

1    **Title:**

2    High-intensity endurance capacity assessment as a tool for talent identification in elite  
3    youth female soccer

4

5    **Preferred Running Head:**

6    Talent identification in elite youth female soccer

7

8    **Key Words:**

9    Football, talent selection, fitness testing, logistic regression, retrospective analysis

10

11   **Text Only Word Count:**

12   4226

13

14   **Abstract Word Count:**

15   200

16

17   **Number of Figures:**

18   3

19

20   **Number of Tables:**

21   2

22

23   **Disclosure Statement:**

24   The authors report no conflict of interest

25 **High-intensity endurance capacity assessment as a tool for talent identification**  
26 **in elite youth female soccer**

27

28 **Abstract**

29 Talent identification and development programmes have received broad attention in  
30 the last decades, yet evidence regarding the predictive utility of physical performance  
31 in female soccer players is limited. Using a retrospective design, we appraised the  
32 predictive value of performance-related measures in a sample of 228 youth female  
33 soccer players previously involved in residential Elite Performance Camps (age range:  
34 12.7 to 15.3 years). With 10-m sprinting, 30-m sprinting, counter-movement jump  
35 height, and Yo-Yo Intermittent Recovery Test Level 1 (IR1) distance as primary  
36 predictor variables, the Akaike Information Criterion (AIC) assessed the relative  
37 quality of four penalised logistic regression models for determining future competitive  
38 international squads U17-U20 level selection. The model including Yo-Yo IR1 was  
39 the best for predicting career outcome. Predicted probabilities of future selection to  
40 the international squad increased with higher Yo-Yo IR1 distances, from 4.5% (95%  
41 confidence interval, 0.8 to 8.2%) for a distance lower than 440 m to 64.7% (95%  
42 confidence interval, 47.3 to 82.1%) for a score of 2040 m. The present study highlights  
43 the predictive utility of high-intensity endurance capacity for informing career  
44 progression in elite youth female soccer and provides reference values for staff  
45 involved in the talent development of elite youth female soccer players.

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49

## 50    **Introduction**

51    In recent years there has been an increased emphasis on the processes of talent  
52    identification and development (Johnston, Wattie, Schorer, & Baker, 2018). Talent  
53    identification refers to the recognition of individuals with potential to become elite,  
54    whereas talent development involves provision of an optimal environment to realise  
55    this potential (Reilly, Bangsbo, & Franks, 2000; A. M. Williams and Reilly, 2000).  
56    Effective talent identification and development not only increases the likelihood of  
57    team success but also generates high financial rewards via the transfer market (Mann,  
58    Dehghansai, & Baker, 2017). National teams do not have the option to purchase  
59    players via the transfer market; therefore, talent identification and development may  
60    be of greater importance to national governing bodies compared to domestic club  
61    teams. The exact composition of talent identification and development programmes  
62    will vary depending on the specific requirements of the sport. However, programmes  
63    are likely to consist of developing the technical/tactical, physiological, psychological  
64    and social skills required for success within a specific sport.

65

66    The early identification of individuals who will be successful at senior level is a  
67    complex and highly challenging process (Mann, et al., 2017). Traditional talent  
68    identification research has often focused on identifying characteristics which  
69    distinguish between elite and sub-elite youth performers (Breitbach, Tug, & Simon,  
70    2014). Such a methodology assumes the most talented youth athletes will become the  
71    most talented senior athletes, i.e. that talent is static (Johnston, et al., 2018), although  
72    youth success is only a weak predictor of success at a senior level (Baker, Schorer, &  
73    Wattie, 2017; Kearney and Hayes, 2018). Identifying the characteristics worthy of  
74    investigation is complex, but a multi-dimensional approach including physical,

