Physical Match Demands in Youth Football: Informing Recruitment Strategies and Pathways to Elite Professional Football for Home-Grown Academy Youth Football Players

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Abstract

Traditionally, the process of identifying talented individual football players is subjective, and less informed by scientific evidence. There is also a lack of knowledge and understanding about the process of identifying and developing talent in young footballers (Larkin and Reeves, 2018). With the Elite Player Performance Plan setting regulations for academy football, a wide range of physical data is accessible from Global Positioning System (GPS). It is relatively unknown how the information from GPS units may facilitate in the pathway of talent development and may help to predict future professional football players. Therefore, the aim of the study was two-fold. Firstly, to understand which physical key performance indicators were influential in the selection and deselection of category one academy football players, and its interaction with age. Secondly, to understand the interaction that position had with selection, and age. Two separate statistical linear mixed models were processed. The first was for players aged between under-14 to under-18. The second accounted for player position aged between under-16 and under-18 due to the imbalances in players at age groups when position was factored. The linear mixed model was used to account for the varied sample sizes and repeated measures. Results revealed a significant main effect of high-intensity accelerations and decelerations, and total accelerations and decelerations, with selected players having a higher frequency compared to deselected players. There was a significant interaction between player selection and age for individualised high-speed running and individualised sprint distance. Selected players individualised high-speed running was consistently steady between under-14 and under-18, whilst individualised sprint distance decreased consistently between under-15 and under-18. Deselected players saw inconsistent patterns between under-14 and under-18 for both metrics. There were no significant interactions for position and selection, and age and selection. It is assumed that selected players had superior tactical awareness, therefore being reactive to game-specific situations resulting in a higher frequency of high-intensity accelerations and decelerations, and accelerations and decelerations. It was also assumed that selected players are more selective with their high-intensity bouts during matches, more specifically at the scholarship age (under-17 to under-18) and is in line with previous research findings. As no significant main effects were found for distance metrics, it was concluded that most academy players were well physically conditioned when part of an academy, meaning the differences in running performance are non-significant. Future research should integrate all aspects of talent identification and development in football in a multi-dimensional way.

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Table of Abbreviations

Abbreviation	Meaning
EPPP	Elite Player Performance Plan
GPS	Global positioning system
HDOP	Horizontal dilution of precision
A HSR	Absolute high-speed running
I HSR	Individualised high-speed running
A SD	Absolute sprint distance
I SD	Individualised sprint distance
HI AD	High-intensity accelerations and decelerations
AD	Accelerations and decelerations
TD	Total distance

Introduction

Football is a multi-faceted, widely practised invasion sport that requires varying levels of technical, tactical, strategical, skill, psychological, sociological, and physical attributes dependent upon a player's role in a team (Bangsbo, Mohr and Krustrup, 2006; Guilianotti, 2012; Horrocks et al., 2016; Larkin et al., 2020). Identifying talented individuals (talent identification) to perform in elite academy football is a first step in developing youth players (talent development) and is a fundamental part of a player's pathway on the Football Association (FA) agenda (Mills et al., 2014). Talent is defined as "an individual's potential for success" (Baker, Cobley and Schorer, 2012 p.177). Talent identification is "the process of recognizing current participants with the potential to excel in a particular sport" and is linked to early recognition (Wiseman et al., 2014 p.447), whilst talent development is "providing the most appropriate learning environment to realise potential" (Vaeyens et al., 2008 p.703). However, not every academy player will reach the top level. Academies, at some point during a youth player's career, will decide whether to retain a player and offer them a contract, or release a player from the academy. Historically, those decisions were made by the coach and head of academy based on player observation. With expanding academy staff and advancements in technology to track the player's progress, those decisions are increasingly supported by data. It remains unclear how those data – such as player tracking technology can contribute to informing player selection decision-making.

The development of talented football players is essential to many English football clubs from a financial perspective. With rising player transfer fees, clubs facilitate the player identification and development with professional staff, financial resources, and equipment to recruit and develop potential future professional football players. Those players can contribute to the club's success or bring financial gain once sold to another team. However, Great Britain leaving the European Union (Brexit) has challenged the player recruitment of many English clubs. Brexit regulations came into effect from January 2021, and effectuate that English clubs cannot sign foreign players under the age of 18 unless taken to a tribunal. It has been revealed by the International Centre for Sports Studies that approximately two-thirds of players in the English Premier League (EPL) were born outside the UK, which was notably more than other European football leagues (Cannon, 2018). This could provide further incentive for English football clubs to focus on developing talented individuals within their academies, as the identification and development processes of football clubs aim to improve or maintain high standards, with significant financial investment in personnel and resources to identify future stars at youth level (Williams, Ford and Drust, 2020).

To aid the process of developing talented individuals, the Elite Player Performance Plan (EPPP) (Premier League, 2011) was designed to assess how professional football clubs create an environment and long-term plans that allow players to excel throughout the youth pathway. Clubs are audited on a regular basis and classified based on meeting the set criteria for each category. These are audited via a three-step audit process. The first step is a self-assessment of the academy on behalf of the club by the Academy Manager, completed annually. Step two is an annual evaluation conducted by Club Support Managers from the leagues, working with the managers, reporting to the leagues and the Professional Game Board and will provide the leagues with a submission for an Academy licence. In step three, the Independent Standards Organisation provide an Academy classification for the club board, the leagues, and the Professional Game Board. All clubs are audited two years following the commencement of the category award, and every three years thereafter.

Academies are classified into four distinct categories, with clubs being awarded a category status in relation to the staffing model they choose to operate. To be awarded the higher categories, a higher level of investment in staffing and infrastructure is required. An academy has three development phases: the foundation phase (under-5 to under-11), the youth-development phase (under-12 to under-16), and the professional development phase (under-17 to under-23). A category one academy aims to provide the optimum development environment for players and aims to produce future EPL players with access to high-quality coaching. A category two academy typically produces players for the English Football League (EFL) and a small number of EPL players. Players in the youth development phase move from a part-time to a hybrid coaching schedule. A category three academy typically produces players for the EFL and have access to a part-time training model from under-9 to the professional development phase. A category four academy is a late development model, where entry is at the professional development phase and provides a full-time training model. They aim to produce late developing players for the EFL and potentially the EPL.

There are two important moments of the academy pathway for youth players. The first is after the under-16 age group when players can be offered a two-year scholarship deal or released. The second key moment is between turning 17 and the end of their scholarship when the club can offer a professional contract or release. To aid talent development processes, a category one academy must employ multi-disciplinary support staff, managed by a Head of Academy Sport Science and Medicine. Category one clubs must also employ a lead sport scientist, a match analyst, and a strength and conditioning coach, along with other support staff. This allows clubs to develop players using the multiple disciplines of sport science, allows staff members to track progression pathways, and deliver interventions that can influence the player's chance of selection.

Identifying individuals to play for a club is an important part of recruitment in youth football and is the beginning of a player's pathway. The process of identifying talented individuals and selecting players' is subjective and not traditionally informed by scientific evidence (Larkin and Reeves, 2018). Williams, Ford and Drust (2020) describe selection as the process of choosing players from the development programme who display attributes appropriate for progression to a higher talent or age group. Alternatively, they describe deselection as the process of removing the player from a development programme due to insufficient attributes that halt their progression to more talented teams or age groups. The key decision making in elite football usually lies with the recruitment department, as they are tasked with identifying future talented individuals. English football clubs tend to select their playing staff through scouts, recruitment staff, and coaches based on subjective intuition and objective criteria (Louzada, Maiorano and Ara, 2016). In a football environment, squad planning meetings would generally take place including a Head of Recruitment, Manager, senior recruitment staff and coaches. In this, discussions would take place on the potential retainment, signing, or release, or sale of a player.

In football, it has been suggested that there is a lack of knowledge and understanding about the process and objective of identifying and developing talent in young footballers (Larkin and Reeves, 2018). Australian football recruiters revealed that the recruiter, process and practice, assessment, and selection were primary themes in the selection of youth players (Larkin et al., 2020). Recruiters perceive technical, tactical, anthropometric, and physiological attributes of high importance when identifying talented individuals (Larkin and O'Connor, 2017; Sarmento et al., 2018). Further research into the process, observations, and perceptions of talent identification staff is required to understand how specialists in this area operate (Larkin and Reeves, 2018). Little is known about the factors influencing decision making due to the extremely subjective nature of predicting future talent (Aquino et al., 2017a).

As fore-mentioned, talent identification and development are important in the pathway of youth football players. Both are important in academy football as talent identification is used to recognise players who can perform in an academy. Subsequently, they are developed through the academy environment, and if identified as talented at the selection stages, they progress through the pathway. Talent is multi-dimensional and built from a combination of competence, commitment, and contribution (Ulrich and Smallwood, 2012). Talent can be portrayed by genetically transmitted and innate properties, and may not be evident at early ages, however indicators will be evident to help talent identification specialists discover talent. Prior research indicated early experiences, preferences, opportunities, habits, training, and practice are determinants of excellence in young people (Howe, Davidson and Sloboda, 1998). In football, this would involve identifying important components of the multi-dimensional aspects, otherwise known as performance indicators.

Previous research has aimed to identify performance indicators, specifically those associated with successful youth-to-senior pathway progressions in football. Performance indicators can be defined as action variables potentially defining aspects of performance (Hughes and Bartlett, 2002). Studies have investigated indicators of performance in football previously, for the multiple aspects of the game such as physical fitness (Rampinini et al., 2007; Bangsbo, 2014; Rebelo et al., 2014; Forsman et al., 2016), anthropometrics (Bidaurrazaga-Letona et al., 2019; Taylor and Collins; 2019; Patel et al., 2020; Sarmento et al., 2020; Williams, Ford and Drust, 2020), and technical attributes (Rampinini et al., 2009; Adams et al., 2013; Kelly et al., 2020). Key performance indicators can aid recruitment staff and scouts when making informed decisions about talented football players. With technologies in football improving and large volumes of data being collected, this data can provide a beneficial source of information to aid the identification of players who have potential to become professionals and track their development through the academy pathway. Currently, research regarding physical performance metrics that could be useful for the player selection of category one youth football players is minimal and is a potential area of interest for football recruitment and development departments.

As football performance is variable due to position (Di Salvo et al., 2010; Gregson et al., 2010; Carling et al., 2012; Bangsbo, 2014; Dalen et al., 2016; Rago, Pizzuto and Raiola, 2017; Abbott, Brickley and Smeeton, 2018; De Silva et al., 2018; Roberts et al., 2019a; Doncaster et al., 2020), prior research has attempted to identify key performance indicators, for specialised positions in football (Mohr, Krustrup and Bangsbo, 2003; Dellal et al., 2010; Waldron and Worsfold, 2010; Waldron and Murphy, 2013; Forsman et al., 2016; Larkin and O'Connor, 2017; Roberts et al., 2019b; Zhou et al., 2020). Hughes et al., (2012) developed seven sets of different key performance indicators for: goalkeepers, full-backs, centre-backs, holding-midfielders, attacking-midfielders, wide-midfielders, and strikers. The key performance indicators in the technical, tactical, physiological, and psychological domain for each position varied due to their relative importance to that specific playing position. Therefore, the importance of football performance metrics differs for position.

Consequently, it is imperative that research be conducted into the attributes of youth footballers, and to gain an understanding of what classes a player as talented. Despite conclusive evidence that indicates talent in football is multi-dimensional, the accessibility to multiple sets of data in academy football is difficult to access, and integrate with other data sets. As global positioning system (GPS) data is widely used in elite youth academies, there is valuable and accessible data that can be utilised to understand what differentiates selection and deselection in elite academy football from a physical perspective. Physical match output can differentiate talent (Mohr, Krustrup and Bangsbo, 2003; Dellal et al., 2010; Waldron and Murphy, 2013; Leyhr et al., 2018). This type of research into physical performance of youth individuals may be informative to club staff who make the ultimate decision on whether the club will invest in youth players careers by offering them a scholarship and/or professional contract.

Literature Review

Previous talent identification research and subsequent development in football suggest that aspects of player performance are multi-dimensional and should be considered even when a one-dimensional approach to an investigation is utilised (Williams, Ford and Drust, 2020). The following literature review covers the technical, psychological, anthropometric, relative age effect (RAE), and physical components of youth football performance. Talent identification and talent development are complex matters, and there are still unanswered questions regarding the best approaches to differentiate talent, despite the best efforts of many authors. Due to the volume of physical data available from the category one EPL academy, the aim of the project was to identify the aspects of physical performance that influence player selection. Although not a focus of the present study, the multi-dimensional aspects of talent identification are reviewed, acknowledged, and considered when interpreting results.

Subjective Talent Identification and Decision Making

Traditionally, the talent identification process has been informed by subjective opinion, rather than scientific evidence (Larkin and Reeves, 2018). A coach's opinion has influenced the identification of youth players as talented and opportunities for subsequent development. A substantial proportion of coaches identify talent using subjective measures (Larking and Reeves, 2018), tacit knowledge, instinct, and "coach's eye" when making key decisions (Reeves and Roberts, 2018; Roberts et al., 2019a).

