3 m/s (m) ÷ Total Minutes Played (min)

A sprinting velocity threshold was placed at 5.6 m/s (20.16 km/hr) based on the same recommendations and previous research cited above (Bradley & Vescovi, 2015; Vescovi & Favero, 2014). SD is the total distance covered above the sprinting velocity threshold.

SD (m/min) = Distance covered above 5.6 m/s (m) ÷ Total Minutes Played (min)

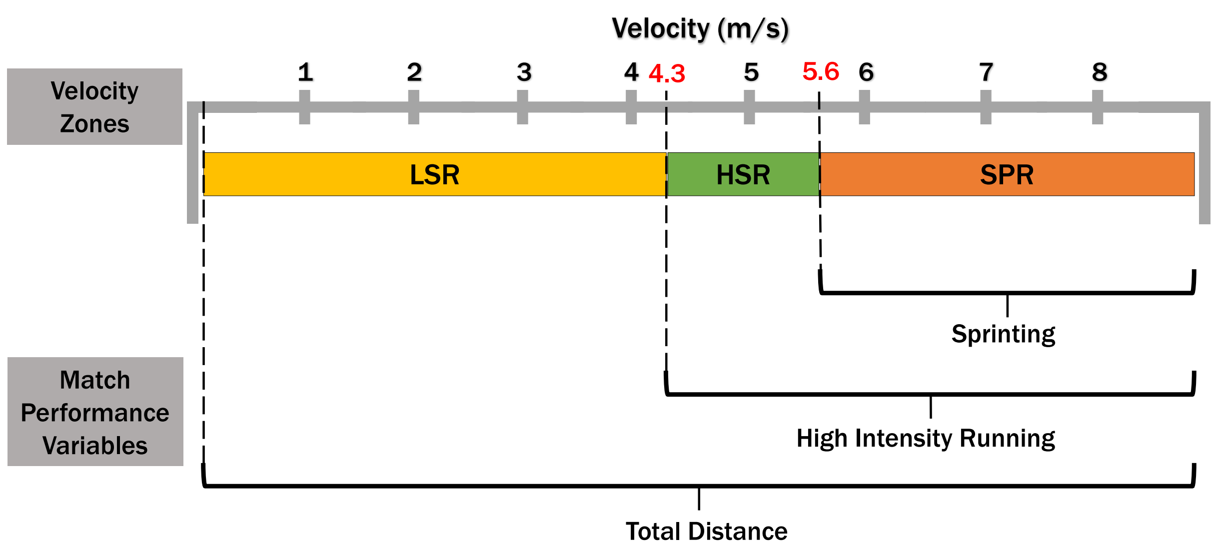


Figure 3: Visual representation of velocity thresholds and match performance variables

Potential Confounding Factors

Data on potential confounding factors of playing position, starting status, season year, season period, match number, match location, score differential, and opponent strength were collected. Season year and playing position were selected *a priori* for inclusion in the main model analysis. The remaining potential confounding factors were assessed through bivariate linear mixed model analysis to determine their inclusion in or exclusion from the main models (see statistical analysis section).

Playing position was determined during the fall 2022 season at the conclusion of each match for each participant. Positions were collected as central defenders, wide defenders, central midfielders, wide midfielders, and forwards. These position distinctions are in alignment with previous research on elite female players (Datson et al., 2017). Positions were categorized as defenders, midfielder, and forwards for analysis. Playing position information was included in the fall 2021 data.

Starting status was determined retroactively utilizing three separate criteria: 1) If a player is part of the initial 11 player line-up at the onset of the match, they were designated as a starter for analysis of that match only 2) Players averaging >40 minutes per game over the course of the season were deemed starters for analysis of all matches (Jajtner et al., 2013) 3) Players in the initial 11 player line-up at the onset of the match for > 80% of matches were deemed starters for analysis of all matches. Results from these three criteria were compared for differences to determine which method would be used for the final analysis. After this comparison it was determined that criteria "1" (starter = in initial 11 player line-up) would be used to designate starter status for each occurrence.

Competitive matches were associated with their respective season year and categorized as either Fall 2021 or Fall 2022, depending on when the match took place. matches were also associated with the respective period of the season and categorized as out of conference (OC), in conference (IC), or post conference (PC), depending on when the match took place within the season calendar and the opponent's conference affiliation. Out of conference games generally occur in the early portion of the season, followed by in conference games, with post conference games concluding the season.

Each match was numbered based on the order they were played in the season (e.g., the third match of the season was numbered “3”). This number was then attributed to each individual occurrence associated with that match. The numbering system was restarted for each season, with the first game of both seasons being designated as game “1” in corresponding occurrences.

Match location was categorized as being either at home (on reference team’s home field), away (on opponent’s home field), or at a neutral site (at a field not home to either participating team). For the assessment of potential covariates, match location categories were further simplified to merge away and neutral categories. With this simplified categorization match location was designated as either home (on reference team’s home field) or away (on opponent’s home field, or at a neutral field). This was done based on the rationale that a neutral game is not drastically different than an away game for the reference team when it comes to many of the logistical factors at play with traveling to, practicing, and competing at a field that is not at home. Both the three category and simplified two category designations for match location were assessed for inclusion in our analysis as potential covariates.

Match score results were collected at the conclusion of each match, with the total number of goals scored for the reference team and opponent team being recorded. Each match had a value associated with it based on the resulting goals scored by each team during the match. The opponent’s score was subtracted from the reference team’s score, resulting in a score differential. This value was attributed to each occurrence associated with the corresponding match.

Opponent strength is the quality of the opponent team during a match, when compared with the reference team containing study participants. Opponent strength was determined based on the NCAA RPI rankings at the conclusion of each season. Rankings have been utilized to determine opponent strength relative to the reference team in several previous studies (Hewitt et al., 2014; E. Rampinini et al., 2009; Wells et al., 2015). End of season rankings have been utilized in two of those studies, with using the

NCAA RPI Rankings for D1 female soccer teams (Wells et al., 2015). The team containing study participants and each opponent were assigned a numeric rank, with a lower number signifying increased strength and a higher number signifying decreased strength. Opponent strength was then calculated by subtracting the opponent rank from the reference team rank, resulting in the difference between ranks. A number close to zero signifies a nearly equal strength opponent, with higher numbers signifying stronger opponents and lower numbers signifying weaker.

Opponent Strength = Reference Team RPI Rank – Opponent RPI Rank

Data Analysis

After the conclusion of each match, data collected through the SPT GPS monitors was uploaded using the “SPT2 Bridge” software, which transfers GPS data from the monitors to the company’s browser-based software, GameTraka. GameTraka is an interactive platform that provides visual and numeric information about each event at a team and individual level. Visual displays depict a minute-by-minute breakdown of distances covered within specified velocity zones. This platform also allows for the segmenting of files to designate distinct periods of time during data collection (i.e., warmup, first half, second half). It also allows for the editing of team and individual data files through a “trim” feature, where any trimmed portions of a datafiles will not factor into distance sums for any speed zones.

After all match performance data was collected and uploaded to GameTraka, event data files were segmented to designate first and second halves of matches. Additionally, visual displays of physical performance were inspected for any signs of biologically infeasible or contextually unlikely outputs (i.e., 400m of distance covered in 1 minute, or 4 minutes of continuous movement above 8m/s). An example of an error spike is represented in Figure 2. Although uncommon, these errors in the data files were found to occur periodically and showed a trend to involve biologically infeasible spikes of continuous HSR and sprint distances, affecting total distance, HSR distance and sprint distance calculations. Rather than relying entirely on visual interpretation, a guideline threshold of a spike displaying a continuous work rate of greater than 216 m/min was set. This threshold is based on previous studies investigating peak 1-minute bouts in competitive elite female soccer matches and reporting average peak work rates of approximately 168 ± 16 m/min (González-García et al., 2022; Harkness-Armstrong et al., 2021). The threshold was set at mean + 3 standard deviations (216 m/min) to provide objective guidance for when a spike can be assessed for trimming.

Figure 4: Screenshot of error spike in GameTraka display. Red spike signifies continuous activity above 6m/s and a work rate of over 350 m/min.

For data files where such occurrences happened notes of the data file, the affected match half, duration of the error, total distance and HSR distance were recorded. After this data was recorded, the affected minutes were “trimmed” so that any data collected in the timeframe was excluded from total distance, HSR distance, and sprint distance values. Notes were made of the number of minutes trimmed, and the post-edit total distance and HSR distance amounts. A sample of observations was taken to estimate the proportion of observations containing errors and better understand the effect these errors may have on outcome variables. 12.5% of observations contained some type of error that required the cropping of a portion of the activity. The average number of minutes cropped was 1.7 ± 0.9 minutes. The average error spike's work rate was 270 ± 48 m/min.

Upon completion of the data processing in GameTraka, match physical performance data was exported for all individuals wearing a monitor during any match included in our analysis. This data was exported to a .csv file where each row was associated with an individual's performance in one of the halves of a match. A custom excel spreadsheet (*Microsoft Corp., Redmond, WA)* was developed and utilized to organize information from these .csv exports. Data were organized such that match total distance, HSR distance, and sprinting distance was displayed for all individuals wearing a monitor on that match.

In addition to match physical performance data, match playing time and confounding factor data was organized and integrated into the above mentioned excel spreadsheet. Information about playing time in each half, starter status, and time in season was collected from the NCAA official box scores. At the conclusion of each collegiate season, RPI rankings were collected from NCAA.org and used to determine opponent strength as described above. Information about playing position was confirmed with the team sport coaches to ensure accuracy.

Lastly, baseline YYIR1 performances were integrated into the excel spreadsheet and associated with the individual match occurrence for each participant.

This was then exported into a separate .csv file and uploaded into the statistical software RStudio (Posit-team, 2023) for statistical analysis.

Statistical Analysis

Statistical analyses were conducted using the statistical programming language “R” (R-Core-Team, 2022) within RStudio. The tidyverse (Wickham et al., 2019) and lme4 (Bates et al., 2015) packages were used to aid in data processing and linear mixed model development.

Descriptive statistics of mean ± SD, minimum, and maximum values were calculated for YYIR1 performance, and match physical performances for included subjects.

Data was analyzed utilizing linear mixed modeling (LMM). A linear mixed model was implemented due to its ability to be applied to repeated measures data from an unbalanced design (players differ in their number of match occurrences) with continuous outcome variables (Cnaan et al., 1997).

Bivariate Analyses

Bivariate analyses were completed to assess each potential confounding factors (covariates) for inclusion in the main model build. Prior to conducting these analyses, two covariates were selected *a priori*. These covariates are Season Year (2021 & 2022) and Playing Position.

The bivariate analyses involved comparing a basic LMM (Outcome Variable ~ YYIR1 Score + (1|Athlete)) with a LMM containing the potential covariate (Outcome Variable ~ YYIR1 Score + Potential Covariate + (1|Athlete)). YYIR1 score is used as the independent variable, match physical performance as the dependent variable. Random intercepts were set for athlete ID to account for subject level variability and unbalanced subject observations.

Bivariate analyses were conducted on all potential covariates for each of the study’s response variables:

- Total Distance (TD)
- High Intensity Running Distance (HIRD)

- Sprinting Distance (SD)

Each covariate was considered for inclusion in the main model based on the following criteria:

- Scientific rationale for that covariate's inclusion
- Visual comparison of model fit (mainly using Q-Q Plots)
- Comparing differences in point estimates for our predictor variable (YYIR1 Score)
- Comparing differences in confidence intervals for those point estimates
- P-Values for likelihood ratio tests

Lastly, an additional analysis was completed to determine the categorization used for describing playing position. This analysis was completed to compare two different categorization strategies for athlete position to better understand which version of the *a priori* covariate should be included in our model. The two categorization strategies were by specific position (central defender, wide defender, central midfielder, wide midfielder, or forward) or by general position (defender, midfielder, or forward). The same outcome variables and criteria were used for this analysis.

A full report of the bivariate analysis is available in the appendix of this document. The following covariates were selected for inclusion in the full linear mixed model build for each outcome variable, in addition to the *a priori* covariates:

Total Distance

- Season game number
- Match location (Home & Away)

High-Intensity Running Distance

- Season game number
- Match location (Home & Away)
- Season period

Sprinting Distance

- Season game number
- Match location (Home & Away)
- Season period

Based on the results of the positional categorization analysis, it was determined the general position group categories are more appropriate for use as the *a priori* covariate in the full model build.

Linear Mixed Model Analyses

The full LMM was built utilizing forward selection after *a priori* inclusion. YYIR1 score is used as the independent variable and match physical performance (TD, HIRD, or SD) as the dependent variable. Random intercepts were set for athlete ID to account for subject level variability and unbalanced subject observations. Covariates were included as fixed effects in the models and adjusted for to assess the association of YYIR1 score with match physical performance. Each new model version was compared to the previous version based on the same 5 criteria of the bivariate analysis to determine if the added covariate should remain. This process was repeated until all covariate additions were assessed and a final model was obtained for each outcome variable.

All identified covariates from the bivariate analysis were included in the final LMMs. A full report of the model building process is available in the appendix of this document.

Significance of YYIR1 Score as a fixed effect was assessed based on the 95% confidence interval of the point estimate. A confidence interval that does not contain 0 was used as evidence of a statistically significant relationship between YYIR1 Score and the outcome variable for match physical performance.

Sensitivity Analyses

Two sensitivity analyses were completed to better understand model fit and interpretation. An additional analysis was conducted on the influence of outlier participants (high match physical performances) on the HIRD and SD LMMs. These individuals regularly displayed high HIRD and SD match physical performances in comparison to the rest of the included participants. Another analysis was completed to assess if the inclusion of a random slope in addition to random intercept would improve model fit for the three final models.

Chapter 4: Results

Participant Descriptive Statistics

The 47 participants collectively had a total of 629 match observations. Of these match observations, 25 were excluded due to missing or erroneous GPS data. The remaining 604 observations were analyzed to assess eligibility for full analysis. Of these observations, 273 (45%) met the inclusion criteria of ≥ 60 minutes of playing time required for inclusion in the linear mixed modeling analysis. After the removal of individuals with no match observations meeting the inclusion criteria, 30 (64%) of the participants remained and were designated as "included" for the main analysis (Figure 5.)

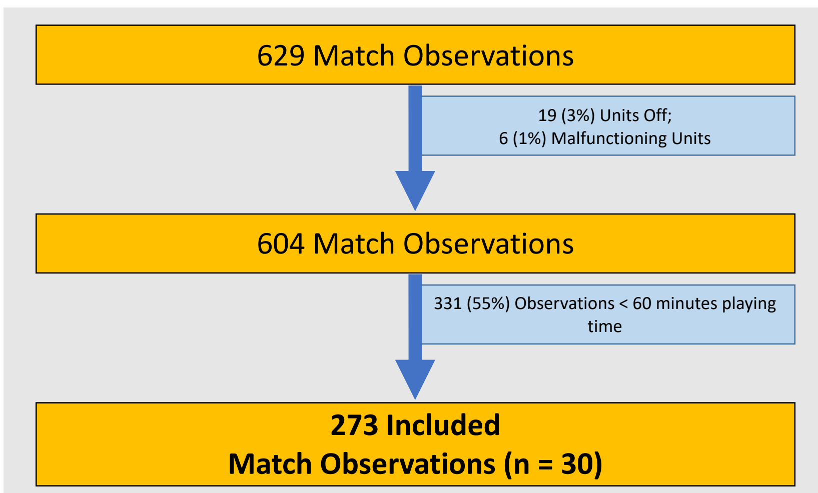


Figure 5: Match observation selection process for inclusion in the main statistical analysis

Data on total soccer experience, collegiate soccer experience, and body mass could only be collected for the 2022 season participants. Total and collegiate soccer experience for included participants was 10.5 ± 3.0 (6 - 17) years and 2 ± 1.4 (0 - 4) years, respectively. Body mass was 64.0 ± 5.6kg (55.4 - 76.0).

Descriptive statistics for included participants can be found in Table 3. The score achieved and total distance covered during the YYIR1 baseline testing was 33.1 ± 5.3 (24 - 50) levels and 1323 ± 211m (960 - 2000m), respectively (Figure 6.).