75 psychological and sports-specific factors has been recommended to provide the most  
76 holistic methodology (Breitbach, et al., 2014). To further advance our understanding  
77 of potential factors contributing to senior success, it seems valuable to prospectively  
78 track players, or retrospectively trace long-term career progression (Till et al., 2015).  
79  
80 Currently there is a paucity of such data with a limited number of studies focusing on  
81 long-term career progression in a range of male team sports; rugby union (Fontana,  
82 Colosio, Da Lozzo, & Pogliaghi, 2017), rugby league (Till, et al., 2015), Australian  
83 football (Burgess, Naughton, & Hopkins, 2012) and soccer (Gonaus and Muller, 2012;  
84 le Gall, Carling, Williams, & Reilly, 2010). Each of these studies identified that a  
85 combination of anthropometric and physical performance characteristics  
86 discriminated between those athletes deemed successful and non-successful in their  
87 future careers. Collectively, these data suggest that fitness testing in youth male team  
88 sport athletes may provide useful information for predicting future career progression  
89 (Till, et al., 2015). However, to date, there is a lack of information available on female  
90 athletes and specifically female soccer players with no information currently available  
91 on predicting future career progression in females. International female match-play  
92 data demonstrates the high physical demands of the sport (Datson et al., 2017) and a  
93 substantial body of evidence has evaluated the physical capacity of female soccer  
94 players (Datson et al., 2014). Previous research has shown differences in physical  
95 performance characteristics based upon competitive playing standard (Mujika,  
96 Santisteban, Impellizzeri, & Castagna, 2009), player selection (Manson, Brughelli, &  
97 Harris, 2014) and age (Wright and Atkinson, 2017). However, the relative importance  
98 and influence that these characteristics have on future career progression has not been  
99 identified.

100 Therefore, using a retrospective design, our study aimed to ascertain the predictive  
101 value of relevant physical performance measures for determining future career  
102 progression in youth elite female soccer players.

103

## 104 **Methods**

### 105 **Experimental Approach to the Problem**

106 Anthropometric and field-based physical performance testing data were collected  
107 from youth elite female soccer players between 2011-2014, with testing sessions  
108 conducted as part of the Elite Performance Camps (EPC) programme for talented  
109 youth players. The English Football Association support a Girls' England Talent  
110 Pathway that aims to identify and develop youth players with potential. As part of the  
111 pathway, *talented* players aged 12-15 years attend residential EPCs for specialised  
112 training.

113

114 Data were retrospectively analysed and for the purposes of this study players were  
115 divided into two career progression levels for comparison: (1) selected for competitive  
116 international squads at U17-U20 level or (2) not selected for competitive international  
117 squads at U17-U20 level.

118

119 Prior to assessment, all players had previously completed each test on at least one  
120 previous occasion, which acted as their familiarisation. Physical performance tests  
121 were performed indoors and players wore shorts, t-shirt and football boots (except for  
122 the jumps when trainers were worn). Players performed a standardised generic warm-  
123 up prior to commencement of the physical assessments as well as specific warm-up  
124 routines prior to each performance test. To ensure consistency between testing

125 occasions, National federation staff coached the warm-up activity and conducted all  
126 measurements.

127

128 All physical performance tests were completed at approximately the same time of day  
129 to reduce any circadian rhythm effect (Reilly and Brooks, 1986). Tests were completed  
130 in a single session and in the same order (anthropometry, jumps, linear speed and Yo-  
131 Yo Intermittent Recovery Test Level 1 [Yo-Yo IR1]) on each test occasion. The test  
132 order was designed in an attempt to minimise the influence of previous tests on  
133 subsequent performance. Players refrained from strenuous exercise in the 24 hours  
134 before fitness testing session and consumed their normal pre-training diet. To  
135 encourage maximal effort, players received consistent verbal encouragement  
136 throughout the physical performance tests. Usual appropriate ethics committee  
137 clearance was not required as data was collected as a condition of employment (Winter  
138 and Maughan, 2009) and all players had previously consented for their data to be used  
139 for research purposes. Nevertheless, all data were anonymized prior to analysis to  
140 ensure player confidentiality.

141

## 142 **Participants**

143 Data were collected from 284 youth elite female soccer players (612 separate  
144 observations; with a median of two testing occasions per player (range = 1-6).  
145 However, for analysis purposes, a complete dataset was required per player and  
146 therefore the effective sample size was reduced to 228 ( $13.9 \pm 0.6$  years). Where  
147 players were tested on multiple occasions, the *best* score for each performance test  
148 was included in the analysis.

149

150 All participants were part of the England Football Association's Talent pathway and  
151 as such they participated in a minimum of two football sessions per week and one  
152 match. In addition, players would complete up to two strength and conditioning  
153 practices per week and have access to specialist support.

154

## 155 **Procedures**

### 156 **Anthropometric and Physical Performance Measures**

157 Player height (m), sitting height and body mass (kg) were measured using a  
158 stadiometer (Seca 217, Germany) and calibrated digital scales (Seca 876, Germany),  
159 respectively. Skinfolds (mm) were taken as an estimate of adiposity and measured at  
160 eight sites: biceps, triceps, subscapular, iliac crest, supraspinale, abdominals, front  
161 thigh and medial calf using skinfold calipers (Harpenden, UK). An International  
162 Society for the Advancement of Kinanthropometry (ISAK) accredited anthropometrist  
163 performed all measurements, with ISAK guidelines followed (Jones et al., 2006).  
164 Height, sitting height and body mass were used to calculate maturity offset for each  
165 player on each testing occasion using the Mirwald (2002) equation.

