

Predicting Factors of Future Performance in Football Players

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S4339940 September 2025 Department of Psychology University of Groningen Examiner/Daily supervisor: Dr. A.S.M. Niessen A thesis is an aptitude test for students. The approval of the thesis is proof that the student has sufficient research and reporting skills to graduate, but does not guarantee the quality of the research and the results of the research as such, and the thesis is therefore not necessarily suitable to be used as an academic source to refer to. If you would like to know more about the research discussed in this thesis and any publications based on it, to which you could refer, please contact the supervisor mentioned.

Abstract

Football clubs have competitive and financial reasons to try and predict if a player will be talented in the future. The literature increasingly researches identifiers of performance in football, but no strong and consistent predictors have been found yet. So, football clubs often rely on scouts and coaches to identify talent. This leaves room for bias and inconsistency. The aim of this study was to make prediction models for future performance based on the cognitive, psychological, and physical tests conducted by the Royal Dutch Football Association (KNVB) on 359 football players (Mean age = 19.9, SD = .29) that were part of a professional football club. Future performance was measured with Professional Level, meaning a player has made their first-team debut and played in a first-team the following seasons, and ELO-rating, calculating the individual rating of a player based on the result of the game and the skill level of the opponent. The models were made for intervals between tests and outcome of one, two, and three years. The results showed no individual tests were consistent over time or between outcome variables for predicting future performance. This was likely due to the range restriction of the sample and the lack of validity of some tests. The models made predictions moderately better, but most models contained different tests, making the models difficult to use in practice.

Predicting Factors of Future Performance in Football Players

Development in football is not a clear and structured path (Den Hartigh et al., 2016). However, football clubs aim to predict young players' performance as early and accurately as possible, as this offers financial and competitive advantages (Till & Baker, 2020). Plenty of research has been done on what factors predict future performance, but no consistent prediction has been found yet (Breitbach et al., 2014). A possible reason is that football is a continuous and dynamic sport, making it hard to identify what the important aspects are that need to be measured (Den Hartigh et al., 2018).

This study examines the predictive value of cognitive, psychological, and physical tests for future football performance. Such tests can support more accurate selection and training decisions (Den Hartigh et al., 2018). When multiple tests are relevant, combining them in a prediction model may give clubs a practical tool for player assessment.

The Royal Dutch Football Association (KNVB) conducted such cognitive, psychological, and physical tests on football players of Dutch football clubs to test their predictive value. However, this dataset has not yet been analyzed. This study examines how well the tests predict future performance one, two, and three years after testing. The goal is to design a prediction model that combines tests with the greatest predictive power. This study has a longitudinal approach to find predictors for future performance, most literature use a cross-sectional method (Johnston et al., 2017). This can give useful insights on the influence of time on the relation between predictors and performance. The relation between predictors across domains (cognitive, psychological, and physical) are also researched, which is not done often. This is important, because it seems predictors in different domains complement each other to predict future performance (Coelho et al., 2022). Therefore, the research questions in this study are:

- 'What tests are significantly correlated with future performance in football players?'
- 'What combination of tests can best predict future performance in football players?'

Predicting Football Performance

One problem faced in football, is how players are evaluated for their potential future success (Bergkamp et al., 2019). Currently, players are assessed through scouts and coaches who judge, based on their expertise and intuition, if a player has the potential to become a top athlete, even though the inter-coach agreement in the same pool of athletes is only small-to-moderate (Roberts et al., 2020). According to Roberts and colleagues, a plausible reason is that coaches find different factors important than other coaches. Another possible explanation is that coaches weigh important factors inconsistently when they judge a player, which results in less accurate predictions (Meijer et al., 2020). A better way of predicting performance in sports is by measuring important predictors and implementing them in a model, this is called mechanical assessment (Den Hartigh et al., 2018). The criteria stay the same, and are weighed consistently in the model, making it more effective.

There are a lot of tests and instruments that can be used to predict future performance, and they can be put on a scale from signs to samples (Den Hartigh et al., 2018). A signs approach is taking one important aspect of the task you want to predict, and test that aspect on their own. An example for footballers would be a sprint test, as speed is important in football (Lovell et al., 2017). On the other hand, the samples approach is an accurate simulation of the actual task. In football, an example is an eight versus eight game. Generally, a samples approach provides better predictions of future performance, because it allows important aspects to interact with each other (Meijer et al., 2020). However, this method is time intensive, requiring organized games and players of comparable ability. In addition, judging performance in such a dynamic

environment is difficult, as many factors influence success and make consistent prediction challenging (Den Hartigh et al., 2018). An alternative is to judge the players in a signs approach. This is a more realistic way of assessing a large sample of players, as it takes less time to perform, and is often used in literature to research talent identification (Bergkamp et al., 2019). Different important aspects of football can be tested and combined to predict future performance. In this study, predictors are categorized into cognitive, psychological and physical domains, and we first examine those identified in the literature within each category.

Cognitive Predictors

Cognitive factors have to do with the ability to understand, think about and know [important aspects of football] (Bayne et al., 2019). Game intelligence is defined as 'the ability to perceive, interpret, and predict relevant patterns [...] in highly dynamic environments, and to make rapid, adaptive decisions that optimize team performance' (Haugan et al., 2025). Players need to anticipate situations, if they do that effectively, they will perform better (Haugan et al., 2025). Haugan and colleagues state that game intelligence consists of executive functions, namely, working memory, inhibitory control, cognitive flexibility, and planning, but also perceptual-cognitive skills, namely, pattern recognition, visual search behaviors and anticipatory decision-making. They conclude that players with better game intelligence have an overall better understanding of football and have better match outcomes. It is even advised to scouts to test players on game intelligence to test whether they are likely to be successful in the future (Roberts et al., 2019).

While game intelligence may be a relevant predictor as a construct, it also needs to be tested using a reliable and valid test, in order to yield high predictive validity. Unlike general intelligence (for example the WAIS; Weiss et al., 2013), to our knowledge, there are no

thoroughly validated tests for game intelligence. Tests used in the sport context, such as BrainsFirst, claim that the test they designed is evidence-based, but no documentation is available to check this. In addition, they calculate an overall score, based on the sub-scores of working memory, anticipation, control, and attention, but it is not clear how the overall score is calculated (Reinhard et al., 2025). Therefore, we do not necessarily expect that the scores on such tests predict football performance. We investigate the relation between the overall score and sub-scores of game intelligence and future performance exploratorily.

Psychological Predictors

Psychological factors refer to factors that relate to the mental and emotional state of a player (Reilly et al., 2000). Psychological factors are important in football, because players will face adversities, and they need to deal with them effectively (Van Yperen, 2009).

Goal-Setting. Goal-setting plays a key role in performance (Van Yperen, 2022). Most athletes pursue an overarching other-based goal (e.g., winning a match), but to achieve this they must also set self- and task-based mastery goals (e.g., achieving 90% pass accuracy). Mastery goals provide a clear pathway to success, and athletes who adopt them generally perform better. Therefore, we expect the more successful footballers to set more mastery goals. Hypothesis 1a is: 'setting mastery goals is positively related to future performance.' Hypothesis 1b: 'setting mastery goals is included in the prediction model.'

Mental Toughness. Mental toughness is related to success in sport (Crust, 2007). Being mentally tough means you are able to handle adverse events well, and you are able to 'bounce back'. Crust reports it as one of the most important psychological factors in sport. However, in this study no test relating to mental toughness is performed.

Perceived Team Cohesion. Perceiving team cohesion is a vital part of the sport. Teams that feel more connected tend to perform better (Grossman et al., 2021). However, little research has been done comparing only professional football clubs, so these results will be researched exploratively.

