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RESEARCH ARTICLE

An examination of signs, samples and subjective expert opinion as predictors of (de) selection in a youth male soccer academy in the UK

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ABSTRACT
Multidisciplinary profiling provides coaches with key information to augment their (de)selection decisions. These profiles often encompass objective and subjective data in the form of signs (isolated assessments), samples (contextualised assessments) and subjective expert opinion (SEO). Whilst multiple sources of information are considered by coaches during their decision-making, research exploring the extent to which objective and subjective multidisciplinary information can classify (de)selection is limited. Multidisciplinary data (physical profiling, match statistics, coach match ratings) were collected on 58 Under-16 ($n = 20$) and Under-18 ($n = 38$) youth male soccer players from a single academy in the United Kingdom. Group-level differences between selected ($n = 39$) and deselected ($n = 24$) players were explored, and binary logistic regression models were created to classify (de)selection. Analysis revealed a significant difference between selected and deselected players for match ratings ($p < 0.0001$), 505 left foot ($p < 0.01$), frequency of passes, percentage of successful aerial duels, and percentage of accurate crosses ($p < 0.05$). A classification model containing signs, samples and SEO data demonstrated the best model fit (AIC = 72.63), the highest discriminatory power (AUC = 0.79) and classified players with the greatest accuracy (78%) for (de)selection purposes. The use of signs, samples and SEO can support (de) selection decisions but fails to fully represent the complexity of the (de)selection process.

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Introduction

Competition to identify and develop young soccer players has become increasingly important for professional soccer academies in the UK, given the possible financial constraints and barriers to the recruitment of professional players. As part of these identification and development processes within youth male academies in the UK, selection, which 'refers to the ongoing process of choosing players *within* the development programme who demonstrate attributes suitable for progression to a future squad or team' (Williams et al., 2020, p. 2), occurs at regular intervals for players already in the academy pathway. Given the complexity of attempting to predict future performance, a key aim of research is to understand and identify potential indicators of (de)selection (i.e., distinguishing between selected and deselected players). Previous research has utilised anthropometric, psychological, physiological, technical, and tactical assessments to identify players who are selected to progress (e.g., Höner & Votteler, 2016; O'Connor et al., 2016). This multidisciplinary approach introduces a range of factors that are potential indicators of future success or antecedents of high-level performance (Williams et al., 2020), however, these indicators are suggested to yield typically low prognostic validity (Güllich & Larkin, 2023). Whilst classifying these predictors within a specific discipline is the traditional approach within research and practice (e.g., Williams et al., 2020), an alternative approach is to develop a deeper understanding of how these predictors are assessed and emerge in practice (Barraclough et al., 2022; Bergkamp et al., 2019; Den Hartigh et al., 2018).

Measuring soccer performance objectively can be extremely difficult (if not impossible) due to its multifaceted nature and the intricate combinations of attributes required for soccer-specific skills (Buekers et al., 2015). One approach in research has been to assess what are deemed to be underpinning or indicative factors of soccer performance itself (e.g., 30-metre sprint speed (Forsman et al., 2016; Fortin-Guichard et al., 2022). This can be termed as a signs approach (Den Hartigh et al., 2018; Wernimont & Campbell, 1968), as skills or traits measured in this way are suggested to provide a sign or indicator of the criterion behaviour (actual soccer performance). Sign measures are often assessed in isolated circumstances, away from soccer performance (Barraclough et al., 2022) and could be challenged for their disconnect. For example, using a '*wall pass*' test (Figueiredo et al., 2009) as a sign of a player's technical ability may have limited transfer to performing sport-specific skills in the dynamic and chaotic nature of the sport itself. Although some research challenges the ecological validity and the effectiveness of signs as valid indicators of future potential (Craig & Swinton, 2021; Deprez et al., 2015), empirical evidence supports using the signs approach with more successful players

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demonstrating advantages in signs assessments (e.g., Murr et al., 2018; Sarmento et al., 2018).

Considering these potential issues, it has been suggested that a more ecologically valid approach is to also take samples of actual soccer performance, as these are expected to provide measures that are more representative of the prediction of future soccer performance (Bergkamp et al., 2019; Den Hartigh et al., 2018). For example, assessing a player's technical ability for the skill of passing would take a sample of their actual passing ability from match situations (e.g., a percentage of completed/accurate passes). A sample approach is thus theorised to provide greater predictive value, particularly in homogeneous groups (Bergkamp et al., 2019; Den Hartigh et al., 2018). Therefore, using samples seems a suitable tool for player profiling in groups such as male youth soccer players, but should also be combined with further multidisciplinary information (e.g., signs and subjective information; Barraclough et al., 2022; Bergkamp et al., 2019).

Notwithstanding its theoretical utility, the use of samples within soccer literature relating to (de)selection is limited (Bennett et al., 2018; Kelly, Wilson, et al., 2020). Studies that have employed a samples approach have typically assessed differences in player's performances or skill levels using notational analysis (i.e., event data; Bennett et al., 2018; Kelly, Williams, et al., 2020), with such research highlighting how soccer-specific samples of performance can be valid tools as part of (de)selection processes. However, such an approach may not be feasible across the wider landscape, particularly considering differences in academies and other organisations, and across different levels of youth participation.

Whilst assessments made using signs or samples approaches have previously been proven to differentiate between higher and lower performing players (Forsman et al., 2016; Gonaus & Müller, 2012; Höner & Feichtinger, 2016), (de) selection decisions typically rest in the hands of experienced coaches, who evaluate players using their own subjective expert opinion (SEO). It is widely acknowledged that a coach's SEO is commonly the deciding factor in (de)selection processes, choosing who will be retained or released from the system. Whilst a coach's SEO is a valuable source of information, demonstrating the ability to discriminate between player performances (Fenner et al., 2016; Hendry et al., 2018), only limited studies exist regarding its efficacy for (de)selection processes (Dugdale et al., 2021; Höner et al., 2021; Kite et al., 2024; O'Connor et al., 2016). It has been suggested that a coach's SEO, when used in isolation, may lead to biased judgements, as a coach's decision-making is borne from their own taste, knowledge, experience, and intuition (Christensen, 2009; Roberts et al., 2021). These factors likely differ from coach to coach, each of whom may be subject to several individual (sub)conscious biases (Hill, Scott, Malina, et al., 2020; Johnston & Baker, 2020).

Given the contrast in findings across signs, samples and SEO approaches, research has recommended that (de)selection practices should attempt to utilise all three data sources, providing a more comprehensive player profile. Objective, signs and samples data may challenge or support a coach's SEO enhancing player (de)selection (Reilly et al., 2000; Williams et al., 2020). A recent review (Güllich & Larkin, 2023) has supported this concept, suggesting utilising both objective (e.g., physical, technical, psychological assessments; signs) and subjective (e.g., coach ratings; SEO) player information performs better when combined than when used in isolation. For example, Höner et al. (2021), in a large sample of U12-U15 German youth players, demonstrated that future selected players outperformed deselected players in objective (e.g., sprint, dribbling, ball control, juggling) and subjective (e.g., kicking skills, endurance, individual tactical skills, psychosocial skills) assessments, and that a model combining these assessments, outperformed using models with objective or subjective assessments in isolation. Similarly (Sieghartsleitner et al., 2019), demonstrated that coaches' subjective assessments of in-game performance combined in a model with multidimensional objective assessments (e.g., motor performance, technical skills, psychological characteristics, maturation, familial support, training history) was superior in predicting U14 Swiss players obtaining a professional contract at the U19 level.

With this in mind, the current study used an exploratory design and aimed to examine the potential predictors of (de) selection within players from a single male youth soccer academy in the UK, utilising integrated (objective and subjective) data sources consisting of signs, samples, and SEOs. To the author's knowledge, this is a novel approach, modelling and employing multidimensional data from multiple sources, allowing the identification of signs, samples, or SEO as valid predictors in the classification of (de)selected players.