166

167 Estimations of player's lower limb muscular power were assessed via  
168 a countermovement jump (CMJ) on a jump mat (KMS Innervations, Australia). The  
169 jump mat was placed on a firm, concrete surface at the edge of the indoor third-  
170 generation turf pitch. Following generic and jump-specific warm-up activity, players  
171 were permitted an additional practice jump on the mat before performing three  
172 recorded trials. Players were instructed to step on to the mat and place their feet in the  
173 middle of the mat (a comfortable distance apart) and with their hands on their  
174 hips. Starting from an upright position, players were instructed to jump as high as

possible while keeping their hands on their hips and legs straight when in the air and refraining from bringing their legs into a pike position or flicking their heels. The highest jump height recorded to the nearest 0.1 cm was retained for analysis. Linear speed times were measured using electronic timing gates (Brower TC Timing System, USA) over distances of 0-30 m. A 50 m steel tape measure (Stanley, UK) was used to measure the 30 m distance and markers were placed at 0, 10 m and 30 m; in addition, a marker was placed 1 m behind the zero line. Tripods were placed directly over each marker at a height of 87 cm above ground level and a timing gate (transmitter) was fitted to each tripod. Opposite each tripod, at a distance of 2 m, another tripod and timing gate (receiver) was positioned. Following a speed-specific warm-up activity, players were permitted an additional practice sprint through the course before performing three recorded trials. Players commenced each sprint with their preferred foot on a line 1 m behind the first timing gate. Each sprint was separated by a 3-min recovery period. The fastest time at each distance to the nearest 0.001 s was retained for analysis. Player's high-intensity endurance capacity was assessed via Yo-Yo IR1 (Krustrup et al., 2003). The reliability of each of the anthropometric and physical performance measures have previously been established in a similar sample to the present study (Datson, 2016).

193

#### 194 **Statistical Analysis**

Data are presented as mean  $\pm$  standard deviation (SD) for continuous variables, and frequency or percentages for categorical variables. To derive consistent estimates for the predicted probabilities of future selection (Grant, 2014), four penalized logistic regression models included 10-m sprinting (s), 30-m sprinting (s), counter-movement jump height (cm), and Yo-Yo IR1 distance (m) as distinct primary predictor variables



controlling for differences in maturity offset and adjusting for chronological age and anthropometric characteristics (Coveney, 2008; Firth, 1993). To provide reference value that might inform staff members involved in talent identification and development processes, predicted probabilities were derived for the 1<sup>st</sup>, 2.5<sup>th</sup>, 25<sup>th</sup>, 50<sup>th</sup>, 75<sup>th</sup>, 97.5<sup>th</sup> and 99<sup>th</sup> percentiles of each performance measure (Williams, 2012). To examine accuracy of the estimated models, we appraised the internal calibration of derived probabilities using a novel method based on a calibration belt approach (Nattino, Lemeshow, Phillips, Finazzi, & Bertolini, 2017). By definition, internal calibration refers to the degree of agreement between the estimated probabilities and observed outcome rates in the sample in which the model was developed (Austin and Steyerberg, 2014). As an alternative to commonly used tests and graphic tools (Steyerberg et al., 2010), the confidence band around the curve (i.e., the calibration belt) is a measure of uncertainty in the estimate of the curve and enables a formal internal calibration appraisal (Nattino, Finazzi, & Bertolini, 2014b). A model correctly predicts the frequency of events if the calibration belt contains the bisector of the axes (Nattino, et al., 2017).

216

The Akaike Information Criterion (AIC) assessed relative quality of each model in the set of candidate models. The Akaike difference ( $\Delta AIC$ ) from the estimated best model (i.e., the model with the lowest AIC value;  $\Delta AIC = 0$ ) was evaluated according to the following scale: 0-2, essentially equivalent; 2-7, plausible alternative; 7-14, weak support;  $> 14$ , no empirical support (Burnham, Anderson, & Huyvaert, 2011). Predicted probabilities are presented as point estimates with the related disposition (95% confidence interval, CI) and model internal validation was illustrated for the best/essentially equivalent models. Analyses were performed using R (version 3.6.0,

225 R Foundation for Statistical Computing, Vienna, Austria) and Stata (StataMP v14.0;  
226 StataCorp LP, College Station, TX).