Coaches' assessment of player talent is said to have a high level of accuracy (Jokuschies, Gut and Conzelmann, 2017). Australian football coaches have been found to successfully predict a player's future talent with a success rate of 63%. However, for early maturing players, only slight agreements were demonstrated between coaches on the perceived potential of an individual's career attainment (52%). Coaches' perceptions of talent are reasonably accurate (Cripps, Hopper and Joyce, 2019), however specific influences can reduce the correctness of predictions, and increase variability in coaches' perceptions of talent. For example, late maturing players will have only increased physical and anthropometric capacities at a later chronological age, unlike early maturing players who will have these capacities at a younger age (Till et al., 2014; Lovell et al., 2015). This can therefore bias coach decision making on youth football player's (Cumming, 2018)

Scientific approaches in football have developed in recent years with the evolution of technology, and research to help inform key decisions on youth football players (Le Gall et al., 2010; Waldron et al., 2013; Huijgen et al., 2014; Deprez et al., 2015; Honer et al., 2015; Forsman et al., 2016; De Silva et al., 2018; Lehyr et al., 2018; Kelly et al., 2020; Patel et al., 2020). A combination of coach assessments, along with multidimensional data, were significantly better at predicting player status at under-19 compared to one-dimensional approaches (Sieghartsleitner et al., 2019). Combining the subjective view of coaches and recruitment staff with objective, valid and reliable data should enhance talent identification decisions made about youth academy players.

Talent should be considered from multi-dimensional aspects (Williams, Ford and Drust, 2020). Multi-dimensional frameworks have been developed that are potential predictors of high performance in future adult football. At the turn of the century, Williams and Reilly (2000) attempted to integrate research findings from anthropometry, physiology, psychology, and sociology to develop a framework for identifying talent. Traditionally in football, players are usually detected by scouting staff identified as talented, selected, and then developed, which progresses in a continuous cycle (figure 1). In the academy setting, player performance is characterised by natural attributes that individuals are born with (genetic) and nurtured attributes (development of skills) (figure 2). It suggests physical, physiological, psychological, cognitive, personality, and sociological factors are multi-dimensional predictors of football talent (figure 3).

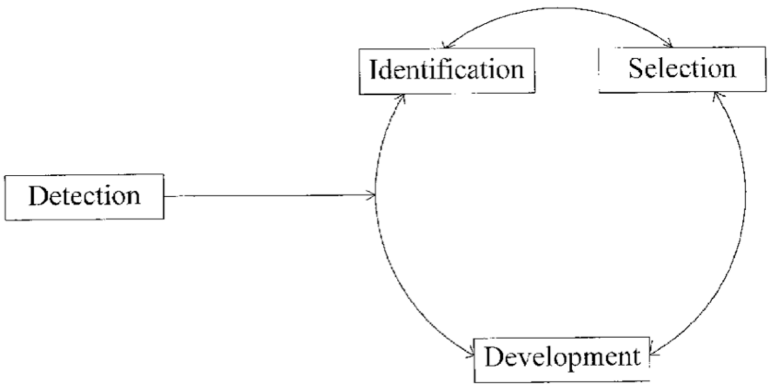

Figure 1: The process of talent identification and development (Williams and Reilly, 2000).

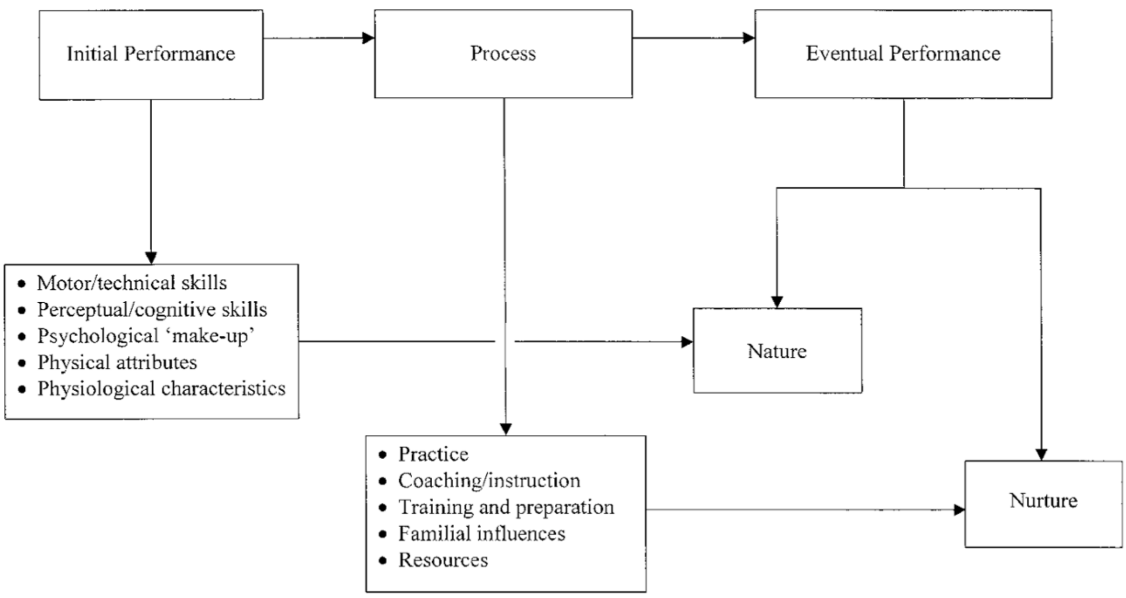

Figure 2: The role of nature and nurture in the development of elite players (Williams and Reilly, 2000).

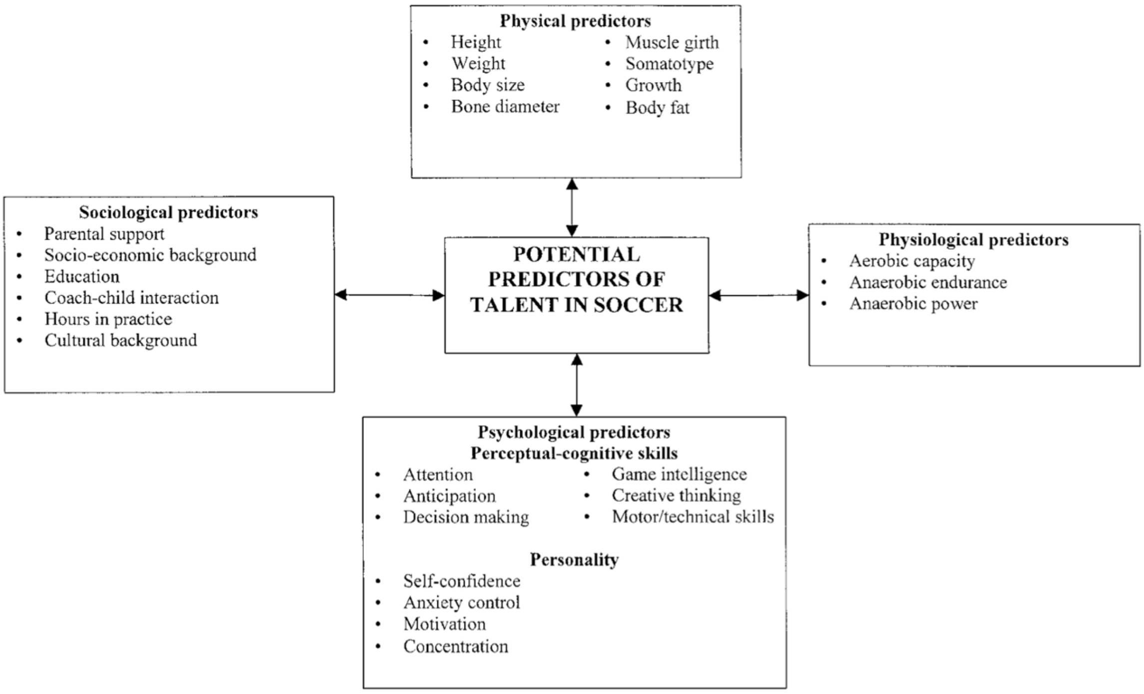

Figure 3: Potential predictors of talent in soccer from each sports science discipline (Williams and Reilly, 2000).

Williams, Ford and Drust (2020) extended the work of Williams and Reilly (2000) by creating a model that illustrated the pathway from participation, through to identification and development, before subsequent player selection (Figure 4). Furthermore, they developed the framework, suggesting talent identification has evolved slightly, now incorporating physical, chance events, sociological, external environment, psychological, development environment, skill, and maturation elements (Figure 5).

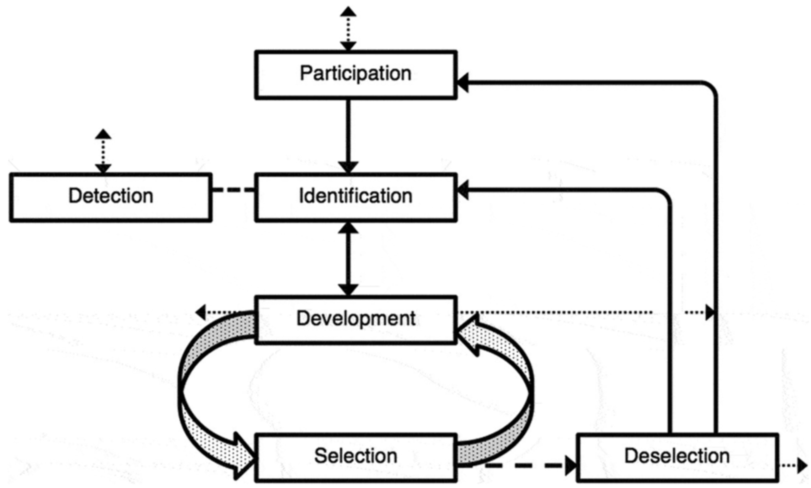

Figure 4: Identification, development, and selection pathway process (Williams, Ford and Drust, 2020).

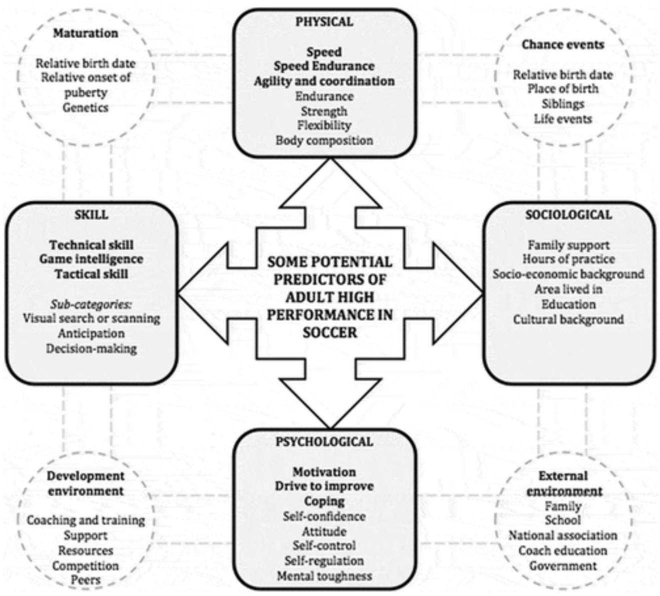

Figure 5: Talent identification framework (Williams, Ford and Drust, 2020).

Sarmento et al., (2018) produced a systematic review on talent identification and development studies, and consequently developed a framework for both. The framework demonstrates that talent identification and development are an outcome of task constraints (specificity and amount of practice), performer constraints (psychological, technical, anthropometrical, and physiological factors), and environmental constraints (RAE, socio-cultural influences). The performer constraints and RAE, structure the multidimensional characteristics of identification and development of talent (Figure 6). It is therefore imperative that a thorough understanding of the multiple aspects of identifying talent and developing footballers are understood, and which differentiate talented players.

From the three reviews on talent identification and development discussed, it has revealed that over time, the process has become multi-dimensional and numerous constraints (task, performer, and environmental constraints) influence the selection or release of an individual (Sarmento et al., 2018). This has evolved from a simple model of detection, identification, selection, and development (Williams and Reilly, 2000) to multi-dimensional models with considerations for physical, sociological, psychological and skill aspects (Williams, Ford and Drust, 2020). Continued research should be carried out in this field as the process of talent identification and development is continuously evolving.

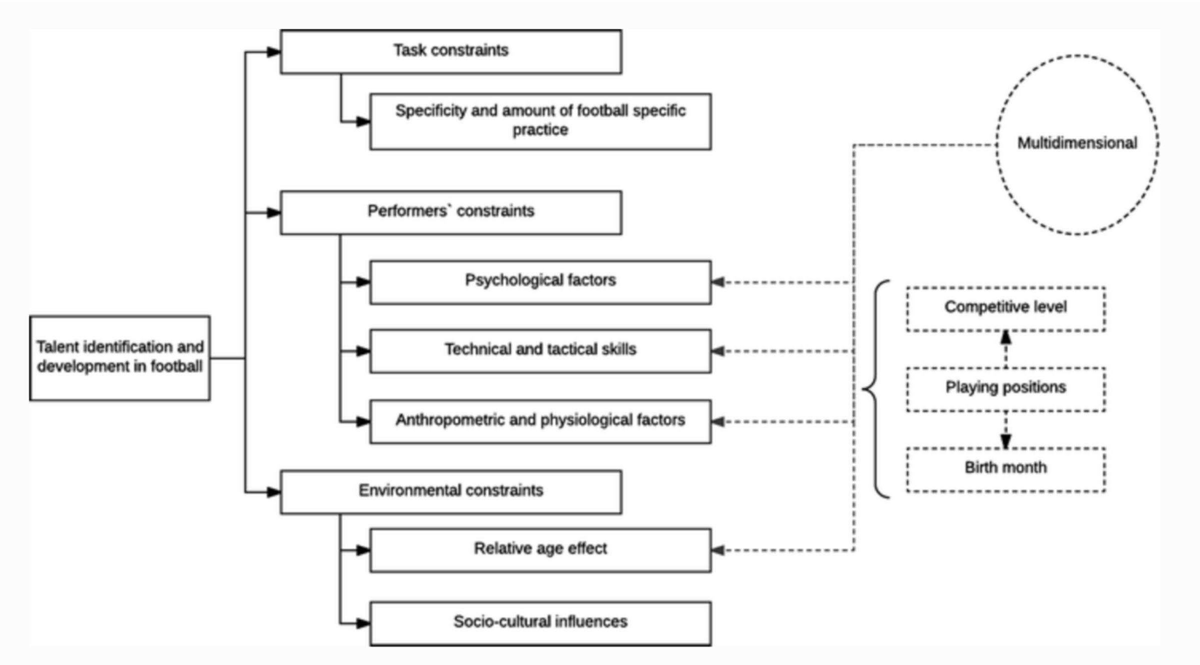

Figure 6: Scopes of talent identification and development (Sarmento et al., 2018).