Coach Autonomy Support. Autonomy is a key factor in maintaining autonomous motivation (Ryan & Deci, 2017). Controlling coaching reduces players' feelings of autonomy, competence, and relatedness, thereby lowering motivation (Bartholomew et al., 2009). Conversely, autonomy-supportive coaching enhances motivation, which promotes commitment to goals and performance (Van Yperen, 2009). So, it is expected that perceived coach autonomy is positively related to future performance. Hypothesis 1c is: 'perceived coach autonomy is positively related to future performance.' However, because motivation is closely tied to types of goals athletes set, it may not explain a unique share of the variance (Van Yperen, 2022).

Mindset. The mindset of a player is also important (Rees et al., 2016; Sternberg, 2017). A player with an incremental mindset believes they can improve if they train effectively, and challenge themselves in contrast to a player with an entity mindset. They believe that their level is predetermined and they have little control over this and they are scared to make mistakes as this shows weakness. However, it is unlikely that the players in the sample show a big difference in this type of mindset, as they have outperformed the majority of their age category.

Enjoyment. Enjoyment seems to be an important factor when it comes to elite versus non-elite football players (Rodrigues et al., 2023; Sigmundsson et al., 2022). However, there is not much research done comparing players at professional clubs. Therefore, enjoyment is researched exploratively.

Self-Efficacy. Self-efficacy is generally higher among elite players (Rees et al., 2016), and is closely related to the concept of perceived competence in self-determination theory (Ryan & Deci, 2017). Because athletes evaluate their competence relative to those around them, talented players surrounded by stronger teammates may experience lower perceived competence and thus reduced chances of success. (Marsh et al., 2017). Therefore, it is predicted that the level of self-efficacy is positively related to future performance. Hypothesis 1d is: 'self-efficacy is positively related to future performance.' Hypothesis 1e is: 'self-efficacy is included in the prediction model.' The relation between process- and performance-focused climate, and future performance included in the data will be researched exploratively.

Physical Predictors

Then there are physical factors that are important for predicting performance. These factors have to do with actual performance in football, like sprint speed and jumping. However, there is little consensus over what physical factors effectively predict performance, because football is a dynamic sport in which a lot of factors can influence the outcome (Fortin-Guichard et al., 2022).

Hand-Eye Coordination. Hand-eye coordination and football performance do not seem to be correlated (Aktop et al., 2017). Aktop and colleagues compared footballers to non-footballers in their hand-eye coordination, but no significant differences were found. So, the relation between hand-eye coordination and future performance will be researched exploratively.

Countermovement Jump and Standing Long Jump. Jump performance has been widely studied, with elite athletes generally outperforming others in both standing vertical and countermovement jumps (Deprez et al., 2015; Fortin-Guichard et al., 2022; Sawyer et al., 2002). However, Platvoet and colleagues (2020) found no significant difference between selected and

deselected academy players. Jump scores seem to correlate with sprint performance (Barrera et al., 2022). Therefore, jump tests are expected to correlate positively with future performance, but are not in the model due to their overlap sprint tests. *Hypothesis 2a* is: 'standing jump forward is positively related to future performance.' *Hypothesis 2b* is: 'countermovement jump is positively related to future performance.'

Sprinting and Agility. For sprinting, both in a straight line and while changing direction, there is a general consensus over its effectiveness (Altmann et al. 2024; Bennett et al., 2019; Deprez et al., 2015; Fortin-Guichard et al., 2022; Platvoet et al., 2020). To keep up with the pace of the game, players must be quick to reach the ball before opponents and to contribute effectively in possession. The 30-meter sprint seems to be the most consistent when it comes to predicting future performance, in comparison to 10, 20 and change of direction sprints (Fortin-Guichard et al., 2022). Hypothesis 2c is: 'the 10-meter sprint is negatively associated with future performance.' Hypothesis 2d is: 'the 20-meter sprint is negatively associated with future performance.' Hypothesis 2e is: 'the 30-meter sprint is negatively associated with future performance.' Hypothesis 2g is: 'the change of direction sprint left is negatively associated with future performance.' Hypothesis 2g is: 'the change of direction sprint right is negatively associated with future performance.' Hypothesis 2g is: 'the change of direction sprint right is negatively associated with future performance.' Hypothesis 2h is: '30-meter sprint is included in the prediction model.' Other tests, namely, balance and moving sideways, will be researched exploratively in their relation to future performance.

Passing and Dribbling. Platvoet and colleagues (2020) reported that passing accuracy and dribbling are also important factors when in relation to performance. An accurate passer and a quick dribbler usually perform better than players who do not pass and dribble well. However in this study no test relating to passing or dribbling was included.

All in all, it is expected that there will be no cognitive predictors in the model for predicting performance. For psychological predictors, goal setting, self-confidence and are predicted to significantly improve the model. For physical predictors only the 30-meter sprint is expected to be included in the model, because of the correlation between the physical predictors. When determining the predictors in the model the intercorrelation for predictors within the sort predictor (cognitive, psychological and physical) is considered, but not between the sorts. These intercorrelations will be explored in this paper.

Measurement of Performance

How do we measure performance? The most used approach is to split the sample into two groups and compare these. This can be based on the level the athlete plays at or status of the athlete, this is classified as elite versus sub- or non-elite (Núñez et al., 2009; Reinhard et al., 2025; Savelsbergh et al., 2002; Vestberg et al., 2012). A method mostly used to assess youth athletes is by looking at players who stayed in the academy versus players who got deselected (Altmann et al., 2024; Deprez et al., 2015; Fortin-Guichard et al., 2022). In some cases, the sample is split into more categories to enhance the analysis (Fruchart & Rulence-Pâques, 2022; Rees et al., 2016). This approach is useful for identifying general differences between several groups and concluding what attributes to becoming a better athlete. However, this approach has an important limitation (Bergkamp et al. 2019). Now, the players are put into one category if they play in the same league, or even across multiple leagues. This assumes that every player is similar in quality within those leagues, but this is not the case. A better approach is to give each player a personal rating. This can make an analysis on differences between players more detailed, as it considers differences in quality of players of the same league.

Football is a team sport, which makes it more difficult to calculate an individual rating (Den Hartigh et al., 2018). A way to do this is by keeping track of the frequency of events in a match (e.g. passes completed and shots on goal; Bergkamp et al., 2019). This method is feasible for first teams, because most statistics are already monitored. However, for youth players this is challenging, as it requires devices to keep track of the statistics, which are often not available. Another suggestion by Bergkamp and colleagues is position data. The player wears a tracking device, and their positioning during the game can be analyzed. A combination of these two measurements can give insightful information for the quality of a player. The downside is the intensity and availability of devices. A more realistic way to track the individual ability of players is by calculating their ELO-rating.

With ELO, the individual quality of a player can be calculated (Bosma & Vuegen, 2020). Players gain points if they win, and lose points if they lose. However, how many points they gain or lose depends on the initial rating of the player and the opposing team. A player with a higher rating that wins from a team with a lower rating will gain less points than when a lower rated player wins. This allows to differentiate quality between players in the same league. However, this method is not validated, and is rarely used in the literature, which makes it difficult to compare the results.

In this article, both elite vs. sub-elite and ELO are used as an outcome variable in separate analyses. The distinction between elite and sub-elite is made based on whether the player made their first team debut, and played in the first team in the following seasons. We will refer to this outcome as 'Professional Level' from now on. Professional Level has its limitations, as discussed before, but we are able to compare the results with previous studies. Whereas the

predictions based on the ELO-ratings will be more difficult to compare to previous literature, as there is little to no research done with ELO as the outcome variable.