227

## 228 **Results**

229 From the original sample size, 228 players with valid performance and maturity  
230 measures at the time of assessment over the examined observation period were eligible.

231 Of these players, 50 players were selected for future competitive international squads  
232 at U17-U20 level and 178 players not selected. The range for chronological age, body  
233 weight, height, and sum-of-skinfolds was 12.7 to 15.3 years, 33.4 to 85.6 kg, 141.5 to  
234 188 cm, 39.5 to 166.9 mm, respectively.

235

236 Summary characteristics for each of the examined variables are illustrated graphically  
237 in dot-and-violin plots, with the bulk of data values describing the centre of the  
238 distribution (Figure 1). For the selected players, the mean 10-m sprinting, 30-m  
239 sprinting, CMJ height, Yo-Yo IR1 distance was 1.805 ( $\pm$  0.121), 4.623 ( $\pm$  0.197),  
240 29.79 ( $\pm$  3.45), and 1393 ( $\pm$  365), respectively. For the unselected players, the mean  
241 10-m sprinting, 30-m sprinting, CMJ height, Yo-Yo IR1 distance was 1.841 ( $\pm$  0.103),  
242 4.724 ( $\pm$  0.232), 28.64 (3.81), and 1077 (353), respectively. The point estimate and  
243 likely range of compatible values for the mean difference in the measure of interest  
244 between selected versus unselected players in the international squad at U17-U20 level  
245 was  $-0.036$  s (95%CI,  $-0.070$  s to  $-0.002$  s) for 10-m sprinting,  $-0.101$  s ( $-0.172$  s to  
246  $-0.030$  s) for 30-m sprinting,  $0.44$  cm ( $-0.67$  cm to  $1.55$  cm) for CMJ height,  $189$  m  
247 ( $93$  m to  $285$  m) for Yo-Yo IR1 distance.

248

249 \*\*\*Figure 1 near here\*\*\*

250

\*\*\*Table 1 near here\*\*\*

251

252 Comparison of separate logistic regression models with penalized maximum  
253 likelihood on information theory grounds revealed that the model including Yo-Yo  
254 IR1 distance as primary predictor was the best of the four candidates for determining  
255 probabilities of international squad selection in later career stages (Table 1).  
256 Additionally, sensitivity analyses revealed a trivial main effect for biological maturity  
257 offset ( $P = 0.664$ ) and for Yo-Yo IR1 distance  $\times$  biological maturity offset interaction  
258 term ( $P = 0.673$ ) in the model. The probabilities for a player of future international  
259 squads U17-U20 level selection increased with higher Yo-Yo IR1 distances, from  
260 4.5% (95% confidence interval, 0.8 to 8.2%) for a distance lower than 440 m to 64.7%  
261 (95% confidence interval, 47.3 to 82.1%) for a score of 2040 m (Figure 2). Table 2  
262 illustrates the probabilities of future selection by Yo-Yo IR1 distance percentile. With  
263 the dataset randomly split into developmental and validation subsets of 166 and 66  
264 players, the 95% calibration belt encompassed the bisector over the whole range of  
265 the predicted probabilities suggesting acceptable model internal calibration (Figure 3).  
266 The penalized logistic regression models including other performance-related  
267 variables were empirically unsupported (Table 1).

268

269

\*\*\*Table 2 near here\*\*\*

270

\*\*\*Figure 2 near here\*\*\*

271

\*\*\*Figure 3 near here\*\*\*

## 272 Discussion

273 For the first time, we ascertained the predictive value of physical performance  
274 measures to determine future career progression in a sample of elite youth female

soccer players. Our results show players with higher Yo-Yo IR1 scores are more likely to be selected for the competitive international squad at U17-U20 level independent of playing position. The present study highlights the predictive value of high-intensity endurance capacity for informing career progression in elite youth female soccer.

The present data showed that 22% of EPC players progressed into competitive international squads at U17-U20 level. This low to moderate success rate is similar to that observed in male soccer (Gonaus and Muller, 2012) and across multiple Olympic sports (Vaeyens, Gullich, Warr, & Philippaerts, 2009). Such a relatively low conversion rate reflects that female soccer in England adopts a pyramid model for talent development and therefore, due to squad sizes, it would never be possible for all players to progress from EPCs to competitive international squads. Indeed, 86% of England's bronze medal winning U20 2018 World Cup squad were part of the EPC programme and were analysed in this dataset as ~14 year old players. Nevertheless, further analysis of players selected into competitive international squads at U17-U20 level whom did not progress through the EPC would be worthy of future research to highlight alternative development pathways (Till et al., 2015).