Technical Performance

Research investigating the relationship between technical demands of football players and the association with talent level appears quite strong, suggesting that players' technical abilities can differentiate their talent level in football. Waldron and Worsfold (2010) revealed elite players were significantly better in matches at shooting, passing, and dribbling when examining game specific skills and talent level. In addition, the association between football players technical demands and talent level appears quite strong, suggesting that players' technical abilities can differentiate their talent level in football. Defenders in more talented teams utilise short passes to create attacking opportunities (Adams et al., 2013), whilst more successful teams in Serie A produce significantly more: short passes, tackles, dribbles, shots, and shots on target compared to less successful teams (Rampinini et al., 2009). This suggests elite-level teams and individuals are better across numerous technical attributes.

Football talent level has previously been found to differentiate players on skill tests such as: dribbling, ball control, passing and shooting tests (Huijgen et al., 2014; Höner et al., 2015; Forsman et al., 2016; Höner, Leyhr and Kelava, 2017; Lehyr et al., 2018). High-potential players in the foundation development phase (i.e., under-9 to under-11) were ranked significantly higher for reliability in possession, pass completion, touches, and lobbed passes, whilst youth development phase (i.e., under-12 to under-16) high-potential players were ranked significantly higher for reliability in possession, dribble completion, touches, ball juggle, slalom dribble, shooting accuracy, and lobbed passes (Kelly et al., 2020). Coaches' subjective ratings of reselected and deselected players due to an academy closure, revealed reselected players rated higher for all skill related performance attributes (Dugdale, McRobert and Unnithan, 2021). The validity of this study was of adequate level as the coach rating methods have previously been found to demonstrate good reliability, and attributes were assigned based on previous research into the recruitment process. With many subjective research methods however, there is potentially an element of bias influencing results.

In summary, more talented footballer players perform significantly more technical skills in matches (Rampinini et al., 2009; Adams et al., 2013). They perform better on skill tests (Huijgen et al., 2014; Höner et al., 2015; Forsman et al., 2016; Höner, Leyhr and Kelava, 2017; Lehyr et al., 2018; Kelly et al., 2020), and are subjectively rated higher for technical performance by coaches (Dugdale, McRobert and Unnithan, 2021). Previous research conclusively suggests that technical performance plays a vital role in determining players talent level.

Psychological Factors

A large volume of research in this sector is dominated by data analysis. Whilst important, it is key to consider the psychological aspect of individual development in football. Academy-to-first team transitions are said to be extremely demanding, and problematic due to athletic and social strains (Finn and McKenna, 2010). Psychological capacities are important in supporting high pressure moments, whilst the characteristics of a player can facilitate individual development (Louzada, Maiorano, and Ara, 2016). Previous research highlighted a relation between higher psychological skills such as goal commitment, coping behaviours (Van Yperen, 2009), motivation (Forsman et al., 2016), mental skills (Taylor and Collins, 2019), positive attitude, concentration, and professionalism (Dugdale, McRobert and Unnithan, 2021), with selection or deselection, and player talent (elite or sub-elite). Psychological factors are a discipline in talent identification that may be overlooked due to the subjective nature, as staff may question the validity of the results in these approaches. The literature implies that psychological characteristics are strongly linked with selection and player talent in football and must be considered by decision-making staff in the academy pathway process.

GPS Measurements and Considerations

GPS data plays an integral role in sport science, facilitating in-depth analysis into physical match activities (Woods et al., 2017). GPS is a satellite navigation system providing information on location and time of tracking (Malone et al., 2017). In football, these devices are worn daily in category one football academies as stated previously, as well as senior professional level to track physical activity and loading. As the data produced from GPS devices are susceptible to error, a thorough understanding of the technology is critical.

Accuracy of GPS data has improved with advancements in the technology, such as an increase in the sampling of Hz (Woods et al., 2017). GPS devices require a minimum of 4 satellites for to establish a sufficient connection, although devices connected to less than 6 satellites tend to have a weaker connection. The more satellites connected, the higher the accuracy of the GPS data, with GPS having 32 available satellites to connect to (Malone et al., 2017). The accuracy of the data can be provided by the horizontal dilution of precision (HDOP), which is a measure of the accuracy of the horizontal position signal. In simpler terms, when satellites are bunched together in the sky, HDOP is high, meaning the precision of the data is poor. When the satellites are spread out, HDOP is low and precision of the data is good (Malone et al., 2017). In training and match activities, random error in GPS data causes spikes in speed. This may cause the data to show high-speed and sprint efforts in the data from the device, therefore it is common practice for practitioners using these devices to set minimum effort durations, also known as ‘dwell times’, meaning a player would have to sustain a speed over a set threshold for a minimum time (e.g. an effort sustained for > 0.4 seconds) (Malone et al., 2017).

To use GPS devices adequately and efficiently, whilst being able to provide accurate data on player's physical performance and loading patterns, the guidelines on reliability of data must be adhered to. These are an integral part of a sport science practitioners' day-to-day responsibilities in their role of feedback to the coach and supporting departments around elite players in academy football.

Physical Characteristics of Performance

Football's activity pattern is intermittent in nature, and bouts vary from longer periods of low intensity activities to brief bouts of high intensity activities (Rampinini et al., 2007). Distances and frequencies vary from match-to-match due to contextual, individual, and tactical factors (Gregson et al., 2010). In elite senior male football matches, players cover 10-13 km in total distance, including intermittent bouts of high intensity actions including sprints, accelerations, decelerations, changes of direction, tackles, and jumps (Rhodes et al., 2021). Youth male football players reach approximately 6.3 km (range: 4.4 – 8.1 km) distance per game, with 12% of the distance deriving from high-intensity activities (Rebelo et al., 2014).

High-intensity running performance is an essential indicator of physical match performance, as it has been previously suggested to differentiate perceived talent due to the ability of players in different leagues, with players in Serie A covering 28% more high-intensity distance and sprints compared to players in the Danish league (Mohr, Krustrup and Bangsbo, 2003). It also distinguishes between top-class and lower talented individuals in football (Bangsbo, 2014). Gomez-Piqueras et al., (2019) compared the physical performance of teams in the Spanish first and second division. Total distance was found to be similar between both divisions, however total high-intensity and very high-intensity distance was greater for Spanish first division teams. Bradley et al., (2010) also concluded that no significant differences were found for total distance between International and elite English players. Difference in high-intensity and very high-intensity (in and out of possession) were also non-significant, suggesting that the difference in quality between the groups of players is small, and could explain the lack of difference in physical match output at high-intensity. In comparison to elite domestic Danish and Swedish leagues however, elite English and International player high-intensity running was 40% more.

Physical demands of players in successful Italian Serie A teams were significantly higher for total distance with the ball and high-intensity efforts running with the ball, compared to less successful teams (Rampinini et al., 2009). Elite players in Ligue 1 were characterised by an ability to produce repeated high-intensity actions (Dellal et al., 2010). The evidence supports the argument that the physical condition of a player is correlated with high performance (Walker and Turner, 2009).

Despite previous research suggesting elite under-14 football players covered more total distance and high-intensity movements compared to sub-elite players (Waldron and Murphy, 2013), research regarding physical match output and its correlation with selection or deselection in youth academy football is minimal. Conclusions can be interpreted however by physical match output data between leagues of differing quality and ability levels, and the effect it has on the output. However, it must be considered that leagues physical match output demands can differ dependent on the tactics and style of play in different leagues (Bradley et al., 2013a).

In adult football, high-intensity running performance decreases as age increases (Zhou et al., 2020) and between the age of under-12 and under-16, an increase was found, however relative to player minutes, no differences were observed (Harley et al., 2010). Prior research has also reported that agility level at 15 years of age was associated with performance level at 19 years of age (Forsman et al., 2016). Tracking individuals across seasons can provide valuable information regarding player development over time, and if they have developed into talented players who are selected to progress through the academy. Running performance including maximal sprints and high-intensity efforts increase with age (Vieira et al., 2019, Zhou et al., 2020) and these physical performance attributes are associated with players who progress in professional academies (Bidaurrazaga-Letona et al., 2019).

Accelerations are a key component of physical and sprint performance, but previous research reported that maximal accelerations are not always associated with number of sprints. Varley et al., (2012) found that number of accelerations were approximately eight times more than the number of sprints per game and that 85% of maximal accelerations do not reach high intensity running thresholds. Acceleration and deceleration involve greater energetic cost compared to maintaining constant speed (Vanrenterghem, 2017), with accelerations contributing to 7-10% of player load, and decelerations contributing 5-7% (Dalen et al., 2016). Acceleration and deceleration profiles are variable due to positional differences in the Spanish La Liga (Oliva-Lozano et al., 2020). Vigh-Larsen, Dalgas and Anderson (2018) discovered under-19 youth players accelerated and decelerated significantly more than senior players, suggesting senior professionals are more selective with their frequency of this metric. Findings from prior research suggest that acceleration profiles vary between national leagues (Dalen et al., 2016; Vigh-Larsen, Dalgas and Andersen, 2018; Oliva-Lozano et al., 2020). The variability in acceleration and deceleration profiles are also a result of impact related events that GPS did not account for until recently (tackles, jostling, blocking, jumping, landing, and falling to the ground) (Hennessy and Jeffreys, 2018).

Contextual, individual, and tactical factors influencing physical performance

Contextual and tactical factors have previously been found to cause variation in physical performance data, and match-to-match variability is high across physical variables for elite players (Gregson et al., 2010). The physical demands of football have evolved over multiple seasons in the EPL, with high-intensity running and sprint distances seeing significant increases (Barnes et al., 2014; Bush et al., 2015), as well as rises in sprint distance, number of sprints, high-speed distance, and high-speed efforts in the Chinese Super League. (Zhou, Gomez and Lorenzo, 2020). This suggests that continued research should be carried out in the field as the physical demands are evolving continuously each season. This will help academy sport science departments use data to compare individuals to normative profiles of previously selected and deselected individuals.

Positional variance is another key factor in physical performance (Bangsbo, 2014) and refers to the differences in performance data due to playing position. Total distance, high-intensity running, intermediate speed, high-speed distance, and very high-speed distance were previously found to be significantly different between defenders, midfielders, and attackers (Rago, Pizzuto and Raiola, 2017), whilst wide midfielders produce the most high-intensity running distance (Carling et al., 2012). Abbott, Brickley and Smeeton (2018) discovered that central midfielders produced significantly higher total distance and moderate-intensity acceleration distance, whilst full-backs and attackers significantly produced more very high-speed running, sprinting and high-intensity acceleration distances. External positions (full back and wide midfielders) accelerated more frequently than central players (centre backs, central midfielders, attackers) for a Norwegian first division club (Dalen et al., 2016). Central defenders and midfielders' variability in physical performance is higher compared to wide midfielders and attackers (Gregson et al., 2010).

When considering youth footballer players, significant differences in demands for high-speed running per minute and total distance per minute at one EPL Club academy were evident when players were defined by position (De Silva et al., 2018). Research suggests that position should be considered when analysing the physical data of players (senior and youth). De Silva et al. (2018) did not consider differences in player talent, and its consequential effect, but a generic review comparing physical match output by position. Whilst important, there are other factors that influence the data such as player age and talent. Previous research found that team and opposition formation have been found to cause variability in physical match data (Bradley et al., 2011; Carling, 2011), therefore this must be considered when interpreting data. Although at youth level it is more difficult to control and track the formations played in each game, academies play the same formations through the age groups from when they play 11-a-side football at the age of under-13 and above, often to mimic the style and philosophy of the 1st team. Therefore, formation could have a smaller effect on the physical match output for youth players than initially perceived.

The age of a player affects a players' physical development and maturation status. Age differences between individuals in the same group is known as the RAE (Musch and Grondin, 2001). European teams have previously found an over-representation of players born in quartile one (Helsen, Van Winckel and Williams, 2005; Del Campo et al., 2010), with quartile one defined as birth dates between January and March in Europe. Recent research in English football suggests that the RAE does not significantly distinguish youth players in relation to player selection and that it has no significant impact on adult performance level (Patel et al., 2020). In contradiction, players born early in the selection year were highly represented in youth academy football players (Carling et al., 2009), however it must be considered that Carling et al. (2009) only used under-14 players in their sample, compared to a wider age range (under-11 to under-21) in more recent studies (Patel et al., 2020). The literature suggests that the RAE may play a substantial role in the initial signing of youth players into academies but may diminish at the older age groups as retainment is correlated with advanced maturity and superior body size (Patel et al., 2020).