Table 3: Baseline characteristics for included subjects by YYIR1 performance (n = 30)

Baseline Characteristics for Included Subjects*

		YYIR1 Performance**		
	All	Low	Moderate	High
	(N= 30)	(N= 8)	(N= 14)	(N= 8)
Age				
Mean (SD)	19.9 (1.36)	20.4 (1.19)	19.6 (1.28)	19.8 (1.67)
Height (cm)				
Mean (SD)	168 (6.04)	169 (5.91)	167 (7.01)	169 (4.88)
Position				
Forward	7 (23.3%)	0 (0%)	7 (50.0%)	0 (0%)
Midfielder	10 (33.3%)	4 (50.0%)	3 (21.4%)	3 (37.5%)
Defender	13 (43.3%)	4 (50.0%)	4 (28.6%)	5 (62.5%)
Season Year				
2021	16 (53.3%)	3 (37.5%)	8 (57.1%)	5 (62.5%)
2022	14 (46.7%)	5 (62.5%)	6 (42.9%)	3 (37.5%)
Matches Started				
Mean (SD)	9.17 (6.44)	11.3 (6.86)	8.79 (5.90)	7.75 (7.27)

Note:

*Any subjects with ≥ 60 minutes of playing time in a match are included in the main analysis

**YYIR1 Performance Categories for <20 years old: Low <28, Moderate = 28-34, High >34

**YYIR1 Performance Categories for 20+ years old: Low <31, Moderate = 31-37, High >37

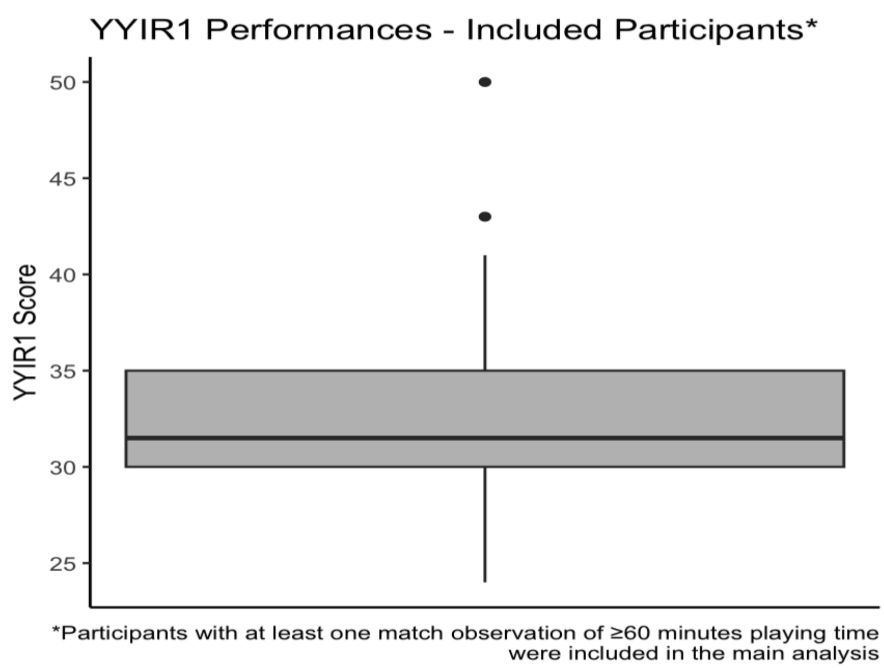


Figure 6: Distribution of YYIR1 performances for included participants

Match Descriptive Statistics

Details of match physical performances for all included participants and each position group are presented in Table 4. Visual representations of the distribution of match physical performance observations by participant and position are available in Figure 7 and Figure 8, respectively.

The 18 matches analyzed in the fall 2021 season were composed of 7 out of conference matches, 8 in conference matches, and 3 post conference matches. 7 matches were played at home while 11 were played away.

The 19 matches analyzed in the fall 2022 season were composed of 9 out of conference matches, 8 in conference matches, and 2 post conference matches. 10 matches were played at home while 9 were played away.

Table 4: Match Physical Performances According to Playing Position

Match Physical Performances According to Playing Position.*

Position	Total Distance (m/min)	High-Intensity Running Distance (m/min)	Sprinting Distance (m/min)
All Positions	107.7 ± 12	7.84 ± 3.34	1.63 ± 1.1
Forwards	107.8 ± 9.5	8.93 ± 2.68	2.18 ± 1.25
Midfielders	111.3 ± 11.4	8.11 ± 3.77	1.5 ± 1.12
Defenders	104.8 ± 12.9	7.04 ± 3.13	1.42 ± 0.9

Note:

* Data are presented as mean ± standard deviation. high-intensity running is > 4.3m/s and sprinting is > 5.6 m/s.

* Means were calculated using all included observations, with multiple and unequal observations occuring for each particpant.

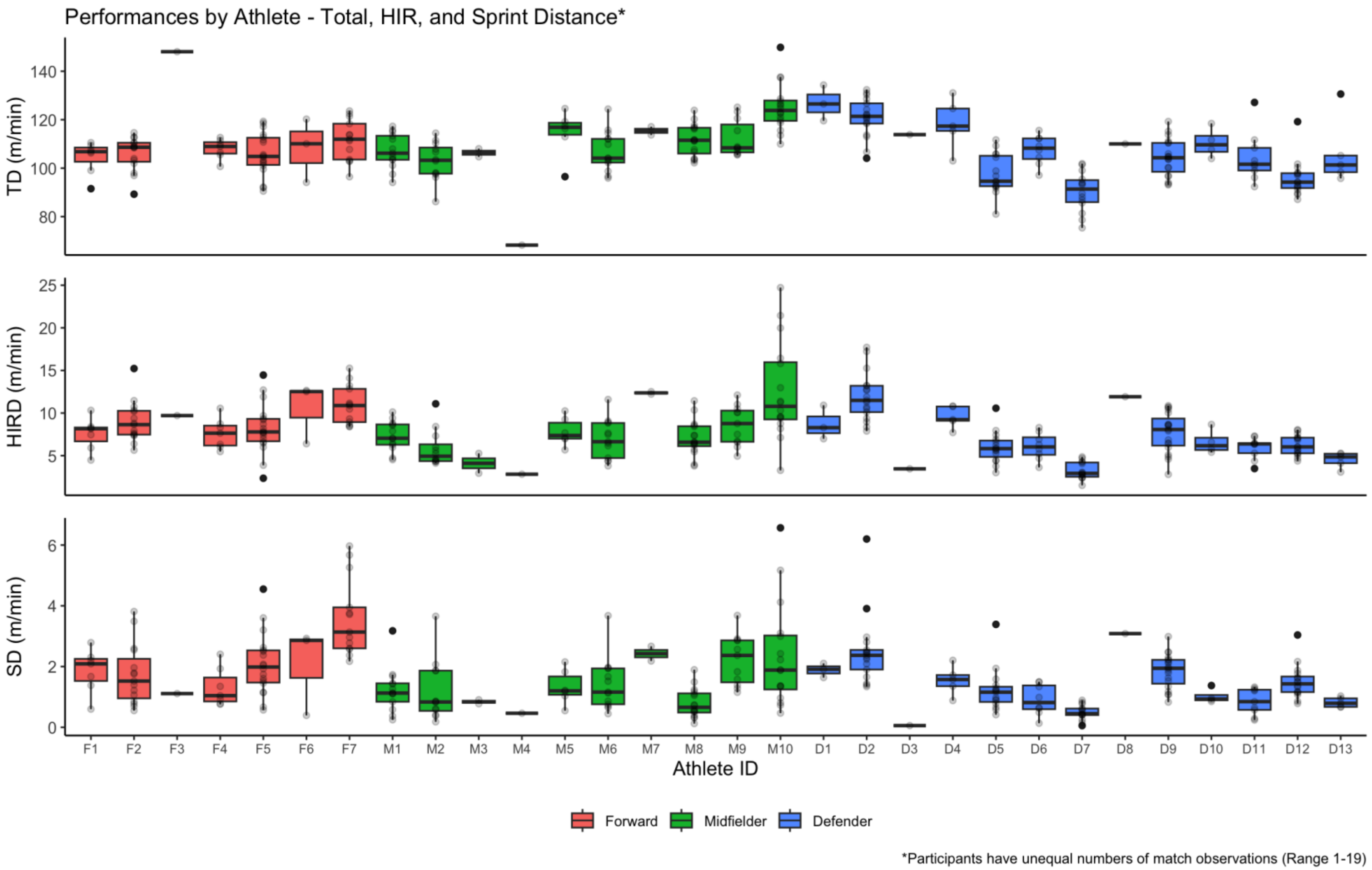


Figure 7: Distribution of match physical performances by participant

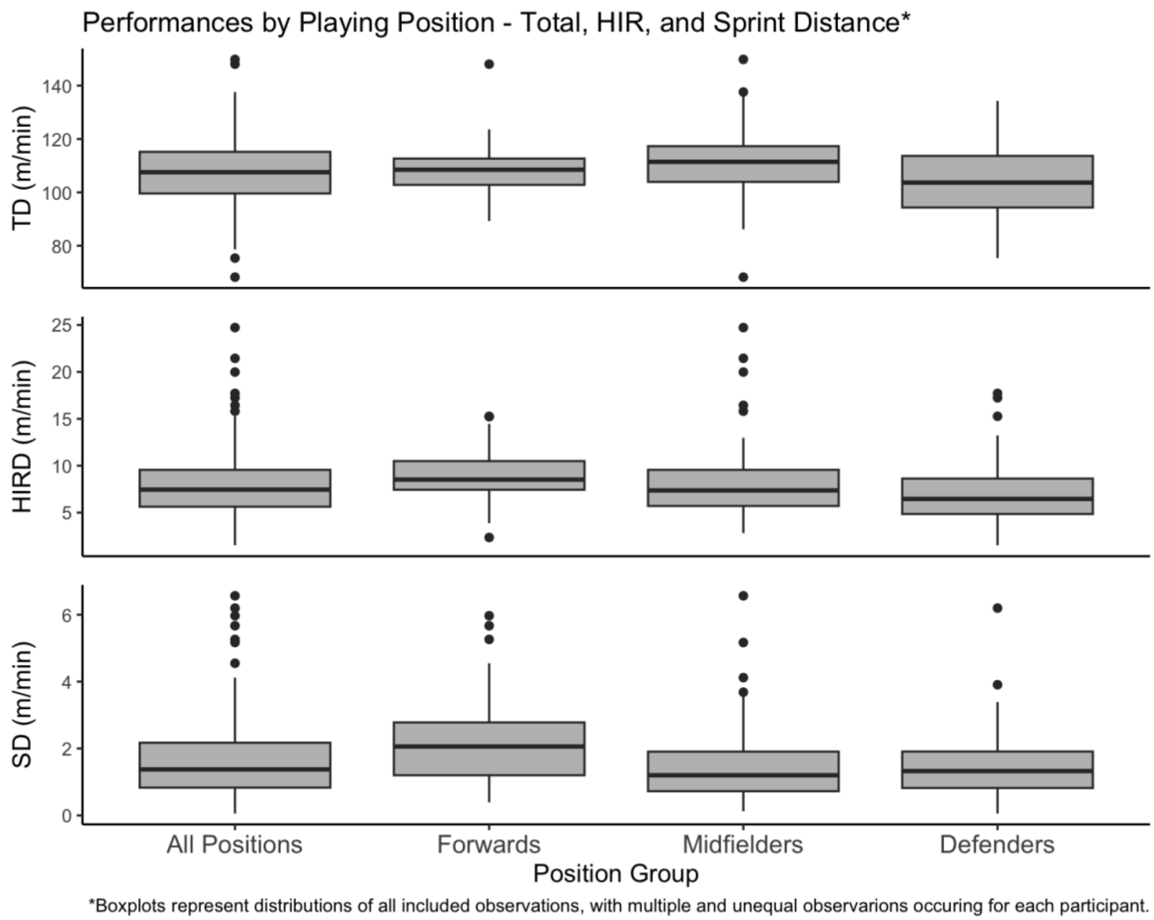


Figure 8: Distribution of match physical performances by playing position

Linear Mixed Model Results

Final model results for each outcome variable are available in Table 5. Significant relationships were displayed between YYIR1 baseline performance and TD, HIRD, and SD. Better YYIR1 performance was associated with increased match physical performance in the fully adjusted model. Interpretation of model results show that an increase in one level of the YYIR1 is associated with increases of 0.95 (95% CI: 0.257 - 1.651), 0.27 (95% CI: 0.138 - 0.405) and 0.05 (95% CI: 0.002 - 0.095) meters per minute of match activity for total distance, high intensity running distance and sprinting distance, respectively, in the fully adjusted model.

Table 5: Linear Mixed Model Results

Fully Adjusted vs. Unadjusted Models (TD, HIRD, SD)

	Total Distance		HIR Distance		Sprint Distance	
	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted
	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate
YYIR1 Score	0.954	0.886	0.272	0.247	0.048	0.039
	(0.257 - 1.651)	(0.226 - 1.546)	(0.138 - 0.405)	(0.103 - 0.391)	(0.002 - 0.095)	(-0.011 - 0.089)
Observations	273	273	273	273	273	273

Note:

* Data are presented as 'Point Estimate (95% CI)'.

Sensitivity Analyses Results

Results of the outlier sensitivity analysis revealed high performing participants influenced HIRD and SD model fit, which was verified using AIC and BIC measures and the displayed residuals of the model Q-Q plot. Results of the altered slope sensitivity analysis revealed a better fit was not achieved by setting a random slope in addition to a random intercept, however including a random slope increased model complexity.

Chapter 5: Discussion

This study is the first to investigate the relationship between baseline YYIR1 performance and match physical performance in collegiate female soccer players. It is also the first study of its kind to utilize linear mixed modeling to assess this relationship. In addition to these novel methods, this study provides valuable descriptive statistics of intermittent endurance performance and match physical performance for this understudied population.

The main findings of this study were that baseline YYIR1 performance was associated with match total distance, high intensity running distance, and sprinting distance. This finding supports our hypothesis and demonstrates evidence for the ecological and construct validity of the YYIR1 as a baseline assessment for determining the match physical performance of collegiate female soccer players. These results extend the findings reported in previous studies investigating this relationship in elite adult and youth soccer players (Castagna et al., 2009; Castagna et al., 2010; Krustrup et al., 2003; Krustrup et al., 2005; Rebelo et al., 2014).

YYIR1 Performance

Limited information on YYIR1 performance in collegiate female soccer players is available. Initial inspection of two published studies reporting YYIR1 performance suggest collegiate female soccer players cover between 1628 - 1700m on average, which is considerably higher than the values reported in this study (1323 ± 211m) (Lockie et al., 2018; Risso et al., 2017). However, these differences in performance may be due to variation in the implementation of YYIR1 testing procedures. These studies reported ending the test after a participant received two *successive* warnings, as opposed to ending the test after two total warnings (Lockie et al., 2018; Risso et al., 2017). This alteration is contrary to original testing procedure and may have resulted in elevated YYIR1 performance values (Bangsbo et al., 2008; Karakoç et al., 2012; Krustrup et al., 2003; Krustrup et al., 2005). The results in the present study are similar to another study in collegiate female soccer players using the original testing procedures (Benjamin et al., 2020). The authors only reported the minimum and maximum values, ranging from 1000m - 1720m, which are similar to the range of values seen in our participants (960m - 2000m). The YYIR1 values seen in this study are similar to values reported in elite female players and average values composed using a compendium of results for sub elite/elite female soccer players (Krustrup et al., 2005; Iñigo Mujika et al., 2009; Schmitz et al., 2018).

Match Physical Performance

Several studies have reported the match physical performances of collegiate female soccer players (McCormack et al., 2014; McFadden et al., 2020; Vescovi & Favero, 2014; Wells et al., 2015). Using a reference match lasting 90 minutes, total distance values reported in this study are comparable with those previously reported and ranging from 8 - 10km. Additionally, when total distance was normalized to playing time, Vescovi and Favero, 2014 reported relatively similar work rates over the course of a match (96 - 107 m/min) (Vescovi & Favero, 2014).

The values seen in this study for match HIRD (>4.3m/s) are comparable to previous studies reporting metrics utilizing similar velocity zones (Vescovi & Favero, 2014; Wells et al., 2015). Vescovi and Favero, 2014 utilized the same velocity zones as the present study and reported forward, midfielders and defenders covered approximately 929m, 762m, 748m above 4.3 m/s during competitive matches, respectively, when match halves were added together (Vescovi & Favero, 2014). Wells et al., 2015 reported distances of approximately 643m - 688m covered by field players at speeds above 4.4m/s (Wells et al., 2015). Using a reference match lasting 90 minutes to calculate distances and allow for comparison, HIRD values reported in this study are similar to these finding.

The values seen in this study for match SD (>5.6m/s) are comparable to previous studies reporting metrics utilizing similar velocity zones (Vescovi & Favero, 2014; Wells et al., 2015). Utilizing the same velocity zones as the present study, Vescovi and Favero reported forward, midfielders and defenders covered approximately 339m, 117m, 266m above 5.6 m/s during competitive matches, respectively, when match halves were added together (Vescovi & Favero, 2014). Wells et al., 2015 reported distances of approximately 85m covered by field players at speeds above 6.1m/s (Wells et al., 2015). Using a reference match lasting 90 minutes to calculate distances and allow for comparison, SD values reported in this study appear to be slightly lower than these findings.