Another relevant aspect, is the time span of the prediction. Den Hartigh and colleagues (2016) describe in their Dynamic Network Model that constant interactions between variables take place to develop the talent of a player. This indicates, as time progresses, more interactions take place, making it harder to predict further into the future. To see how elapsed time influences the prediction model, the outcome variables are measured approximately a year, two years and three years after the tests. These results will be researched exploratorily.

Method

Data Collection

This study used an existing dataset collected by the KNVB. In the seasons 2021/2022 and 2022/2023, the KNVB organized days at Dutch football clubs to measure first-team and academy players on different cognitive, psychological, and physical tests. This was measured at the grounds of the clubs. All players gave consent explicitly before participating in the tests.

Participants

In total 1.186 players were in the dataset, but only 359 (100% male) (youth) football players, born in 2002 and 2003, were selected for analysis. These birth years were chosen because the participants were of sufficiently similar age to allow meaningful comparisons of the test results. Additionally, players born in 2002 and 2003 had enough time to potentially reach the first team, unlike players born in 2004 or later, of whom only a few had made this transition.

The cognitive, psychological, and physical measurements were conducted on different days and not every player was measured on every test and each outcome variable. The sample size per test ranges from 66 to 305. See Table 1 for the sample size of every test, and each

outcome variable. The mean ages at the time of testing were 19.81 (SD= .29) for the cognitive test, 20.14 (SD= .28) for the psychological tests, and 19.74 (SD= .30) for the physical tests. All players were part of the first team or academy of a professional Dutch football club at the point of measurement. Most players were measured once per season. For players with multiple measurements, the test containing the most data was used. If measurements contained equal amounts of data, the measurements closest to the mean interval (in days) between testing and outcome for the other players was selected.

Table 1Number of Participants per Test

		ELO			Profe	essional I	Level
Years between t	est and outcome	1	2	3	1	2	3
Cognitive test	test Working Memory		160	110	249	250	159
	Anticipation	146	155	105	240	241	149
	Control	147	156	107	242	243	154
	Attention	143	152	103	240	241	150
	Game intelligence	150	160	110	249	250	159
Psych. tests	Mastery Goal Setting	111	112	NA	170	170	NA
	Ego Goal Setting	111	112	NA	170	170	NA
	Perceived Team Cohesion	111	112	NA	170	170	NA
	Coach Autonomy Support	111	112	NA	170	170	NA
	Process-Focused Climate	111	112	NA	170	170	NA
	PerforFocused Climate	111	112	NA	170	170	NA
	Enjoyment	111	112	NA	170	170	NA
	Entity Mindset	67	66	NA	99	100	NA
	Incremental Mindset	67	66	NA	99	100	NA
	Self-Efficacy	67	66	NA	99	100	NA
Physical tests	Balance	149	155	111	266	268	171
	Countermov. Jumping	167	177	137	294	294	208

Table 1 (continued)Number of Participants per Test

			ELO			Professional Level		
Years between test and outcome		1	2	3	1	2	3	
Physical Tests	Moving Sideways	162	175	136	290	291	206	
	Hand-Eye Coordination	176	184	141	304	305	215	
	10-Meter Sprint	152	162	127	269	269	191	
	20-Meter Sprint	152	162	127	269	269	191	
	30-Meter Sprint	152	162	127	269	269	191	
	Agility Sprint Left	144	158	127	266	264	190	
	Agility Sprint Right	144	158	127	266	264	190	
	Standing Jump Forward	157	168	129	282	283	195	
	Overall Motor Skills	131	141	102	245	247	158	

Procedures

The outcome variables, ELO-rating and Professional Level, were monitored from 2021 onwards until December 2024. Even the smallest sample size is large enough to distinguish a small correlation (>.18) from zero, with a power of .80, assuming two-tailed testing and $\alpha = .05$.

Cognitive Test

The cognitive test was conducted by BrainFirst (BF), and aims to measure cognitive ability in a football context (Reinhard et al., 2025). They test on the subcategories working memory, ability to anticipate, mental control, and attention. Based on these scores, an overall

score of game intelligence is calculated. They claim that their tests are based on evidence-based research, but there are no public articles available about the validity and reliability of their tests, and on what literature the tests are based (Reinhard et al., 2025). How the overall score is calculated, is also unknown.

Psychological Tests

Multiple validated questionnaires were conducted by the KNVB to measure psychological aspects of the participants. Because the data is archival, the scores of the participants per item were not available. Therefore, Cronbach's alpha reported in the literature was used.

Goal-Setting. The first test is the 12-item Achievement Goal Scale for Youth Sports (AGSYS) measures to what extent participants set mastery (α = .78; Cumming et al., 2008) or ego goals (α = .88; Cumming et al., 2008). The final score is the average score of six items for each type of goal. An example item for mastery goals is: 'I feel successful when I learn new skills'. An example item for ego goals is: 'I want to show that I am better than others'. Items were answered on a 5-point Likert scale ranging from 1 (not at all true) to 5 (very true).

Perceived Team Cohesion. The 4-item Peer Motivational Climate in Youth Sports Questionnaire (peerMCYSQ) measures how much the participant feels a positive team cohesion (α=.81; Ntoumanis & Vazou, 2005). An example item is: 'Most players in this team help each other to improve'. Items were answered on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

Coach Autonomy Support. The 7-item Health Care Climate Questionnaire (HCCQ) measures whether players feel support for their autonomy by their coach (α = .88; Williams et al., 1996). The final score was the average score of the 15 items. An example item is: 'I feel that the

staff has provided me with choices and options'. Items were answered on a 7-point Likert scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*).

Process- or Performance-Focused Climate. The 12-item Motivational Climate Questionnaire in Youth Sports (MCQYS) measures to what extent players experience a process- $(\alpha = .78-.84;$ Smith et al., 2008) or performance-focused climate $(\alpha = .74-.75;$ Smith et al., 2008). A score for both variables, based on the average of each six items, was calculated. An example item for a process-focused climate is: 'The coach made players feel good when they improved a skill'. An example item for a performance-focused climate is: 'Winning games was the most important thing for the coach'. Items were answered on a 5-point Likert scale ranging from 1 (not at all true) to 5 (very true).

Enjoyment. The 5-item Satisfaction/Interest in Sport Scale (SSS; Duda & Nicholls, 1992) measures the amount of enjoyment the participant experiences in football (α = .83; Myung & Yang, 2016). The final score is the average of the four items. An example item is: 'I usually enjoy playing sports'. Items were answered on a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*).

Mindset. The growth and entity mindset were measured with a 12-item Growth Mindset Scale, but no validation paper was found. Midkiff and colleagues (2018) validated a 8-item version of this questionnaire called Growth Mindset Scale (GMS; α = .94-.98). Six of the items tested for an entity mindset, and six items for an incremental mindset, the final scores were an average of the items for each mindset. An example item for entity mindset is: 'To be honest, you can't really change how intelligent you are'. An example item for incremental mindset is: 'You can always substantially change how intelligent you are'. Items were answered on a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*).

Self-Efficacy. The 5-item Intrinsic Motivation Inventory (IMI) measures how strongly players believed in their own abilities (α = .78; McAuley et al., 1989). An example item is: 'I think I am good at football'. Items were answered on a 7-point Likert scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*).

Physical Tests

The tests of the physical factors were conducted by the College of Arnhem and Nijmegen (HAN). First, the Körperkoordinationstest für Kinder (KTK; Kiphard & Schilling, 1974 in Platvoet, 2020) was performed. The test was validated for children between five and 14 years-old, the test is standardized and reliable (r > .85; Cools et al., 2009). The KTK consisted of a balance test, countermovement jumping, moving sideways, and a hand-eye coordination test.