Anthropometrics are the measurements of physical characteristics of human beings (Pheasant, 1990). Previous research suggests that there is a strong genetic component in sporting performance (Williams and Reilly, 2000) and is a key consideration for coaches and scouts when identifying talent (Sarmento et al., 2020) as players who have superior anthropometrics, maturation and physical performance are found to be retained or have higher talent (Le Gall et al., 2010; Bidaurrazaga-Letona et al., 2019; Taylor and Collins; 2019;

Patel et al., 2020; Williams, Ford and Drust, 2020). In contrast, research regarding player selection suggests that anthropometry and estimated maturity status does not discriminate between selected and deselected players between the ages of under-8 to under-16. (Deprez et al., 2015). Anthropometrics may therefore discriminate between talent groups, but not discriminate between players already in a youth football academy due to the range in talent being smaller. With recruited players' anthropometrics showing nominal differences over more than a decade, a philosophical lack of change in recruitment and coach practices may be an explanatory factor (Carling, Le Gall and Malina, 2012).

The research may suggest that players are identified on their anthropometrical traits, however, this says little about the probabilities of those reaching professional football. Nevertheless, it may suggest that due to the RAE and differences in growth spurts, there are differences in anthropometrics amongst youth players, thus affecting their physical capacities. Players who mature earlier tend to be taller, which can lead to them being on the ball more often and lead to superior technical skills (Malina et al., 2005), compared to players who mature late. This effect may disappear once growth spurts between players reach an equilibrium. The phenomenon may influence the recruitment process, making it difficult to predict a player's future performance.

In summary, the research suggests that talent is differentiated by physical performance (Mohr, Krustrup and Bangsbo, 2003; Rampinini et al., 2009; Dellal et al., 2010; Waldron and Murphy, 2013; Leyhr et al., 2018; Bidaurrazaga-Letona et al., 2019), and that age (Vieira et al., 2019), positional variance (Carling et al., 2012; Dalen et al., 2016; Rago, Pizzuto and Raiola, 2017; Abbott, Brickley and Smeeton, 2018; Silva et al., 2018), and formation (Bradley et al., 2011; Carling, 2011) influence physical match data in football. It seems plausible that research be conducted into the physical demands of academy football and its relationship with selection and deselection, in reference to age and position.

Statistical Approaches

Statistical approaches in research are essential when comparatively analysing different quantitative data sets, as it will determine whether differences are significant, helping to answer a research question (Hinton, 2014). There are numerous types of statistical tests which are suited to different types of data sets when comparing single-level data. One criticism of these tests is that datasets generally need an even distribution of balance, as uneven datasets can overestimate significance between groups (Field, 2013).

When data is multilevel, the statistical analysis becomes more complex, and choosing the correct statistical test is essential for producing accurate results. Multilevel linear models allow quantitative data to be assessed between groups, also with repeated measures. Unlike other statistical tests, uneven data sets can be overcome by using multilevel models. It will also display the effect of which an individual players will affect the dependent variable (Field, 2013).

In football, this type of statistical test is beneficial when analysing multi-level, longitudinal data. For example, these tests could be used when interpreting differences between teams at different age groups over several seasons, as it can account for individual players (random effect), the age group (fixed effect), and the team (fixed effect). This is important because it can enhance the depth into which practitioners can use the large amount of data available in professional football. The flexibility of using repeated measures in this statistical method can be appealing for practitioners interested in the development of youth players over a period of time in a football youth academy, and opens the door for numerous types of studies from the different aspects of which youth players have to perform (e.g. physical performance over several seasons of academy football for a player who becomes a professional).

Aims and Objectives

Physical performance is suggested to distinguish between talent in football (Mohr, Krustrup and Bangsbo, 2003; Rampinini et al., 2009; Dellal et al., 2010, Waldron and Murphy, 2013). It is also variable due to position (Di Salvo et al., 2010; Gregson et al., 2010; Carling et al., 2012; Bangsbo, 2014; Dalen et al., 2016; Rago, Pizzuto and Raiola, 2017; Abbott, Brickley and Smeeton, 2018; De Silva et al., 2018; Roberts et al., 2019 a; Doncaster et al., 2020) and player age (Forsman et al., 2016; Lehyr et al., 2018). However, known to the author, research identifying key performance indicators in physical match data and its correlation with selection or deselection within youth football is minimal. Evidence from English football academies suggests that academies are not able to determine and explain specific attributes that are observed when identifying talent in young players (Reeves et al., 2019). It has also been suggested that it is vital to consider positions when analysing match data, and that it must be considered as part of a strategy towards talent identification and player recruitment (Roberts et al., 2019b).

The aim of the current research was two-fold. Firstly, the aim was to analyse key physical performance indicators for youth academy players in an EPL category one academy. There is a specific focus on selection and release at under-16 and under-18 age groups. In those age groups, players are typically offered 2-year scholarships (under-16) and then professional contracts (under-18). The research intends to develop an understanding of mechanisms underlying player selection at those key stages of the academy pathway. The current research aims to provide information on future strategy in both developing and recruiting players for academy football, as physical attributes can assist in the discrimination between selected and deselected players (Aquino et al., 2017a). To address this research aim, a longitudinal approach is used where player tracking technology data is used from three seasons. A longitudinal study has previously been suggested as a beneficial way to profile performance that leads to football expertise (Bennett, Vaeyens and Fransen, 2019). Previous longitudinal research into talent identification investigated the speed and technical abilities of players, finding a significant relationship with adult performance level for agility, dribbling, ball control, and shooting (Lehyr et al., 2018). Known to the author, there is no longitudinal study investigating physical demands of category one academy football in relation to selection and deselection.

The second aim of the research was to compare selected and deselected players by playing position, as previous research has indicated that positional variance effects physical performance match data. The secondary analysis excluded the under-14 and under-15 age groups, to give the depth of age for each position (defenders/midfielders/attackers) an equal distribution. To address both research aims, a linear mixed model approach was utilised and accounted for the variation in the data caused by tactical and contextual factors, and the repeated measures nature of the study.

The present research aims to inform recruitment and academy departments on the physical performance indicators underpinning player selection, on the pathway to a professional contract. It was hypothesised that selected players would produce higher distances and frequencies for the selected physical performance indicators in comparison to deselected players through the academy, specifically at the scholarship and professional contract stage.

Methods

Participants

A total of 54 EPL academy (category one) players (age: 17.2 ± 2.0 years) participated in this study. Match data was collected via player tracking technology (GPS) over three seasons (2017-2020). Matches were part of the regular season with competition, league, and friendly matches, played in accordance with official Football Association (FA) rules and playing durations. Therefore, under-14 played 2x35 minutes, under-15 and under-16 played 2x40 minutes, and under-17 and under-18 2x45 minutes.

Each player was classified as 'selected' or 'deselected'. A selected player was a player who stayed in the academy past under-18 level and signed a professional contract, transferred to another category one academy and signed a professional contract, or a player who transferred abroad and played in a professional league. A deselected player was a player who was not offered a professional contract at the club, nor a different category one academy.

Variables

The chosen variables were selected due to their perceived importance in football performance from performance analysis experts. Across all outfield positions, speed, stamina, and power were acknowledged as being key performance indicators (Hughes et al., 2012). The knowledge of football experts at the club where the present research took place was also considered in the selection of the physical performance variables in the present study. Individualised thresholds were used to account for differences in maturation, and would also be indicative of workload, effort, and fatigue levels (Thorpe, 2016).

Data on physical demands were recorded using 10 Hz GPS devices and micro-electromechanical systems technology (Viper Pod, STATSport, Newry, UK). The metrics used in the data set were: absolute high-speed running distance (A HSR; ≥ 5.5 m/s maintained for ≥ 1 second in m), individualised high-speed running distance (I HSR; ≥ 55% of personal maximum speed in m), absolute sprint distance (A SD; ≥ 7 m/s in m), individualised sprint distance (I SD; ≥ 70% of personal maximum speed in m), high-intensity accelerations and decelerations (HI AD; HI acceleration ≥ 5 m/s^2, HI deceleration ≥ -5 m/s^2), accelerations and decelerations (AD; acceleration ≥ 3 m/s^2, deceleration ≥ -3 m/s^2), and total distance (TD; in m). Individualised values were set based on sprint testing.

Previous research on physical demands of football have alluded to the removal of player match data from their data analysis if they failed to fulfil the duration of the full game (Bush et al., 2015; Di Salvo et al., 2009; Di Salvo et al., 2013), whilst others have used 60 minutes as the minimum benchmark (Oliveira et al., 2019; Oliveira et al., 2020). Due to the frequent nature of substitutions in youth football and the different durations compared to the adult match duration, the inclusion criteria were set differently for different age groups. Outfield players who had fulfilled a minimum of half the match fixture (U14=≥ 35 minutes, U15/U16=≥ 40 minutes, U18/U23/first team=≥ 45 minutes) were included in the data. The game length minimum requirement was half of the maximum duration allowed at the corresponding age group. Each metric was divided by the mean duration of the game, then multiplied by the game length at their age group to give a full game total. The chosen metrics were selected based upon the previous literature on key physical performance indicators, by performance analysis experts, alongside research that differentiated players' talent levels (Dellal et al., 2010; Hughes et al., 2012; Williams, Ford and Drust, 2020).

Design and Procedures

Permission to access the dataset was granted by a category one football academy, who are an established member of the EPL. Data protection was outlined during the research ethics application, and player names were anonymised once the data was received by the researcher. Data was stored on an encrypted and secure password protected laptop to ensure that data protection legislation was met. Ethical approval was granted by the Liverpool John Moore's University Ethics Committee.

Data Collection

Due to fulfilments of the EPPP (2011) set out in category one football academies, academy players were obligated to wear GPS devices for both training and matches for player monitoring purposes. The GPS device (STATsports Outdoor, Northern Ireland) provides position, distance, and velocity data. These are sampled at 10-Hz and are integrated with a 100-Hz triaxial accelerometer, 100-Hz gyroscope, and 100-Hz triaxial magnetometer. GPS units were placed into a vest and placed on the scapula of the individual. Dwell times were set to increase the reliability of the high-speed and sprint distance data as the end point of a high-intensity or sprint effort may oscillate around a threshold (Malone et al., 2017). Post-match, GPS devices were collected and uploaded onto STATSport Software (119 STATSport

Software), before being inputted into a Microsoft Excel spreadsheet (Microsoft Corporation, California, USA).

Data Analysis/Processing

From the initial match data provided by the club, there were 6741 unique observations containing 129 individual players ranging from U14 to U23 age groups. These were produced in an Excel spreadsheet and classified into the 'selected' and 'deselected' categories through individual player club history via football websites Transfermarkt and Wyscout. First and second year scholarship players who had not been selected or deselected were excluded from the dataset as they did not fall into either category. The secondary analysis aimed to investigate the effect of position, and the interaction with group (selected/deselected) and age group from under-16 to under-18 age groups.

Alternate tracking systems (TRACAB, Second Spectrum, Estimated) were removed from the dataset as video tracking systems have previously been found to over-estimate actual values by approximately 5.8% (Edgecomb and Norton, 2006) and interunit reliability across varied GPS units have been reported to contain high error rates (Malone et al., 2017). Loan and International fixture data were removed as guarantees of the tracking system validity and processes used could not be made. Data from players post under-18 age group were removed along with all data from the incomplete 2020/21 season. Failed GPS data (cropped incorrectly/ GPS vests not worn) were also removed. A minimum of 4 available satellites were required for the GPS data to be valid, however across the three seasons, available satellites did not fall below 10 at any point. Goalkeepers were excluded from the analysis, due to the different nature of their positional role.

This left the dataset with 2321 unique observations of match data across 54 players (Selected n=31 and Deselected n=23) after 51 rows of data were removed due to GPS failure. When position was included into the secondary analysis, this left 1876 unique observations of match data with 54 individual players (n=31 Selected and n=23 Deselected), and an even distribution of players across positions (defender n=18, midfielder n=18, attacker n=18).

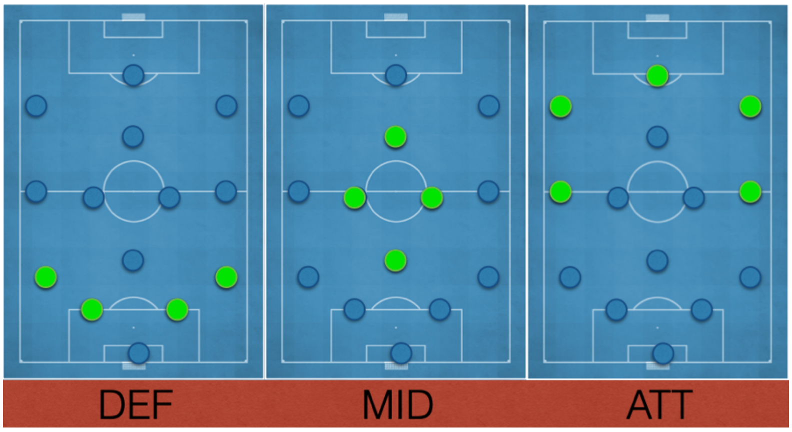

Figure 7: Categorised playing positions. DEF=Defender, MID=Midfielder, ATT=Attacker.

Statistical Analysis

Data were analysed via linear mixed modelling using statistical software package IBM SPSS Statistics (Version 26, New York, USA) on a MacBook Pro (macOS Catalina 10.15.6, California, USA). Linear mixed modelling was used due to the flexibility of the method when considering varied sample sizes between groups with repeated measures, and due to the data being hierarchical rather than single level (Field, 2013). Individual players were classed as the random effect and position, group, and age group were classed as fixed effects. Field (2013) described a fixed variable as one that is not supposed to change over time. In contrast, random variables vary over time. Position was classed as a fixed effect as it was players grouped together based on their playing history, rather than a position played in each individual game.