Association Between YYIR1 and Match Physical Performance

A significant positive association between baseline YYIR1 score and match TD was seen. A higher baseline YYIR1 score was associated with an increase in TD covered per minute of match play. Interpretation of model results shows a 1 level increase in YYIR1 score is associated with an increase in total distance by approximately 1 m/min during a competitive match, when covariates are adjusted for. This finding is in alignment with previous studies demonstrating positive correlations between YYIR1 performance and match total distance (Castagna et al., 2009; Krustrup et al., 2003; Krustrup et al., 2005). Previous studies in elite soccer players demonstrated moderate correlations between YYIR1 performance and match total distance in females ($r = 0.56$, $p = 0.038$) and males ($r = 0.53$, $p<0.05$) (Krustrup et al., 2003; Krustrup et al., 2005). It is also in alignment with previous work investigating this relationship in male youth soccer players ($r = 0.65$, $p = 0.002$) (Castagna et al., 2009). Interestingly, a separate investigation by the same author showed no significant correlation between YYIR1 and total distance covered during competitive matches (Castagna et al., 2010). It should be noted all these studies utilized either video analysis or low frequency (1hz) GPS monitoring units to quantify match physical performance and therefore direct comparison with the current investigations results should be done with caution (Randers et al., 2010; Scott et al., 2016).

A significant positive association between baseline YYIR1 score and match HIRD was seen. A higher baseline YYIR1 score was associated with an increase in HIRD covered per minute of match play. Interpretation of model results shows a 1 level increase in YYIR1 score is associated with an increase in HIRD by approximately 0.27 m/min during a competitive match, when covariates are adjusted for. This finding is in alignment with previous studies demonstrating positive correlations between YYIR1 performance and match high intensity running distance (Castagna et al., 2009; Castagna et al., 2010; Krustrup et al., 2003; Krustrup et al., 2005; Rebelo et al., 2014). Previous studies in elite soccer players demonstrated moderate correlations between YYIR1 performance and match high intensity running (>4.17m/s) distance in females ($r = 0.76$, $p = 0.002$) and males ($r = 0.71$, $p < 0.05$) (Krustrup et al., 2003; Krustrup et al., 2005). It is also in alignment with three previous works investigating this relationship (>3.6m/s) in male youth soccer players ($r = 0.56 - 0.77$, $p < 0.016$) (Castagna et al., 2009; Castagna et al., 2010; Rebelo et al., 2014). Again, caution should be taken when comparing match physical performance analyses utilizing different measurement methodologies.

A significant positive association between baseline YYIR1 score and match SD was seen. A higher baseline YYIR1 score was associated with an increase in SD covered per minute of match play. Interpretation of model results shows a 1 level increase in YYIR1 score is associated with an increase in SD by approximately 0.05 m/min during a competitive match, in the fully adjusted model. This finding is in alignment with previous studies demonstrating positive correlations between YYIR1 performance and match sprinting distance in youth male soccer players (Castagna et al., 2010; Rebelo et al., 2014). Two works investigating the relationship between YYIR1 performance and match sprinting distance (>5m/s) in male youth soccer players found significant correlations between the variables ($r = 0.63 - 0.76$, $p < 0.01$) (Castagna et al., 2010; Rebelo et al., 2014). While these studies in male youth players demonstrated significant correlations, a study by the same research group utilizing a similar design did not show the same findings (Castagna et al., 2009). The authors hypothesized the low sampling rate (1Hz) GPS monitors employed in their study may have hindered the ability to effectively capture short running bouts involving high velocities. While this may still be a concern in the present investigation, the monitors utilized have 10x the sampling rate of the previously mentioned study which would result in an improved ability to capture sprinting activity (Aughey, 2011; Scott et al., 2016).

Utilizing the demonstrated associations between a 1 level increase in YYIR1 performance and approximate increases in match physical performance metrics, it may be helpful to contextualize the impact a normal YYIR1 performance increase may have on match physical performance. The off-season period for collegiate soccer usually lasts from mid-January to the start of August and spans the athletes' spring academic semester (January - April) and summer break (May - August). During the spring academic period, approximately 10 - 12 weeks of training are completed by the athletes under the supervision of a certified strength and conditioning professional. During this period the athletes may complete anywhere from 1-3 conditioning sessions per week, in addition to resistance training and soccer practice activities (Lockie et al., 2018; Miller et al., 2007; Peart et al., 2018). During only 5 weeks of training in the off season, increases in YYIR1 performance was reported to be 186m (17%) (Flatt & Esco, 2016) and 215m (13%) (Rowan et al., 2012) in collegiate female soccer players. If these values are used as a conservative estimate of the improvement that can be achieved over the entire off-season period, an improvement of 5 levels in YYIR1 score may be reasonable. Based on the displayed associations between and increase YYIR1 score and match physical performance metrics, and assuming a 90-minute game, increases of approximately 450m, 122m and 23m may be estimated through this training intervention for match TD, HIRD, and SD, respectively. Using this study's reported average match physical performance values as a reference, this improvement in YYIR1 performance would result in approximate average increases of 5%, 17%, and 16% in match TD, HIRD, and SD, respectively.

The yo-yo intermittent fitness test level 1 (YYIR1) is regularly used to assess soccer players' physical capacity under the assumption that test results will relate to match physical performance and game success. The implication of increases in match physical performance on match success is unknown. Competitive soccer matches are complex environments where athletes must employ a mixture of technical, tactical, and physical performances to support the chances of success. Recent work has been done to investigate the interaction between physical and technical factors and their association with match success (Andrzejewski et al., 2022; Chmura et al., 2022; Lorenzo-Martinez et al., 2021; Modric et al., 2022). Discussions of these associations and implications on match success, while important, are beyond the scope of this study's aims as they relate to physical performances. The ability to meet match physical demands can be assessed through physical capacity testing designed to determine an athlete's readiness to meet those demands. Fitness testing is utilized by numerous soccer programs as a means for evaluation of player physical readiness and adaptation to training programs. Specific to the collegiate soccer setting, results from a field-based fitness test, such as the YYIR1, often influence eligibility to compete, playing time determinations, and assessments of response to training. A protocol's inclusion in a baseline testing battery must be justified due to the scarcity of time available for such testing and the need for true indicators of physical preparation.

The results of our analysis demonstrate the ecological and construct validity of the YYIR1 as a baseline measure in collegiate female soccer players prior to the competitive season. Until now, these relationships have not been investigated in the women's collegiate soccer setting, despite the YYIR1 being regularly utilized at the collegiate level. This provides evidence for the inclusion of the YYIR1 in a pre-season testing battery to assess the physical preparation of collegiate female soccer players for competitive demands. This extends previous evidence in elite male and female players as well as youth male players.

While increases in match physical demands may not inherently increase the chances of success in a match, it is important to consider that physical movements in a match are performed with the intent of supporting team victory. An increase in match physical performance can therefore be a representation of athletes having the capacity to meet or exceed the demands of the match, as needed. Additionally, while average match demands may provide an overview of the physiological and movement demands of the match, it is often the “worst case scenario” that strength and conditioning practitioners are preparing athletes for. Recent studies have emphasized the importance of physical preparation targeting match peak performances, rather than average performances (Dalen et al., 2021; Harkness-Armstrong et al., 2021).

Limitations

While this study provides novel insight into the relationship between YYIR1 performance and match physical performance in an understudied population, it is not without its limitations. The study utilizes a relatively small sample size of participants (n = 30) for its main analysis and includes some participants with as low as 1 observation. High match to match variability has been seen in elite football players which requires larger sample sizes (Gregson et al., 2010). The nature of collegiate soccer substitution rules results in a larger number of substitutions and reentries into match play than is allowed in FIFA regulation matches. This results in playing time being shared between more participants and decreasing the number of participants meeting the 60-minute inclusion criteria for matches. However, in comparison to previous studies investigating similar relationships, this study does have a comparable or larger sample size. Additionally, the use of linear mixed modeling has allowed for the retention of participants that would have otherwise been excluded due to having unequal numbers of observations.

A second limitation is the necessary reliance on the proprietary GPS monitor manufacturer’s software for the calculation of match physical performance metrics. The underlying calculations performed on raw

GPS data is unknown and therefore cannot be verified. While this limitation is inherent to the study's reliance on a GPS monitoring system, steps were taken to mitigate erroneous data through a thorough data file vetting process that utilized research based objective criteria for determining if errors occurred (see methods "data analysis" section for more details).

Additionally, while many confounding factors were assessed and adjusted for in final linear mixed models, not all influential factors could be accounted for. Several factors not assessed, either due to logistical restraints or infeasibility, may have had significant impacts on match physical performance. For example, environmental factors such as altitude, wet-bulb globe temperature, or smoke due to forest fires may have impacted match physical performance.

Lastly, it should be noted that GPS monitoring of whole match running activity alone may not be able to accurately capture important aspects of match physical demands. Match activities such as repeated sprint sequences, accelerations, decelerations and running activity with the ball may all play an important role in match outcome and the physical demands imposed on the athlete (Dalen et al., 2016; Gabbett et al., 2013; Girard et al., 2011; Harper et al., 2019; Modric et al., 2022; E. Rampinini et al., 2009). This match analysis strategy also does not consider specific time periods of matches, such as peak performance periods of matches, which requiring a higher level of physical preparation than average work rates (Dalen et al., 2021; González-García et al., 2022; Harkness-Armstrong et al., 2021). Despite these limitations, the results presented in this study provide valid and valuable information regarding the physical capacity, match physical performances, and association between the two in collegiate female soccer players.

Additional minor limitations relating to our linear mixed model analysis should be noted. First the use of score (level achieved) as our YYIR1 performance variable has some limitation due to an increase in one unit (a level) does not always represent a consistent change throughout the test. For example, there is a change in shuttle run speed from level 27 to 28. These changes in speed, though infrequent, do occur periodically throughout the test to make its intensity progressive, and therefore exhaustive, in nature. This may provide some limitation when attempting to assess how a change in one unit of YYIR1 score is associated with match physical performance but is an inherent feature of the testing protocol. A second minor limitation was shown when a sensitivity analysis was done to better understand the influence of "high" performers on model results. These are individuals who regularly had increased HIRD, and SD match physical performance values compared to the other participants. When these participants were removed from the model, model fit was improved (observations = 240). This demonstrates these individuals may be altering model fit for our final models. While this is something to consider when interpreting our analysis, these individuals represent a portion of our population of interest and were therefore included in our final analysis.

Future Research

Future studies should aim to investigate if these results extend to male collegiate soccer players utilizing a larger sample size. Researchers should investigate the relationship between baseline YYIR1 performance and other match physical performance metrics such as accelerations, decelerations, repeated sprint sequences and running with the ball. Additional analyses should be conducted to see if these associations between baseline fitness and match physical performance are present during match "worst case scenarios." These analyses should be done on male and female collegiate soccer players to broaden the population in which findings can be applied.

Additionally, future research should aim to build on elite player investigations of the interaction between match physical performances and match success. These investigations should aim to better understand the implication that increased running performances may have on team success.

Practical Applications

Increased performance in the YYIR1 is associated with an increase in match physical performances in collegiate female soccer players. The YYIR1 should be considered a valuable tool for athletic performance and sport medicine professionals when assessing physical preparation for competition in collegiate female soccer players. Professionals should consider targeting improvements in high intensity intermittent endurance exercise performance to support match physical performances for collegiate female soccer players.

References

Alexandre, D., da Silva, C. D., Hill-Haas, S., Wong del, P., Natali, A. J., De Lima, J. R., Bara Filho, M. G., Marins, J. J., Garcia, E. S., & Karim, C. (2012). Heart rate monitoring in soccer: interest and limits during competitive match play and training, practical application. *J Strength Cond Res*, *26*(10), 2890-2906. https://doi.org/10.1519/JSC.0b013e3182429ac7

Ali, A., & Farrally, M. (1991). Recording soccer players' heart rates during matches. *J Sports Sci*, *9*(2), 183-189. https://doi.org/10.1080/02640419108729879

Andersson, H., Karlsen, A., Blomhoff, R., Raastad, T., & Kadi, F. (2010). Plasma antioxidant responses and oxidative stress following a soccer game in elite female players. *Scand J Med Sci Sports*, *20*(4), 600-608. https://doi.org/10.1111/j.1600-0838.2009.00987.x

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

Andersson, H. A., Randers, M. B., Heiner-Møller, A., Krustrup, P., & Mohr, M. (2010). Elite female soccer players perform more high-intensity running when playing in international games compared with domestic league games. *J Strength Cond Res*, *24*(4), 912-919. https://doi.org/10.1519/JSC.0b013e3181d09f21

Andrzejewski, M., Oliva-Lozano, J. M., Chmura, P., Chmura, J., Czarniecki, S., Kowalczuk, E., Rokita, A., Muyor, J. M., & Konefał, M. (2022). Analysis of team success based on match technical and running performance in a professional soccer league. *BMC Sports Sci Med Rehabil*, *14*(1), 82. https://doi.org/10.1186/s13102-022-00473-7

Aughey, R. J. (2011). Applications of GPS Technologies to Field Sports. *International Journal of Sports Physiology & Performance*, *6*(3), 295-310. https://search.ebscohost.com/login.aspx?direct=true&db=s3h&AN=66889803&site=ehost-live

Bangsbo, J., Iaia, F. M., & Krustrup, P. (2007). Metabolic response and fatigue in soccer. *Int J Sports Physiol Perform*, *2*(2), 111-127. https://doi.org/10.1123/ijspp.2.2.111

Bangsbo, J., Iaia, F. M., & Krustrup, P. (2008). The Yo-Yo Intermittent Recovery Test: A Useful Tool for Evaluation of Physical Performance in Intermittent Sports. *Sports Med*, *38*(1), 37-51. https://doi.org/10.2165/00007256-200838010-00004

Bangsbo, J., Nørregaard, L., & Thorsø, F. (1991). Activity profile of competition soccer. *Can J Sport Sci*, *16*(2), 110-116.

Barris, S., & Button, C. (2008). A review of vision-based motion analysis in sport. *Sports Med*, *38*(12), 1025-1043. https://doi.org/10.2165/00007256-200838120-00006

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software*, *67*(1), 1 - 48. https://doi.org/10.18637/jss.v067.i01

Benjamin, C. L., Hosokawa, Y., Curtis, R. M., Schaefer, D. A., Bergin, R. T., Abegg, M. R., & Casa, D. J. (2020). Environmental Conditions, Preseason Fitness Levels, and Game Workload: Analysis of a Female NCAA DI National Championship Soccer Season. *The Journal of Strength & Conditioning Research*, *34*(4), 988-994. https://doi.org/10.1519/jsc.0000000000003535

Bozzini, B. N., McFadden, B. A., Walker, A. J., & Arent, S. M. (2020). Varying Demands and Quality of Play Between In-Conference and Out-of-Conference Games in Division I Collegiate Women's Soccer. *The Journal of Strength & Conditioning Research*, *34*(12), 3364-3368. https://doi.org/10.1519/jsc.0000000000003841

Bradley, P. S., Carling, C., Gomez Diaz, A., Hood, P., Barnes, C., Ade, J., Boddy, M., Krustrup, 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., Dellal, A., Mohr, M., Castellano, J., & Wilkie, A. (2014). Gender differences in match performance characteristics of soccer players competing in the UEFA Champions League. *Hum Mov Sci*, *33*, 159-171. https://doi.org/10.1016/j.humov.2013.07.024

Bradley, P. S., & Noakes, T. D. (2013). Match running performance fluctuations in elite soccer: indicative of fatigue, pacing or situational influences? *J Sports Sci*, *31*(15), 1627-1638. https://doi.org/10.1080/02640414.2013.796062

Bradley, P. S., & Vescovi, J. D. (2015). Velocity thresholds for women's soccer matches: sex specificity dictates high-speed running and sprinting thresholds - Female Athletes in Motion (FAiM). *Int J Sports Physiol Perform*, *10*(1), 112-116. https://doi.org/10.1123/ijspp.2014-0212

Buchheit, M., Mendez-villanueva, A., Simpson, B. M., & Bourdon, P. C. (2010). Repeated-sprint sequences during youth soccer matches. *Int J Sports Med*, *31*(10), 709-716. https://doi.org/10.1055/s-0030-1261897

Carling, C. (2013). Interpreting Physical Performance in Professional Soccer Match-Play: Should We be More Pragmatic in Our Approach? *Sports Medicine*, *43*(8), 655-663.