Balance. Players had to walk backwards on a balance beam with a width of six, 4.5 and three centimeters. For each beam the participants had three tries, every successful step backwards counted as a point, each try they could score a maximum score of eight. The final score was the score of every try added up.

Countermovement Jumping. Players had to jump over a wooden lath back and forth as many times in 15 seconds. The participants got two tries, and their final score was the addition of both tries.

Moving Sideways. The participant had two small boxes. He stands on one and has to place the other to his right, and step on that box, then he picks up the other box and places it again to his right, etcetera. The participant's score is the number of successful repetitions completed in 20 seconds. Their total score is the addition of both tries.

Hand-Eye Coordination. The participant had 30 seconds to throw the ball against the wall with one hand and catch it with the other, and vice versa. Every catch is a point. The participants get two tries and their final score is the total of both tries.

Sprinting. Furthermore, HAN conducted multiple sprint tests. The first tests were straight line sprints for 10, 20, and 30 meters. For each distance, players got two tries. Their final score was their best time per distance.

Agility. In the Arrowhead agility test the player sprints 15 meters straight, then turns left or right, sprints five meters to the side, five meters back to the middle and ten meters back (Chalil et al., 2017). This test was conducted twice for each side and the best score for each side was their final score. Chalil and colleagues reported that this test has a high reliability (r = .995).

Standing Long Jump. The participants have to jump their furthest without a runup. The participants have two tries and their furthest jump counts as their final score.

Overall Motor Skills. Finally, an overall score of motor skills was calculated. This score is a sum of the scores of the balance beam, countermovement jumping, moving sideways and hand-eye coordination.

So the physical tests are balance beam, countermovement jumping, moving sideways, hand-eye coordination, 10-meter sprint, 20-meter sprint, 30-meter sprint, Arrowhead sprint test right, Arrowhead sprint test left, standing jump forward and an overall score of motor skills.

Outcome Variables

The outcome variable ELO-rating is a way to individually rate the ability of football players (Bosma & Vuegen, 2020). After every match the rating is adjusted. This is done based on the current rating of the player, the average rating of the team, the average rating of the opponent, the result of the match, home advantage and a growth factor. The growth factor is

based on the age of the player. A younger player has a higher growth factor, because there is less data about them and this way they can reach their actual rating quicker. Also, players that play in a different age category during the session have a higher growth factor, because in most cases, their rating will likely be different from the rating they deserve. If they play more matches in the age category, their growth factor will decrease. The average ELO-rating is 1,500 for every age category, with a minimum score of 0 and a maximum of 5,000. If a player goes up in age category, their ELO-rating will decrease accordingly. This outcome variable has yet to be tested on its reliability and validity.

For the outcome variable Professional Level, the distinction between elite and sub-elite is based on whether they made their first-team debut, and played at first-team level in the subsequent seasons. If both conditions apply, a player is categorized as elite.

Data Analysis

Correlations between each predictor test and each outcome variable were calculated in SPSS (version 29.0.1) for one-, two-, and three-year intervals between measurement and outcome. When two or more predictors showed significant correlations with the same outcome, a multiple linear regression was conducted using the stepwise method. Predictors were entered based on the strength of their correlation with the outcome, beginning with the variable with the highest correlation. If a predictor did not add significantly to the model, it was excluded. Similarly, a binary logistic regression was conducted in SPSS with the tests that significantly predicted Professional Level. Again, the predictors were added stepwise, based on the strength of the correlation. Predictors were excluded if they did not add significantly to the model. If only one predictor was included in the model, a logistic regression was still performed to calculate Nagelkerke R^2 for the explained variance. Initially, the intent was to cross-validate the results by

testing the results of one part of the sample on another part. However, the sample sizes for each test were smaller than expected, which made cross-validation impossible while keeping enough power.

Results

Assumptions

Before a test was conducted, the assumptions were checked. For Pearson's correlations, the following assumptions were checked. (1) linearity between the variables, (2) no significant outliers, and (3) normality of the variables. Linearity was assessed with scatterplots between each predictor, outcome variable, and the interval between test and outcome. Outliers were identified using boxplots, with extreme values defined as greater than three times the interquartile range (IQR) below Q1 or above Q3. For mastery goal-setting, process-focused climate, 20-meter sprint, agility sprint left, and standing jump forward one outlier per variable was removed. When these outliers were removed, the assumptions were met and the correlations remained similar. Therefore, correlations including outliers are reported. Normality was evaluated using Q-Q plots. Normality was sometimes violated due to outliers but was met after their removal.

When a multiple linear regression was conducted, the following assumptions were tested.

(1) linear relation between predictors and outcome, (2) homoscedasticity, (3) no multicollinearity, (4) no significant outliers, and (5) normally distributed residuals. Linearity and outliers were inspected via scatterplots. Homoscedasticity and normality of residuals were assessed with residual plots. Multicollinearity was evaluated using the Variance Inflation Factor (VIF), with values above five considered problematic. All assumptions were met.

For the point-biseral correlations, the following assumptions were tested. (1) no outliers within each outcome category, (2) normality of continuous variables, and (3) homogeneity of variance across outcome categories for predicting variables. Outliers were checked via boxplots, normality with Q-Q plots, and equality of variances using Levene's test. Some violations occurred due to outliers, but after removing values exceeding three times IQR, assumptions were met. For mastery goal-setting, coach autonomy support, performance-focused climate, process-focused climate, enjoyment, moving sideways, 20-meter sprint, agility sprint left and right, and standing jump forward one or two outliers per variable were removed. For PL-1 and PL-2, the significant correlations and models changed, so results without outliers are reported, because the outliers heavily influenced the correlations. Without the outliers, results project a better overview of the important predictor variables for these outcomes. For PL-3 results remained similar, and the results including the outliers were reported.

For a binary logistic regression, the following assumptions were checked. (1) linearity between continuous predictors and the logit of the outcome, (2) no multicollinearity, and (3) no outliers. Multicollinearity was assessed using VIF (< 5 is acceptable), and outliers were checked via Cook's distance. All assumptions were satisfied.

Correlations ELO-rating

All correlations between the scores of the players on the tests and their ELO-rating one, two and three years later (ELO-1, 2 and 3) can be found in Table 2. For the ELO-1, the cognitive sub-score of Anticipation showed a small-to-moderate positive correlation with performance (r = .23). None of the psychological tests were significant. Among the physical tests, Hand-Eye Coordination (r = .28, *moderate*), and Overall Motor Skills (r = .18, *small*) were significant. For

ELO-2 and ELO-3 no tests were significantly correlated with ELO-rating. *Hypotheses 1a, 1c, 1d, 2a, 2b, 2c, 2d, 2e, 2f and 2g* were all not supported by the analysis of ELO-1, 2 and 3.