Method

Research design

Data was collected on elite youth male soccer players registered to a single Category 1 soccer academy in the UK across the 2019/20, 2020/21, 2021/22 and 2022/23 seasons. The study received ethical approval from Leeds Beckett University (Ethics Application No: 119713). Data included objective match analysis statistics (samples), subjective coach ratings of match performance (SEO), and objective physical profiling data (signs).

At the end of each season, classification for (de)selection was operationalised as players being retained or released by the club (i.e., selected or deselected). Selection represented player's transitioning from the U16 to the U18 age group or transitioning from the U18 to the U21 age group. It is common practice within UK academies for players within the U18 age group to represent those aged both U17 and U18, and within the U21 age group to represent those aged U19, U20 and U21, leading to large squad sizes. Given that players could be awarded either a scholarship or professional contract during their transition regardless of their age group or squad, progression and selection can often be non-linear (e.g., players (de)selected at different periods) and as such criteria for (de)selection were hypothesised to be similar and data were aggregated to represent a single decision. Deselection represented players who were released from the club (no contract offer). The lead and assistant age-group coaches, along with key stakeholders, including the academy head of performance, the academy head of coaching, and the academy manager, were all involved in player (de)selection decisions as per normal procedures within the academy.

Participants

Fifty-eight male academy players within the U16 ($n = 20$) and U18 ($n = 38$) age groups across the four seasons with complete data were included for analysis. The sample represented the latter stages of participation within elite youth soccer academies, as these age groups signify key transition points in the academy pathway, where players receive scholarship contracts (U16) or professional contracts (U18 (The Premier League, 2011). Within this sample, the (de)selection processes described above resulted in 39 selected (U16: $n = 18$, U18: $n = 21$) and 24 deselected (U16: $n = 7$, U18: $n = 17$) players across the four seasons.

Measures

Signs (physical profiling data)

As part of normal procedures within the academy, objective physical profiling data were routinely collected (~3× per season) under a national profiling strategy (The Premier League, 2011). Physical profiling was conducted separately (i.e., isolated) following standardised procedures (The Premier League, 2011). The physical profiling data were considered signs of performance (i.e., distinct measures of physical attributes that underpin the ability to perform soccer-specific skills).

Physical profiling included a countermovement vertical jump (CMJ; Glatthorn et al., 2011), a 20-metre linear sprint (20 m; Murtagh et al., 2018), a modified version of the 505 change of direction test (505 (Taylor et al., 2019),; and a one-kilometre running time-trial (1 KM; Clancy et al., 2020). These tests have previously demonstrated acceptable test-retest reliability with intraclass correlation coefficients (ICC) greater than 0.75, and coefficients of variation (CV) of less than 5% (20 m; Altmann et al., 2019; 1 KM; Clancy et al., 2020, p. 505; Dugdale et al., 2019; CMJ; Rago et al., 2018). In addition, these tests are commonly used in youth male soccer (e.g., Emmonds et al., 2016; Murtagh et al., 2018). Physical profiling was conducted in the following order: CMJ (3 repetitions), 20 m (3 repetitions), 505 (2 repetitions per leg) and 1 KM (1 repetition) and were conducted by practitioners from the club's physical development department in conjunction with staff provided by the Premier League. All physical profiling was conducted on an indoor 3 G playing surface, a minimum of 48 hours following competitive match play and after a standardised warm-up of light jogging, dynamic stretching and progressive familiarisation attempts. Verbal instructions and demonstrations were provided to players, and the tests were familiar to the players, forming a regular part of their annual physical development programme. The best score from each test, at any of the corresponding testing points across the season, was chosen as a representation of a player's best overall physical ability and used for subsequent analysis.

Samples (match analysis statistics)

Video footage of players during competitive match play allowed the collection of samples data. All matches were performed on grass, however, environmental and surface conditions may have varied depending on the stage of the season. Participants played a mean (±SD) of 14.2 (±10.8) matches within a season. Specialist software used by trained analysts at Opta© provided match analysis statistics for every competitive match across the relevant season. Opta© adopted technical definitions of specific soccer events that were used to code individual soccer behaviours for each player in each competitive match, consistent with soccer literature (Harkness-Armstrong et al., 2023; Liu et al., 2013; Varley et al., 2017).

As the match analysis statistics valued within each academy will vary based on playing styles and philosophies, the data used in the current study reflected the academy performance analysis department's existing protocols. The event data used consisted of the following soccer actions: number of goals, number of shots on target, shots on target percentage, number of passes, pass completion percentage, number of assists, number of crosses, cross accuracy percentage, number of aerial duels, successful aerial duel percentage, number of ground duels, successful ground duel percentage, and number of interceptions. These actions have previously demonstrated high reliability (ICC ≥0.88) when coded by different operators (inter-operator reliability) using the Opta© system (Liu et al., 2013). An average score for each soccer action across the entire season was included for analysis within the study. The accumulation of

Table 1. Technical definitions of the soccer-specific actions used for match analysis statistics.

Soccer-Specific Action	Technical Definition
Goal	Attributing a goal to the goal-scoring player.
Shot on Targets	A deliberate attempt to score that is on target.
Shots on Target Percentage	A calculation of shots on target divided by all shots.
Pass	A deliberate attempt to pass the ball directly to a teammate.
Pass Completion Percentage	A calculation of successful passes divided by total attempted passes.
Assist	The final touch from a teammate, which leads to the recipient of the ball scoring a goal.
Cross	A ball played from a wide position targeting a teammate(s) in a central area within proximity to the goal.
Cross Accuracy Percentage	A calculation of successful crosses divided by total attempted crosses.
Aerial Duel	This is where two players challenge in the air against each other. The player that wins the ball is deemed to have won the duel.
Successful Aerial Duel Percentage	A calculation of aerial duels won divided by total aerial duels.
Ground Duel	A ground duel is a 50–50 contest between two players of opposing sides in the match when the ball is not in the air.
Successful Ground Duel Percentage	A calculation of ground duels won divided by total ground duels.
Interception	This is where a player reads an opponent's pass and intercepts the ball by moving into the line of the intended pass.

Table 2. Overview of the included predictors in the seven logistic regression models.

Model	Predictors Included
Model 1 (Signs Model)	Mean z-value of physical attributes (signs).
Model 2 (Samples Model)	Mean z-value of match analysis statistics (samples).
Model 3 (SEO Model)	Z-value of coach's seasonal mean match rating (SEO).
Model 4 (Signs and Samples Model)	Combination of models 1 and 2.
Model 5 (Signs and SEO Model)	Combination of models 1 and 3.
Model 6 (Samples and SEO Model)	Combination of models 2 and 3.
Model 7 (Full Model – Signs, Samples and SEO)	Mean z-values of signs, samples, and z-value of SEO.

event frequencies (e.g., number of shots on target) was normalised to a 90-minute average to represent frequencies relevant to a full match (i.e., number of shots on target per 90 minutes). The soccer-specific actions used (13 in total) and their technical definitions are displayed in Table 1.

Subjective expert opinion (coach match ratings)

Coaches' SEOs were used to provide match ratings for each player for each competitive match. The lead coach would assign a rating to each player based on their own opinion of a player's match performance, relative to other players of a similar age and skill level. Ratings were provided following each match, with players having to have played at least 30 minutes per match. Ratings were made independently based solely on the lead coach's SEO, with no input from other staff members or data. Given players represented different age groups and data were collected across numerous seasons, not all ratings were made by the same coach, with a total of 4 coaches being involved across the data collection period (2 at U16 and 2 at U18). Such coach-based ratings have been utilised in previous research (Hill et al., 2021; Hill, Scott, McGee, et al., 2020) and suggests coach subjective ratings demonstrate acceptable intra-rater reliability ($.50 \le r_s \le .85$; Jokuschies et al., 2017) but poor inter-rater reliability (ICC = 0.14, 95%CI = −0.04–0.39 (Bergkamp et al., 2022).; Internal estimates demonstrated slight to moderate inter-rater reliability (α = 0.34, CI = 0.12–0.53).