From a real-world perspective, our findings are not surprising as previous studies revealed difference in Yo-Yo IR1 score to distinguish between competitive level in females, with elite players out-performing their sub-elite counterparts (Mujika, et al., 2009). Furthermore, high-intensity endurance capacity represents an important aspect of soccer performance in elite female players, with an increased Yo-Yo IR1 test score largely associated with a higher match running performance (Krustrup, Mohr, Ellingsgaard, & Bangsbo, 2005). Translated into a soccer-specific context, a greater

300 Yo-Yo IR1 performance may allow players to out-run their opponents and if coupled  
301 with a sufficient tactical understanding, may allow a player to have a greater influence  
302 on the match (Young and Pryor, 2007).

303

304 The fact that the penalized logistic regression model with Yo-Yo IR1 as primary  
305 predictor variable emerged as the best in the candidate pool highlighted the greater  
306 relative importance of this aspect relevant to female soccer performance than sprinting  
307 and jumping qualities. The limited predictive value of linear sprint performance to  
308 determine future youth international career outcome supports previous research which  
309 observed no differences in 15-m sprint performance between elite and sub-elite female  
310 soccer players (Mujika, et al., 2009). Nonetheless, our results are in contrast with  
311 previous research in male youth soccer players where superior jumping and sprinting  
312 performance characteristics were observed in successful versus unsuccessful career  
313 progression in Austrian and French players (Gonaus and Muller, 2012; le Gall, et al.,  
314 2010). An explanation for these gender differences might be related to the greater  
315 talent pool in male players, thus potentially placing increased emphasis on  
316 physiological and performance measures to help discriminate between talented male  
317 players. Indeed, in the study by Gonaus and Muller (2012) there were a similar  
318 number of players per year compared to the present study. However, the players were  
319 attending one of the twelve National youth academies in Austria and hence the total  
320 number of players in the National programme was likely to be ~12 times greater than  
321 the female EPC programme evaluated in the current study. However, we also point  
322 out that the study by Gonaus and Muller (2012) adopted modelling approaches  
323 different from our logistic regression analyses, which, therefore, may limit the extent  
324 of any comparison with our study outcomes. Furthermore, it should also be considered

325 that talent development programmes generally start at a younger age for males  
326 compared to females with structured academy programmes starting for boys from the  
327 age of 9 years (Goto, Morris and Nevill, 2015).

328

329 A further novel aspect of our study was that we provide reference values to help inform  
330 and guide decisions of staff members involved in a talent identification process in  
331 youth female soccer. For example, to illustrate the practical value of our data, consider  
332 a new youth female soccer player aged 13.5 years, who has been selected for an elite  
333 camp, and registered a Yo-Yo IR1 score of 1890 m. According to our data, this value  
334 would occur in fewer than 3 players in 100 and indicates that, at approximately the  
335 97.5<sup>th</sup> percentile, this new player has an average predicted probability of future  
336 international career ranging from 40.4% to 71.5% (Table 2). From a real-world  
337 perspective, given the multifactorial nature of soccer performance (Impellizzeri and  
338 Marcora, 2009), our study results suggest that high-intensity endurance capacity  
339 assessment can serve as a valuable complementary tool for talent identification in  
340 youth female soccer players.

341

342 In general, an underlying purpose of gathering physical performance data is to provide  
343 coaches and practitioners with information which may guide talent identification and  
344 development programmes. Within this particular context and facing similar challenges  
345 to those of the clinician with diagnosis and prognosis (Steyerberg, et al., 2010), a coach  
346 may be interested in to know how this may translate to meaningful real-world impact  
347 either in the short (identification) or long (development) term. Therefore, a critical  
348 appraisal of decision-analytic measures as indices of model internal calibration is  
349 fundamental to ascertain the validity and accuracy of the estimated probabilities

350 (Steyerberg and Harrell, 2016). Unlike the current practices for alternative regression  
351 modelling strategies illustrated in the sports science literature (Carey, Ong, Morris,  
352 Crow, & Crossley, 2016; Jaspers et al., 2018; Woods, Raynor, Bruce, McDonald, &  
353 Robertson, 2016; Woods, Veale, Fransen, Robertson, & Collier, 2018), we adopted a  
354 novel approach which outperforms the commonly used yet stringent graphical  
355 approaches for model internal calibration of the predicted probabilities emerging from  
356 our model (Nattino, Finazzi, & Bertolini, 2014a). If a predictive model is not carefully  
357 evaluated for nor fails to show acceptable internal calibration, any probability  
358 prediction lacks empirical support and real-world practical value for coaches and staff  
359 members involved in talent identification and development processes (Austin and  
360 Steyerberg, 2014; Nattino, et al., 2017; Steyerberg and Harrell, 2016; Steyerberg, et  
361 al., 2010).