Carling, C., Bloomfield, J., Nelsen, L., & Reilly, T. (2008). The role of motion analysis in elite soccer: contemporary performance measurement techniques and work rate data. *Sports Med*, *38*(10), 839-862. https://doi.org/10.2165/00007256-200838100-00004

Castagna, C., Impellizzeri, F., Cecchini, E., Rampinini, E., & Alvarez, J. C. (2009). Effects of intermittent-endurance fitness on match performance in young male soccer players. *J Strength Cond Res*, *23*(7), 1954-1959. https://doi.org/10.1519/JSC.0b013e3181b7f743

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

Castellano, J., Blanco-Villaseñor, 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

Chambers, R., Gabbett, T. J., Cole, M. H., & Beard, A. (2015). The Use of Wearable Microsensors to Quantify Sport-Specific Movements. *Sports Medicine*, *45*(7), 1065-1081. https://doi.org/10.1007/s40279-015-0332-9

Chmura, P., Oliva-Lozano, J. M., Muyor, J. M., Andrzejewski, M., Chmura, J., Czarniecki, S., Kowalczuk, E., Rokita, A., & Konefał, M. (2022). Physical Performance Indicators and Team Success in the German Soccer League. *J Hum Kinet*, *83*, 257-265. https://doi.org/10.2478/hukin-2022-0099

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

Cummins, C., Orr, R., O'Connor, H., & West, C. (2013). Global positioning systems (GPS) and microtechnology sensors in team sports: a systematic review. *Sports Med*, *43*(10), 1025-1042. https://doi.org/10.1007/s40279-013-0069-2

Dalen, T., Ingebrigtsen, J., Ettema, G., Hjelde, G. H., & Wisløff, U. (2016). Player Load, Acceleration, and Deceleration During Forty-Five Competitive Matches of Elite Soccer. *J Strength Cond Res*, *30*(2), 351-359. https://doi.org/10.1519/jsc.0000000000001063

Dalen, T., Sandmæl, S., Stevens, T. G. A., Hjelde, G. H., Kjøsnes, T. N., & Wisløff, U. (2021). Differences in Acceleration and High-Intensity Activities Between Small-Sided Games and Peak Periods of Official Matches in Elite Soccer Players. *J Strength Cond Res*, *35*(7), 2018-2024. https://doi.org/10.1519/jsc.0000000000003081

Datson, N., Drust, B., Weston, M., Jarman, I. H., Lisboa, P. J., & Gregson, W. (2017). Match Physical Performance of Elite Female Soccer Players During International Competition. *The Journal of Strength & Conditioning Research*, *31*(9), 2379-2387. https://doi.org/10.1519/jsc.0000000000001575

Datson, N., Hulton, A., Andersson, H., Lewis, T., Weston, M., Drust, B., & Gregson, W. (2014). Applied physiology of female soccer: an update. *Sports Med*, *44*(9), 1225-1240. https://doi.org/10.1007/s40279-014-0199-1

Datson, N., Weston, M., Drust, B., Atkinson, G., Lolli, L., & Gregson, W. (2022). Reference values for performance test outcomes relevant to English female soccer players. *Science and Medicine in Football*, null-null. https://doi.org/10.1080/24733938.2022.2037156

Davis, J. A., & Brewer, J. (1993). Applied physiology of female soccer players. *Sports Med*, *16*(3), 180-189. https://doi.org/10.2165/00007256-199316030-00003

Dawson, B., Goodman, C., Lawrence, S., Preen, D., Polglaze, T., Fitzsimons, M., & Fournier, P. (1997). Muscle phosphocreatine repletion following single and repeated short sprint efforts. *Scand J Med Sci Sports*, *7*(4), 206-213. https://doi.org/10.1111/j.1600-0838.1997.tb00141.x

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., 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

Esposito, F., Impellizzeri, F. M., Margonato, V., Vanni, R., Pizzini, G., & Veicsteinas, A. (2004). Validity of heart rate as an indicator of aerobic demand during soccer activities in amateur soccer players. *Eur J Appl Physiol*, *93*(1-2), 167-172. https://doi.org/10.1007/s00421-004-1192-4

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

Flatt, A. A., & Esco, M. R. (2016). Evaluating Individual Training Adaptation With Smartphone-Derived Heart Rate Variability in a Collegiate Female Soccer Team. *J Strength Cond Res*, *30*(2), 378-385. https://doi.org/10.1519/jsc.0000000000001095

Gabbett, T. J., & Mulvey, M. J. (2008). Time-motion analysis of small-sided training games and competition in elite women soccer players. *J Strength Cond Res*, *22*(2), 543-552. https://doi.org/10.1519/JSC.0b013e3181635597

Gabbett, T. J., Wiig, H., & Spencer, M. (2013). Repeated high-intensity running and sprinting in elite women's soccer competition. *Int J Sports Physiol Perform*, *8*(2), 130-138. https://doi.org/10.1123/ijspp.8.2.130

Gaitanos, G. C., Williams, C., Boobis, L. H., & Brooks, S. (1993). Human muscle metabolism during intermittent maximal exercise. *J Appl Physiol (1985)*, *75*(2), 712-719. https://doi.org/10.1152/jappl.1993.75.2.712

Girard, O., Mendez-Villanueva, A., & Bishop, D. (2011). Repeated-sprint ability - part I: factors contributing to fatigue. *Sports Med*, *41*(8), 673-694. https://doi.org/10.2165/11590550-000000000-00000

González-García, J., Giráldez-Costas, V., Ramirez-Campillo, R., Drust, B., & Romero-Moraleda, B. (2022). Assessment of Peak Physical Demands in Elite Women Soccer Players: Can Contextual Variables Play a Role? *Research quarterly for exercise and sport*, *ahead-of-print*(ahead-of-print), 1-9. https://doi.org/10.1080/02701367.2021.2004297

Gregson, W., Drust, B., Atkinson, G., & Salvo, V. D. (2010). Match-to-match variability of high-speed activities in premier league soccer. *Int J Sports Med*, *31*(4), 237-242. https://doi.org/10.1055/s-0030-1247546

Hargreaves, M., & Spriet, L. L. (2006). *Exercise metabolism* (2nd ed.). Human Kinetics. Table of contents http://www.loc.gov/catdir/toc/ecip0516/2005021690.html

Harkness-Armstrong, A., Till, K., Datson, N., & Emmonds, S. (2021). Whole and peak physical characteristics of elite youth female soccer match-play. *Journal of Sports Sciences*, *39*(12), 1320-1329. https://doi.org/10.1080/02640414.2020.1868669

Harper, D. J., Carling, C., & Kiely, J. (2019). High-Intensity Acceleration and Deceleration Demands in Elite Team Sports Competitive Match Play: A Systematic Review and Meta-Analysis of Observational Studies. *Sports Med*, *49*(12), 1923-1947. https://doi.org/10.1007/s40279-019-01170-1

Haugen, T., Tønnessen, E., Hisdal, J., & Seiler, S. (2014). The role and development of sprinting speed in soccer. *Int J Sports Physiol Perform*, *9*(3), 432-441. https://doi.org/10.1123/ijspp.2013-0121

Haugen, T. A., Tønnessen, E., Hem, E., Leirstein, S., & Seiler, S. (2014). VO2max characteristics of elite female soccer players, 1989-2007. *Int J Sports Physiol Perform*, *9*(3), 515-521. https://doi.org/10.1123/ijspp.2012-0150

Hewitt, A., Norton, K., & Lyons, K. (2014). Movement profiles of elite women soccer players during international matches and the effect of opposition's team ranking. *J Sports Sci*, *32*(20), 1874-1880. https://doi.org/10.1080/02640414.2014.898854

Ingebrigtsen, J., Dillern, T., & Shalfawi, S. A. (2011). Aerobic capacities and anthropometric characteristics of elite female soccer players. *J Strength Cond Res*, *25*(12), 3352-3357. https://doi.org/10.1519/JSC.0b013e318215f763

Jajtner, A. R., Hoffman, J. R., Scanlon, T. C., Wells, A. J., Townsend, J. R., Beyer, K. S., Mangine, G. T., McCormack, W. P., Bohner, J. D., Fragala, M. S., & Stout, J. R. (2013). Performance and Muscle Architecture Comparisons Between Starters and Nonstarters in National Collegiate Athletic Association Division I Women's Soccer. *The Journal of Strength & Conditioning Research*, *27*(9), 2355-2365. https://doi.org/10.1519/JSC.0b013e31829bd7c5

Karakoç, B., Akalan, C., Alemdaroğlu, U., & Arslan, E. (2012). The relationship between the yo-yo tests, anaerobic performance and aerobic performance in young soccer players. *J Hum Kinet*, *35*, 81-88. https://doi.org/10.2478/v10078-012-0081-x

Krustrup, P., & Bangsbo, J. (2001). Physiological demands of top-class soccer refereeing in relation to physical capacity: effect of intense intermittent exercise training. *J Sports Sci*, *19*(11), 881-891. https://doi.org/10.1080/026404101753113831

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 SPORT EXER*, *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

Krustrup, P., Mohr, M., Nybo, L., Draganidis, D., Randers, M. B., Ermidis, G., Ørntoft, C., Røddik, L., Batsilas, D., Poulios, A., Ørtenblad, N., Loules, G., Deli, C. K., Batrakoulis, A., Nielsen, J. L., Jamurtas, A. Z., & Fatouros, I. G. (2022). Muscle metabolism and impaired sprint performance in an elite women's football game. *Scand J Med Sci Sports*, *32 Suppl 1*, 27-38. https://doi.org/10.1111/sms.13970

Lago, C., Casais, L., Dominguez, E., & Sampaio, J. (2010). The effects of situational variables on distance covered at various speeds in elite soccer. *European Journal of Sport Science*, *10*(2), 103-109. https://doi.org/10.1080/17461390903273994
Lockie, R. G., Moreno, M. R., Lazar, A., Orjalo, A. J., Giuliano, D. V., Risso, F. G., Davis, D. L., Crelling, J. B., Lockwood, J. R., & Jalilvand, F. (2018). The Physical and Athletic Performance Characteristics of Division I Collegiate Female Soccer Players by Position. *J Strength Cond Res*, *32*(2), 334-343. https://doi.org/10.1519/jsc.0000000000001561
Lorenzo-Martinez, M., Kalén, A., Rey, E., López-Del Campo, R., Resta, R., & Lago-Peñas, C. (2021). Do elite soccer players cover less distance when their team spent more time in possession of the ball? *Sci Med Footb*, *5*(4), 310-316. https://doi.org/10.1080/24733938.2020.1853211
Lutz, J., Memmert, D., Raabe, D., Dornberger, R., & Donath, L. (2019). Wearables for Integrative Performance and Tactic Analyses: Opportunities, Challenges, and Future Directions. *International journal of environmental research and public health*, *17*(1), 59. https://doi.org/10.3390/ijerph17010059
Mackenzie, R., & Cushion, C. (2013). Performance analysis in football: A critical review and implications for future research. *J Sports Sci*, *31*(6), 639-676. https://doi.org/10.1080/02640414.2012.746720
Mara, J. K., Thompson, K. G., Pumpa, K. L., & Morgan, S. (2017a). The acceleration and deceleration profiles of elite female soccer players during competitive matches. *J Sci Med Sport*, *20*(9), 867-872. https://doi.org/10.1016/j.jsams.2016.12.078
Mara, J. K., Thompson, K. G., Pumpa, K. L., & Morgan, S. (2017b). Quantifying the High-Speed Running and Sprinting Profiles of Elite Female Soccer Players During Competitive Matches Using an Optical Player Tracking System. *J Strength Cond Res*, *31*(6), 1500-1508. https://doi.org/10.1519/jsc.0000000000001629
McCormack, W. P., Stout, J. R., Wells, A. J., Gonzalez, A. M., Mangine, G. T., Fragala, M. S., & Hoffman, J. R. (2014). Predictors of High-Intensity Running Capacity in Collegiate Women During a Soccer Game. *The Journal of Strength & Conditioning Research*, *28*(4), 964-970. https://doi.org/10.1519/jsc.0000000000000359
McFadden, B. A., Walker, A. J., Bozzini, B. N., Hofacker, M., Russell, M., & Arent, S. M. (2021). Psychological and Physiological Changes in Response to the Cumulative Demands of a Women's Division I Collegiate Soccer Season. *J Strength Cond Res*. https://doi.org/10.1519/jsc.0000000000004062
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. *The Journal of Strength & Conditioning Research*, *34*(4), 969-974. https://doi.org/10.1519/jsc.0000000000003485
McLean, B. D., Petrucelli, C., & Coyle, E. F. (2012). Maximal Power Output and Perceptual Fatigue Responses During a Division I Female Collegiate Soccer Season. *The Journal of Strength & Conditioning Research*, *26*(12), 3189-3196. https://doi.org/10.1519/JSC.0b013e318273666e
Miller, T. A., Thierry-Aguilera, R., Congleton, J. J., Amendola, A. A., Clark, M. J., Crouse, S. F., Martin, S. M., & Jenkins, O. C. (2007). Seasonal changes in VO2max among Division 1A collegiate women soccer players. *J Strength Cond Res*, *21*(1), 48-51. https://doi.org/10.1519/00124278-200702000-00009
Modric, T., Versic, S., Chmura, P., Andrzejewski, M., Konefał, M., Raskovic, B., Drid, P., & Sekulic, D. (2022). The effect of ball possession on physical and technical performance in UEFA Champions league matches. *J Sports Sci*, *40*(24), 2750-2759. https://doi.org/10.1080/02640414.2023.2191389

Mohr, M., Ellingsgaard, H., Andersson, H., Bangsbo, J., & Krustrup, P. (2003). Physical demands in high-level female soccer–application of fitness tests to evaluate match performance. Fifth World Congress of Soccer and Science,

Mohr, M., Krustrup, P., Andersson, H., Kirkendal, D., & Bangsbo, J. (2008). Match activities of elite women soccer players at different performance levels. *J Strength Cond Res*, *22*(2), 341-349. https://doi.org/10.1519/JSC.0b013e318165fef6

Mohr, M., Krustrup, P., & Bangsbo, J. (2003). Match performance of high-standard soccer players with special reference to development of fatigue. *J Sports Sci*, *21*(7), 519-528. https://doi.org/10.1080/0264041031000071182

Mohr, M., Krustrup, P., & Bangsbo, J. (2005). Fatigue in soccer: A brief review. *Journal of Sports Sciences*, *23*(6), 593-599. https://search.ebscohost.com/login.aspx?direct=true&db=s3h&AN=17267223&site=ehost-live

Mohr, M., Vigh-Larsen, J. F., & Krustrup, P. (2022). Muscle Glycogen in Elite Soccer – A Perspective on the Implication for Performance, Fatigue, and Recovery [Perspective]. *Frontiers in Sports and Active Living*, *4*. https://doi.org/10.3389/fspor.2022.876534

Mujika, I., Santisteban, J., Impellizzeri, F. M., & Castagna, C. (2009). Fitness determinants of success in men's and women's football. *J Sports Sci*, *27*(2), 107-114. https://doi.org/10.1080/02640410802428071

Mujika, I., Santisteban, J., Impellizzeri, F. M., & Castagna, C. (2009). Fitness determinants of success in men's and women's football. *J SPORT SCI*, *27*(2), 107-114. https://doi.org/10.1080/02640410802428071

Nakamura, F. Y., Pereira, L. A., Loturco, I., Rosseti, M., Moura, F. A., & Bradley, P. S. (2017). Repeated-Sprint Sequences During Female Soccer Matches Using Fixed and Individual Speed Thresholds. *J Strength Cond Res*, *31*(7), 1802-1810. https://doi.org/10.1519/jsc.0000000000001659

Panduro, J., Ermidis, G., Røddik, L., Vigh-Larsen, J. F., Madsen, E. E., Larsen, M. N., Pettersen, S. A., Krustrup, P., & Randers, M. B. (2022). Physical performance and loading for six playing positions in elite female football: full-game, end-game, and peak periods. *Scand J Med Sci Sports*, *32 Suppl 1*, 115-126. https://doi.org/10.1111/sms.13877

Paulsen, K. M., Butts, C. L., & McDermott, B. P. (2018). Observation of Women Soccer Players' Physiology During a Single Season. *The Journal of Strength & Conditioning Research*, *32*(6), 1702-1707. https://doi.org/10.1519/jsc.0000000000002025

Peart, A. N., Nicks, C. R., Mangum, M., & Tyo, B. M. (2018). Evaluation of Seasonal Changes in Fitness, Anthropometrics, and Body Composition in Collegiate Division II Female Soccer Players. *The Journal of Strength & Conditioning Research*, *32*(7), 2010-2017. https://doi.org/10.1519/jsc.0000000000002578

Posit-team. (2023). *RStudio: Integrated Development Environment for R*. In (Version 2023.3.0.386) Posit Software, PBC. http://www.posit.co/

R-Core-Team. (2022). *R: A Language and Environment for Statistical Computing*. In R Foundation for Statistical Computing. https://www.R-project.org/

Rampinini, E., Bishop, D., Marcora, S. M., Ferrari Bravo, D., Sassi, R., & Impellizzeri, F. M. (2007). Validity of Simple Field Tests as Indicators of Match-Related Physical Performance in Top-Level Professional Soccer Players. *Int J Sports Med*, *28*(3), 228-235. https://doi.org/10.1055/s-2006-924340

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., & Wisløff, 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

Rampinini, E., Sassi, A., Azzalin, A., Castagna, C., Menaspà, P., Carlomagno, D., & Impellizzeri, F. M. (2009). Physiological determinants of Yo-Yo intermittent recovery tests in male soccer players. *European Journal of Applied Physiology*, *108*(2), 401. https://doi.org/10.1007/s00421-009-1221-4

Randers, M. B., Mujika, I., Hewitt, A., Santisteban, J., Bischoff, R., Solano, R., Zubillaga, A., Peltola, E., Krustrup, 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

Rebelo, A., Brito, J., Seabra, A., Oliveira, J., & Krustrup, P. (2014). Physical match performance of youth football players in relation to physical capacity. *Eur J Sport Sci*, *14 Suppl 1*, S148-156. https://doi.org/10.1080/17461391.2012.664171

Reilly, T. (1976). A motion analysis of work-rate in different positional roles in professional football match-play. *J Human Movement Studies*, *2*, 87-97. https://cir.nii.ac.jp/crid/1572824500553316736

Reilly, T. (2005). An ergonomics model of the soccer training process. *Journal of Sports Sciences*, *23*(6), 561-572. https://doi.org/10.1080/02640410400021245

Risso, F. G., Jalilvand, F., Orjalo, A. J., Moreno, M. R., Davis, D. L., Birmingham-Babauta, S. A., Stokes, J. J., Stage, A. A., Liu, T. M., Giuliano, D. V., Lazar, A., & Lockie, R. G. (2017). Physiological Characteristics of Projected Starters and Non-Starters in the Field Positions from a Division I Women's Soccer Team. *International journal of exercise science*, *10*(4), 568-579. https://pubmed.ncbi.nlm.nih.gov/28674601

https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5466405/

Rowan, A. E., Kueffner, T. E., & Stavrianeas, S. (2012). Short Duration High-Intensity Interval Training Improves Aerobic Conditioning of Female College Soccer Players. *International journal of exercise science*, *5*, 6.