Ratings were conducted on a 7-point scale, with the following descriptors: 1 – below academy standard, 2 – approaching academy standard, 3 – meeting academy standard, 4 – exceeding academy standard, with 0.5 increments between each descriptor for players falling between standards. Consequently, for each competitive match a player participated in, they had a corresponding match rating between 1 and 4. A seasonal average match rating was used for analysis as it represented general performance over multiple matches.

Statistical analysis

Initial analysis investigated group-level differences between the selected and non-selected players. Firstly, predictors were checked to be normally distributed using the Shapiro-Wilk test and homogeneity of variances checked using Levene's test (Field, 2017). A MANOVA, including all predictors, was conducted to evaluate between-group differences. As sample sizes in each group (selected and deselected) were > 20, multivariate normality was presumed (Tabachnick & Fidell, 2013). Post-hoc analysis examined the between-group differences for each dependent variable. For predictors that failed to satisfy assumptions of normality, Wilcoxon's rank-sum tests were conducted to evaluate the differences between the (de)selected players. Employing both multivariate and univariate approaches was deemed beneficial as multivariate analysis (e.g., MANOVA) accounted for the interrelationships among dependent variables and provided an evaluation of overall effects, while the univariate analysis permitted insight into differences between individual dependent variables in (de)selected players.

Secondly, a series of binary logistic regression models were implemented to model (de)selection based on predictors within the different assessment approaches (i.e., signs, samples, and SEO) rather than predictor domains (e.g., physical, technical, tactical, psychological). No significant main or interaction effects were found when adding age group or season into the models, and so data were aggregated for simplicity and to enhance interpretability. Additionally, a small number of players participating at both U16 and U18 levels were incorporated in the dataset, whilst this could introduce dependencies within the data, incorporating random effects into the models for the inclusion of these participants did not subsequently alter results, and so simpler model structures were chosen.

Seven models were created, using combinations of the signs, samples, and SEO data, transformed into composite scores (mean of z-scores). Such composite scores are frequently utilised in both research and practice (Sieghartsleitner et al., 2019; Turner et al., 2019) and can address issues regarding multicollinearity as well as complement the interpretation of information regarding multiple related predictors (Song et al., 2017). Details of each model are shown in Table 2.

Model comparisons were assessed via likelihood-ratio tests, the AIC, and Nagelkerke's R^2 to select a final model. Model coefficients were assessed via the Wald statistic, and the classification quality of the final model was investigated using receiver operating characteristics (ROC). ROC permitted the evaluation of a threshold for classification of (de)selection through calculating and maximising sensitivity (true positive rate; i.e., proportion of correctly classified selected players) and 1-specificity (false positive rate; i.e., proportion of deselected players incorrectly classified as selected) for each possible threshold value, known as the Youden index (Youden, 1950). Additionally, ROC was used

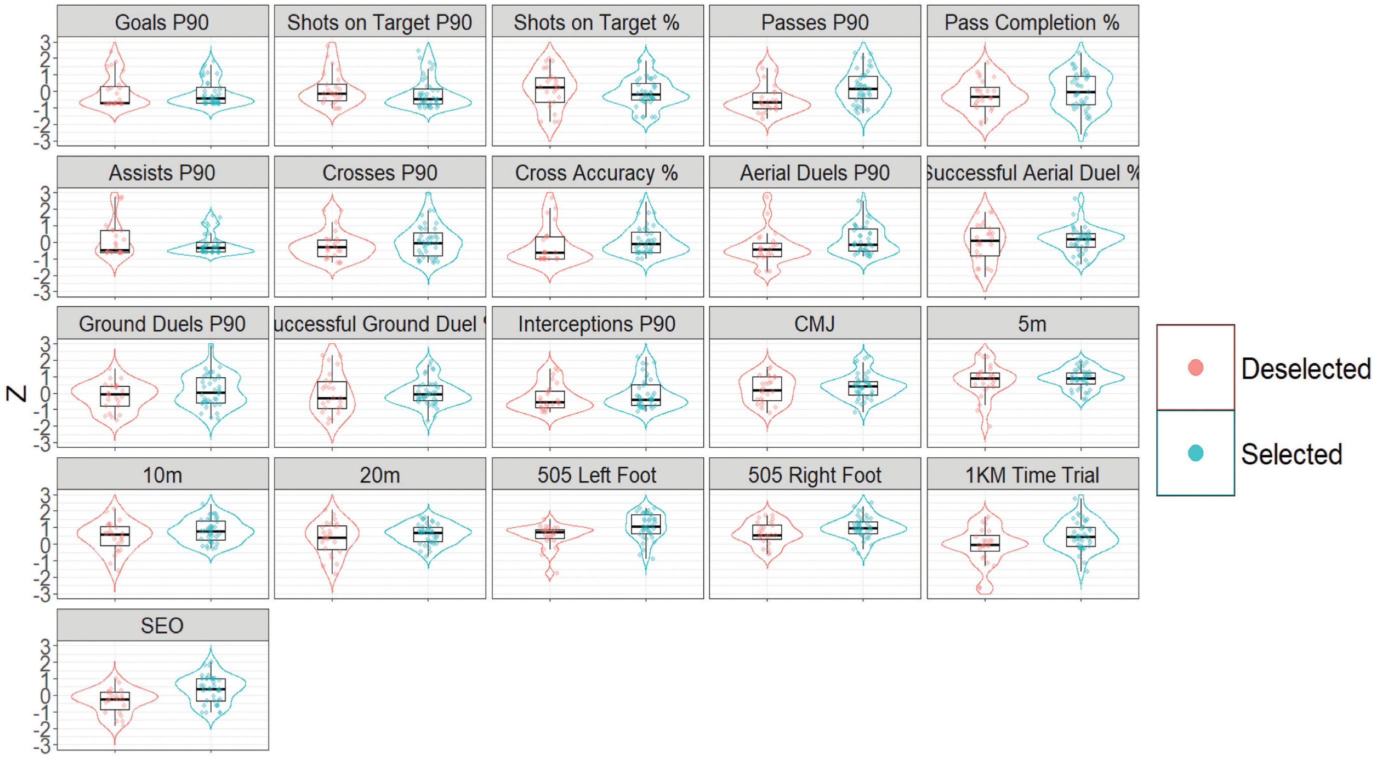

Figure 1. Distribution, median, first and third quartiles (the 25th and 75th percentiles) of each dependent variable.

to assess the overall diagnostic performance of the final model, through assessing the area under the curve (AUC) and model accuracy (total percentage of correctly classified players). Where applicable, the level of significance was set at $p < 0.05$ for all tests. All logistic regression analyses were conducted using a binary outcome of selected versus deselected, as the dependent variable. Data analyses were conducted with the open-source software R Studio (R Core Team, 2023).

Results

Group-level differences

Figure 1 shows the visualisation of z-score data distributions separated by selection status (selected vs. deselected), for each dependent variable.

Initial MANOVA analysis revealed a significant difference between the groups of selected and deselected players ($V = 0.53$, $F(21, 41) = 2.20$, $p < 0.05$, partial $\eta2 = 0.53$). Post-hoc power analysis revealed that the study was sufficiently powered to detect large effects (Cohen's $d = 0.83$), with 80% power at a significance level of 0.05, but that it may be underpowered to detect smaller effects. This may explain the failure to observe statistically significant differences in some variables despite observing some moderate effect sizes (e.g., 505 right foot). Post-hoc analysis using Pillai's trace revealed significant differences for SEO match ratings ($p < 0.001$) with selected players demonstrating a higher match rating. Table 3 presents the non-standardised means (±SD), z-scores and post-hoc test results for each predictor, by (de)selection.