362

363 Nonetheless, our study is not without limitations. The predicted probabilities of future  
364 youth international career outcome were estimated using one-time-only (best score)  
365 retrospective performance data gathered in the previous years. Arguably, future  
366 research based on repeated high-intensity endurance data could potentially advance  
367 further the understanding of what longitudinal increment in Yo-Yo IR1 should be  
368 targeted to increase the probability of future international career in female soccer.  
369 Such an investigation may be possible only following a model external validation,  
370 with any potential study involving an adequate sample of player and a consistent  
371 number of multiple assessments over subsequent years. However, we maintain that,  
372 due to the nature of this and other talent development programmes, it is unlikely to be  
373 possible to include repeated measures over a number of years since players are  
374 regularly deselected from the development programme. Furthermore, given the

375 multifactorial nature of soccer performance (Impellizzeri and Marcora, 2009),  
376 measures of technical ability were not examined in this study (Impellizzeri et al., 2008).

377

## 378 **Conclusions**

379 Our findings substantiate novel evidence regarding the utility of physical performance  
380 variables to determine future international career in elite youth female soccer players.

381 This study highlights the value of high-intensity endurance capacity as an important  
382 aspect relevant to elite youth female soccer performance and illustrates predicted  
383 probabilities for Yo-Yo IR1 centiles that can inform talent identification and  
384 development processes.

385

## 386 **References**

387

388 Austin, P. C., & Steyerberg, E. W. (2014). Graphical assessment of internal and  
389 external calibration of logistic regression models by using loess smoothers.  
390 *Statistics in Medicine*, 33(3), pp. 517-535. doi:10.1002/sim.5941

391 Baker, J., Schorer, J., & Wattie, N. (2017). Compromising Talent: Issues in  
392 Identifying and Selecting Talent in Sport. *Quest*, 70(1), pp. 48-63.  
393 doi:10.1080/24733938.2018.1427883

394 Breitbach, S., Tug, S., & Simon, P. (2014). Conventional and genetic talent  
395 identification in sports: will recent developments trace talent? *Sports*  
396 *Medicine*, 44(11), pp. 1489-1503. doi:10.1007/s40279-014-0221-7

397 Burgess, D., Naughton, G., & Hopkins, W. (2012). Draft-camp predictors of  
398 subsequent career success in the Australian Football League. *J Sci Med*  
399 *Sport*, 15(6), pp. 561-567. doi:10.1016/j.jsams.2012.01.006

400 Burnham, K. P., Anderson, D. R., & Huyvaert, K. P. (2011). AIC model selection  
401 and multimodel inference in behavioral ecology: some background,  
402 observations, and comparisons. *Behavioral Ecology and Sociobiology*, 65(1),  
403 pp. 23-35. doi:10.1007/s00265-010-1029-6 Retrieved from <Go to  
404 ISI>://WOS:000285786000003



405 Carey, D. L., Ong, K. L., Morris, M. E., Crow, J., & Crossley, K. M. (2016).  
 406 Predicting ratings of perceived exertion in Australian football players:  
 407 methods for live estimation. *Int J Comput Sci Sport*, 15(2), pp. 64-77.  
 408 doi:10.1515/ijcss-2016-0005  
 409 Coveney, J. (2008). firthlogit: Stata module to calculate bias reduction in logistic  
 410 regression. Statistical Software Components S456948, Department of  
 411 Economics, Boston College.  
 412 <http://econpapers.repec.org/software/bocbocode/s456948.htm>. Accessed June  
 413 23, 2019.  
 414 Datson, N., Drust, B., Weston, M., Jarman, I. H., Lisboa, P. J., & Gregson, W.  
 415 (2017). Match physical performance of elite female soccer players during  
 416 international competition. *J Strength Cond Res*, 31(9), pp. 2379-2387.  
 417 doi:10.1519/JSC.0000000000001575  
 418 Firth, D. (1993). Bias reduction of maximum likelihood estimates. *Biometrika*,  
 419 80(1), pp. 27-38. doi:10.2307/2336755  
 420 Fontana, F. Y., Colosio, A. L., Da Lozzo, G., & Pogliaghi, S. (2017). Player's  
 421 success prediction in rugby union: From youth performance to senior level  
 422 placing. *Journal of Science and Medicine in Sport*, 20(4), pp. 409-414.  
 423 doi:10.1016/j.jsams.2016.08.017  
 424 Gonaus, C., & Muller, E. (2012). Using physiological data to predict future career  
 425 progression in 14- to 17-year-old Austrian soccer academy players. *J Sports*  
 426 *Sci*, 30(15), pp. 1673-1682. doi:10.1080/02640414.2012.713980  
 427 Goto, H., Morris, J. and Nevill, M.E. (2015). Match analysis of U9 and U10 English  
 428 Premier League academy soccer players using a global positioning system:  
 429 relevance for talent identification and development. *Journal of Strength and*  
 430 *Conditioning Research*, 29(4), pp. 954-963. doi:  
 431 10.1519/JSC.0b013e3182a0d751  
 432 Grant, R. L. (2014). Converting an odds ratio to a range of plausible relative risks for  
 433 better communication of research findings. *BMJ*, 348, p f7450.  
 434 doi:10.1136/bmj.f7450