Table 2

Correlations tests and outcomes

		ELO			Profe	essional I	Level
Years between t	est and outcome	1	2	3	1	2	3
Cognitive test	Working Memory	.07	.03	07	.08	.08	.02
	Anticipation	.23**	.04	04	.02	.02	.03
	Control	.13	.07	.01	.02	.03	02
	Attention	14	15	15	.05	.04	.03
	Game intelligence	.08	.07	01	.11	.12	.04
Psych. tests	Mastery Goal Setting	.06	.06	NA	.07	.01	NA
	Ego Goal Setting	06	.04	NA	.00	.00	NA
	Perceived Team Cohesion	02	.09	NA	03	.00	NA
	Coach Autonomy Support	.05	.06	NA	.18*	.08	NA
	Process Focused Climate	.03	.12	NA	.08	.08	NA
	Perfor. Focused Climate	.06	.14	NA	18*	07	NA
	Enjoyment	09	.01	NA	.07	.10	NA
	Entity Mindset	.03	03	NA	18	19	NA
	Incremental Mindset	.15	.15	NA	.05	.09	NA
	Self-efficacy	.15	.16	NA	15	01	NA
Physical tests	Balance	.09	06	03	06	05	.02
	Countermov. Jumping	01	.14	.16	.01	.02	.00

Table 2 (continued)

Correlations tests and outcomes

			ELO			Professional Level		
Years between test and outcome		1	2	3	1	2	3	
Physical tests	Moving Sideways	.14	.05	.14	.07	.07	.15*	
	Hand-Eye Coordination	.28**	.13	.11	.14*	.15**	.13	
	10-Meter Sprint	.00	02	.02	09	10	12	
	20-Meter Sprint	03	.04	04	09	10	11	
	30-Meter Sprint	06	04	02	11	11	11	
	Agility Sprint Left	.00	09	11	08	06	14	
	Agility Sprint Right	05	11	11	11	09	20**	
	Standing Jump Forward	08	.01	.05	.12	.13*	.15*	
	Overall Motor Skills	.18*	.15	.17	.10	.11	.14	

Prediction Models ELO-rating

For ELO-1, a multiple regression was performed. Hand-Eye Coordination was first added to the model, and contributed significantly to the model ($\Delta R^2 = .127, p < .001$), Anticipation was added second, and was also significant ($\Delta R^2 = .043, p = .02$). Overall Motor Skills was not included, because it did not add significantly to the model ($\Delta R^2 = .000, p = .91$). The overall model was significant, F(2, 119) = 12.18, p < .001, with an R-squared of .170, so 17.0% of the variance can be explained by this model, representing a moderate effect size. The results are also

shown in Table 3. *Hypotheses 1b, 1e and 2h* were all not supported. For ELO-2 and 3, no model was made, so *Hypotheses 1b, 1e and 2h* were not supported for these outcomes.

Table 3

Multiple Linear Regression ELO-1

	Unstandardize	ed Coefficients				
Model	В	Std. Error	t	Sig.	VIF	ΔR^2
Constant	1692.37	113.08	14.97	<.001		
Hand-eye coordination	4.97	1.25	3.99	<.001	1.01	.127
Anticipation	2.22	.90	2.47	.02	1.01	.043

Dependent variable: ELO-rating

Correlations Professional Level

The correlations between the tests and Professional Level one, two and three years after (PL-1, 2 and 3) the tests were conducted, can be seen in Table 2. For PL-1, Coach Autonomy Support (r = .18, small), Performance-Focused Climate (r = .18, small), and Hand-Eye Coordination (r = .13, small) were significant. For PL-2, Hand-Eye Coordination (r = .15, small) and Standing Jump Forward (r = .13, small) were significant. For PL-3, Standing Jump Forward was again significant (r = .15, small), and also Moving Sideways (r = .15, small) and Agility Sprint Right (r = .20, small) were significant. Hypothesis 2a was supported for PL-2 and PL-3, but not for PL-1, Hypothesis 2g was only supported for PL-3, and Hypothesis 1c was only supported for PL-1. Hypotheses 1a, 1c, 1d, 2b, 2c, 2d, 2e, and 2f were not supported by the results of PL.

Prediction Models Professional Level

For PL-1, a binary logistic regression was performed, without the outliers. First, Coach Autonomy Support was added, and contributed significantly to the model ($\Delta R^2 = .086, p = .045$). Next, Hand-Eye Coordination was added, and also contributed significantly ($\Delta R^2 = .082, p = .03$). Performance-Focused Climate not included, because it did not add significantly to the model ($\Delta R^2 = .061, p = .30$). The full model was statistically significant, $\chi^2(2, 136) = 9.84, p = .01$. The Nagelkerke R^2 was .166, indicating approximately 16.6% of the variance was explained by the model, representing a moderate effect size. The results can be found in Table 4. *Hypotheses 1b, 1e, and 2h* were all not supported.

Table 4Logistic Regression for PL-1

Model	В	S.E.	df	Sig.	Exp(B)	ΔR^2
Coach Autonomy	1.13	.56	1	.045	3.10	.084
Support						
Hand-Eye	.04	.02	1	.03	1.04	.082
Coordination						
Constant	-10.60	2.92	1	<.001	.00	

Dependent variable: Professional Level

For the logistic regression, without outliers, of PL-2, Hand-Eye Coordination was added first, and added significantly to the model ($\Delta R^2 = .045$, p = .01). Standing Jump Forward was not included, because it did not add significantly to the model ($\Delta R^2 = .030$, p = .09) The full model was statistically significant, $\chi^2(1, 305) = 6.40$, p = .01. The Nagelkerke R^2 was .045, indicating

that approximately 4.5% of the variance was explained by the model, representing a small effect size. The results can be found in Table 5. *Hypotheses 1b, 1e, and 2h* were all not supported.

Table 5

Logistic Regression for PL-2

Model	В	S.E.	df	Sig.	Exp(B)	ΔR^2
Hand-Eye	.03	.01	1	.01	1.03	.045
Coordination						
Constant	-4.77	1.03	1	<.001	.01	

Dependent variable: Professional Level

For PL-3, a binary logistic regression was performed. Agility Sprint Right was first added to the model, and added significantly to the model ($\Delta R^2 = .087, p = .01$). Moving Sideways was added next, and also added significantly to the model ($\Delta R^2 = .053, p = .04$). Standing Jump Forward was also significantly correlated with PL-3, but did not add significantly to the model ($\Delta R^2 = .028, p = .10$). The full model was statistically significant, $\chi^2(2, 184) = 11.44, p = .003$. The Nagelkerke R^2 was .140, indicating that approximately 14.0% of the variance was explained by the model, representing a moderate effect size. The results can be found in Table 6. *Hypotheses 1b, 1e, and 2h* were all not supported.

Table 6Logistic Regression for PL-3

Model	В	S.E.	df	Sig.	Exp(B)	ΔR^2
Agility Sprint	-3.35	1.36	1	.01	.04	.087
Right						
Moving Sideways	.06	.03	1	.04	1.07	.053
Constant	19.36	10.36	1	.06	255,634,	
					227.48	

Dependent variable: Professional Level

Intercorrelations Predictive Tests

The cognitive scores were correlated with some of the physical tests. Working Memory was significantly correlated with Hand-Eye Coordination (r = .15, small), Agility Sprint Right (r = .16, small), and Overall Motor Skills (r = .15, small). Anticipation was significantly correlated with Balance (r = .16, small), Jumping Sideways (r = .23, small-to-moderate), and Overall Motor Skills (r = .17, small). Control was significantly correlated with Balance (r = .15, small). Attention was significantly related to Jumping Sideways (r = .16, small). Lastly, Game Intelligence was significantly related to Balance (r = .21, small-to-moderate), Jumping Sideways (r = .25, small-to-moderate), Hand-Eye Coordination (r = .20, small), Agility Sprint Right (r = .15, small), and Overall Motor Skills (r = .30, moderate). A few psychological tests were significantly correlated to a physical test. Perceived Team Climate was related to Overall Motor Skills (r = .18, small), Perceived Coach Autonomy was correlated to Moving Sideways (r = .17, small), Entity Mindset was related to Standing Jump Forward (r = .23, small-to-moderate),

and Incremental Mindset was related to 20-Meter Sprint (r = .23, small-to-moderate). No cognitive scores were significantly related to psychological tests. All intercorrelations can be found in Appendix A.