Sanders, G. J., Turner, Z., Boos, B., Peacock, C. A., Peveler, W., & Lipping, A. (2017). Aerobic Capacity is Related to Repeated Sprint Ability with Sprint Distances Less Than 40 Meters. *Int J Exerc Sci*, *10*(2), 197-204.

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

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

Spencer, M., Dawson, B., Goodman, C., Dascombe, B., & Bishop, D. (2008). Performance and metabolism in repeated sprint exercise: effect of recovery intensity. *Eur J Appl Physiol*, *103*(5), 545-552. https://doi.org/10.1007/s00421-008-0749-z

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

Svensson, M., & Drust, B. (2005). Testing soccer players. *J Sports Sci*, *23*(6), 601-618. https://doi.org/10.1080/02640410400021294

Trewin, J., Meylan, C., Varley, M. C., Cronin, J., & Ling, D. (2018). Effect of Match Factors on the Running Performance of Elite Female Soccer Players. *The Journal of Strength & Conditioning Research*, *32*(7), 2002-2009. https://doi.org/10.1519/jsc.0000000000002584

Vescovi, J. D. (2012). Sprint speed characteristics of high-level American female soccer players: Female Athletes in Motion (FAiM) study. *J Sci Med Sport*, *15*(5), 474-478. https://doi.org/10.1016/j.jsams.2012.03.006

Vescovi, J. D., Brown, T. D., & Murray, T. M. (2006). Positional characteristics of physical performance in Division I college female soccer players. *Journal of Sports Medicine and Physical Fitness*, *46*(2), 221-226.

Vescovi, J. D., & Falenchuk, O. (2019). Contextual factors on physical demands in professional women's soccer: Female Athletes in Motion study. *European Journal of Sport Science*, *19*(2), 141-146. https://doi.org/10.1080/17461391.2018.1491628

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/ijspp.2013-0526

Vescovi, J. D., Rupf, R., Brown, T. D., & Marques, M. C. (2011). Physical performance characteristics of high-level female soccer players 12-21 years of age. *Scand J Med Sci Sports*, *21*(5), 670-678. https://doi.org/10.1111/j.1600-0838.2009.01081.x

Wells, A. J., Hoffman, J. R., Beyer, K. S., Hoffman, M. W., Jajtner, A. R., Fukuda, D. H., & Stout, J. R. (2015). Regular- and postseason comparisons of playing time and measures of running performance in NCAA Division I women soccer players. *APPL PHYSIOL NUTR ME*, *40*(9), 907-917. https://doi.org/10.1139/apnm-2014-0560

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T., Miller, E., Bache, S., Müller, K., Ooms, J., Robinson, D., Seidel, D., Spinu, V., & Yutani, H. (2019). Welcome to the Tidyverse. *Journal of Open Source Software*, *4*, 1686. https://doi.org/10.21105/joss.01686

Appendices

Linear Mixed Model Analysis Report

Model Build Introduction

Data was analyzed utilizing a linear mixed model. A linear mixed model was implemented due to its ability to be applied to repeated measures data from an unbalanced design. Our study design included both repeated measures and continuous outcome variables, along with players that differ in their number of match occurrences, hence this choice in statistical model.

The programming language for statistical computing, R, was used to conduct all statistical analyses. The lmer4 package was used to build the linear mixed model. Several model statistics and graphical representations were used to inform the model building process. Bivariate analyses were conducted for potential covariates to determine which covariates would be included in the full model.

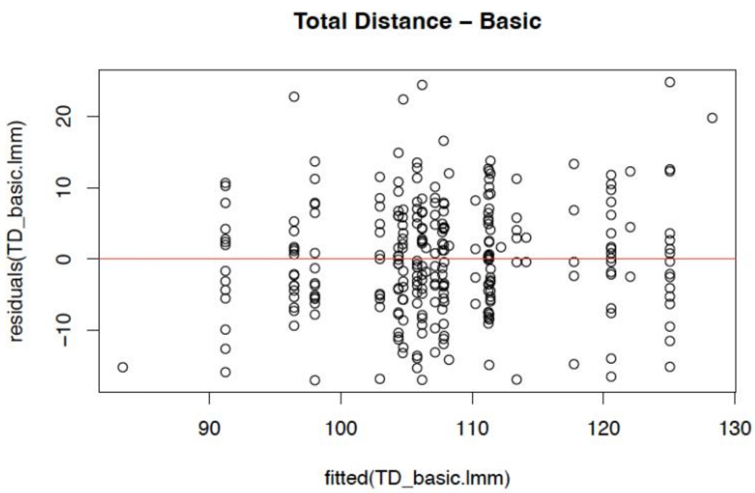
Two covariates, season year and playing position, were selected *a priori* based on scientific rationale for their inclusion. Following the inclusion of these *a priori* covariates, the full model was built using forward selection, where covariates were included in the model based on bivariate analysis results in comparison to designated criteria (see bivariate analysis section of these appendices). Each stage of the model building process has been included in the following analysis in addition to likelihood ratio test results and QQ-plots. Maximum likelihood parameter estimation criterion was used for likelihood ratio testing. This change was made only for the purpose of comparing models in LRT and all other model results use the restricted maximum likelihood (REML) parameter estimation criteria.

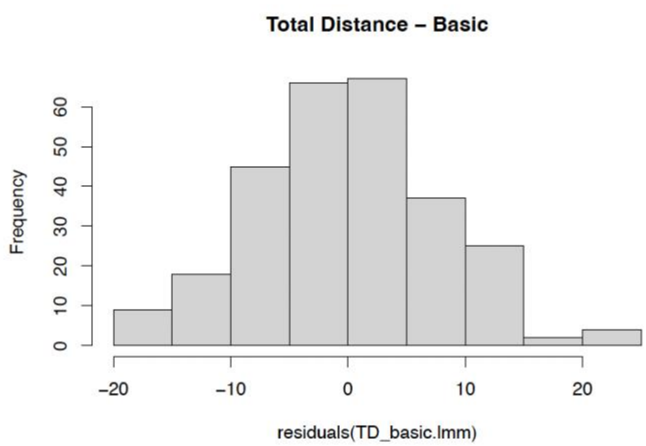
TD Model Build

Below is a table describing the results of the TD basic (unadjusted) linear mixed model (Total Distance ~ YYIR1 Score (1|Athlete)) and visualization of this model's residuals.

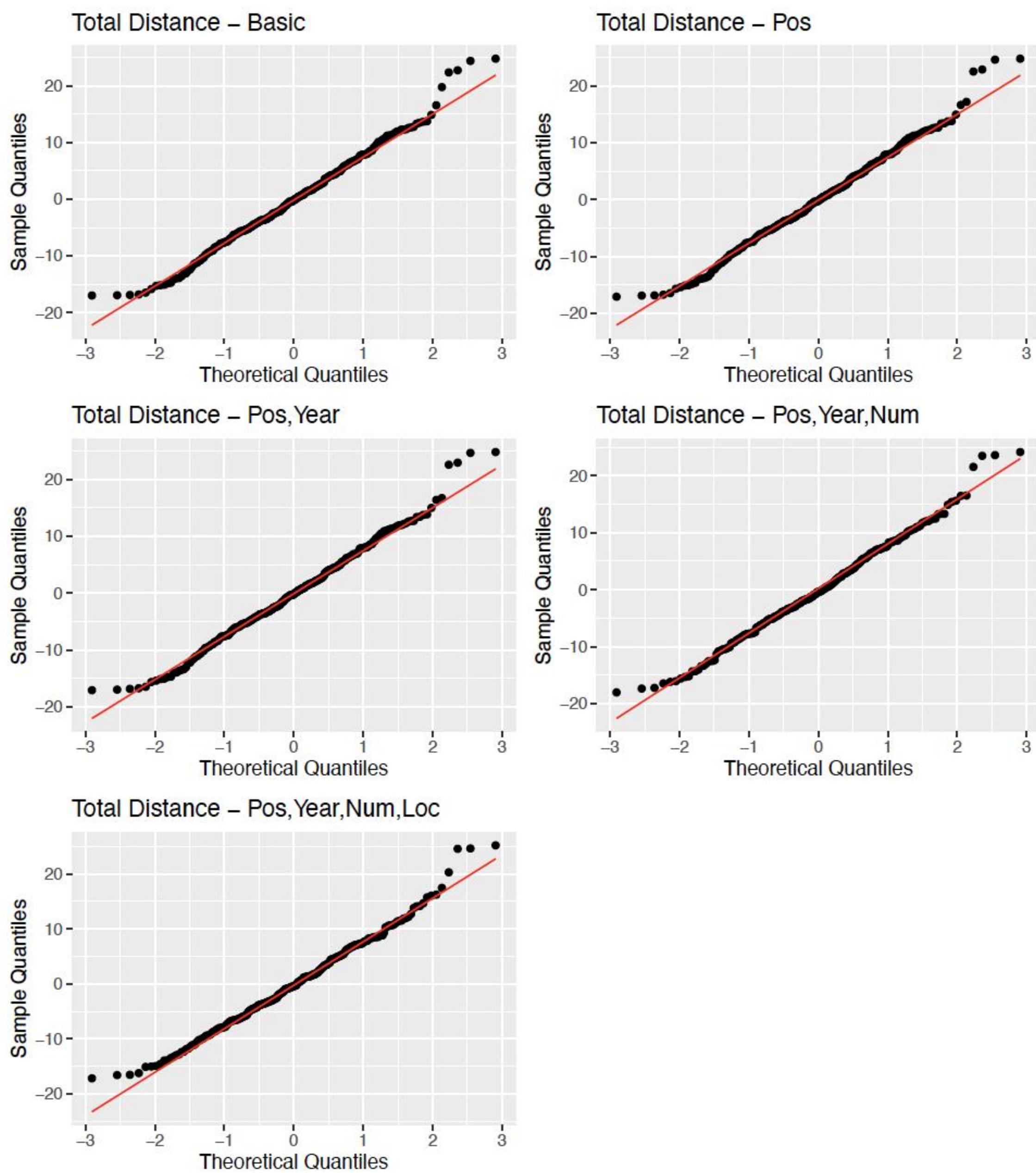
TD basic (unadjusted) model results

	Dependent variable:
	totdist_rel
Constant	79.327
	(57.262-101.392)
YYIR1 Score	0.886
	(0.229-1.543)
Observations	273
Log Likelihood	−995.871





Below are the results of the model build for the TD variable, including Q-Q plots for each step in the model build process, a table describing the results of each model, and a table describing the results of likelihood ratio testing for each model in comparison to the previous.



TD model build results

	Dependent variable:				
	totdist_rel				
	(1)	(2)	(3)	(4)	(5)
Constant	79.33	76.35	76.38	74.27	72.54
	(57.26-101.39)	(52.54-100.16)	(51.78-100.99)	(50.50-98.04)	(48.52-96.57)
YYIR1_Score	0.89	0.93	0.94	0.95	0.95
	(0.23-1.54)	(0.24-1.63)	(0.23-1.66)	(0.26-1.64)	(0.26-1.65)
Athlete_PositionMidfielder		0.77	0.76	0.53	0.56
		(−7.55-9.08)	(−7.84-9.36)	(−7.75-8.82)	(−7.80-8.92)
Athlete_PositionForward		4.85	5.02	4.84	4.82
		(−4.46-14.16)	(−4.67-14.72)	(−4.49-14.17)	(−4.60-14.24)
Season_Year2022			−0.53	−0.62	−0.93
			(−8.06-7.00)	(−7.86-6.63)	(−8.24-6.38)
Season_Game_Num				0.18	0.24
				(−0.01-0.36)	(0.05-0.42)
Match_Location_H.AHome					2.69
					(0.63-4.75)
Observations	273	273	273	273	273
Log Likelihood	−995.87	−990.60	−988.34	−988.03	−983.83
Akaike Inf. Crit.	1,999.74	1,993.20	1,990.68	1,992.07	1,985.67
Bayesian Inf. Crit.	2,014.18	2,014.85	2,015.94	2,020.95	2,018.15

TD model build LRT results

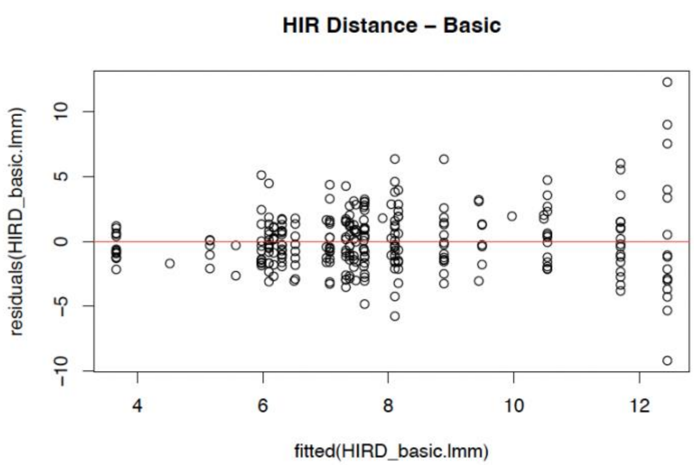
Model	npar	AIC	BIC	logLik	deviance	Chisq	Df	Pr(>Chisq)
TD_ML_basic.lmm	4	2002.254	2016.692	-997.127	1994.254	NA	NA	NA
TD_ML_pos.lmm...2	6	2005.074	2026.731	-996.537	1993.074	1.180	2	0.554
TD_ML_pos.lmm...3	6	2005.074	2026.731	-996.537	1993.074	NA	NA	NA
TD_ML_pos_year.lmm...4	7	2007.061	2032.327	-996.530	1993.061	0.013	1	0.908
TD_ML_pos_year.lmm...5	7	2007.061	2032.327	-996.530	1993.061	NA	NA	NA
TD_ML_pos_year_num.lmm...6	8	2005.190	2034.066	-994.595	1989.190	3.871	1	0.049
TD_ML_pos_year_num.lmm...7	8	2005.190	2034.066	-994.595	1989.190	NA	NA	NA
TD_ML_pos_year_num_loc.lmm	9	2000.804	2033.289	-991.402	1982.804	6.387	1	0.011

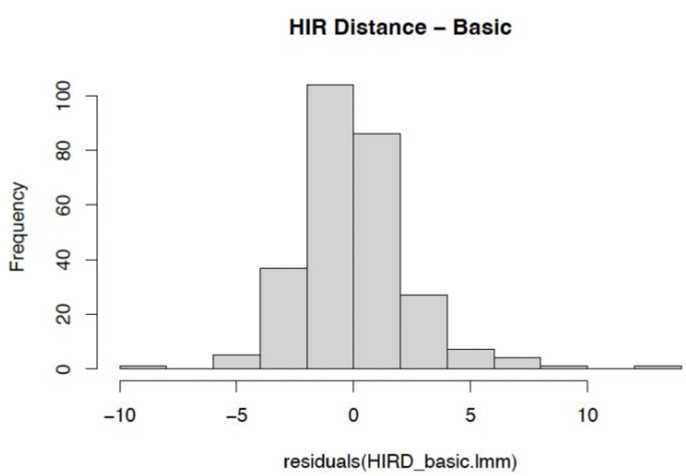
HIRD Model Build

Below is a table describing the results of the HIRD basic (unadjusted) linear mixed model (HIR Distance ~ YYIR1 Score (1|Athlete)) and visualization of this model's residuals.