Results for non-normally distributed predictors revealed significant differences between selected and de-selected players for 505 left foot test ($p = 0.006$), passes (per 90 minutes) ($p = 0.02$),

Table 3. Descriptive statistics of mean z-scores, ANOVA results and non-standardised means.

	Selected		Deselected	
Predictor	Mean ± SD	Z-Score ± SD	Mean ± SD	Z-Score ± SD
Signs				
CMJ (cm)	39.7 ± 3.8	0.42 ± 0.76	38.9 ± 4.1	0.22 ± 0.80
5m (s)	0.93 ± 0.03	0.86 ± 0.61	0.94 ± 0.06	0.73 ± 1.03
10m (s)	1.64 ± 0.05	0.81 ± 0.69	1.66 ± 0.06	0.45 ± 0.92
20m (s)	2.86 ± 0.07	0.61 ± 0.61	2.89 ± 0.12	0.34 ± 1.01
505 Right Foot (s)	2.36 ± 0.06	1.00 ± 0.66	2.39 ± 0.07	0.64 ± 0.69
1KM Time Trial (s)	190 ± 11.7	0.49 ± 0.88	196 ± 14.0	−0.07 ± 1.11
Samples				
Pass Completion (%)	73 ± 8	0.02 ± 1.14	71 ± 7	−0.03 ± 0.98
Ground Duels (n/90)	11.1 ± 1.0	0.14 ± 0.99	9.6 ± 0.8	−0.19 ± 0.83
SEO				
Match Rating (AU)	2.84 ± 0.40	0.36 ± 0.83***	2.45 ± 0.40	−0.46 ± 0.92

Significant differences in ANOVA comparisons denoted by * = p < 0.05, ** = p < 0.01, *** = p < 0.001.

Table 4. Wilcoxon rank-sum test results and median (IQR) values.

	Selected		Deselected	
Predictor	Mean Rank	Median (IQR)	Mean Rank	Median (IQR)
Signs				
505 Left Foot (s)	27.0	2.35 (0.10)**	40.1	2.40 (0.07)
Samples				
Goals (n/90)	31.8	0.1 (0.2)	32.3	0.0 (0.3)
Shots on Target (n/90)	29.8	0.3 (0.5)	35.6	0.5 (0.5)
Shots on Target (%)	29.9	42 (26)	35.4	57 (31)
Passes (n/90)	36.2	24.8 (16.0)*	25.2	16.4 (12.5)
Assists (n/90)	31.5	0.1 (0.1)	32.9	0.0 (0.2)
Crosses (n/90)	33.8	0.9 (0.7)	29.0	0.7 (0.7)
Cross Accuracy (%)	35.6	17 (22)*	26.2	0 (22)
Aerial Duels (n/90)	35.7	1.3 (1.1)*	26.1	1.0 (0.9)
Successful Aerial Duels (%)	31.5	50 (19)	32.9	50 (33)
Successful Ground Duels (%)	33.3	49 (11)	29.9	46 (18)
Interceptions (n/90)	33.0	1.6 (2.0)	30.3	1.3 (2.9)

Significant differences in Wilcoxon rank-sums denoted by * = p <0.05, ** = p <0.01, *** = p <0.001.

Table 5. Binary logistic regression classification model comparisons.

	Model Statistics				
	Likelihood-Ratio Tests			Model Fit	
Classification Model	χ2	df	p-value	AIC	Nagelkerke's R^2
Model 1 (Signs Model)	6.37	1	<0.05	81.36	0.13
Model 2 (Samples Model)	2.19	1	0.14	85.54	0.05
Model 3 (SEO Model)	12.25	1	<0.001	75.48	0.24
Model 4 (Signs and Samples Model)	9.26	2	<0.01	80.47	0.19
Model 5 (Signs and SEO Model)	16.80	2	<0.0001	72.93	0.32
Model 6 (Samples and SEO Model)	14.30	2	<0.001	75.43	0.28
Model 7 (Full Model – Signs, Samples and SEO)	19.10	3	<0.001	72.63	0.36

percentage of accurate crosses (p = 0.04), and aerial duels (per 90 minutes; p = 0.04), with selected players scoring higher for each predictor (see Table 4).

Classification models

Results of the binary logistic regression classification models are displayed in Table 5. Results demonstrate that all models, with the exception of Model 2 (Samples Model), outperform the null (intercept only) model ($p < 0.05$). Model AIC values ranged from 85.5 to 72.6. Model 5 (AIC = 72.93) and Model 7 (AIC = 72.63) had the lowest AIC values. Nagelkerke's R^2 scores for the logistic regression models ranged from 0.05 to 0.36, with Model 7 (Nagelkerke's $R^2 = 0.36$) demonstrating the highest explanatory power of any model. As such, Model 7 (AIC = 72.63, Nagelkerke's $R^2 = 0.36$) was chosen as the final model. Additionally, although some dependency was present in the data (i.e., players having data points at both U16 and U18), this was minimal (<10% of the data) and a simpler fixed effects only model was chosen based on a superior model fit (AIC 72.63 vs. 74.55). Further, likelihood ratio tests demonstrated no significant improvement from incorporating random effects for participants into the model. Therefore, a fixed-effects only model was chosen as a more parsimonious, interpretable model.

The statistics for Model 7 parameters are displayed in Table 6, including model coefficients, standard errors, odds ratios and their confidence intervals, and significance values for each individual predictor. Only the composite scores for Signs ($p < 0.05$) and SEO ($p < 0.01$) showed a significant association with (de)selection, indicating that changes in those predictors have a statistically meaningful impact on classification.

Odds ratios suggest that for the coaches' SEO, a one-unit increase in the z-score for seasonal match rating would equate to just under three times higher odds of being a selected player. Equally, a one-unit increase in the composite score for signs is associated with approximately three times higher odds of being a selected player. The samples predictor was non-significant. The interval for the 95% CI of the samples predictor was both below and above 1, highlighting uncertainty about how an increase in this predictor changes the odds of a player being classified as selected versus deselected.

Receiver operating characteristics (ROC)

The ROC graph for the full model is displayed in Figure 2.

The AUC from the ROC curve for Model 7 was 79.4% ($p < 0.001$), indicating acceptable discriminatory power over random classification (Hosmer et al., 2013). Sensitivity and

Table 6. Model 7 (full Model) parameter statistics.

						95% Confidence Interval	
Predictor	Estimate	SE	z-statistic	p-value	Odds Ratio	Lower	Upper
Signs	1.21	0.59	2.04	<0.05	3.34	1.13	11.86
Samples	1.28	0.88	1.45	0.15	3.59	0.70	23.53
SEO	1.06	0.39	2.73	<0.01	2.87	1.45	6.71

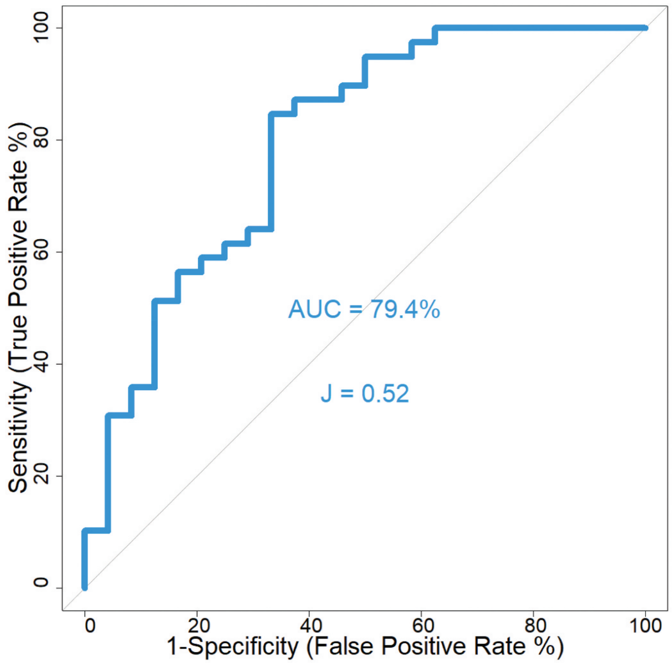

Figure 2. ROC curve displaying Model 7 performance at all classification thresholds.