Discussion

It was expected that setting mastery goals, perceived coach autonomy, self-efficacy, standing jump forward, countermovement jump, sprint performance (10-30 meter), and agility sprints would be significantly correlated with future performance. However, only standing jump forward and hand-eye coordination seemed to be somewhat consistent predictors, because these tests had a significant correlation with the outcome multiple times, though their effects were mostly small. All other predictors were never statistically significant, or only significant once, indicating limited and inconsistent predictive value over time. This was especially true for the psychological tests, which showed no significant associations, except performance-focused climate and coach autonomy support for PL-1. One possible explanation lies in the operationalization used in this thesis. Professional Level distinguished between elite and subelite players based on whether a player made their debut, and played in a first team in following seasons, providing an objective measure rather than a subjective classification (e.g., categorizing academies as elite or sub-elite). Distinctions like selected versus deselected players (Deprez et al., 2015; Fortin-Guichard et al., 2022) were not possible, because that data was unavailable. Other approaches in the literature (e.g., experience versus novice players, or clustering certain divisions; Núñez et al., 2009; Vestberg et al, 2012) also rely on subjective criteria. Furthermore, since ELO-ratings have not been used previously in literature, this may partly explain why the results differ from earlier studies. An additional explanation is range restriction (Bergkamp et al., 2019), which occurs when participants' test scores are relatively similar, reducing variability and

making it harder to detect differences within the sample. This study included only players already selected into professional football clubs, making the range restricted. In contrast, many previous studies included broader samples (e.g. selected versus deselected academy players, or experienced versus novice players; Johnston et al., 2017) and therefore captured greater variability. A third explanation is that most prior research examined cross-sectional correlations between predictors and playing level at one point in time (e.g., Johnston et al., 2017; Bergkamp et al., 2019). In contrast, this study applied a longitudinal design, comparing test results with performance one, two, and three years later.

The analysis of intercorrelations between tests showed small to moderate correlations between cognitive and physical predictors. However, due to the lack of validation of the cognitive test, no meaningful conclusions can be drawn. The psychological tests showed no significant correlations with the cognitive scores and only a few small significant results with the physical tests. The most plausible reason is that the tests lacked sensitivity to distinguish between players in this sample, as most scored similarly.

The prediction models varied in predictive power. No models could be made for ELO-2 and ELO-3, the model for PL-2 had a small effect, and the models for ELO-1, PL-1, and PL-3 showed moderate predictive power. The expectation was that the models would consist of setting mastery goals, self-efficacy and 30-meter sprint. However, these tests were never included in any model, but other tests were included, like hand-eye coordination and standing jump forward. Possible reasons for these differences are similar to those explaining the unexpected correlations. The models predominantly included physical predictors. Only ELO-1 contained a cognitive predictor, suggesting that cognitive and psychological variables did not contribute additional explained variance beyond the physical measures. Given the dynamic and non-linear nature of

football development (Den Hartigh et al., 2016; Till & Baker, 2020), it is plausible predictors lose strength across longer timespans, making long-term predictions more difficult than cross-sectional correlations. However, for the models of PL, the predictive power increased when the interval between tests and outcome was bigger. This is likely due to coincidence, rather than a meaningful result.

Limitations

This study had some shortcomings. Firstly, not all tests are validated appropriately. The cognitive test of BrainFirst claims to be evidence-based, but no independent validation studies are available, nor is it clear how the overall score is calculated (Reinhard et al., 2025). This prevents drawing useful conclusions from the results of the test. Furthermore, the KTK was only validated for children between the ages of five and 14. However, our participants were older, so it is uncertain the validity holds for our sample.

A second limitation is that not all participants were tested on every test. The power was still large enough to be able to draw conclusions, but larger sample sizes per test could have given more insightful results. In addition to that, the interval between the tests and outcome is not the same for every participant per outcome variable. For instance, ELO-1 had a range of 142 and 429 days. This likely added noise to the results.

An additional limitation is the lack of generalizability for this sample. It consisted of male players aged 18 to 20 years-old when conducting the tests, who were a part of a professional football club. This makes generalizing to, for instance, amateur players, female players, or younger and older players not possible.

A further limitation is seen in the outcome variables. Professional Level generalizes players that can have different performance levels, as the same. ELO-rating is not a validated

measurement for performance, because of this the literature has not used ELO as an outcome variable, making it difficult to compare our results with the literature.

The data analysis also had some limitations. All outcomes had outliers for some predictive tests, which violated the assumptions. When deleting those outliers, the assumptions were met. For most outcomes, the results stayed the same, but for PL-1 and PL-2 the results differed with and without outliers. This influenced the comparability of outcomes and should be considered when comparing the results.

A last limitation is that the item-level scores of the psychological tests were not available. This meant the reliability could not be checked. Based on the literature, most of the tests seemed to be reliable, but we cannot be sure.

Practical Implications and Future Research

Most tests do not appear suitable to identify differences within this sample. Although some showed significant correlations with performance outcomes, these associations were generally small and inconsistent across time and outcome measures. While some models improved performance prediction, their instability over time limits their usefulness for player selection decisions. Future research should apply the same tests to a broader sample to determine whether greater variability allows the predictors to better differentiate between players.

Although the results are not convincing, ELO-rating seems to be a promising measurement of performance, as it is able to differentiate between the skill level of players in the same league. This makes it a useful addition to the elite versus sub- or non-elite distinction. The ELO-rating needs to be researched for validity, and it should also be noted that ELO-rating is still partly dependent on the team result. This does not make it a perfect operationalization of performance, but a step in the right direction, when it comes to individual ratings.

For future research, some tests could be useful to add for assessment. Firstly, a test for mental toughness. The Connor-Davidson Resilience Scale (Gonzalez et al., 2016) is a questionnaire on mental toughness that is validated in a sports context. As mental toughness seems to be an important factor in football (Crust, 2007), this test could give useful insights. Furthermore, a passing and dribbling drill should be added, because these factors also seem to be related to performance (Platvoet et al., 2020). The F-MARC test battery has a dribbling, long-passing, and short-passing drill that are reliable (Rösch et al., 2000).

A better, but more work intensive method of predicting future performance is by analyzing match data of a player (Bergkamp et al., 2019). Statistics like passing accuracy, successful dribbles, and successful tackles can be tracked and based on those statistics a prediction model per position can be made. This method is likely more effective than the current method, as it uses match data, instead of isolated tests.

Conclusion

With a few tests, the prediction for future performance can improve considerably. However, due to the inconsistency of predictors that seem to be relevant, we should be careful about using these models in practice. This study, like most literature, showed that identifying consistent predictors in football can be challenging. Den Hartigh and colleagues (2016) suggest looking at dynamic models for predicting future performance. However, we need to first identify those consistent predictors to build such a model.

References

- Aktop, A., Kuzu, O., & Cetin, E. (2017). Analysis of Attention, Eye-Hand Coordination and reaction time of young soccer players. *the European Proceedings of Social & Behavioural Sciences*, 13–19. https://doi.org/10.15405/epsbs.2017.06.2
- Altmann, S., Ruf, L., Thiem, S., Beckmann, T., Wohak, O., Romeike, C., & Härtel, S. (2024).

 Prediction of talent selection in elite male youth soccer across 7 seasons: A machine-learning approach. *Journal of Sports Sciences*, 1–14.

 https://doi.org/10.1080/02640414.2024.2442850
- Barrera, J., Figueiredo, A. J., Duarte, J., Field, A., & Sarmento, H. (2022). Predictors of linear sprint performance in professional football players. *Biology of Sport*, *40*(2), 359–364. https://doi.org/10.5114/biolsport.2023.114289
- Bartholomew, K. J., Ntoumanis, N., & Thogersen-Ntoumani, C. (2009). A review of controlling motivational strategies from a self-determination theory perspective: implications for sports coaches. *International Review of Sport and Exercise Psychology*, 2(2), 215–233. https://doi.org/10.1080/17509840903235330
- Bayne, T., Brainard, D., Byrne, R. W., Chittka, L., Clayton, N., Heyes, C., Mather, J., Ölveczky,
 B., Shadlen, M., Suddendorf, T., & Webb, B. (2019). What is cognition? *Current Biology*, 29(13), R608–R615. https://doi.org/10.1016/j.cub.2019.05.044
- Bennett, K. J., Novak, A. R., Pluss, M. A., Coutts, A. J., & Fransen, J. (2019). A multifactorial comparison of Australian youth soccer players' performance characteristics.