A variance components model was utilised to calculate interclass correlation (ICC) of the random factors. This implicates that if the effect of an individual player has a large effect on the dependent variable, the variability will be smaller. Alternatively, a small effect on the dependent variable will mean larger variability. This therefore gives an adequate gauge of the extent to which the contextual variable influences the outcome. Wald Z statistics were used to test the null hypothesis of the population variance being zero. If rejected, the random factors were included in larger scale models. Model fit was analysed using Akaike's information criterion, which for each independent variable revealed the model that best fitted the data was auto-regressive repeated covariance structure and is generally recommended for data using repeated measures. Picking the correct covariance structure is important as it is used as a starting point to estimate model parameters. Specifying a covariance structure which is too simple will increase the likelihood of a type I error (finding a parameter significant when non-significant). A covariance structure that is too complicated increases the chances of a type II error (finding parameters non-significant when significant) (Field, 2013). Significance was set at $P < 0.05$.

Data was presented as mean difference ± standard error and 95% confidence intervals (CI). The two sets of data were processed separately due to the age range of players in positions being different. Therefore, the first linear mixed model used players between under-14 and under-18 age groups. The second linear mixed model used players between under-16 and under-18 age groups to give an even age-group distribution for position comparison.

Results

Variance Calculations:

Table 1 shows the intra-class correlation (ICC in %) of a player as the random factor accounted for in the linear mixed model. Individual players accounted for significant variance ($p < 0.05$) for each dependent variable and were included in all hierarchical models as a result. The ICC can be used as a measure of dependency between scores and represents the proportion of total variability of the outcome that is attributable to the classes (Field, 2013). It is calculated by dividing the random effect variance by the total variance.

Table 1. The ICC's (%) of player regarding each dependent variable.

Physical Performance Variable	**Player (%)**
Absolute High-Speed Running (m)	56.3 *
Individualised High-Speed Running (m)	47.5 *
Absolute Sprint Distance (m)	56.2 *
Individualised Sprint Distance (m)	46.21 *
High Intensity Accelerations and Decelerations	57.1 *
Accelerations and Decelerations	57.2 *
Total Distance (m)	69.4 *

* Significance of the random factor ($p < 0.05$)

Table 2. Mean ± standard error (and 95% CI) of physical match demands per group (selected vs. deselected).

Physical Performance Variable	Selected	Deselected
Absolute High-Speed Running (m)	492.6 ± 21.8 CI=449.4 to 535.8	417.4 ± 33.6 CI=350.8 to 484.1
Individualised High-Speed Running (m)	750.9 ± 30.1 CI=691.0 to 810.7	716.3 ± 46.4 CI=624.1 to 808.4
Absolute Sprint Distance (m)	75.6 ± 8.3 CI=59.0 to 92.2	62.1 ± 12.9 CI=36.5 to 87.6
Individualised Sprint Distance (m)	249.0 ± 15.8 CI=217.6 to 280.3	235.9 ± 24.3 CI=187.6 to 284.2
High Intensity Accelerations and Decelerations	43.1 ± 1.8 CI=39.4 to 46.7 *	35.0 ± 2.8 CI=29.4 to 40.6
Accelerations and Decelerations	338.2 ± 6.1 CI=326.1 to 350.3 *	312.7 ± 9.4 CI=294.0 to 331.4
Total Distance (m)	8868.5 ± 110.0 CI=8650.2 to 9086.7	8710.4 ± 169.7 CI=8373.5 to 9047.3

* Statistically different from deselected players ($p<.05$).

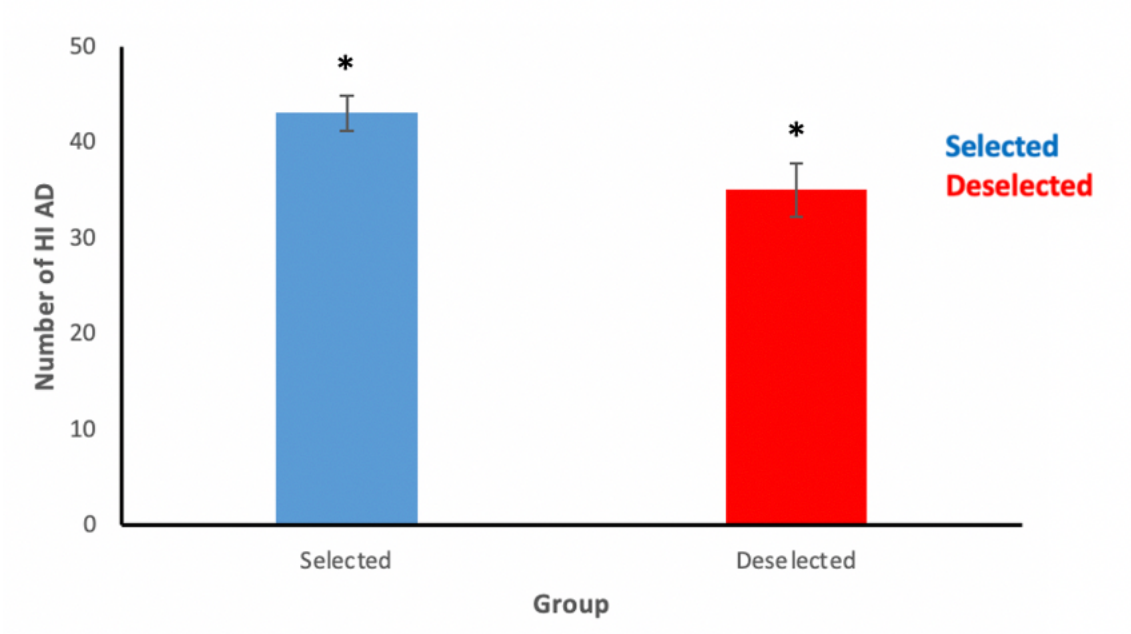

Figure 8. High-intensity accelerations and decelerations between selected (blue) and deselected (red) players. * Significant main effect between groups ($p < 0.05$).

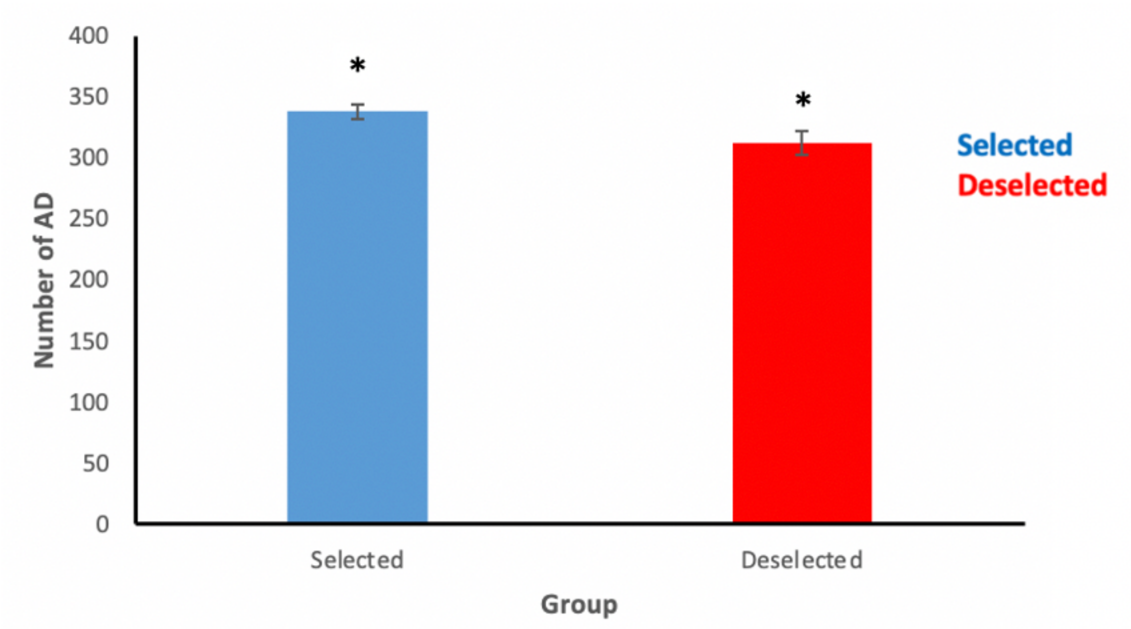

Figure 9. Accelerations and decelerations between selected (blue) and deselected (red) players. * Significant main effect between groups ($p < 0.05$).

Table 3. Main effect and interaction effect for group and age group on each dependent variable.

Age Group	Selected	Deselected
	Absolute High-Speed Running (m)	
U14	318.8 ± 81.2	128.1 ± 141.0
	CI=157.5 to 480.0	CI=-152.0 to 408.3
U15	462.3 ± 41.1	312.2 ± 58.9
	CI=381.1 to 543.5	CI=195.3 to 429.1
U16	454.0 ± 29.2	472.1 ± 36.4
	CI=396.3 to 511.7	CI=400.2 to 543.9
U17	618.0 ± 33.6	572.0 ± 42.7
	CI=551.3 to 684.8	CI=487.1 to 656.9
U18	609.9 ± 34.2	602.9 ± 40.7
	CI=542.0 to 677.9	CI=522.0 to 683.8
	**** Individualised High-Speed Running (m)**	
U14	697.5 ± 112.1	568.4 ± 194.6
	CI=474.8 to 920.2	CI=181.7 to 955.1
U15	750.3 ± 57.9	910.1 ± 81.4
	CI=635.7 to 864.9	CI=748.5 to 1071.6 *
U16	794.6 ± 41.0	620.6 ± 51.8
	CI=713.5 to 875.7	CI=518.5 to 722.7

U17	793.5 ± 46.6	778.4 ± 59.0
	CI=701.0 to 886.1	CI=661.1 to 895.6
U18	718.4 ± 47.3	703.9 ± 56.4
	CI=624.4 to 812.5	CI=592.0 to 815.9
	Absolute Sprint Distance (m)	
U14	18.9 ± 31.2	3.7 ± 54.2
	CI=-43.1 to 80.9	CI=-104.0 to 111.4
U15	69.4 ± 15.4	16.0 ± 22.5
	CI=39.0 to 99.8	CI=-28.8 to 60.7
U16	66.7 ± 11.0	92.0 ± 13.5
	CI=45.0 to 88.4	CI=65.4 to 118.5
U17	110.3 ± 13.1	89.9 ± 16.4
	CI=84.7 to 136.0	CI=57.3 to 122.5
U18	112.6 ± 13.1	108.8 ± 15.7
	CI=86.4 to 138.7	CI=77.7 to 139.9
	**** Individualised Sprint Distance (m)**	
U14	238.0 ± 58.5	137.0 ± 101.6
	CI=121.8 to 354.2	CI=-64.9 to 338.9
U15	308.4 ± 31.0	325.6 ± 42.8
	CI=247.0 to 369.8	CI=240.7 to 410.5

U16	267.3 ± 22.0	186.9 ± 28.5
	CI=223.7 to 310.8	CI=130.7 to 243.1
U17	225.9 ± 24.5	296.3 ± 30.9
	CI=177.3 to 274.4	CI=235.0 to 357.7
U18	205.4 ± 24.8	233.8 ± 29.5
	CI=156.2 to 254.6	CI=175.2 to 292.3
	High-Intensity Accelerations and Decelerations	
U14	24.5 ± 6.8	17.8 ± 11.9
	CI=10.9 to 38.1	CI=-5.9 to 41.4
U15	40.9 ± 3.5	28.3 ± 5.0
	CI=34.0 to 47.8	CI=18.5 to 38.2
U16	40.6 ± 2.5	39.3 ± 3.1
	CI=35.7 to 45.5	CI=33.2 to 45.4
U17	55.8 ± 2.8	44.5 ± 3.6
	CI=50.2 to 61.5	CI=37.4 to 51.7
U18	53.4 ± 2.9	45.2 ± 3.4
	CI=47.7 to 59.1	CI=38.3 to 512.0
	Accelerations and Decelerations	
U14	272.4 ± 22.8	222.3 ± 49.5
	CI=227.2 to 317.6	CI=143.7 to 300.8

U15	314.8 ± 11.8	304.1 ± 16.6
	CI=291.5 to 338.2	CI=271.2 to 337.0
U16	332.4 ± 8.4	315.0 ± 10.6
	CI=315.9 to 348.9	CI=294.1 to 335.9
U17	386.6 ± 9.5	362.3 ± 12.0
	CI=367.8 to 405.4	CI=338.5 to 386.2
U18	384.7 ± 9.6	359.8 ± 11.4
	CI=365.7 to 403.8	CI=337.1 to 382.5
	Total Distance (m)	
U14	7560.3 ± 412.3	7116.3 ± 715.7
	CI=6741.4 to 8379.3	CI=5694.9 to 8537.7
U15	8528.4 ± 198.7	8740.6 ± 297.1
	CI=8136.1 to 8920.8	CI=8151.1 to 9330.1
U16	8657.9 ± 142.8	8529.4 ± 173.1
	CI=8375.5 to 8940.2	CI=8188.1 to 8870.8
U17	9809.1 ± 170.0	9602.7 ± 216.6
	CI=9471.5 to 10146.6	CI=9172.6 to 10032.8
U18	9786.6 ± 173.1	9562.9 ± 206.7
	CI=9441.8 to 10131.3	CI=9152.4 to 9973.3

Data presented as mean ± standard error with 95% confidence intervals (CI) for the differences. * Denotes significant difference from deselected U16 age group. ** denotes a significant interaction of group and age group.