1-specificity of the full model (Model 7), estimated the Youden index (optimal threshold value) to be J = 0.52, leading to an overall model accuracy of 78%. To explain, for each prediction made by the model of a player being classified as selected or deselected, those whose predicted probabilities of being classified as selected, which were greater than 0.52 (52% chance), were defined as such. This led to the model accurately classifying 49 out of the 63 players. The confusion matrix in Figure 3 depicts the sensitivity (85%), specificity (67%) and accuracy for the model (78%), highlighting the (in)correct classifications from the model's predictions against the reference (actual) classifications.

Discussion

This study aimed to examine the potential predictors of (de) selection within elite youth male academy soccer players through analysing a combination of objective and subjective data sources consisting of signs, samples, and SEOs. Our findings demonstrated statistically significant differences overall between selected and deselected players, across signs, samples, and SEO. Modelling of the data demonstrated that a full model, consisting of signs, samples and SEO data, could accurately classify 78% of (de)selection decisions. Significant coefficients for signs and SEO data suggested that more physically capable players, with perceived greater match performance, were more likely to be classified as selected players.

Findings revealed significant differences between selected and deselected players for the 505 left foot test, number of attempted passes (per 90 minutes), mean percentage of accurate crosses, number of aerial duels (per 90 minutes) and mean match rating (as assessed via a coach's SEO), with selected players outperforming their deselected peers in these predictors. However, it should be noted that group-level differences may be inadequate in explaining the intricate differences between individual players that may have contributed to their (de)selection decision. The diversity of predictors displaying statistically significant differences between the groups is perhaps in agreement with the majority of the literature (e.g., (Huijgen et al., 2014; Vaeyens et al., 2006), highlighting that no single variable has the explanatory power to predict the outcomes in such processes, and that adopting a frequently recommended multidisciplinary approach may be best practice

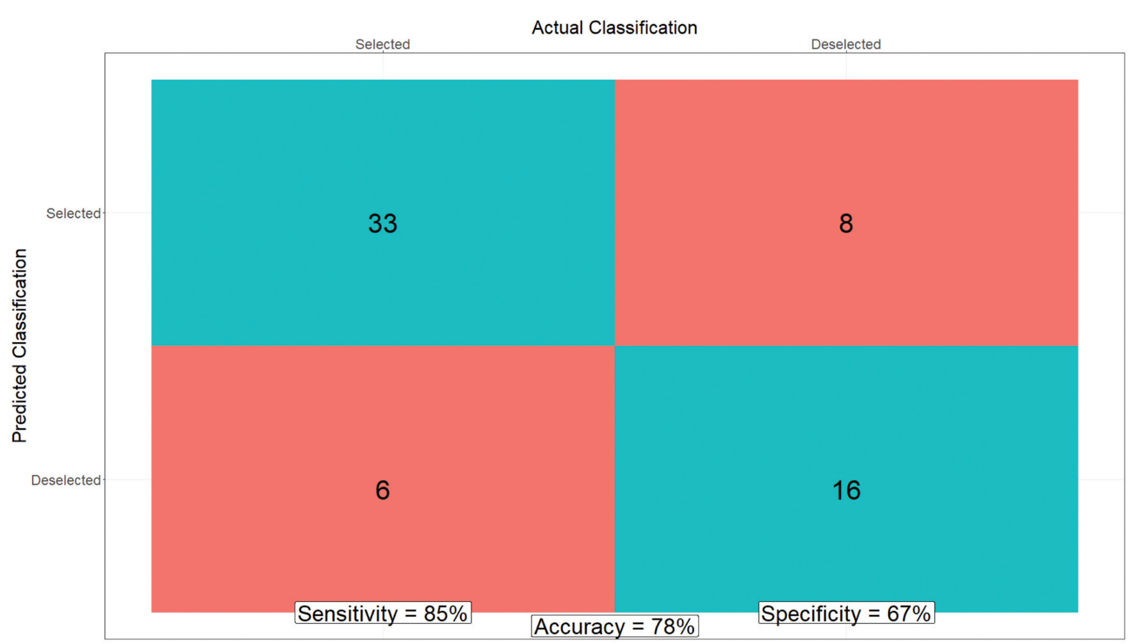

Figure 3. Confusion matrix from Model 7, displaying actual and predicted classifications between selected and deselected players. Sensitivity represents the true positive rate (correctly predicted selected players), with specificity representing the true negative rate (correctly predicted deselected players). Accuracy denotes the overall correct classification percentage of the model.

(Forsman et al., 2016; Sieghartsleitner et al., 2019; Williams et al., 2020).

Signs

Significant differences between the groups from the signs data (physical attributes) demonstrated that only the 505 left foot test differed between the groups. This finding is in agreement with previous research highlighting change of direction (COD) ability as a key physical attribute required for soccer performance (Dos Santos et al., 2022; Jeffreys, 2008; Morgan et al., 2022), that can discriminate between performance levels (Mujika et al., 2009), despite potential issues relating to the reliability of such tests (Dugdale et al., 2020; Taylor et al., 2019). No further differences between the selected and deselected players were found in the present study for signs data, which contrasts previous research suggesting objective signs data do differentiate between (de)selected players within homogeneous samples (e.g., Höner et al., 2021; Huijgen et al., 2014). This perhaps suggests a relatively consistent level of athleticism across the sample of players used and may also highlight the multifactorial nature of (de)selection, where further signs data (e.g., technical, tactical, and psychological skills) may have a more significant influence on the selection decision.

Samples

The lack of significant differences between the groups for samples data (match analysis statistics) provided a contrasting finding to previous research (Kelly, Wilson, et al., 2020), with only passes (per 90 minutes), percentage of accurate crosses and the number of aerial duels (per 90 minutes) showing significant differences. A higher median number of attempted passes in selected players is consistent with previous findings (Bennett et al., 2018; Waldron & Murphy, 2013), and provides further support for the importance of passing as a technical action in match play, with successful senior teams generally exhibiting more passes and higher rates of pass completion (Bradley et al., 2013; Rampinini et al., 2009). Deselected players outperformed selected players in terms of cross accuracy and number of aerial duels, which is difficult to interpret, particularly without knowledge of player positions and context within individual games, which may have impacted involvement in these specific actions. Equally, without knowing the nature and context of individual matches, or the impact of samples data on a match, data derived from samples can be difficult to interpret and may need complementing through subjective sources of data such as the coach's SEO.

SEO

The coaches' SEOs proved to be a significant difference between the selected and deselected players, confirming the impact of subjective data on the processes for (de)selection. This finding is in agreement with previous research that highlights coaches' subjective ratings of players contribute to (de) selection (Kelly et al., 2022; Sieghartsleitner et al., 2019), and is perhaps unsurprising when considering that the coaches who are responsible for providing match ratings are also key stakeholders in the (de)selection process. In contrast, some research has demonstrated that a coach's SEO may be inconclusive in determining selection status in elite youth soccer players (Kite et al., 2024), suggesting that the proximity of ratings to the (de) selection decisions may affect results. Equally, when considering a coach's SEO, the ratings made by coaches and the (de) selection decision itself are possibly confounded by (sub)conscious biases (Barraclough et al., 2024; Hill et al., 2023; Johnston & Baker, 2020).