 *International Journal of Sports Science & Coaching, 15(1), 17–25.

 https://doi.org/10.1177/1747954119893174

- Bergkamp, T. L. G., Niessen, A. S. M., Hartigh, R. J. R. D., 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
- Bosma, M., & Vuegen, J. (2020). Documentatie eQuality Project. SciSports.
- Breitbach, S., Tug, S., & Simon, P. (2014). Conventional and genetic talent identification in sports: Will recent developments trace talent? *Sports Medicine*, *44*(11), 1489–1503. https://doi.org/10.1007/s40279-014-0221-7
- Chalil, D. H., Febrianty, M. F., & Sartono, H. (2017). The validity and reliability of Arrowhead Agility Test in football. *2nd International Conference on Sports Science, Health and Physical Education*, 414–417. https://doi.org/10.5220/0007062104140417
- Cools, W., De Martelaer, K., Samaey, C., & Andries, C. (2009). Movement skill assessment of typically developing preschool children: A review of seven movement skill assessment tools. *Journal of sports science & medicine*, 8(2), 154.
- Crust, L. (2007). Mental toughness in sport: A review. *International Journal of Sport and Exercise Psychology*, 5(3), 270–290. https://doi.org/10.1080/1612197x.2007.9671836
- Cumming, S. P., Smith, R. E., Smoll, F. L., Standage, M., & Grossbard, J. R. (2008).

 Development and validation of the Achievement Goal Scale for Youth Sports.

 *Psychology of Sport and Exercise, 9(5), 686–703.

 https://doi.org/10.1016/j.psychsport.2007.09.003
- 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 and*

- Conditioning Research, 29(6), 1692–1704. https://doi.org/10.1519/jsc.000000000000000000
- Duda, J. L., & Nicholls, J. G. (1992). Dimensions of achievement motivation in schoolwork and sport. *Journal of Educational Psychology*, 84(3), 290–299. https://doi.org/10.1037/0022-0663.84.3.290
- Fortin-Guichard, D., Huberts, I., Sanders, J., Van Elk, R., Mann, D. L., & Savelsbergh, G. J. (2022). Predictors of selection into an elite level youth football academy: A longitudinal study. *Journal of Sports Sciences*, 40(9), 984–999. https://doi.org/10.1080/02640414.2022.2044128
- Fruchart, E., & Rulence-Pâques, P. (2022). Predicting sports performance from well-being: A mapping of professional athletes', amateur athletes' and non-athletes' positions.

 European Review of Applied Psychology, 72(6), 100793.

 https://doi.org/10.1016/j.erap.2022.100793
- Gonzalez, S. P., Moore, E. W. G., Newton, M., & Galli, N. A. (2015). Validity and reliability of the Connor-Davidson Resilience Scale (CD-RISC) in competitive sport. *Psychology of Sport and Exercise*, *23*, 31–39. https://doi.org/10.1016/j.psychsport.2015.10.005
- Grossman, R., Nolan, K., Rosch, Z., Mazer, D., & Salas, E. (2021). The team cohesion-performance relationship: A meta-analysis exploring measurement approaches and the changing team landscape. *Organizational Psychology Review*, *12*(2), 181–238. https://doi.org/10.1177/20413866211041157
- Hartigh, R. J. R. D., 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
- Hartigh, R. J. R. D., Van Dijk, M. W. G., Steenbeek, H. W., & Van Geert, P. L. C. (2016). A dynamic network model to explain the development of excellent human performance.
 Frontiers in Psychology, 7. https://doi.org/10.3389/fpsyg.2016.00532
- Haugan, J. A., Lervold, K., Kaalvik, H., & Moen, F. (2025). A scoping review of empirical research on executive functions and game intelligence in soccer. *Frontiers in Psychology*, 16. https://doi.org/10.3389/fpsyg.2025.1536174
- Johnston, K., Wattie, N., Schorer, J., & Baker, J. (2017). Talent Identification in Sport: A Systematic Review. Sports Medicine, 48(1), 97–109.
 https://doi.org/10.1007/s40279-017-0803-2
- Kiphard, E.J. and Schilling, F. (1974). Körperkoordinationstest für Kinder. Weinheim: Beltz Test GmbH.
- Lovell, T. W. J., Bocking, C. J., Fransen, J., & Coutts, A. J. (2017). A multidimensional approach to factors influencing playing level and position in a school-based soccer programme. *Science and Medicine in Football*, *2*(3), 237–245. https://doi.org/10.1080/24733938.2017.1420208
- Marsh, H. W., Martin, A. J., Yeung, A. S., & Craven, R. G. (2017). Competence self-perceptions. In A. J. Elliot, C. S. Dweck, & D. S. Yeager (Eds.), *Handbook of competence and motivation: Theory and application* (2nd ed., pp. 85–115). The Guilford Press.
- McAuley, E., Duncan, T., & Tammen, V. V. (1989). Psychometric Properties of the Intrinsic Motivation inventory in a competitive sport setting: A confirmatory Factor analysis.

- Research Quarterly for Exercise and Sport, 60(1), 48–58. https://doi.org/10.1080/02701367.1989.10607413
- Meijer, R. R., Neumann, M., Hemker, B. T., & Niessen, A. S. M. (2020). A tutorial on Mechanical Decision-Making for Personnel and Educational selection. *Frontiers in Psychology*, 10. https://doi.org/10.3389/fpsyg.2019.03002
- Midkiff, B., Langer, M., Demetriou, C., & Panter, A. T. (2018). An IRT analysis of the growth Mindset scale. In *Springer proceedings in mathematics & statistics* (pp. 163–174). https://doi.org/10.1007/978-3-319-77249-3 14
- Myung, W., & Yang, C. (2016). Relationship between Interest in Sports and Leisure Satisfaction of People in Clubs of Sports for All. *Indian Journal of Science and Technology*, 9(44). https://doi.org/10.17485/ijst/2016/v9i44/105105
- Ntoumanis, N., & Vazou, S. (2005). Peer Motivational Climate in Youth Sport: Measurement development and validation. *Journal of Sport and Exercise Psychology*, 27(4), 432–455. https://doi.org/10.1123/jsep.27.4.432
- Núñez, F. J., Oña, A., Raya, A., & Bilbao, A. (2009). Differences between Expert and Novice Soccer Players When Using Movement Precues to Shoot a Penalty Kick. *Perceptual and Motor Skills*, 108(1), 139–148. https://doi.org/10.2466/pms.108.1.139-148
- Platvoet, S. W., Opstoel, K., Pion, J., Elferink-Gemser, M. T., & Visscher, C. (2020).