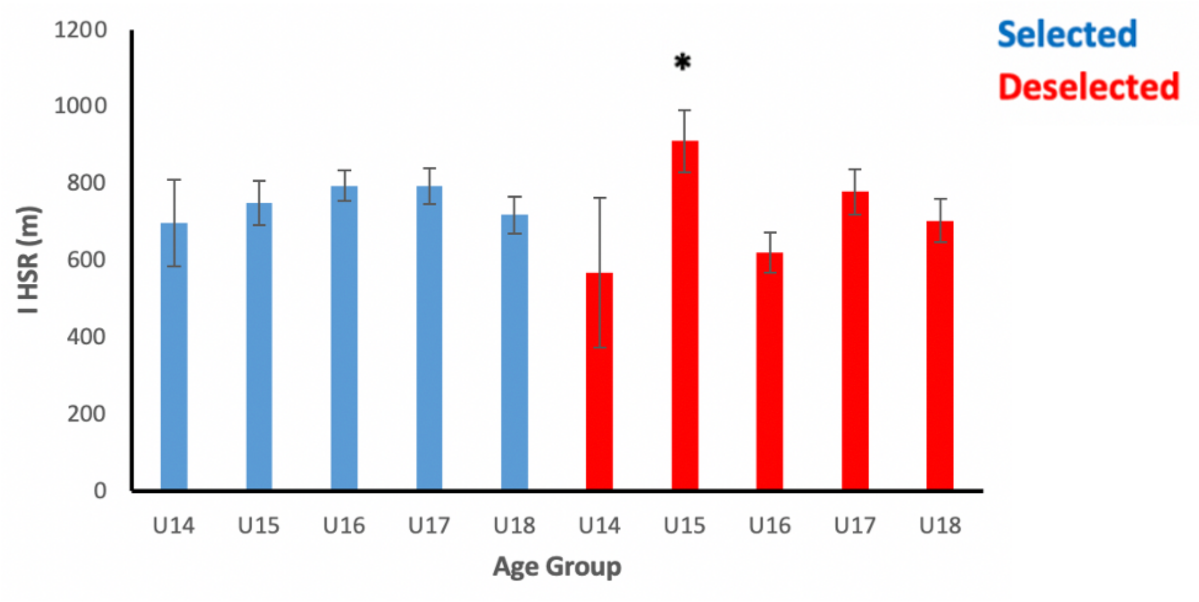

Figure 10. Individualised high-speed running (m) between U14 to U18 age groups between selected (blue) and deselected (red) players. * Denotes significant difference from deselected U16 age group.

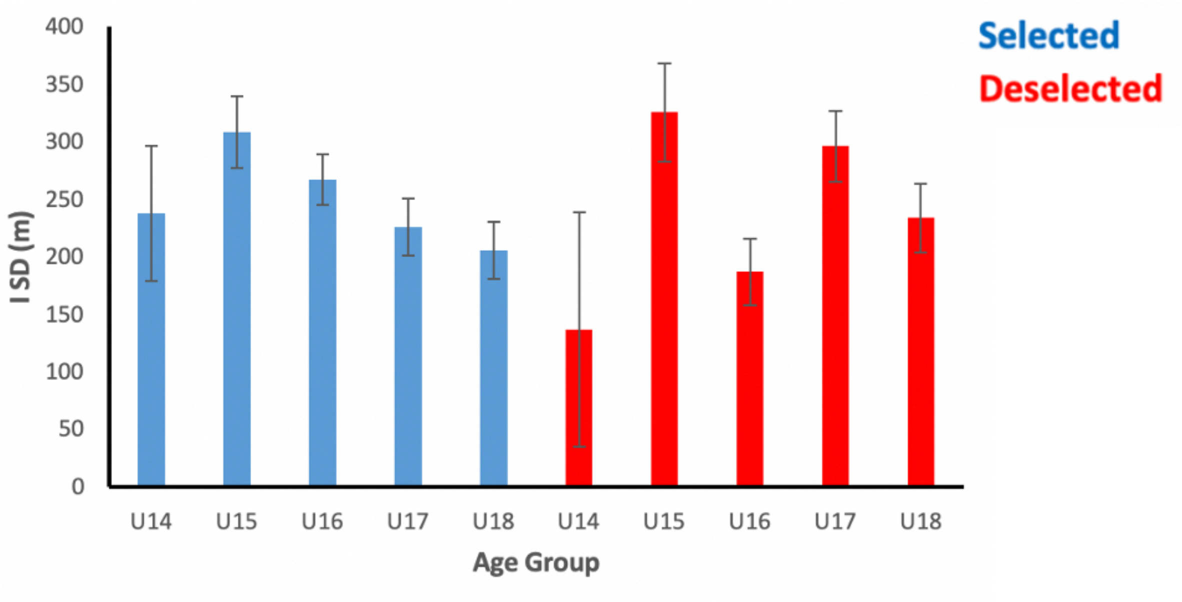

Figure 11. Individualised sprint distance (m) between U14 to U18 age groups between selected (blue) and deselected (red) players.

Group Main Effect

A significant group main effect was found for AD (p=0.024) and HI AD (p=0.018), with higher mean frequency for selected compared to deselected players (Table 2). There was no significant main effect for A HSR (p=0.06), I HSR, A SD, I SD, and TD.

Group and Age Group Interaction

A significant group and age group interaction was found for I HSR (P=0.036) and I SD (P=0.026). A significant reduction in high-speed running distance at an individualised ratio (P=0.033) was found between under-15 and under-16 for deselected players (289.4 ± 96.5, CI=13.4 to 565.5 m) (Table 3). Selected players had higher I HSR compared to deselected players at under-14, under-16, under-17, and under-18, however the under-15 mean was higher for deselected players (Table 3). With reference to I SD, selected players covered more distance sprinting at under-14 and under-16, whilst deselected players had a higher mean at under-15, under-17, and under-18 (Table 3). No significant interaction was found for A HSR, A SD (p=0.066), HI AD, AD, and TD (Table 3).

Table 4. The ICC's (%) of player regarding each dependent variable for U16 to U18 players.

Dependent Variable	Player (%)
Absolute High-Speed Running (m)	65.5 *
Individualised High-Speed Running (m)	50.8 *
Absolute Sprint Distance (m)	51.1 *
Individualised Sprint Distance (m)	45.3 *
High Intensity Accelerations and Decelerations	51.9 *
Accelerations and Decelerations	43.1 *
Total Distance (m)	51.4 *

* Significance of the random factor (p < 0.05)

Table 5. Main effect and interaction effect for group and position on each dependent variable

Position	Selected	Deselected
	*Absolute High-Speed Running Distance (m)	
Defenders	459.7 ± 35.7 CI=387.4 to 529.9	481.7 ± 38.2 CI=405.6 to 557.8
Midfielders	532.5 ± 26.3 CI=480.0 to 584.9	503.7 ± 56.1 CI=391.7 to 615.7
Attackers	679.4 ± 29.2 CI=621.2 to 738.0	634.2 ± 37.5 CI=559.4 to 709.0
	*Individualised High-Speed Running Distance (m)	
Defenders	578.4 ± 54.5 CI=469.7 to 687.2	685.5 ± 58.0 CI=570.0 to 801.0
Midfielders	805.7 ± 40.1 CI=725.6 to 885.9	835.8 ± 85.6 CI=665.0 to 1006.6
Attackers	839.7 ± 44.6 CI=750.8 to 928.6	714.3 ± 57.2 CI=600.3 to 828.3
	*Absolute Sprint Distance (m)	
Defenders	79.3 ± 14.1 CI=51.1 to 107.6	71.2 ± 15.0 CI=41.4 to 101.1
Midfielders	77.2 ± 10.4 CI=56.4 to 97.9	63.3 ± 22.2 CI=19.0 to 107.7
Attackers	137.9 ± 11.5 CI=114.9 to 160.8	124.7 ± 14.8 CI=95.2 to 154.1
	*Individualised Sprint Distance (m)	
Defenders	180.0 ± 26.0 CI=128.0 to 232.0	222.5 ± 28.0 CI=166.8 to 278.3

Midfielders	196.9 ± 19.2 CI=158.5 to 235.2	231.9 ± 41.0 CI=150.1 to 313.7
Attackers	301.0 ± 21.5 CI=258.2 to 343.8	268.3 ± 27.6 CI=213.3 to 323.3
	*High-Intensity Accelerations and Decelerations	
Defenders	43.3 ± 3.2 CI=36.8 to 49.7	38.5 ± 3.4 CI=31.6 to 45.3
Midfielders	48.2 ± 2.4 CI=43.5 to 52.9	49.2 ± 5.1 CI=39.1 to 59.3
Attackers	57.24 ± 2.63 CI=51.99 to 62.50	49.1 ± 3.4 CI=42.3 to 55.8
	Accelerations and Decelerations	
Defenders	358.9 ± 11.6 CI=335.7 to 382.2	350.0 ± 12.4 CI=325.3 to 374.7
Midfielders	372.1 ± 8.6 CI=355.0 to 389.2	385.9 ± 18.3 CI=349.4 to 422.5
Attackers	365.1 ± 9.5 CI=346.2 to 384.1	343.0 ± 12.2 CI=318.7 to 367.4
	*Total Distance (m)	
Defenders	8914.4 ± 194.8 CI=8525.3 to 9303.5	9210.8 ± 205.1 CI=8802.0 to 9619.7
Midfielders	9853.2 ± 143.1 CI=9567.4 to 10139.0	9809.0 ± 305.5 CI=9198.9 to 10419.1
Attackers	9173.1 ± 157.9 CI=8857.9 to 9488.2	9106.9 ± 202.3 CI=8703.4 to 9510.4

* Denotes significant main effect of position.

Group and Position Interaction

Position was found to have a statistically significant main effect on A HSR (p=<0.001), I HSR (p=0.006), A SD (p=<0.001), I SD (p=0.006), HI AD (p=0.002) and TD (p=0.002). When factoring group and position, there was no statistically significant interaction effect on A HSR, I HSR (p=0.08), A SD, I SD, HI AD, AD, and TD (Table 5). A HSR was higher for deselected defenders, but lower for midfielders and attackers (Table 5). I HSR was higher for deselected defenders and midfielders, but not attackers (Table 5). A SD was higher for selected players for defenders, midfielders, and attackers (Table 5). I SD was higher for deselected defenders and midfielders but not attackers (Table 5). HI AD was higher for selected defenders and attackers but lower for midfielders, although the differences were nominal (Table 5). AD was higher for selected defenders and attackers, but not midfielders (Table 5). TD was higher for deselected defenders, but higher for selected midfielders and attackers, although differences between groups were nominal between midfielders and attackers (Table 5).

Table 6. Main effect and interaction of group, age group and position on each dependent variable.

Position	Age-Group	Selected	Deselected
		Absolute High-Speed Running Distance (m)	
Defenders	U16	313.0 ± 71.2 CI=170.8 to 455.2	331.9 ± 93.9 CI=145.2 to 518.6
	U17	551.4 ± 62.5 CI=426.7 to 676.1	538.0 ± 46.5 CI=445.0 to 631.0
	U18	511.7 ± 49.0 CI=411.9 to 611.5	575.1 ± 46.5 CI=482.3 to 668.0
Midfielders	U16	468.9 ± 41.0 CI=386.9 to 550.8	328.2 ± 74.0 CI=180.7 to 475.8
	U17	573.1 ± 44.7 CI=483.9 to 662.4	647.9 ± 123.7 CI=400.7 to 895.1
	U18	555.4 ± 50.2 CI=455.0 to 655.8	534.9 ± 86.7 CI=361.6 to 708.2
Attackers	U16	526.7 ± 45.7 CI=436.0 to 617.5	552.1 ± 47.3 CI=458.3 to 645.9
	U17	715.5 ± 50.1 CI=615.3 to 815.7	636.4 ± 72.9 CI=490.9 to 781.9
	U18	796.0 ± 55.4 CI=685.3 to 906.6	714.1 ± 71.5 CI=571.3 to 856.9
		Individualised High-Speed Running Distance (m)	
Defenders	U16	531.8 ± 108.7 CI=314.7 to 749.0	649.3 ± 142.0 CI=366.8 to 931.9
	U17	654.9 ± 95.2 CI=464.8 to 844.9	767.5 ± 71.0 CI=625.7 to 909.2