Modelling (de)selection outcome

Considering the study aims, the full model utilising all data sources (Signs, Samples, SEO) and combined objective and subjective data was the best classifier of (de)selection. The findings emphasise the benefits of a multidisciplinary approach and the practical utility of using both objective and subjective data during (de)selection processes (Dugdale et al., 2021; Höner et al., 2021; Sieghartsleitner et al., 2019). Relatively large CIs were produced for the model coefficients, possibly due to the small sample size, highlighting some variability in the ORs. However, whilst the final full model (Model 7) only slightly outperformed the combination of signs and SEO in Model 5, the inclusion of the samples data improved the model fit. Such findings are in keeping with previous research advocating the use of objective and subjective multidimensional data sources in the creation of classification models (Höner et al., 2021; Sieghartsleitner et al., 2019).

Despite the inclusion of samples data, it failed to reach significance as a predictor in the model. This lack of significance may be due to the technical performance similarities between players within the academy. Overall, despite the statistically significant impact of the signs data and SEO data as predictors, the full model's accuracy only reached 78%, meaning 14 players were incorrectly classified as either selected or deselected, highlighting the inability of data alone to fully represent the complexity involved in the (de)selection process (Baker et al., 2018; Den Hartigh et al., 2018).

Limitations

This study provided a novel approach to examining real-world (de)selection decisions in an elite youth male soccer academy. Whilst the results of the study highlight the utility of using both objective and subjective sources in understanding (de)selection decisions, some methodological limitations were present within the study. Firstly, the use of retrospective data to establish (de)selection classification fails to consider the importance of longitudinal changes (Barraclough et al., 2022; Johnston et al., 2018; Till & Baker, 2020). Equally, such an approach does not provide confirmation of the rationale for the (de) selection decisions, rather, it provides a theoretical explanation and insight into such processes.

It is important to highlight that the coaches used in the current study were involved in both providing their subjective match ratings (i.e., SEO) and the (de)selection decision itself. As discussed previously, the ratings and the selection decision may therefore be related and are possibly confounded by (sub)conscious biases (e.g., Barraclough et al., 2024; Hill et al., 2023; Johnston & Baker, 2020). However, such a situation is a representative of typical practice in real-world applied environments.

Further, the sample size from within a single academy reduces the generalisability of the results. For example, different academy environments may demonstrate unique organisational structures, environments, and philosophies, which may influence or alter the way their (de)selection processes occur. Equally, the sample utilised within the study had already been 'selected' for inclusion within an academy, likely leading to a more homogeneous sample. This *restriction of range* (Bergkamp et al., 2019) may be characterised by minimal differences between players within specific squads, including not accounting for positional differences, perhaps explaining only 5 of 21 observed predictors displaying statistically significant differences between selected and deselected players.

Additionally, whilst our analysis included 5 players with data points at both age groups, no improvement was found in model fit when trying to incorporate possible dependency or correlations between the data. Finally, as the best score for each player and predictor was utilised in the analysis, the effects of potential development or changes in scores were not accounted for, which may be an equally important avenue for future research.

Practical applications

This study may inform youth sports organisations utilising similar (de)selection processes. The classification models employed are a potentially effective demonstration of the application of data within such a setting. Our findings suggest that more physically capable players (signs), perceived to be performing better in matches (SEO), had increased odds of being classified as a selected player. Such findings may provide further insight and reflection into (sub)conscious biases involved surrounding (de)selection processes. Additionally, the statistical significance of the coaches' SEOs and the signs data within the full model highlight how both objective and subjective data may be associated with (de)selection decisions. Findings of the current study can be applied practically to raise awareness, promote discussion, and demonstrate the potential for reflective practice in relation to the rationale for (de)selection decisions in youth sports organisations.

Conclusion

This study showed that a combination of signs, samples and SEO data provides some explanation when classifying (de) selected elite youth male soccer players. Overall, a combination of both objective and subjective signs, samples and SEO information provided the highest accuracy for classifying (de)selection outcome. The use of physical attribute data combined with a coach's SEO demonstrated significant associations with the (de)selection decision. Coaches and practitioners should reflect on their current (de)selection practices and consider the potential use of multiple multidisciplinary data sources to augment decision-making. Further, the potential of machine learning techniques and analysis should be acknowledged to explore the understanding of (de)selection processes.

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References

Altmann, S., Ringhof, S., Neumann, R., Woll, A., & Rumpf, M. (2019). Validity and reliability of speed tests used in soccer: A systematic review. *PLOS ONE*, *14*(8), e0220982. https://doi.org/10.1371/journal.pone.0220982

Baker, J., Schorer, J., & Wattie, N. (2018). Compromising talent: Issues in identifying and selecting talent in sport. *Quest*, *70*(1), 48–63.

Barraclough, S., Till, K., Kerr, A., & Emmonds, S. (2022). Methodological approaches to talent identification in team sports: A narrative review. *Sports*, *10*(6), 81. https://doi.org/10.3390/sports10060081

Barraclough, S., Till, K., Kerr, A., & Emmonds, S. (2024). Exploring the relationships between potential, performance, and athleticism in elite youth soccer players. *International Journal of Sports Science & Coaching*, *19*(6), 2424–2437. https://doi.org/10.1177/17479541241270192

Bennett, K. J. M., Novak, A. R., Pluss, M. A., Stevens, C. J., Coutts, A. J., & Fransen, J. (2018). The use of small-sided games to assess skill proficiency in youth soccer players: A talent identification tool. *Science and Medicine in Football*, *2*(3), 231–236. https://doi.org/10.1080/24733938.2017.1413246

Bergkamp, T. L. G., Meijer, R. R., Den Hartigh, R. J. R., den Frencken, W. G. P., & Niessen, A. S. M. (2022). Examining the reliability and predictive validity of performance assessments by soccer coaches and scouts: The influence of structured collection and mechanical combination of information. *Psychology of Sport & Exercise*, *63*, 102257. https://doi.org/10.1016/j.psychsport.2022.102257

Bergkamp, T. L. G., Niessen, A. S. M., Den Hartigh, R. J. R., den Frencken, W. G. P., & Meijer, R. R. (2019). Methodological issues in soccer talent identification research. *Sports Medicine*, *49*(9), 1317–1335. https://doi.org/10.1007/s40279-019-01113-w

Bradley, P. S., Carling, C., Gomez Diaz, A., Hood, P., Barnes, C., Ade, J., Boddy, M., Krustrup, P., & Mohr, M. (2013). *Match performance and physical capacity of players in the top three competitive standards of English professional soccer human movement science*. Retrieved October 24, 2023, from https://doi.org/10.1016/j.humov.2013.06.002

Buekers, M., Borry, P., & Rowe, P. (2015). Talent in sports. Some reflections about the search for future champions. *Movement and Sports Sciences - Science Et Motricite*, *n° 88*(2), 3–12. https://doi.org/10.3917/sm.088.0003

Christensen, M. K. (2009). "An eye for talent": Talent identification and the "practical sense" of top-level soccer coaches. *Sociology of Sport Journal*, *26*(3), 365–382. https://doi.org/10.1123/ssj.26.3.365

Clancy, C., Green, P., Curnyn, S., Donaldson, E., & Ring, N. (2020). *The concurrent validity and between-session reliability of A, 1000m, time trial for the assessment of aerobic fitness in elite development soccer players*. Retrieved August 30, 2023, from https://sportperfsci.com/wp-content/uploads/2020/05/SPSR96_Clancy-Final.pdf