 Performance characteristics of selected/deselected under 11 players from a professional youth football academy. *International Journal of Sports Science & Coaching*, 15(5–6), 762–771. https://doi.org/10.1177/1747954120923980
- Rees, T., Hardy, L., Güllich, A., Abernethy, B., Côté, J., Woodman, T., Montgomery, H., Laing, S., & Warr, C. (2016). The Great British Medalists Project: a review of current

- knowledge on the development of the world's best sporting talent. *Sports Medicine*, 46(8), 1041–1058. https://doi.org/10.1007/s40279-016-0476-2
- 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
- Reinhard, M. L., Mann, D. L., & Höner, O. (2025). The role of generic cognitive skills: an empirical investigation into the association between generic and sport-specific cognitive skills and playing level in youth football. *Journal of Science and Medicine in Sport*. https://doi.org/10.1016/j.jsams.2025.01.010
- Roberts, A. H., Greenwood, D., Humberstone, C., & Raynor, A. J. (2020). Pilot study on the Reliability of the Coach's Eye: Identifying talent throughout a 4-Day cadet judo camp. Frontiers in Sports and Active Living, 2. https://doi.org/10.3389/fspor.2020.596369
- Roberts, S. J., McRobert, A. P., Lewis, C. J., & Reeves, M. J. (2019). Establishing consensus of position-specific predictors for elite youth soccer in England. *Science and Medicine in Football*, *3*(3), 205–213. https://doi.org/10.1080/24733938.2019.1581369
- Rodrigues, F., Monteiro, D., Matos, R., Jacinto, M., Antunes, R., & Amaro, N. (2023). Exploring the dynamics of Athletes' Enjoyment and Self-Determined Motivation, and of the motivational climate in Youth Football: a Longitudinal perspective. *Perceptual and Motor Skills*, *131*(2), 551–567. https://doi.org/10.1177/00315125231222152
- Rosch, D., Hodgson, R., Peterson, L., Graf-Baumann, T., Junge, A., Chomiak, J., & Dvorak, J. (2000). Assessment and evaluation of football performance. *The American Journal of Sports Medicine*, 28(5_suppl), 29-39.

- Ryan, R. M., & Deci, E. L. (2017). Self-Determination Theory: Basic Psychological Needs in Motivation, Development, and Wellness. Guilford Publications.
- Savelsbergh, G. J., Williams, A. M., Van Der Kamp, J., & Ward, P. (2002). Visual search, anticipation and expertise in soccer goalkeepers. *Journal of Sports Sciences*, 20(3), 279–287. https://doi.org/10.1080/026404102317284826
- Sawyer, D. T., Ostarello, J. Z., Suess, E. A., & Dempsey, M. (2002). Relationship between football playing ability and selected performance measures. *The Journal of Strength and Conditioning Research*, *16*(4), 611. https://doi.org/10.1519/1533-4287(2002)016
- Sigmundsson, H., Dybendal, B., Loftesnes, J., Ólafsson, B., & Grassini, S. (2022). Passion a key for success: Exploring motivational factors in football players. *New Ideas in Psychology*, 65, 100932. https://doi.org/10.1016/j.newideapsych.2022.100932
- Smith, R. E., Cumming, S. P., & Smoll, F. L. (2008). Development and validation of the motivational climate scale for youth sports. *Journal of Applied Sport Psychology*, 20(1), 116–136. https://doi.org/10.1080/10413200701790558
- Sternberg, R. J. (2017). Challenge and threat appraisals. In A. J. Elliot, C. S. Dweck, & D. S. Yeager (Eds.), *Handbook of competence and motivation: Theory and application* (2nd ed., pp. 9–24). Guilford Press.
- Till, K., & Baker, J. (2020). Challenges and [Possible] solutions to optimizing talent identification and development in sport. *Frontiers in Psychology*, 11. https://doi.org/10.3389/fpsyg.2020.00664
- Van Yperen, N. W. (2009). Why some make it and others do not: Identifying psychological factors that predict career success in professional adult soccer. *The Sport Psychologist*, 23(3), 317–329. https://doi.org/10.1123/tsp.23.3.317

- Van Yperen, N. W. (2022). In the context of a sports match, the goal to win is most important, right? Suggestive evidence for a hierarchical achievement goal system. *Psychology of Sport and Exercise*, 60, 102134. https://doi.org/10.1016/j.psychsport.2022.102134
- Vestberg, T., Gustafson, R., Maurex, L., Ingvar, M., & Petrovic, P. (2012). Executive functions predict the success of Top-Soccer players. *PLoS ONE*, 7(4), e34731. https://doi.org/10.1371/journal.pone.0034731
- Weiss, L. G., Keith, T. Z., Zhu, J., & Chen, H. (2013). WAIS-IV and clinical validation of the Four- and Five-Factor Interpretative Approaches. *Journal of Psychoeducational Assessment*, 31(2), 94–113. https://doi.org/10.1177/0734282913478030
- Williams, G. C., Grow, V. M., Freedman, Z. R., Ryan, R. M., & Deci, E. L. (1996). Motivational predictors of weight loss and weight-loss maintenance. *Journal of Personality and Social Psychology*, 70(1), 115–126. https://doi.org/10.1037/0022-3514.70.1.115

Appendix A: Intercorrelations between Test Domains

Table ACorrelations Cognitive Scores and Psychological Tests

	Working	Anticipation	Control	Attention	Game
	Memory				Intelligence
Mastery Goal-Setting	07	13	15	.01	12
Ego Goal-Setting	08	08	12	05	06
Perc. Team Cohesion	15	10	.07	.06	11
Coach Auto. Support	.02	08	.00	.05	02
ProcFocused Climate	06	16	.00	.01	02
PerfFocused Climate	11	13	.02	14	.00
Enjoyment	07	17	10	.02	13
Entity Mindset	.03	17	06	11	08
Incremental Mindset	.13	.01	.04	.04	.12
Self-Efficacy	.03	11	02	09	.00

Table BCorrelations Cognitive Scores and Physical Tests

	Working	Anticipation	Control	Attention	Game
	Memory				Intelligence
Balance	.08	.16*	.15*	.09	.21**
Countermov. Jumping	.12	.23**	.11	16*	.25**
Moving Sideways	.07	.08	10	08	.09
Hand-Eye Coordination	.15*	.07	.11	03	.20**
10-Meter Sprint	02	07	04	04	04
20-Meter Sprint	.02	.02	.05	.02	.04
30-Meter Sprint	.03	01	04	.01	02
Agility Sprint Left	10	.04	01	02	07
Agility Sprint Right	16*	02	03	02	15*
Standing Jump Forward	.08	01	03	06	.10
Overall Motor Skills	.15*	.17*	.15	11	.30**

Table CCorrelations Psychological Tests and Physical Tests

	Mastery	Ego Goal-	Perc. Team	Coach Auto.	ProcFoc.
	Goal-Setting	Setting	Cohesion	Support	Climate
Balance	04	.03	.03	03	.03
Countermov. Jumping	04	02	02	.03	.12
Moving Sideways	09	11	11	17*	01
Hand-Eye Coordination	01	06	10	.01	02
10-Meter Sprint	.14	.13	.09	.01	.00
20-Meter Sprint	.13	.11	02	.00	.00
30-Meter Sprint	.10	.08	.00	06	02
Agility Sprint Left	.07	.06	11	11	01
Agility Sprint Right	.01	02	08	13	08
Standing Jump Forward	07	08	04	02	05
Overall Motor Skills	11	08	-18*	11	04

Table C (continued)Correlations Psychological Tests and Physical Tests

	PerfFoc.	Enjoyment	Entity	Incremental	Self-efficacy
	Climate		Mindset	Mindset	
Balance	14	02	07	06	08
Countermov. Jumping	.08	01	.02	05	.05
Moving Sideways	06	.02	.06	10	06
Hand-Eye Coordination	11	07	07	.12	05
10-Meter Sprint	.10	.09	.06	.16	.01
20-Meter Sprint	.06	02	.04	.23*	.00
30-Meter Sprint	.07	.04	.06	.07	05
Agility Sprint Left	.12	.16	09	.01	.00
Agility Sprint Right	.13	.00	14	09	09
Standing Jump Forward	11	03	23*	01	05
Overall Motor Skills	05	10	.02	04	09