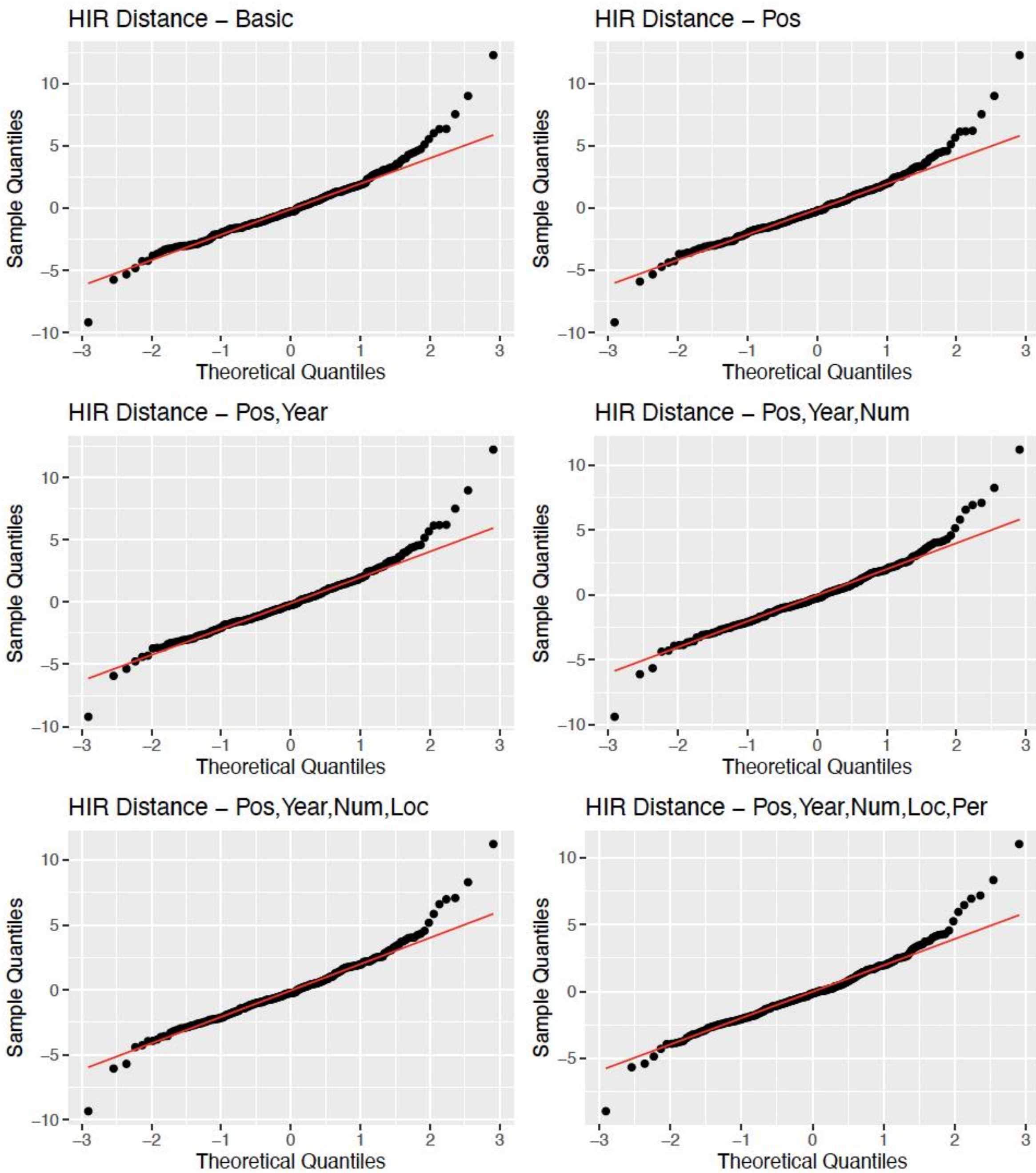
HIRD basic (unadjusted) model results

	Dependent variable:
	HIRD_rel
Constant	−0.486
	(−5.315-4.343)
YYIR1 Score	0.247
	(0.104-0.391)
Observations	273
Log Likelihood	−660.620





Below are the results of the model build for the HIRD variable, including Q-Q plots for each step in the model build process, a table describing the results of each model, and a table describing the results of likelihood ratio testing for each model in comparison to the previous.



HIRD model build results

	Dependent variable:					
	HIRD_rel					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	−0.49	−1.77	−1.97	−3.39	−3.46	−4.60
	(−5.31-4.34)	(−6.39-2.84)	(−6.66-2.72)	(−8.01-1.22)	(−8.10-1.19)	(−9.47-0.26)
YYIR1_Score	0.25	0.26	0.26	0.27	0.27	0.27
	(0.10-0.39)	(0.13-0.40)	(0.12-0.40)	(0.14-0.40)	(0.14-0.40)	(0.14-0.40)
Athlete_PositionMidfielder		0.68	0.61	0.42	0.42	0.41
		(−0.97-2.32)	(−1.07-2.28)	(−1.21-2.05)	(−1.21-2.05)	(−1.22-2.04)
Athlete_PositionForward		2.33	2.22	2.21	2.21	2.20
		(0.49-4.16)	(0.34-4.09)	(0.38-4.03)	(0.38-4.03)	(0.38-4.03)
Season_Year2022			0.58	0.52	0.51	0.43
			(−0.88-2.04)	(−0.90-1.94)	(−0.91-1.94)	(−0.99-1.86)
Season_Game_Num				0.11	0.11	0.18
				(0.06-0.16)	(0.06-0.17)	(0.06-0.30)
Match_Location_H.AHome					0.10	0.12
					(−0.51-0.71)	(−0.52-0.75)
Season_PeriodOC						0.96
						(−0.20-2.11)
Season_PeriodPC						0.04
						(−1.14-1.22)
Observations	273	273	273	273	273	273
Log Likelihood	−660.62	−656.12	−655.20	−650.08	−650.29	−648.00
Akaike Inf. Crit.	1,329.24	1,324.25	1,324.40	1,316.17	1,318.58	1,318.00
Bayesian Inf. Crit.	1,343.68	1,345.90	1,349.66	1,345.04	1,351.06	1,357.70

HIRD model build LRT results

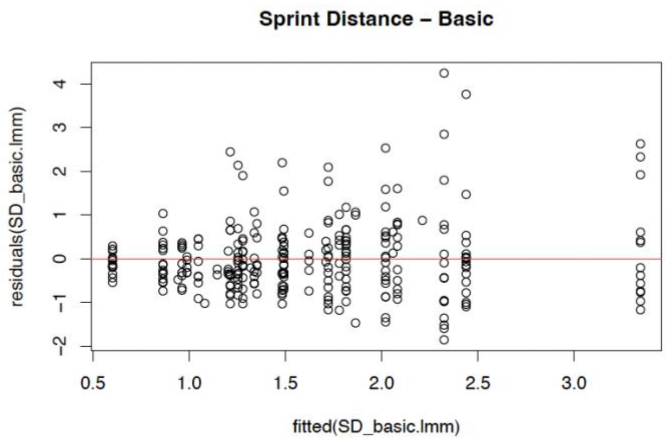
Model	npar	AIC	BIC	logLik	deviance	Chisq	Df	Pr(>Chisq)
HIRD_ML_basic.lmm	4	1325.72	1340.16	-658.86	1317.72	NA	NA	NA
HIRD_ML_pos.lmm...2	6	1323.22	1344.88	-655.61	1311.22	6.50	2	0.04
HIRD_ML_pos.lmm...3	6	1323.22	1344.88	-655.61	1311.22	NA	NA	NA
HIRD_ML_pos_year.lmm...4	7	1324.50	1349.77	-655.25	1310.50	0.72	1	0.40
HIRD_ML_pos_year.lmm...5	7	1324.50	1349.77	-655.25	1310.50	NA	NA	NA
HIRD_ML_pos_year_num.lmm...6	8	1310.64	1339.52	-647.32	1294.64	15.86	1	0.00
HIRD_ML_pos_year_num.lmm...7	8	1310.64	1339.52	-647.32	1294.64	NA	NA	NA
HIRD_ML_pos_year_num_loc.lmm...8	9	1312.56	1345.05	-647.28	1294.56	0.08	1	0.78
HIRD_ML_pos_year_num_loc.lmm...9	9	1312.56	1345.05	-647.28	1294.56	NA	NA	NA
HIRD_ML_pos_year_num_loc_per.lmm	11	1313.40	1353.10	-645.70	1291.40	3.17	2	0.21

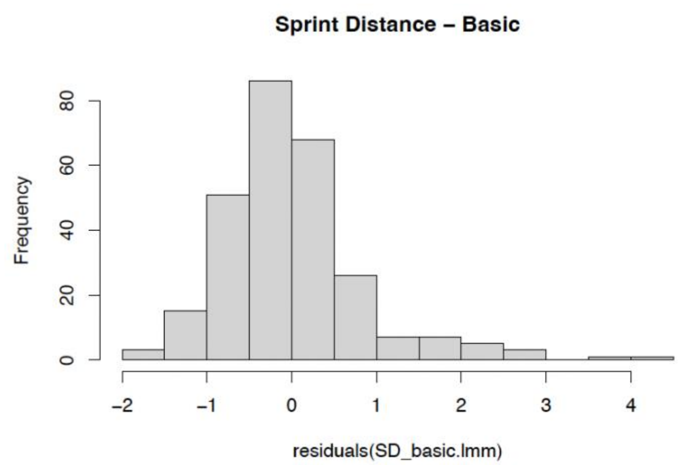
SD Model Build

Below is a table describing the results of the SD basic (unadjusted) linear mixed model (Sprint Distance ~ YYIR1 Score (1|Athlete)) and visualization of this model's residuals.

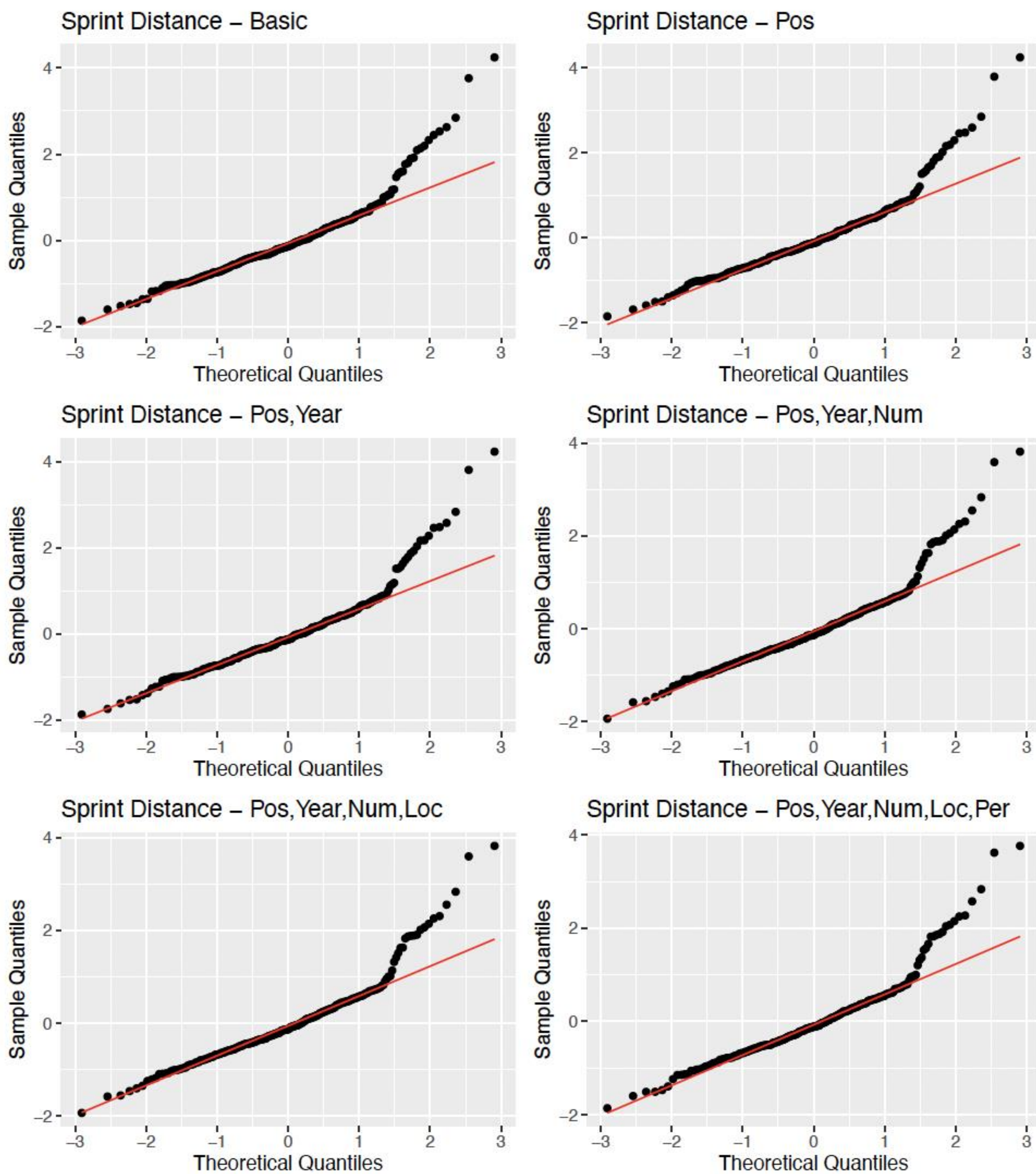
SD basic (unadjusted) model results

	Dependent variable:
	sprintdist_rel
Constant	0.261
	(−1.425-1.948)
YYIR1 Score	0.039
	(−0.011-0.089)
Observations	273
Log Likelihood	−377.989





Below are the results of the model build for the SD variable, including Q-Q plots for each step in the model build process, a table describing the results of each model, and a table describing the results of likelihood ratio testing for each model in comparison to the previous.



SD model build results

	Dependent variable:					
	sprintdist_rel					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.26	−0.15	−0.24	−0.82	−0.82	−1.00
	(−1.43-1.95)	(−1.74-1.44)	(−1.83-1.35)	(−2.42-0.79)	(−2.44-0.79)	(−2.69-0.70)
YYIR1_Score	0.04	0.05	0.04	0.05	0.05	0.05
	(−0.01-0.09)	(−0.001-0.09)	(−0.002-0.09)	(0.002-0.09)	(0.002-0.09)	(0.002-0.09)
Athlete_PositionMidfielder		0.10	0.06	−0.01	−0.01	−0.01
		(−0.47-0.66)	(−0.51-0.63)	(−0.58-0.55)	(−0.58-0.55)	(−0.58-0.55)
Athlete_PositionForward		0.78	0.72	0.72	0.72	0.72
		(0.14-1.41)	(0.08-1.36)	(0.08-1.35)	(0.08-1.35)	(0.08-1.35)
Season_Year2022			0.28	0.25	0.25	0.24
			(−0.22-0.77)	(−0.24-0.75)	(−0.24-0.75)	(−0.25-0.74)
Season_Game_Num				0.04	0.04	0.05
				(0.02-0.06)	(0.02-0.06)	(0.01-0.09)
Match_Location_H.AHome					0.01	0.02
					(−0.20-0.22)	(−0.20-0.24)
Season_PeriodOC						0.15
						(−0.26-0.55)
Season_PeriodPC						0.05
						(−0.37-0.46)
Observations	273	273	273	273	273	273
Log Likelihood	−377.99	−375.71	−375.56	−369.19	−370.49	−371.46
Akaike Inf. Crit.	763.98	763.41	765.12	754.37	758.97	764.92
Bayesian Inf. Crit.	778.42	785.07	790.39	783.25	791.46	804.62

SD model build LRT results

Model	npar	AIC	BIC	logLik	deviance	Chisq	Df	Pr(>Chisq)
SD_ML_basic.lmm	4	756.257	770.695	-374.129	748.257	NA	NA	NA
SD_ML_pos.lmm...2	6	753.896	775.553	-370.948	741.896	6.361	2	0.042
SD_ML_pos.lmm...3	6	753.896	775.553	-370.948	741.896	NA	NA	NA
SD_ML_pos_year.lmm...4	7	754.472	779.739	-370.236	740.472	1.424	1	0.233
SD_ML_pos_year.lmm...5	7	754.472	779.739	-370.236	740.472	NA	NA	NA
SD_ML_pos_year_num.lmm...6	8	736.190	765.065	-360.095	720.190	20.283	1	0.000
SD_ML_pos_year_num.lmm...7	8	736.190	765.065	-360.095	720.190	NA	NA	NA
SD_ML_pos_year_num_loc.lmm...8	9	738.188	770.673	-360.094	720.188	0.002	1	0.964
SD_ML_pos_year_num_loc.lmm...9	9	738.188	770.673	-360.094	720.188	NA	NA	NA
SD_ML_pos_year_num_loc_per.lmm	11	741.406	781.111	-359.703	719.406	0.781	2	0.677

Final Models (TD, HIRD, SD)

	Dependent variable:		
	Total Distance	HIR Distance	Sprint Distance
Constant	72.54	−4.60	−1.00
	(48.52-96.57)	(−9.47-0.26)	(−2.69-0.70)
YYIR1 Score	0.95	0.27	0.05
	(0.26-1.65)	(0.14-0.40)	(0.002-0.09)
Observations	273	273	273
Log Likelihood	−983.83	−648.00	−371.46

Bivariate Analysis Report

Bivariate Analysis Introduction

The below analyses were completed to assess potential covariates for inclusion in the main model build. Prior to conducting this analysis, two covariates had already been selected *a priori* These covariates are Season Year (2021 & 2022) and Playing Position. The specific categories used for describing playing position were completed in an additional analysis, which is included in this document (see final section for further details).