Craig, T. P., & Swinton, P. (2021). Anthropometric and physical performance profiling does not predict professional contracts awarded in an elite Scottish soccer academy over a 10-year period. *European Journal of*

Sport Science, *21*(8), 1101–1110. https://doi.org/10.1080/17461391.2020.1808079

Den Hartigh, R. J. R., Den Niessen, A. S. M., Frencken, W. G. P., & Meijer, R. R. (2018). Selection procedures in sports: Improving predictions of athletes' future performance. *European Journal of Sport Science*, *18*(9), 1191–1198. https://doi.org/10.1080/17461391.2018.1480662

Deprez, D. N., Fransen, J., Lenoir, M., Philippaerts, R. M., & Vaeyens, R. (2015). A retrospective study on anthropometrical, physical fitness, and motor coordination characteristics that influence dropout, contract status, and first-team playing time in high-level soccer players aged eight to Eighteen years. *The Journal of Strength & Conditioning Research*, *29*(6), 1692–1704. https://doi.org/10.1519/JSC.0000000000000806

Dos Santos, T., Cowling, I., Challoner, M., Barry, T., & Caldbeck, P. (2022). What are the significant turning demands of match play of an English Premier league soccer team? *Journal of Sports Sciences* 40 15 1750–1759 doi:https://doi.org/10.1080/02640414.2022.2109355.

Dugdale, J. H., Arthur, C. A., Sanders, D., & Hunter, A. M. (2019). Reliability and validity of field-based fitness tests in youth soccer players. *European Journal of Sport Science*, *19*(6), 745–756. https://doi.org/10.1080/17461391.2018.1556739

Dugdale, J. H., McRobert, A. P., & Unnithan, V. B. (2021). Selected, deselected, and reselected: A case study analysis of attributes associated with player reselection following closure of a youth soccer academy. *Frontiers in Sports and Active Living*, *3*, 633124. https://doi.org/10.3389/fspor.2021.633124

Dugdale, J. H., Sanders, D., & Hunter, A. M. (2020). Reliability of change of direction and agility assessments in youth soccer players. *Sports*, *8*(4), 51. https://doi.org/10.3390/sports8040051

Emmonds, S., Till, K., Jones, B., Mellis, M., & Pears, M. (2016). Anthropometric, speed and endurance characteristics of English academy soccer players: Do they influence obtaining a professional contract at 18 years of age? *International Journal of Sports Science & Coaching*, *11*(2), 212–218. https://doi.org/10.1177/1747954116637154

Fenner, J. S. J., Iga, J., & Unnithan, V. (2016). The evaluation of small-sided games as a talent identification tool in highly trained prepubertal soccer players. *Journal of Sports Sciences*, *34*(20), 1983–1990.

Field, A. (2017). *Discovering statistics using IBM SPSS statistics*. Sage Publications.

Figueiredo, A. J., Gonçalves, C. E., Coelho Silva, M. J., & Malina, R. M. (2009). Characteristics of youth soccer players who drop out, persist or move up. *Journal of Sports Sciences*, *27*(9), 883–891.

Forsman, H., Blomqvist, M., Davids, K., Liukkonen, J., & Konttinen, N. (2016). Identifying technical, physiological, tactical and psychological characteristics that contribute to career progression in soccer. *International Journal of Sports Science & Coaching*, *11*(4), 505–513.

Fortin-Guichard, D., Huberts, I., Sanders, J., Elk, R., van Mann, D. L., & Savelsbergh, G. J. P. (2022). Predictors of selection into an elite level youth football academy: A longitudinal study. *Journal of Sports Sciences*. https://www.tandfonline.com/doi/full/10.1080/02640414.2022.2044128

Glatthorn, J. F., Gouge, S., Nussbaumer, S., Stauffacher, S., Impellizzeri, F. M., & Maffiuletti, N. A. (2011). Validity and reliability of optojump photoelectric cells for estimating vertical jump height. *The Journal of Strength & Conditioning Research*, *25*(2), 556–560. https://doi.org/10.1519/JSC.0b013e3181ccb18d

Gonaus, C., & Müller, E. (2012). Using physiological data to predict future career progression in 14- to 17-year-old Austrian soccer academy players. *Journal of Sports Sciences*, *30*(15), 1673–1682. https://doi.org/10.1080/02640414.2012.713980

Güllich, A., & Larkin, P. (2023). Talent identification and talent promotion. Williams, A.M., Ford, P., Drust, B. In *Science and soccer: Developing elite performers*. (pp. 363–381). Taylor and Francis.

Harkness-Armstrong, A., Till, K., Datson, N., & Emmonds, S. (2023). Influence of match status and possession status on the physical and technical characteristics of elite youth female soccer match-play. *Journal of Sports Sciences*, *41*(15), 1437–1449. https://doi.org/10.1080/02640414.2023.2273653

Hendry, D. T., Williams, A. M., & Hodges, N. J. (2018). Coach ratings of skills and their relations to practice, play and successful transitions from youth-elite to adult-professional status in soccer. *Journal of Sports Sciences*, *36*(17), 2009–2017. https://doi.org/10.1080/02640414.2018.1432236

Hill, M., John, T., McGee, D., & Cumming, S. P. (2023). Beyond the coaches eye: Understanding the 'how' and 'why' of maturity selection biases in male academy soccer. *International Journal of Sports Science & Coaching*, *18*(6), 1913–1928. https://doi.org/10.1177/17479541231186673

Hill, M., Scott, S., Malina, R. M., McGee, D., & Cumming, S. P. (2020). Relative age and maturation selection biases in academy football. *Journal of Sports Sciences*, *38*(11), 1359–1367.

Hill, M., Scott, S., McGee, D., & Cumming, S. (2020). Coaches' evaluations of match performance in academy soccer players in relation to the adolescent growth spurt. *Journal of Science in Sport and Exercise*, *2*(4), 359–366. https://doi.org/10.1007/s42978-020-00072-3

Hill, M., Scott, S., McGee, D., & Cumming, S. P. (2021). Are relative age and biological ages associated with coaches' evaluations of match performance in male academy soccer players? *International Journal of Sports Science & Coaching*, *16*(2), 227–235. https://doi.org/10.1177/1747954120966886

Höner, O., & Feichtinger, P. (2016). Psychological talent predictors in early adolescence and their empirical relationship with current and future performance in soccer. *Psychology of Sport & Exercise*, *25*(July), 17–26. https://doi.org/10.1016/j.psychsport.2016.03.004

Höner, O., Murr, D., Larkin, P., Schreiner, R., & Leyhr, D. (2021). Nationwide subjective and objective assessments of potential talent predictors in elite youth soccer: An investigation of prognostic validity in a prospective study. *Frontiers in Sports and Active Living*, *3*, 638227. https://doi.org/10.3389/fspor.2021.638227

Höner, O., & Votteler, A. (2016). Prognostic relevance of motor talent predictors in early adolescence: A group- and individual-based evaluation considering different levels of achievement in youth football. *Journal of Sports Sciences*, *34*(24), 2269–2278. https://doi.org/10.1080/02640414.2016.1177658

Hosmer, D. W., Jr., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression*. John Wiley & Sons.

Huijgen, B. C. H., Elferink-Gemser, M. T., Lemmink, K. A. P. M., & Visscher, C. (2014). Multidimensional performance characteristics in selected and deselected talented soccer players. *European Journal of Sport Science*, *14*(1), 2–10.