435 Impellizzeri, F. M., & Marcora, S. M. (2009). Test validation in sport physiology:  
 436 lessons learned from clinimetrics. *International Journal of Sports Physiology*  
 437 *and Performance*, 4(2), pp. 269-277.

438 Impellizzeri, F. M., Rampinini, E., Maffiuletti, N. A., Castagna, C., Bizzini, M., &  
 439 Wisloff, U. (2008). Effects of aerobic training on the exercise-induced  
 440 decline in short-passing ability in junior soccer players. *Appl Physiol Nutr*  
 441 *Metab*, 33(6), pp. 1192-1198. doi:10.1139/H08-111

442 Jaspers, A., De Beeck, T. O., Brink, M. S., Frencken, W. G. P., Staes, F., Davis, J. J.,  
 443 & Helsen, W. F. (2018). Relationships Between the External and Internal  
 444 Training Load in Professional Soccer: What Can We Learn From Machine  
 445 Learning? *Int J Sports Physiol Perform*, 13(5), pp. 625-630.  
 446 doi:10.1123/ijssp.2017-0299

447 Johnston, K., Wattie, N., Schorer, J., & Baker, J. (2018). Talent Identification in  
 448 Sport: A Systematic Review. *Sports Medicine*, 48(1), pp. 97-109.  
 449 doi:10.1007/s40279-017-0803-2

450 Kearney, P. E., & Hayes, P. R. (2018). Excelling at youth level in competitive track  
 451 and field athletics is not a prerequisite for later success. *J Sports Sci*, 36(21),  
 452 pp. 2502-2509. doi:10.1080/02640414.2018.1465724

453 Krstrup, P., Mohr, M., Ellingsgaard, H., & Bangsbo, J. (2005). Physical demands  
 454 during an elite female soccer game: importance of training status. *Medicine*  
 455 *and Science in Sports and Exercise*, 37(7), pp. 1242-1248.

456 le Gall, F., Carling, C., Williams, M., & Reilly, T. (2010). Anthropometric and  
 457 fitness characteristics of international, professional and amateur male  
 458 graduate soccer players from an elite youth academy. *J Sci Med Sport*, 13(1),  
 459 pp. 90-95. doi:10.1016/j.jsams.2008.07.004

460 Mann, D. L., Dehghansai, N., & Baker, J. (2017). Searching for the elusive gift:  
 461 advances in talent identification in sport. *Curr Opin Psychol*, 16, pp. 128-  
 462 133. doi:10.1016/j.copsyc.2017.04.016

463 Manson, S. A., Brughelli, M., & Harris, N. K. (2014). Physiological characteristics  
 464 of international female soccer players. *J Strength Cond Res*, 28(2), pp. 308-  
 465 318. doi:10.1519/JSC.0b013e31829b56b1

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

469 Nattino, G., Finazzi, S., & Bertolini, G. (2014a). Comments on 'Graphical  
 470 assessment of internal and external calibration of logistic regression models  
 471 by using loess smoothers' by Peter C. Austin and Ewout W. Steyerberg.  
 472 *Statistics in Medicine*, 33(15), pp. 2696-2698. doi:10.1002/sim.6126

473 Nattino, G., Finazzi, S., & Bertolini, G. (2014b). A new calibration test and a  
 474 reappraisal of the calibration belt for the assessment of prediction models  
 475 based on dichotomous outcomes. *Statistics in Medicine*, 33(14), pp. 2390-  
 476 2407. doi:10.1002/sim.6100