Analyses were conducted for each of the study's response variables:

- Total Distance (TD)
- High Intensity Running Distance (HIRD)
- Sprinting Distance (SD)

The following potential covariates were assessed:

- Game Number: Each game was numbered based on the order they were played in the season (e.g., the third game of the season was numbered "3"). This number was then attributed to each occurrence associated with that game. The numbering system was restarted for each season, with the first game of both seasons being designated as game “1” in corresponding occurrences. This is a discrete numerical variable.

  - Analyzed models including this variable will have the following naming: “ResponseVariable”_game.lmm

- Match Location (Home, Away & Neutral): Each game was categorized as being either a home game (on reference team’s home field), away game (on opponent’s home field), or neutral game (at a field not home to either participating team). This is a nominal categorical variable.
  - Analyzed models including this variable will have the following naming: “ResponseVariable”_Location.lmm
- Match Location (Home & Away): For this covariate, each game was categorized as being either a home game (on reference team’s home field) or an away game (on opponent’s home field, or at a neutral field). This was done based on the rationale that a neutral game is not very different than an away game for the reference team when it comes to many of the logistical factors at play with traveling to, practicing, and competing at a field that is not at home. This is a nominal categorical variable.
  - Analyzed models including this variable have the following naming: “ResponseVariable”_Location_H.A.lmm
- Season Period (Out-of-Conference (OC), In-Conference (IC), Post-Conference (PC)): Each game was categorized as being completed during one of the three different season periods. The OC designation was for games completed against non-conference opponents in the early season, prior to the start of the regular season. The IC designation was for games completed against conference opponents during the regular season. The PC designation was for any games completed after the conclusion of the regular season. This includes the conference tournament and the NCAA tournament. This is an ordinal categorical variable.

- Analyzed models including this variable will have the following naming: “ResponseVariable”_Period.lmm

- RPI Differential: RPI differential is a metric representing the strength of an opponent in relation to the reference team. The strength of each opponent was determined based on the NCAA RPI rankings at the conclusion of each season. The reference team and each opponent were assigned a numeric rank matching their NCAA RPI ranking, with a lower number signifying increased strength and a higher number signifying decreased strength. Opponent strength was then calculated by subtracting the opponent rank from the reference team rank, resulting in the difference between ranks (RPI Differential). A number close to zero signifies a nearly equal strength opponent, with higher numbers signifying stronger opponents and lower numbers signifying weaker. The RPI differential was attributed to each occurrence associated with the appropriate opponent. This is a discrete numeric variable.
    - Analyzed models including this variable will have the following naming: “ResponseVariable”_RPI.lmm
- Score Differential: Each game had a value associated with it based on the resulting goals scored by each team during the game. The opponent’s score was subtracted from the reference team’s score, resulting in a score differential. This value was attributed to each occurrence associated with the corresponding game. This is a discrete numeric variable.
    - Analyzed models including this variable will have the following naming: “ResponseVariable”_score.lmm
- Starter Status: If a player was part of the initial 11 player line-up at the onset of the match, they were designated as a starter for that occurrence. Starter status was designated as either “Y” or “N”. This is a nominal categorical variable.

- Analyzed models including this variable will have the following naming: “ResponseVariable”_starter.lmm

Each Covariate was considered for inclusion in the main model based on the following:

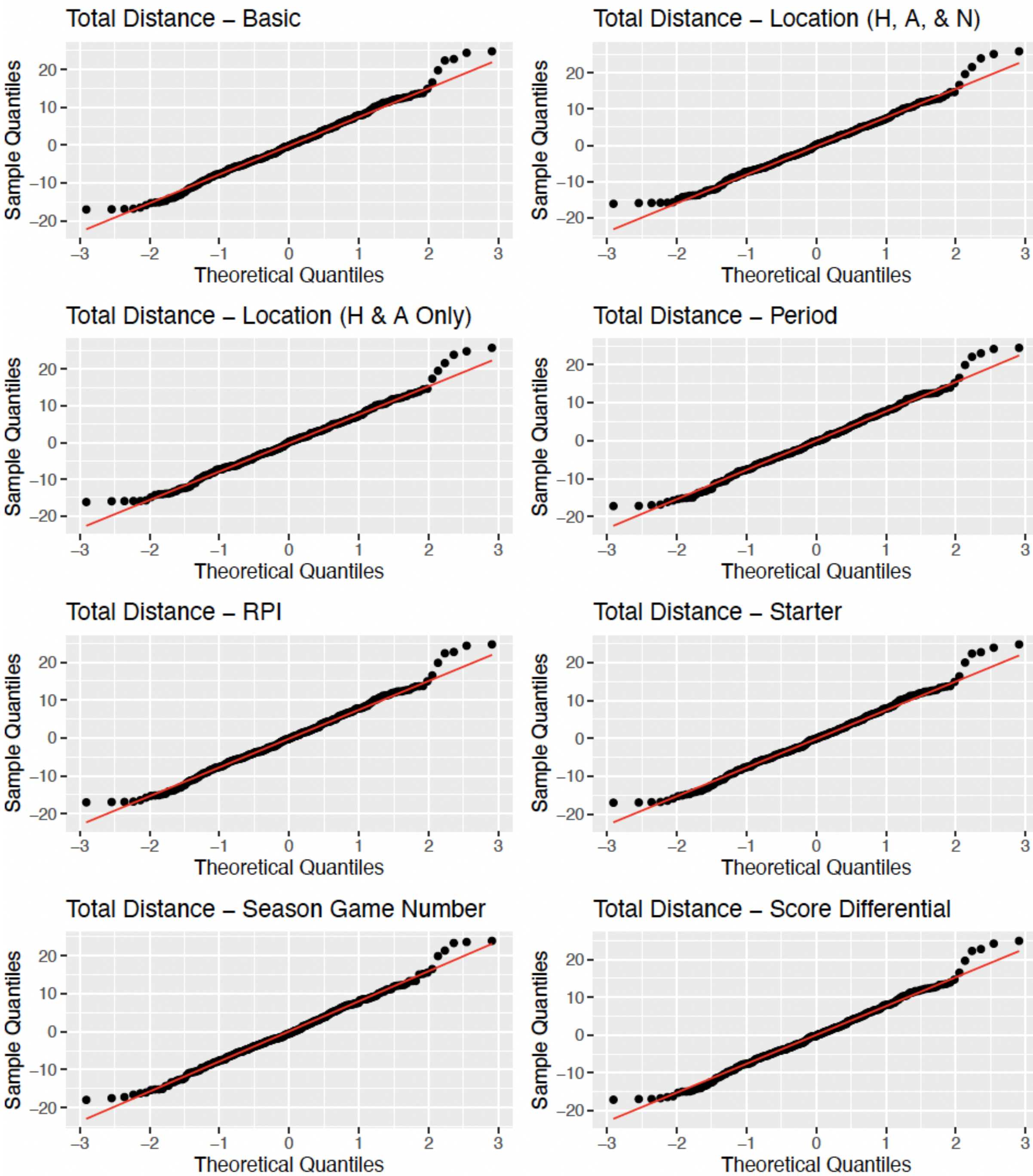
- Scientific rationale for that covariate’s inclusion
- Visual comparison of model fit (mainly using Q-Q Plots)
- Comparing differences in point estimates for our predictor variable (YYIR1 Score)
- Comparing differences in confidence intervals for those point estimates
- P-Values for likelihood ratio tests

Lastly, an additional analysis was completed to compare two different categorization strategies for athlete position in an attempt to better understand which version of the *a priori* covariate should be included in our model. The same criteria were considered for this analysis.

TD Bivariate Analysis

Comparison of the TD basic model with bivariate models. Q-Q Plots of the residuals for each model have been provided. Model results can be compared using the following table. Lastly, A likelihood ratio test was completed for each bivariate model to compare it to the basic model, the results of which can be found in the second table. Note that the maximum likelihood parameter estimation criterion was used for likelihood ratio testing using the “REML = False” argument in the lmer4 package. This change was made only for the purpose of comparing models in LRT and all other model results use the restricted maximum likelihood (REML) parameter estimation criteria.

Q-Q Plots for TD bivariate model analysis



TD bivariate model results

	Dependent variable:							
	totdist_rel							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	79.33 (57.26-101.39)	76.96 (55.61-98.31)	78.44 (55.98-100.90)	78.46 (55.97-100.94)	79.55 (57.53-101.57)	79.30 (57.22-101.38)	79.35 (57.30-101.41)	77.26 (54.60-99.92)
YYIR1_Score	0.89 (0.23-1.54)	0.90 (0.27-1.53)	0.88 (0.21-1.55)	0.89 (0.22-1.55)	0.89 (0.23-1.54)	0.89 (0.23-1.54)	0.89 (0.23-1.54)	0.88 (0.23-1.53)
Season_Game_Num		0.18 (−0.002-0.37)						
Match_LocationHome			2.17 (0.09-4.25)					
Match_LocationNeutral			0.89 (−3.70-5.48)					
Match_Location_H.AHome				2.07 (0.06-4.09)				
Season_PeriodOC					−0.59 (−2.79-1.60)			
Season_PeriodPC					−0.29 (−3.47-2.90)			
RPI_Differential						−0.0005 (−0.01-0.01)		
Score_Differential							−0.11 (−0.74-0.53)	
Started_StatusY								2.62 (−5.06-10.30)
Observations	273	273	273	273	273	273	273	273
Log Likelihood	−995.87	−995.47	−991.07	−992.91	−993.34	−1,000.09	−996.03	−993.37
Akaike Inf. Crit.	1,999.74	2,000.93	1,994.14	1,995.82	1,998.69	2,010.18	2,002.06	1,996.73
Bayesian Inf. Crit.	2,014.18	2,018.98	2,015.79	2,013.87	2,020.34	2,028.22	2,020.11	2,014.78

TD bivariate LRT results

Model	npar	AIC	BIC	logLik	deviance	Chisq	Df	Pr(>Chisq)
TD_ML_basic.lmm	4	2002.254	2016.692	-997.127	1994.254	NA	NA	NA
TD_ML_game.lmm	5	2000.414	2018.461	-995.207	1990.414	3.841	1	0.050
TD_ML_location.lmm	6	2002.152	2023.809	-995.076	1990.152	4.102	2	0.129
TD_ML_Location_H.A.lmm	5	2000.303	2018.351	-995.152	1990.303	3.951	1	0.047
TD_ML_Period.lmm	6	2005.960	2027.617	-996.980	1993.960	0.294	2	0.863
TD_ML_RPI.lmm	5	2004.248	2022.295	-997.124	1994.248	0.006	1	0.937
TD_ML_score.lmm	5	2004.145	2022.192	-997.072	1994.145	0.109	1	0.741
TD_ML_starter.lmm	5	2003.745	2021.792	-996.873	1993.745	0.509	1	0.476

Summary of TD Bivariate Analyses

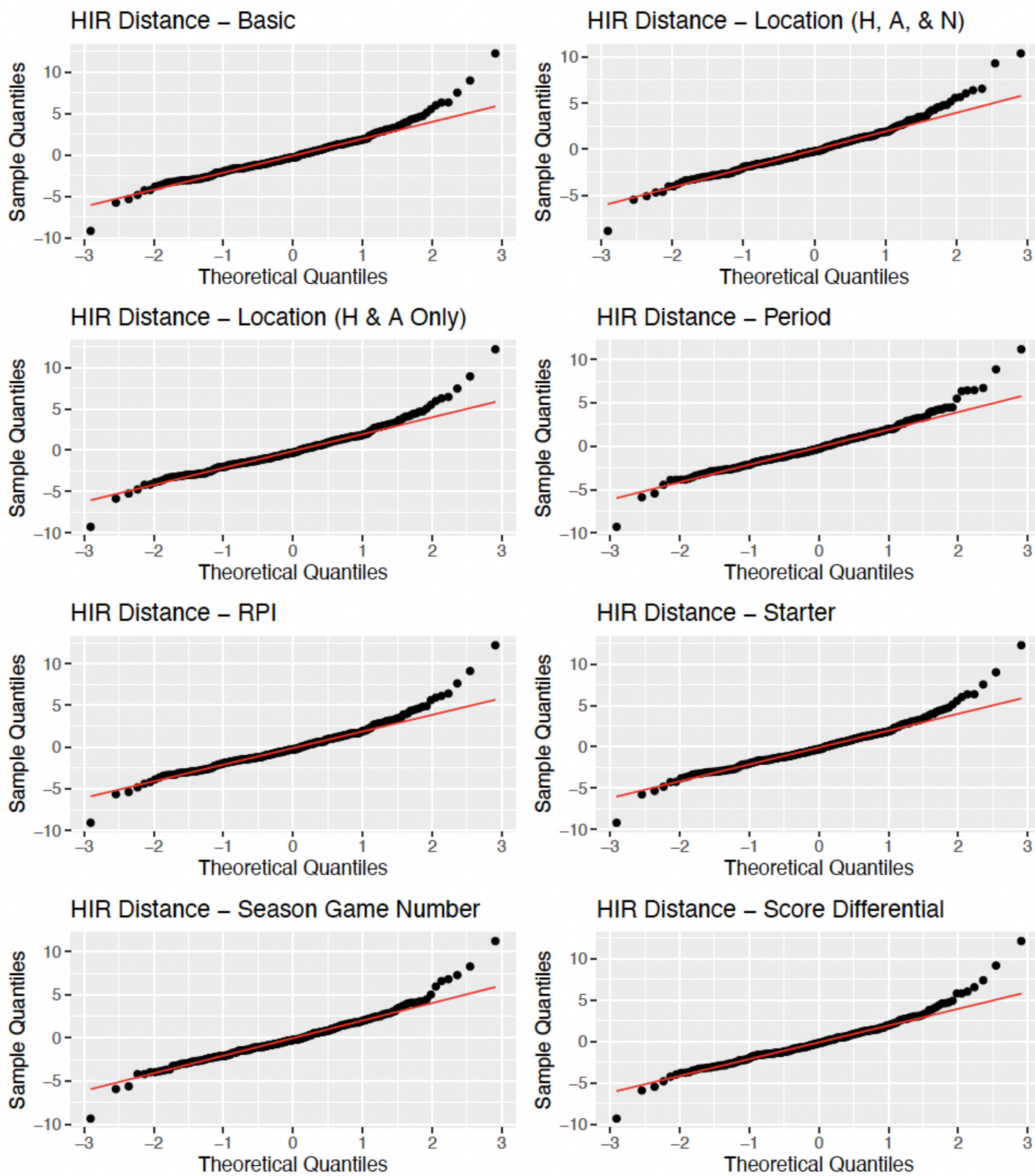
Based on the above analyses, the following covariates have been selected for inclusion in the full linear mixed model build for Total Distance:

- Season Game Number
    - Based on confidence interval changes, likelihood ratio test results
- Match Location (Home & Away)
    - Based on confidence interval changes, likelihood ratio test results, and scientific rationale

HIRD Bivariate Analysis

Comparison of the HIRD basic model with bivariate models. Q-Q Plots of the residuals for each model have been provided. Model results can be compared using the following table. Lastly, A likelihood ratio test was completed for each bivariate model to compare it to the basic model, the results of which can be found in the second table. Note that the maximum likelihood parameter estimation criterion was used for likelihood ratio testing using the “REML = False” argument in the lmer4 package. This change was made only for the purpose of comparing models in LRT and all other model results use the restricted maximum likelihood (REML) parameter estimation criteria.