Jeffreys, I. (2008). Movement training for field sports: Soccer. *Strength & Conditioning Journal*, *30*(4), 19–27. https://doi.org/10.1519/SSC.0b013e31818021c1

Johnston, K., & Baker, J. (2020). *Waste reduction strategies: Factors affecting talent wastage and the efficacy of talent selection in sport*. Retrieved August 18, 2023, from

Johnston, K., Wattie, N., Schorer, J., & Baker, J. (2018). Talent identification in sport: A systematic review. *Sports Medicine*, *48*(1), 97–109. https://doi.org/10.1007/s40279-017-0803-2

Jokuschies, N., Gut, V., & Conzelmann, A. (2017). Systematizing coaches' 'eye for talent': Player assessments based on expert coaches' subjective talent criteria in top-level youth soccer. *International Journal of Sports Science & Coaching*, *12*(5), 565–576.

Kelly, A. L., Williams, C. A., Cook, R., Sáiz, S. L. J., & Wilson, M. R. (2022). A multidisciplinary investigation into the talent development processes at an English football academy: A machine learning approach. *Sports*, *10*(10), 159. https://doi.org/10.3390/sports10100159

Kelly, A. L., Williams, C. A., & Wilson, M. R. (2020). Technical testing and match analysis statistics as predictors for age-specific talent development in an English football academy. *International Journal of Performance Analysis in Sport*, *20*(6), 1035–1051. https://doi.org/10.1080/24748668.2020.1824865

Kelly, A. L., Wilson, M. R., Jackson, D. T., & Williams, C. A. (2020). Technical testing and match analysis statistics as part of the talent development process in an English football academy. *International Journal of Performance Analysis in Sport*, *20*(6), 1035–1051. https://doi.org/10.1080/24748668.2020.1824865

Kite, R. J., Noon, M. R., Morris, R., Mundy, P., & Clarke, N. D. (2024). Observations of player (de)Selection within a professional UK soccer academy. *Journal of Science in Sport and Exercise*, *6*(1), 71–80. https://doi.org/10.1007/s42978-023-00222-3

Liu, H., Hopkins, W., Gómez, M. A., & Molinuevo, J. S. (2013). Inter-operator reliability of live football match statistics from OPTA sportsdata.

International Journal of Performance Analysis in Sport, *13*(3), 803–821. https://doi.org/10.1080/24748668.2013.11868690

Morgan, O. J., Drust, B., Ade, J. D., & Robinson, M. A. (2022). Change of direction frequency off the ball: New perspectives in elite youth soccer. *Science and Medicine in Football*, *6*(4), 473–482. https://doi.org/10.1080/24733938.2021.1986635

Mujika, I., Santisteban, J., Impellizzeri, F. M., Castagna, C., In˜, I., & Mujika, I. (2009). *Fitness determinants of success in Men's and Women's football*. Retrieved October 24, 2023, from https://www.tandfonline.com/action/journalInformation?journalCode=rjsp20/

Murr, D., Raabe, J., & Höner, O. (2018). The prognostic value of physiological and physical characteristics in youth soccer: A systematic review. *European Journal of Sport Science*, *18*(1), 62–74.

Murtagh, C. F., Brownlee, T. E., O'Boyle, A., Morgans, R., Drust, B., & Erskine, R. M. (2018). Importance of speed and power in elite youth soccer depends on maturation status. *The Journal of Strength & Conditioning Research*, *32*(2), 297–303.

O'Connor, D., Larkin, P., & Mark Williams, A. (2016). Talent identification and selection in elite youth football: An Australian context. *European Journal of Sport Science*, *16*(7), 837–844. https://doi.org/10.1080/17461391.2016.1151945

The Premier League. (2011). *Elite player performance plan*.

Rago, V., Brito, J., Figueiredo, P., Carvalho, T., Fernandes, T., Fonseca, P., & Rebelo, A. (2018). Countermovement jump analysis using different portable devices: Implications for field testing. *Sports*, *6*(3), 3. https://doi.org/10.3390/sports6030091

Rampinini, E., Impellizzeri, F. M., Castagna, C., Coutts, A. J., & Wisløff, U. (2009). Technical performance during soccer matches of the Italian serie a league: Effect of fatigue and competitive level. *Journal of Science & Medicine in Sport*, *12*(1), 227–233.

R Core Team. (2023). *R: A language and environment for statistical computing*.

Reilly, T., Williams, A. M., Nevill, A., & Franks, A. (2000). A multidisciplinary approach to talent identification in soccer. *Journal of Sports Sciences*, *18*(9), 695–702. https://doi.org/10.1080/02640410050120078

Roberts, A. H., Greenwood, D., Stanley, M., Humberstone, C., Iredale, F., & Raynor, A. (2021). Understanding the "gut instinct" of expert coaches during talent identification. *Journal of Sports Sciences*, *39*(4), 359–367.

Sarmento, H., Anguera, M. T., Pereira, A., & Araújo, D. (2018). Talent identification and development in male football: A systematic review. *Sports Medicine*, *48*(4), 907–931. https://doi.org/10.1007/s40279-017-0851-7

Sieghartsleitner, R., Zuber, C., Zibung, M., & Conzelmann, A. (2019). Science or coaches' eye? - Both! Beneficial collaboration of multidimensional measurements and coach assessments for efficient talent selection in elite youth football. *Journal of Sports Science & Medicine*, *18*(1), 32–43.

Song, M.-K., Lin, F.-C., Ward, S. E., & Fine, J. P. (2017). Composite variables: When and how. *Nursing Research*, *62*(1), 45–49. https://doi.org/10.1097/NNR.0b013e3182741948

Tabachnick, B. G., & Fidell, L. S. (2013). *Using multivariate statistics*. Pearson Education.

Taylor, J. M., Cunningham, L., Hood, P., Thorne, B., Irvin, G., & Weston, M. (2019). The reliability of a modified 505 test and change-of-direction deficit time in elite youth football players. *Science and Medicine in Football*, *3*(2), 157–162. https://doi.org/10.1080/24733938.2018.1526402

Till, K., & Baker, J. (2020). Challenges and [possible] solutions to optimizing talent identification and development in sport. *Frontiers in Psychology*, *11*, 11. https://doi.org/10.3389/fpsyg.2020.00664

Turner, A. N., Jones, B., Stewart, P., Bishop, C., Parmar, N., Chavda, S., & Read, P. (2019). Total score of athleticism: Holistic Athlete profiling to enhance decision-making. *Strength & Conditioning Journal*, *41*(6), 91–101. http://journals.lww.com/nsca-scj

Vaeyens, R., Malina, R. M., Janssens, M., Renterghem, B., Van Bourgois, J., Vrijens, J., & Philippaerts, R. M. (2006). A multidisciplinary selection model for youth soccer: The ghent youth soccer project. *British Journal of Sports Medicine*, *40*(11), 928–934.

Varley, M. C., Gregson, W., McMillan, K., Bonanno, D., Stafford, K., Modonutti, M., & Salvo, V. (2017). Physical and technical performance of elite youth soccer players during International tournaments: Influence of playing position and team success and opponent quality. *Science and Medicine in Football*, *1*(1), 18–29. https://www.tandfonline.com/doi/abs/10.1080/02640414.2016.1230676

Waldron, M., & Murphy, A. (2013). Acomparison of physical abilities and match performance characteristics among elite and subelite under-14 soccer players. *Pediatric Exercise Science*. (Vol. 25).3, 423–434

Wernimont, P. F., & Campbell, J. P. (1968). Signs, samples, and criteria. *Journal of Applied Psychology*, *52*(5), 372–376. https://doi.org/10.1037/h0026244

Williams, A. M., Ford, P. R., & Drust, B. (2020). Talent identification and development in soccer since the Millennium. *Journal of Sports Sciences*, *38*(11–12), 1199–1210. https://doi.org/10.1080/02640414.2020.1766647

Youden, W. J. (1950). Index for rating diagnostic tests. *Cancer*, *3*, 32–35. https://doi.org/10.1002/1097-0142(1950)3:1<32:AID-CNCR2820030106>3.0.CO;2-3