	U18	548.6 ± 76.3 CI=396.2 to 701.1	639.6 ± 71.0 CI=497.8 to 781.4
Midfielders	U16	783.3 ± 62.6 CI=658.3 to 908.4	713.0 ± 112.7 CI=488.4 to 937.6
	U17	838.9 ± 68.4 CI=702.5 to 975.4	940.5 ± 188.7 CI=563.6 to 1317.4
	U18	795.0 ± 76.8 CI=641.6 to 948.4	854.0 ± 132.6 CI=589.14 to 1118.8
Attackers	U16	871.3 ± 69.7 CI=732.9 to 1009.7	636.9 ± 72.1 CI=493.9 to 779.9
	U17	822.5 ± 76.6 CI=669.5 to 975.5	755.5 ± 111.1 CI=533.8 to 977.2
	U18	825.4 ± 84.6 CI=656.4 to 994.4	750.4 ± 109.0 CI=532.7 to 968.1
		Absolute Sprint Distance (m)	
Defenders	U16	50.0 ± 28.2 CI=-6.4 to 106.4	31.2 ± 36.6 CI=-41.8 to 104.2
	U17	93.9 ± 24.7 CI=44.5 to 143.2	84.7 ± 18.5 CI=47.8 to 121.6
	U18	94.1 ± 19.8 CI=54.5 to 133.8	97.8 ± 18.4 CI=61.0 to 134.7
Midfielders	U16	75.3 ± 16.3 CI=42.8 to 107.8	36.4 ± 29.1 CI=-21.6 to 94.5
	U17	81.9 ± 17.6 CI=46.7 to 117.1	78.3 ± 49.0 CI=-19.7 to 176.3
	U18	74.2 ± 20.1 CI=34.4 to 114.1	75.3 ± 34.4 CI=6.4 to 144.1
Attackers	U16	74.9 ± 17.8 CI=39.5 to 110.2	107.9 ± 18.3 CI=71.66 to 144.2

	U17	157.1 ± 19.9	108.5 ± 28.8
		CI=117.3 to 196.9	CI=51.1 to 165.9
	U18	181.6 ± 21.9	157.6 ± 28.3
		CI=137.8 to 225.5	CI=101.0 to 214.2
		Individualised Sprint Distance (m)	
Defenders	U16	188.60 ± 51.96	168.99 ± 69.03
		CI=84.86 to 292.34	CI=31.83 to 306.15
	U17	196.47 ± 45.62	310.16 ± 33.84
		CI=105.45 to 287.49	CI=242.57 to 377.75
	U18	155.06 ± 36.36	188.41 ± 33.88
		CI=82.40 to 227.71	CI=120.75 to 256.07
Midfielders	U16	241.44 ± 29.89	189.67 ± 54.49
		CI=181.75 to 301.13	CI=81.21 to 298.13
	U17	176.20 ± 32.95	234.99 ± 90.21
		CI=110.53 to 241.87	CI=54.90 to 415.07
	U18	172.99 ± 36.69	271.04 ± 63.27
		CI=99.71 to 246.26	CI=144.65 to 397.42
Attackers	U16	297.63 ± 34.19	201.63 ± 35.75
		CI=229.75 to 365.52	CI=130.78 to 272.48
	U17	304.25 ± 36.54	290.32 ± 53.51
		CI=231.26 to 377.24	CI=183.68 to 396.95
	U18	301.15 ± 40.49	313.01 ± 52.10
		CI=220.32 to 381.97	CI=209.00 to 417.03
		High-Intensity Accelerations and Decelerations	
Defenders	U16	32.5 ± 6.4	35.0 ± 8.4
		CI=18.7 to 44.4	CI=18.3 to 51.8
	U17	49.6 ± 5.6	38.7 ± 4.2
		CI=38.3 to 60.8	CI=30.3 to 47.1

	U18	48.8 ± 4.5 CI=39.7 to 57.8	41.7 ± 4.2 CI=33.3 to 50.1
Midfielders	U16	40.8 ± 3.7 CI=33.4 to 48.2	37.6 ± 6.7 CI=24.3 to 50.9
	U17	54.7 ± 4.0 CI=46.6 to 62.7	63.1 ± 11.2 CI=40.7 to 85.4
	U18	49.1 ± 4.5 CI=40.0 to 58.2	46.9 ± 7.8 CI=31.2 to 62.5
Attackers	U16	46.6 ± 4.1 CI=38.5 to 54.8	43.1 ± 4.2 CI=34.8 to 51.5
	U17	61.1 ± 4.5 CI=52.0 to 70.1	52.2 ± 6.6 CI=39.1 to 65.3
	U18	64.1 ± 5.0 CI=54.1 to 74.1	51.9 ± 6.5 CI=39.02 to 64.8
		Accelerations and Decelerations	
Defenders	U16	307.8 ± 23.2 CI=261.3 to 354.2	348.0 ± 30.3 CI=287.6 to 408.4
	U17	392.6 ± 20.4 CI=352.0 to 433.3	351.8 ± 15.2 CI=321.5 to 382.2
	U18	376.4 ± 16.3 CI=343.8 to 409.0	350.3 ± 15.2 CI=319.9 to 380.6
Midfielders	U16	327.3 ± 13.4 CI=300.5 to 354.0	315.9 ± 24.0 CI=268.0 to 363.8
	U17	395.6 ± 14.6 CI=366.5 to 424.7	443.2 ± 40.4 CI=362.6 to 523.8
	U18	393.3 ± 16.4 CI=360.5 to 426.1	398.7 ± 28.3 CI=342.1 to 455.3
Attackers	U16	341.3 ± 14.8 CI=312.0 to 370.7	314.8 ± 15.2 CI=284.6 to 345.0

	U17	370.3 ± 16.4	359.3 ± 23.7
		CI=337.6 to 403.0	CI=312.0 to 406.7
	U18	383.7 ± 18.1	355.0 ± 23.3
		CI=347.6 to 419.8	CI=308.4 to 401.6
		Total Distance (m)	
Defenders	U16	7941.5 ± 388.8	8663.3 ± 499.1
		CI=7164.7 to 8718.2	CI=7669.4 to 9657.3
	U17	9476.6 ± 339.7	9554.8 ± 254.5
		CI=8798.5 to 10154.8	CI=9046.2 to 10063.3
	U18	9325.2 ± 273.7	9414.4 ± 254.2
		CI=8778.2 to 9872.2	CI=8906.6 to 9922.3
Midfielders	U16	8878.8 ± 224.3	8765.8 ± 398.2
		CI=8430.6 to 9326.9	CI=7971.6 to 9560.0
	U17	10370.5 ± 241.9	10649.4 ± 675.2
		CI=9887.8 to 10853.2	CI=9300.8 to 11998.0
	U18	10310.4 ± 274.7	10011.9 ± 474.9
		CI=9761.5 to 10859.3	CI=9062.9 to 10961.0
Attackers	U16	8503.0 ± 240.5	8360.5 ± 245.8
		CI=8024.5 to 8981.5	CI=7872.1 to 8848.8
	U17	9303.2 ± 274.5	9351.7 ± 394.4
		CI=8754.7 to 9851.6	CI=8564.5 to 10138.9
	U18	9713.0 ± 302.1	9608.6 ± 390.1
		CI=9109.5 to 10316.5	CI=8829.3 to 10387.8

Group, Position, and Age Group Interaction

No significant interaction effect was found for group, position, and age group for A HSR, I HSR, A SD, I SD, HI AD, AD, and TD. Selected defenders had higher A HSR at under-17, higher A SD at under-16 and under-17, and higher I SD at under-16. Selected defenders had higher HI AD and AD at under-17 and under-18. I SD and TD was lower across the three age groups for selected defenders compared to deselected defenders. Selected midfielders had higher A HSR at under-16 and under-18, and higher I HSR at under-16. A SD was higher for selected midfielders at under-16 and under-17, and higher at under-16 for I SD. HI AD and AD was higher for selected midfielders across all three age groups, and TD was higher at under-16 and under-18 for selected midfielders compared to deselected midfielders. Selected attackers had higher A HSR and A SD at under-17 and under-18. I SD was higher for selected attackers at under-16 and under-17. Selected attackers had higher I HSR, HI AD and AD across all age groups. TD was higher for selected attackers at under-16 and under-18 compared to deselected attackers (Table 6).

Discussion

The aim of the present research was two-fold, firstly, to identify differences in physical match performance between selected and deselected players across age groups. Secondly, to investigate in more detail the interactions that selection and deselection had with age group and position. The findings suggest that selected players accelerate and decelerate at normal and high intensity more frequently, as well as covering less distance sprinting, when compared to deselected counter parts at under-17 and under-18. Results suggest selected players are more explosive and reactive in game situations compared to deselected players, and individualised speed thresholds distinguish between groups when age is considered.

A significant group main effect for HI AD and total AD was found, with selected players producing higher mean frequency compared to deselected players. This potentially implicates that selected players are stronger, therefore more explosive in their movements and reactive to game situations (Spinks et al., 2007), for example a change in speed during an attacking or defensive transition, changing direction to track a run, or moving quickly into the space. From a tactical perspective, a player who is more tactically aware may spot a potential threat in a game situation, and react quickly, whereas a player with a lack of tactical awareness may be unaware of the potential threat, meaning there is no instant change of speed to adapt to the context of the game. This could therefore lead to players with superior tactical awareness having a higher frequency of HI AD and AD.

Compared to previous studies, selected and deselected players produced more AD in comparison to professional players in Spanish La Liga at the same threshold ($3 \geq m/s^2$) in CD, FB, MF, WM and FW (Oliva-Lozano et al., 2020). Professional first team players accelerated (76±22) and decelerated (54±16) less than selected and deselected players in the present study (Dalen et al., 2016). In addition, elite players in the Danish division accelerated (81±2) and decelerated (84±3) less in comparison to the present research. The threshold in the study was set lower in comparison ($2 \geq m/s^2$) (Vigh-Larsen, Dalgas and Andersen, 2018). Prior research suggests higher quality players (international top class and lower professional players) are more selective with their high-intensity efforts (Mohr, Krustrup and Bangsbo, 2003), however findings from the present study revealed contradictory findings. This may suggest that the range in talent between selected and deselected players is smaller compared to studies who compare elite and non-elite players, and this may lead to contradictory findings. It must also be considered that players in the discussed study were adult players (mean age of 26.4) compared to youth players in the current study.

The present study suggests that selection and deselection have a significant effect on mean HI AD and AD frequency (Table 2). When age is considered, the interaction of selection and deselection with age becomes non-significant (Table 3). Secondary analysis revealed no significant main effect for HI AD and AD when the under-14 and under-15 groups were removed. This may suggest that the significance of HI AD and AD is mainly an influencing factor at the younger age groups and the pathway to earning a scholarship, rather than the pathway to signing a professional contract. This may be influenced by RAE and growth spurts, and youth coaches should consider this finding of importance, particularly in the younger age groups. It has previously been suggested that the RAE influences selection because of the physical advantages older players have over younger peers (Helsen, Van Winckel and Williams, 2005), however recent research suggests that birth quartile had no significant correlation with physical fitness (Huertas et al., 2019).

Previous research indicates that both speed and power are key physical performance indicators for all outfield positions in football (Hughes et al., 2012). The findings from the present study are in line with Hughes et al., (2012) as AD are force and velocity components (Morin et al., 2021). Prior studies suggest number of sprints and high-intensity efforts are associated with players who progress in academies (Bidaurrazaga-Letona et al., 2019), and have higher perceived football talent (Mohr, Krustrup and Bangsbo, 2003), however sprints are not necessarily associated with AD (Varley et al., 2012). Previous research also suggests AD are high in youth football compared to senior football (Dalen et al., 2016; Vigh-Larsen, Dalgas and Andersen, 2018; Oliva-Lozano et al., 2020). One possible explanation might be that youth football players may not pace themselves through the game due to a lack of experience, as well as the style of play during youth football matches (Vigh-Larsen, Dalgas and Andersen, 2018). Particularly in the younger age groups when there is a lack of emphasis on a tactical set up, this will be more apparent as there is more emphasis on physical development, enjoyment, and participation in these age groups. When the game becomes more results based, there is an increase in the amount off tactical responsibility, thus leading to more selective movements and lower physical outputs in matches.

No significant main effect was found for A HSR, I HSR, A SD, I SD, and TD. In contrast, previous findings suggest that HSR and SD differentiates football talent level as top-class (Italian Serie A, International, and European Champions League) players produced significantly more efforts and distance for HSR and sprints compared to moderate ability (Danish league) players (Mohr, Krustrup and Bangsbo, 2003). One possible explanation for contradicting findings might be that data on players were only assessed from 2-7 matches, whereas the present study used a longitudinal approach and a large game sample. Another explanation for the differences could be that the present study focuses on youth players, compared to adult players, however research suggests that youth football players can produce similar physical performances in matches compared to adults (Vigh-Larsen, Dalgas and Andersen, 2018). Results from the present study did reveal a significant group and age group interaction effect on I HSR and I SD, with the reduction in I HSR for deselected players between under-15 and under-16 being significant (289±96, CI=13 to 565). A reduction at the same age group for deselected players was also found for I SD, however the difference was non-significant. Selected players' I HSR remained consistent between under-14 to under-18 groups. In relation to I SD, findings from the present study suggest players who are selected and offered professional contracts decrease their sprint distances with age. This is in line with previous findings (Mohr, Krustrup and Bangsbo, 2003).

A gradual decline in I SD for selected players was found between under-15 to under-18, although non-significant between the age groups, in contrast to previous talent development models (Williams and Reilly, 2000; Williams, Ford and Drust, 2020; Sarmento et al., 2018). It must be considered that with the game length being 80 minutes for players at under-15 and under-16, compared to 90 minutes for under-17 and under-18 players, the reduction relative to match duration could be slightly larger than what first appears, meaning the initial results are not a true reflection of the significance in reduction relative to minutes. No consistent patterns were apparent for I SD and I HSR for deselected players between under-14 and under-18. In comparison, consistent trends were found for selected players across the same age groups, and a possible justification for the interactions being significant. The results would suggest that selected players become more selective with their individualised high-intensity movements from under-16 to under-18, and sprint efforts from under-15 to under-18 as their chronological age increased, whereas deselected players were inconsistent. In a football context, this could mean selected players were more disciplined with their high-intensity efforts, due to their tactical awareness improving with age, for example being more disciplined in their positioning so they have less recovery movements or presses to make. Due to the one-dimensional nature of this study, these are only assumptions, however recent studies have attempted to contextualise the physical demands of football with tactical context (Ju et al., 2021). This is therefore the next stage of research for investigations into selection in youth football that could provide contextual information about the physical demands.