Q-Q Plots for HIRD bivariate model analysis



HIRD bivariate model results

	Dependent variable:							
	HIRD_rel							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	−0.49	−1.95	−0.51	−0.41	−0.54	−0.41	−0.43	−0.90
	(−5.31-4.34)	(−6.74-2.84)	(−5.31-4.28)	(−5.23-4.41)	(−5.30-4.22)	(−5.23-4.41)	(−5.22-4.37)	(−6.03-4.23)
YYIR1_Score	0.25	0.26	0.24	0.25	0.25	0.25	0.25	0.25
	(0.10-0.39)	(0.11-0.40)	(0.10-0.38)	(0.10-0.39)	(0.11-0.39)	(0.10-0.39)	(0.10-0.39)	(0.10-0.39)
Season_Game_Num		0.11						
		(0.06-0.16)						
Match_LocationHome			0.07					
			(−0.54-0.69)					
Match_LocationNeutral			2.19					
			(0.86-3.53)					
Match_Location_H.AHome				−0.17				
				(−0.78-0.43)				
Season_PeriodOC					−0.50			
					(−1.15-0.14)			
Season_PeriodPC					0.96			
					(0.03-1.89)			
RPI_Differential						0.001		
						(−0.002-0.005)		
Score_Differential							−0.16	
							(−0.34-0.03)	
Started_StatusY								0.50
								(−1.66-2.65)
Observations	273	273	273	273	273	273	273	273
Log Likelihood	−660.62	−655.54	−655.10	−660.72	−656.13	−665.85	−660.67	−659.50
Akaike Inf. Crit.	1,329.24	1,321.07	1,322.20	1,331.44	1,324.26	1,341.70	1,331.34	1,329.01
Bayesian Inf. Crit.	1,343.68	1,339.12	1,343.85	1,349.49	1,345.92	1,359.75	1,349.39	1,347.06

HIRD bivariate LRT results

Model	npar	AIC	BIC	logLik	deviance	Chisq	Df	Pr(>Chisq)
HIRD_ML_basic.lmm	4	1325.718	1340.156	-658.859	1317.718	NA	NA	NA
HIRD_ML_game.lmm	5	1312.110	1330.158	-651.055	1302.110	15.608	1	0.000
HIRD_ML_location.lmm	6	1319.156	1340.813	-653.578	1307.156	10.562	2	0.005
HIRD_ML_Location_H.A.lmm	5	1327.393	1345.441	-658.697	1317.393	0.325	1	0.569
HIRD_ML_Period.lmm	6	1320.526	1342.183	-654.263	1308.526	9.192	2	0.010
HIRD_ML_RPI.lmm	5	1327.283	1345.331	-658.642	1317.283	0.435	1	0.509
HIRD_ML_score.lmm	5	1324.917	1342.965	-657.459	1314.917	2.801	1	0.094
HIRD_ML_starter.lmm	5	1327.475	1345.522	-658.737	1317.475	0.244	1	0.622

Summary of HIRD Bivariate Analyses

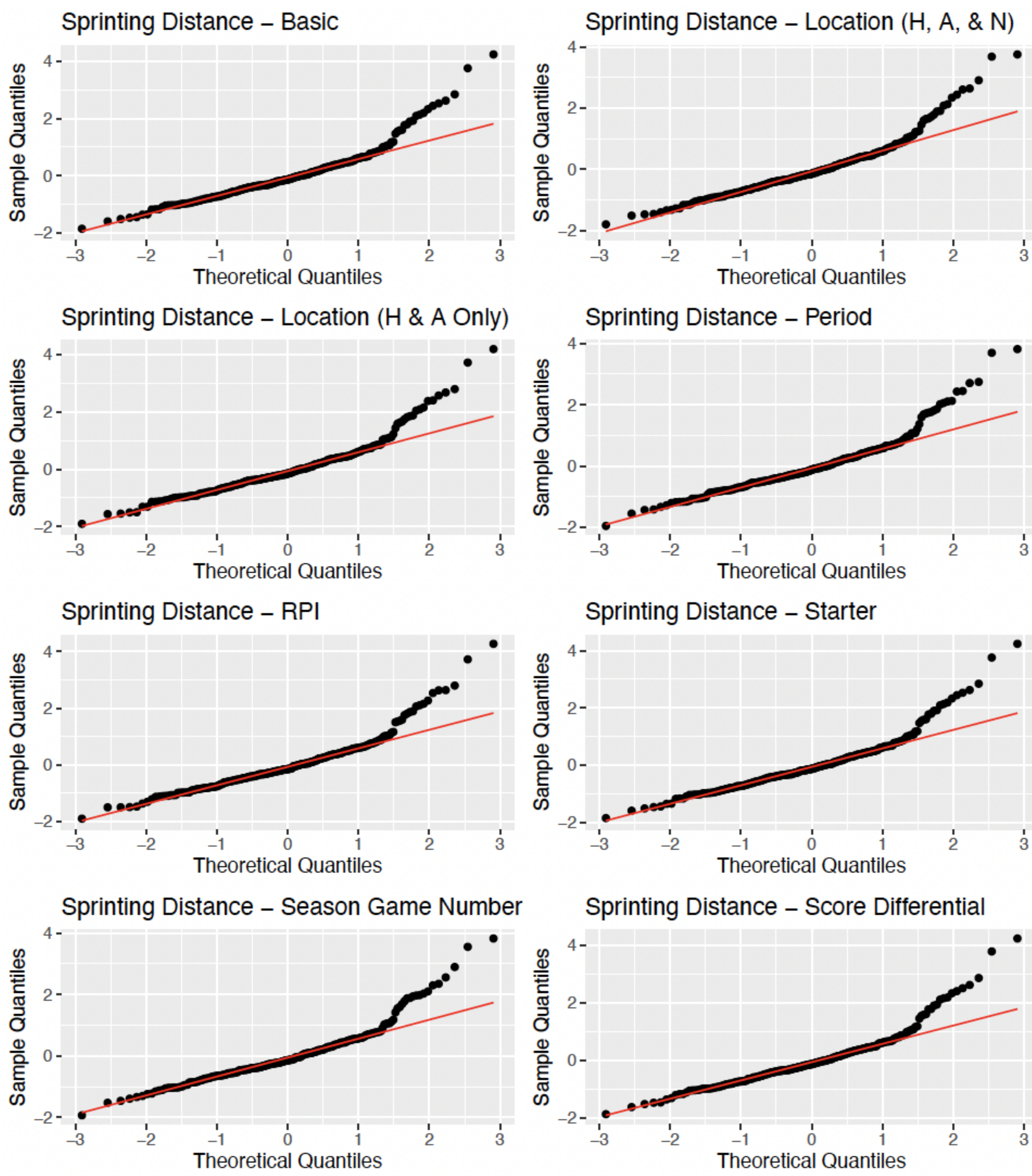
Based on the above analyses, the following covariates have been selected for inclusion in the full linear mixed model build for HIR Distance:

- Season Game Number
  - Based on confidence interval changes, likelihood ratio test results
- Match Location (Home & Away)
  - Based on confidence interval changes, likelihood ratio test results, and scientific rationale
- Season Period
  - Based on point estimate changes, likelihood ratio test results

SD Bivariate Analysis

Comparison of the SD basic model with bivariate models. Q-Q Plots of the residuals for each model have been provided. Model results can be compared using the following table. Lastly, A likelihood ratio test was completed for each bivariate model to compare it to the basic model, the results of which can be found in the second table. Note that the maximum likelihood parameter estimation criterion was used for likelihood ratio testing using the “REML = False” argument in the lmer4 package. This change was made only for the purpose of comparing models in LRT and all other model results use the restricted maximum likelihood (REML) parameter estimation criteria.

Q-Q Plots for SD bivariate model analysis



SD bivariate model results

	Dependent variable:							
	sprintdist_rel							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.261	−0.337	0.274	0.305	0.260	0.226	0.267	0.194
	(−1.425-1.948)	(−2.050-1.377)	(−1.409-1.957)	(−1.378-1.987)	(−1.444-1.963)	(−1.475-1.928)	(−1.417-1.951)	(−1.610-1.998)
YYIR1_Score	0.039	0.043	0.038	0.039	0.041	0.040	0.039	0.039
	(−0.011-0.089)	(−0.008-0.093)	(−0.012-0.088)	(−0.011-0.089)	(−0.009-0.092)	(−0.011-0.090)	(−0.011-0.089)	(−0.011-0.089)
Season_Game_Num		0.044						
		(0.025-0.062)						
Match_LocationHome			−0.027					
			(−0.244-0.191)					
Match_LocationNeutral			0.625					
			(0.151-1.099)					
Match_Location_H.AHome				−0.097				
				(−0.311-0.117)				
Season_PeriodOC					−0.282			
					(−0.506-−0.057)			
Season_PeriodPC					0.326			
					(0.002-0.650)			
RPI_Differential						−0.0005		
						(−0.002-0.001)		
Score_Differential							−0.013	
							(−0.079-0.053)	
Started_StatusY								0.081
								(−0.679-0.840)
Observations	273	273	273	273	273	273	273	273
Log Likelihood	−377.989	−371.630	−376.083	−378.892	−373.181	−384.152	−380.393	−377.998
Akaike Inf. Crit.	763.978	753.260	764.167	767.783	758.362	778.305	770.786	765.995
Bayesian Inf. Crit.	778.416	771.307	785.824	785.830	780.019	796.352	788.834	784.042

SD bivariate LRT results

Model	npar	AIC	BIC	logLik	deviance	Chisq	Df	Pr(>Chisq)
SD_ML_basic.lmm	4	756.257	770.695	-374.129	748.257	NA	NA	NA
SD_ML_game.lmm	5	738.085	756.132	-364.042	728.085	20.173	1	0.000
SD_ML_location.lmm	6	752.799	774.456	-370.399	740.799	7.458	2	0.024
SD_ML_Location_H.A.lmm	5	757.449	775.497	-373.725	747.449	0.808	1	0.369
SD_ML_Period.lmm	6	746.302	767.959	-367.151	734.302	13.955	2	0.001
SD_ML_RPI.lmm	5	757.639	775.686	-373.819	747.639	0.618	1	0.432
SD_ML_score.lmm	5	758.107	776.154	-374.054	748.107	0.150	1	0.698
SD_ML_starter.lmm	5	758.201	776.249	-374.101	748.201	0.056	1	0.813

Summary of SD Bivariate Analyses

Based on the above analyses, the following covariates have been selected for inclusion in the full linear mixed model build for HIR Distance:

- Season Game Number
    - Based on confidence interval changes, likelihood ratio test results
- Match Location (Home & Away)
    - Based on confidence interval changes, likelihood ratio test results, and scientific rationale
- Season Period
    - Based on point estimate changes, likelihood ratio test results

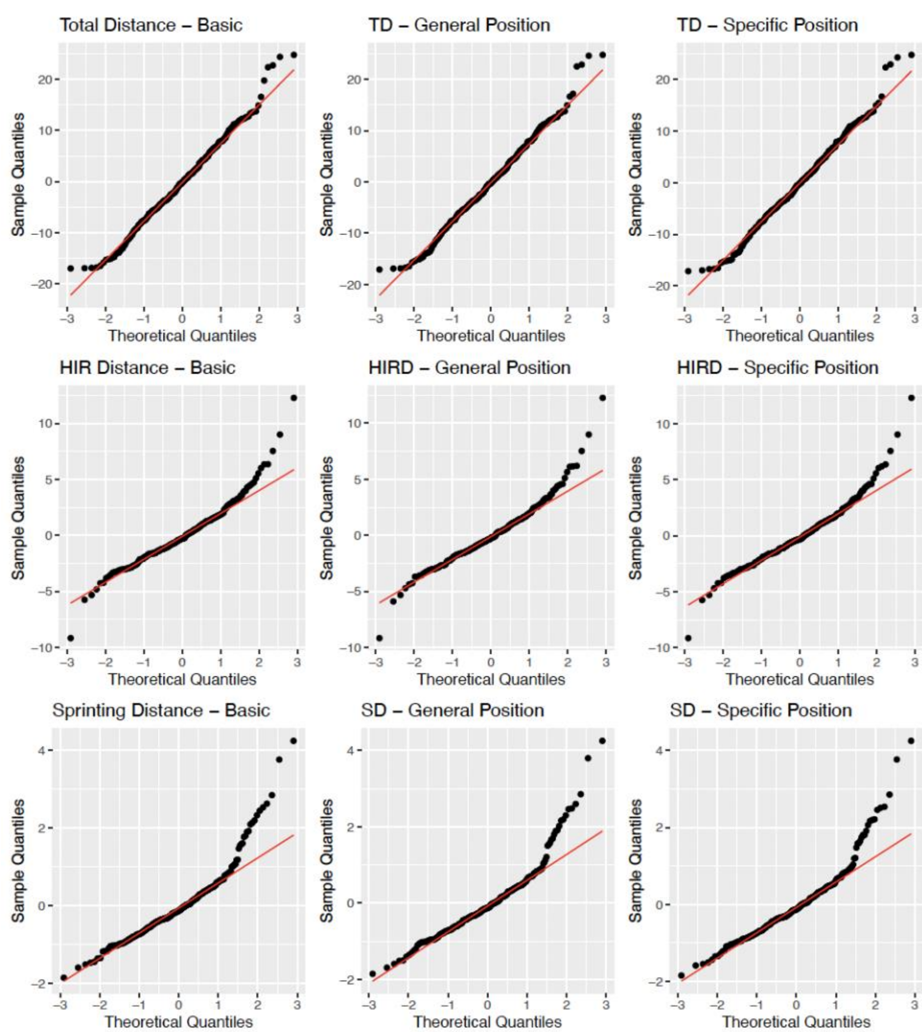
Assessment of Different Position Categorizations

This section of the analysis performs further bivariate analyses on the influence of general and specific categorizations for player position. The general position categories are Defender ("D"), Midfielder ("M"), or Forward ("F"). The specific position categories are Wide Defender ("WD"), Central Defender ("CD"), Midfielder ("M"), Wide Forward ("WF"), Central Forward ("CF"). Previous research has demonstrated differences in match physical performances between players with different specific position categorizations. Although this has been shown for general position categorizations as well, it is thought that specific position categories better demonstrate the demands as they relate to an athlete's positional role during a match.

The following analysis was done to see if there is a difference between position categorizations in model fit for any of the outcome variables.

Based on the results of the following analysis, it was determined the general position group categories are more appropriate for use as the *a priori* covariate in the full model build.

Q-Q Plots for position categorization bivariate model analysis



Position categorization bivariate model results

	Dependent variable:								
	totdist_rel			HIRD_rel			sprintdist_rel		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	79.327 (57.262-101.392)	76.352 (52.540-100.164)	76.457 (51.909-101.006)	−0.486 (−5.315-4.343)	−1.773 (−6.389-2.842)	−1.591 (−6.276-3.093)	0.261 (−1.425-1.948)	−0.151 (−1.742-1.440)	−0.109 (−1.729-1.511)
YYIR1_Score	0.886 (0.229-1.543)	0.934 (0.241-1.627)	0.877 (0.137-1.617)	0.247 (0.104-0.391)	0.263 (0.128-0.397)	0.243 (0.101-0.384)	0.039 (−0.011-0.089)	0.045 (−0.001-0.092)	0.042 (−0.007-0.091)
Athlete_PositionMidfielder		0.765 (−7.549-9.080)			0.677 (−0.968-2.322)			0.095 (−0.473-0.663)	
Athlete_PositionForward		4.852 (−4.457-14.161)			2.327 (0.493-4.162)			0.775 (0.142-1.408)	
Specific_PositionCF			8.631 (−4.424-21.685)			2.651 (0.070-5.232)			0.502 (−0.392-1.396)
Specific_PositionM			2.545 (−7.603-12.693)			1.168 (−0.804-3.140)			0.155 (−0.528-0.837)
Specific_PositionWD			3.627 (−7.595-14.848)			1.254 (−0.923-3.431)			0.258 (−0.496-1.012)
Specific_PositionWF			6.138 (−9.777-22.053)			3.426 (0.398-6.454)			1.329 (0.282-2.376)
Observations	273	273	273	273	273	273	273	273	273
Log Likelihood	−995.871	−990.598	−984.383	−660.620	−656.123	−653.058	−377.989	−375.706	−374.808
Akaike Inf. Crit.	1,999.741	1,993.195	1,984.766	1,329.240	1,324.245	1,322.116	763.978	763.412	765.616
Bayesian Inf. Crit.	2,014.179	2,014.852	2,013.642	1,343.678	1,345.902	1,350.992	778.416	785.069	794.492