477 Nattino, G., Lemeshow, S., Phillips, G. S., Finazzi, S., & Bertolini, G. (2017).  
 478 Assessing the calibration of dichotomous outcome models with the  
 479 calibration belt. *Stata Journal*, 17(4), pp. 1003-1014.  
 480 doi:10.1177/1536867X1801700414

481 Reilly, T., Bangsbo, J., & Franks, A. (2000). Anthropometric and physiological  
 482 predispositions for elite soccer. *J Sports Sci*, 18(9), pp. 669-683.  
 483 doi:10.1080/02640410050120050

484 Reilly, T., & Brooks, G. A. (1986). Exercise and the circadian variation in body  
 485 temperature measures. *Int J Sports Med*, 7(6), pp. 358-362. doi:10.1055/s-  
 486 2008-1025792

487 Steyerberg, E. W., & Harrell, F. E., Jr. (2016). Prediction models need appropriate  
 488 internal, internal-external, and external validation. *J Clin Epidemiol*, 69, pp.  
 489 245-247. doi:10.1016/j.jclinepi.2015.04.005

490 Steyerberg, E. W., Vickers, A. J., Cook, N. R., Gerds, T., Gonen, M., Obuchowski,  
 491 N., . . . Kattan, M. W. (2010). Assessing the performance of prediction  
 492 models: a framework for traditional and novel measures. *Epidemiology*,  
 493 21(1), pp. 128-138. doi:10.1097/EDE.0b013e3181c30fb2

494 Till, K., Cobley, S., O'Hara, J., Morley, D., Chapman, C., & Cooke, C. (2015).  
 495 Retrospective analysis of anthropometric and fitness characteristics  
 496 associated with long-term career progression in Rugby League. *J Sci Med*  
 497 *Sport*, 18(3), pp. 310-314. doi:10.1016/j.jsams.2014.05.003

498 Vaeyens, R., Gullich, A., Warr, C. R., & Philippaerts, R. (2009). Talent  
 499 identification and promotion programmes of Olympic athletes. *J Sports Sci*,  
 500 27(13), pp. 1367-1380. doi:10.1080/02640410903110974

501 Williams, A. M., & Reilly, T. (2000). Talent identification and development in  
 502 soccer. *J Sports Sci*, 18(9), pp. 657-667. doi:10.1080/02640410050120041

- 503 Williams, R. (2012). Using the margins command to estimate and interpret adjusted  
 504 predictions and marginal effects. *Stata Journal*, 17(1), pp. 308–331.  
 505 doi:10.1177/1536867X1201200209
- 506 Winter, E. M., & Maughan, R. J. (2009). Requirements for ethics approvals. *J Sports*  
 507 *Sci*, 27(10), p 985. doi:10.1080/02640410903178344
- 508 Woods, C. T., Raynor, A. J., Bruce, L., McDonald, Z., & Robertson, S. (2016). The  
 509 application of a multi-dimensional assessment approach to talent  
 510 identification in Australian football. *J Sports Sci*, 34(14), pp. 1340-1345.  
 511 doi:10.1080/02640414.2016.1142668
- 512 Woods, C. T., Veale, J., Fransen, J., Robertson, S., & Collier, N. F. (2018).  
 513 Classification of playing position in elite junior Australian football using  
 514 technical skill indicators. *J Sports Sci*, 36(1), pp. 97-103.  
 515 doi:10.1080/02640414.2017.1282621
- 516 Wright, M. D., & Atkinson, G. (2017). Changes in sprint-related outcomes during a  
 517 period of systematic training in a girls' soccer academy. *J Strength Cond*  
 518 *Res*doi:10.1519/JSC.0000000000002055
- 519 Young, W. B., & Pryor, L. (2007). Relationship between pre-season anthropometric  
 520 and fitness measures and indicators of playing performance in elite junior  
 521 Australian Rules football. *J Sci Med Sport*, 10(2), pp. 110-118.  
 522 doi:10.1016/j.jsams.2006.06.003

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530 **Figure legends**

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532 **Figure 1.** Dot-and-violin plots for physical performance variables in elite youth  
533 female soccer players. Green represents individuals selected for competitive  
534 international squads at U17-U20 level and red represents individuals not selected for  
535 competitive international squads at U17-U20 level.

536

537 **Figure 2.** Predicted probabilities of selection by Yo-Yo IR1 distance.

538

539 **Figure 3.** Calibration belt (95% confidence level) plot and calibration statistic for the  
540 relationship between the model's fit probabilities and the observed proportions of the  
541 response.

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545 **Table legends**

546 **Table 1.** Relative quality of the four candidate models

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548 **Table 2.** Predicted probability of selection by Yo-Yo IR1 distance centile

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