The inconsistency of I SD of deselected players was mirrored with that of I HSR. In the secondary analysis with position as a factor for the under-16 to under-18 age groups, the interactions of group and age group were non-significant. This suggests the longitudinal aspect of I HSR and I SD over time are a better indication of why players are selected or deselected, and sport science academy staff should track the physical match profiles of their youth players over numerous years, instead of a focus from under-16 to under-18. With GPS being used consistently in academy football, over-time a longitudinal set of data will be readily available for these types of analysis in future studies. This could be instrumental in building normative profiles of previously selected players and in the future, comparing current youth players to those who have progressed successfully through an academy pathway previously.

Previous research in the talent identification and development sector has used absolute velocity thresholds in most studies. The individualisation of thresholds has been previously found to significantly alter HSR distance (Murray, Gabbett and Townsend, 2018).

Whilst individualised thresholds do not represent an individual's ability to repeatedly reach a set sprint speed, they can provide valuable information on the workload and effort levels of a player during a match and can be used as a cross comparison with players, whilst also being indicative of fatigue levels (Thorpe, 2016). In the case of the present study, relative distances were more sensitive at detecting differences between selection and deselection in EPL academy players with age as a factor, in comparison to absolute thresholds. From a football perspective, this could relate to the level of tactical awareness a player has. For example, if a midfield player does not position himself correctly in a formation, they would have to produce more frequent high-intensity efforts to recover and get back into position. Therefore, compared to a player who would position themselves correctly, the physical output could be higher for the player with less tactical awareness in games.

In the secondary analysis containing players aged between under-16 to under-18 due to the varied age groups across positions, a significant main effect for position was found for: A HSR, I HSR, A SD, I SD, HI AD and TD. This is in line with previous research on variance in physical match output across player positions (Di Salvo et al., 2010; Gregson et al., 2010; Carling et al., 2012; Bangsbo, 2014; Dalen et al., 2016; Rago, Pizzuto and Raiola, 2017; Abbott, Brickley and Smeeton, 2018; De Silva et al., 2018; Roberts et al., 2019a; Doncaster et al., 2020), and suggests position influences physical output in category one youth football. When group (selection/deselection), position, and age group were factored, the interactions were non-significant for all metrics. This suggests the differences between selected and deselected players when refined by position (defender/midfielders/attackers) are not distinguishable and may not play a role in the decision on whether a player is retained or offered a professional contract to continue at the club. Other performance domains might be more influential in why a player is selected or deselected (e.g., a selected midfielder having better technical ability compared to a deselected midfielder).

A critique and explanation as to why the interactions were non-significant may be due to the grouping of positions. Previous studies have broken down position into to sub-categories of defenders (full-back and centre-backs), midfielders (defensive-midfielders, central-midfielders, attacking-midfielders) and attackers (wide-attackers and strikers). The current dataset did not allow to use more specialised positions, because limited number of players for each position in the selected and deselected group. Therefore, the current design was used to analyse the generic positions.

As previously reported, selection and deselection had no significant effect on A HSR, A SD, and TD. A previous study (Di Salvo et al., 2013) comparing EPL and English Championship (second tier) player physical match performance found statistically significant differences in high-intensity-activities, however the absolute differences were only small, meaning the significance was misleading in context. Findings were similar to this study as the differences were small, but non-significant, despite selected players having a higher mean for all seven physical performance metrics. This would suggest that absolute running activities (A HSR/A SD/TD) are not an influencing factor on the player selection of a category one academy football player.

As A HSR, A SD, and TD were not found to have any significant main effects or interactions across both analyses, it would suggest these metrics are not sensitive enough to detect differences in selected and deselected players in an elite category one academy football. Due to fulfilments for academy clubs to achieve category one status and the investment in sport science staff, players are part of an environment where they will receive the same physical development training plans, thus leading to similar well-conditioned physical profiles. This may explain the non-significant findings in the present study and suggest other factors influence selection and deselection, rather than physical performance.

As discussed in the prior introduction and literature review, talent identification and development in elite youth football is multi-dimensional. However, it was apparent that research into the physical demands of match performance were researched to differentiate between selected and deselected players, as areas of talent such as technical ability (Rampinini et al., 2009; Waldron and Worsfold, 2010; Adams et al., 2013; Huijgen et al., 2014; Höner et al., 2015; Forsman et al., 2016; Höner, Leyhr and Kelava, 2017; Lehyr et al., 2018; Kelly et al., 2020; Dugdale, McRobert and Unnithan, 2021) and psychological skills (Van Yperen, 2009; Louzada, Maiorano, and Ara, 2016; Forsman et al., 2016; Taylor and Collins, 2019; Dugdale, McRobert and Unnithan, 2021) appeared conclusive in their findings (higher technical and psychological ability appears to correlate with improved performance). With the evolving nature of sport science, as well as the depth in GPS data available to football clubs, this type of research and information is readily available to clubs and can be used longitudinally to track physical performance.

The present findings suggest both HI AD and AD significantly distinguish between selected and deselected youth players, with selected players producing a higher mean frequency for both metrics. As previously mentioned, this suggests that selected players are more explosive and reactive to game situations. The results also suggest that the use of individualised metrics were sensitive to the prediction of selection and deselection with reference to age in academy football, compared to absolute values due to the significant interactions of group (selected/deselected) and age group on I HSR and I SD. Individualised thresholds have previously been found to significantly alter amounts of HSR (Murray, Gabbett and Townsend, 2018). Previous research has recommended lowering the thresholds in women's football for HSR and sprinting categories compared to absolute values (Bradley and Vescovi, 2015; Park, Scott and Lovell, 2019). A similar approach seems vital in academy football, specifically considering academy football players will not have fully developed and reached their predicted height, potentially until post-scholarship. Therefore, the desire to use individualised thresholds seems practical. As players mature at various stages of their youth career, a percentage of a player's individual maximum speed seems a plausible method of setting individual thresholds, a method which was used in the present study. This will allow practitioners to feedback evidence from the data on the effort levels of individuals to a coach. For example, relative to a selected players physical capacity, they have covered more I HSR and I SD compared to a deselected player, suggesting their effort levels are higher in comparison during games. This type of information can be contextualised, and coaches may use it to be indicative of a player's effort or motivation levels in a match context.

Limitations

This study is not without limitation, although due to the appropriate statistical test being selected, the study therefore accounts for numerous potential limitations. Weight and anthropometrics have previously been found to cause variance in youth physical performance (Malina et al., 2004). Differences in anthropometrics are a subsequent result of growth and maturation, which have previously been found to influence physical match data (Eisenmann, Till and Baker, 2020). The anthropometrics of an individual were accounted for in the present study as players were included as a random effect. By using I HSR and I SD, the study also accounts for the influence of anthropometrics on A HSR and A SD values as a taller player would have a larger stride length compared to a smaller individual, subsequently leading to higher distance covered sprinting at the same speed over the same time period (Malina et al., 2005). Individualised thresholds therefore give a representation of the demands of youth football players, relative to their genetic and maturation status and characteristics. It must be considered that the validity of individualised thresholds has previously been questioned as the tests that measure individualised speed are based off straight line sprints and do not consider direction change and frequent acceleration movements in football (Sweeting et al., 2017), therefore the specificity of the tests may not represent a true football nature.

Despite the focus of the present research being centred around the physical aspect of youth football and its links with selection or deselection, there is no doubt that the variability in the data is present because of numerous contextual variables that make the nature of football unpredictable. The prior literature review previously discussed the effect that formation (Bradley et al., 2011; Carling, 2011), tactics (Gregson et al., 2010; Bradley et al., 2013b) and evolution (time) (Barnes et al., 2014; Bush et al., 2015; Zhou, Gomez and Lorenzo, 2020) had on physical match performance. However, this would still affect both selected and deselected players in the present study. The quality of the opposition should however be considered as better-quality opposition results in higher total distance covered (Aquino et al., 2017b). Knowing the context behind running activities could also provide more detail (e.g., selected players produce significantly more high-intensity activity in possession, but not out of possession), and would provide specific information when youth players produce high-intensity activities, potentially highlighting a differentiation factor between selected and deselected players.

Score line is a contextual factor that has caused variability in physical match output. TD is found to be greater when drawing compared to when a team is winning or losing (Redwood-Brown et al., 2018). Central defenders cover more high-intensity distance when heavily losing (≥3 goals), whilst attackers cover more high-intensity distance when winning heavily (≥ 3 goals). Location is another contextual variable of football, and previous research has indicated that crowd factors are a dominant cause of home advantage (Nevill and Holder, 1999). This may not be a specific element of youth football due to academy games usually being played in front of staff, scouts, and parents as spectators for a substantial proportion of games. However, it has been previously discovered that home teams covered more total distance than away teams (Aquino et al., 2017b). Match-to-match variability in football is ever present because of the contextual and tactical factors, and high-intensity performance has previously been found to vary by 16.2±6.4% in adult male football from game-to-game (Gregson et al., 2010). Sprint efforts are 53% variable, and accelerations are 17% variable respectively from match-to-match in female football (Trewin et al., 2018). The discussed contextual and tactical variables are a key influence on why the data will see large variations and must be taken into context when interpreting the data. Having a context of score line would also improve the quality of the study as it would potentially produce findings of importance (e.g., deselected players produce less high-intensity activities during a heavy defeat) and assumptions could be made from these findings, such as deselected players lose motivation during a defeat, thus affecting their physical match performance.

Whilst GPS data can provide sport science departments with valuable player loading and performance information, it is still important to factor the limitations of the devices. First, GPS has previously been found to overestimate distances by 4.8% (Edgecomb and Norton, 2006). It is important as measures of velocity and distance require validation independently and in combination, there is no “gold standard” guidelines to objectively manage poor data quality (Malone et al., 2017). It has also been reported that GPS performance tracking can vary significantly under flood-lit conditions (Skone, Knudsen and De Jong, 2001), thus meaning GPS under flood-light conditions are potentially susceptible to increased error, especially during winter mid-week evening games, which are common practice during category one academy football.

A large proportion of studies have strictly used competitive matches in their dataset and removed friendly matches. Due to the nature of academy football, and the importance of friendlies for game time for squad players, friendlies were not excluded from the present study. Bradley and Noakes (2013) investigated match running performance between games of differing importance and discovered that physical performance was unchanged. In contradiction, it was revealed that players cover more distance and have a higher frequency of sprints in official matches compared to 11 v 11 training games (Olthof, Frencken and Lemmink, 2019), therefore the importance of the fixtures played may have influenced the variability in the physical match data. An uncontrollable limitation of the present study was that players were grouped into positions based on their playing history, rather than being given a position for the game they played in, due to this complex information being unavailable at academy football. This may have influenced the data and it has previously been discovered that when the same individual plays in an alternative position, a notable effect on their distances covered at numerous speed thresholds will be found (Schuth et al., 2016).

Previous studies reviewed the different talent identification and development approaches. However, they tend not to account for numerous circumstantial factors that can influence a player's development pathway. For example, football is associated with high-risk injury (Waldén et al., 2011) and 36.5% of youth footballers reported injuries over the space of a season, with 14.4% reporting multiple injuries. Furthermore, historic research states the risk of injury is said to increase with each succeeding year group (Goldberg et al., 1988). Recent research states elite youth player injuries cause between 2 and 19.4 injuries per 1000 hours of football, with sprains and muscular strains being the most common injury (Pfirrmann et al., 2016). Injuries in academy football have been found to cause 21.9 days of absence per season and an individual's injury equates to approximately 6% of each players development time (Price et al., 2004). Moreover, the risk of sustaining a time-loss injury ranges between 50 to 91% for players between under-18 to under-21, and 18% of reported injuries are classified as severe and requiring more than 28 days recovery, with a subsequent effect on health, well-being, and finances (Jones et al., 2019). Injuries will therefore have an adverse effect on youth player development with a decrease in training and match play. Studies should take this into consideration when discovering outliers in performance data.

Conclusion

To conclude, both HI AD and AD significantly differentiated selected and deselected youth football players. This may suggest selected players are more explosive and powerful in their movements and have higher mean HI AD and AD because of superior tactical awareness, as they can react quicker and better to game situations compared to deselected players. The main effect was significant when under-14 to under-18 groups were part of the sample, but non-significant when under-16 to under-18 players were part of the sample. HI AD and AD may therefore influence selection in the younger age groups. Although a significant interaction was discovered for group (selection/deselection) and age group, selected players mean I HSR was consistent between under-14 and under-18, and I SD gradually reduced from under-15 to under-18. I HSR and I SD was inconsistent for both metrics for deselected players, however I SD was higher for deselected players at under-17 and under-18. It was suggested that selected players were more selective with their sprint movements due to superior tactical awareness, specifically at the scholarship age. Finally, due to the evolution of football and the fulfilments of the EPPP, it was concluded that most academy players are well physically conditioned, thus no significant main effects were found for distance metrics between selected and deselected players. It is suggested that a multi-disciplinary and integrated approach to selection and deselection in elite football academies is utilised in future studies to understand what attributes distinguish selected and deselected players. Findings suggest that youth football academies should monitor HI AD and AD, as they were significantly different between selected and deselected players, as well as monitoring I SD and I HSR distances longitudinally, rather than using absolute thresholds.

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