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1 **Quantifying and modeling the game speed outputs of English Championship soccer**
2 **players**

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13

14 **Abstract**

15 This study aims to quantify and model the game speed demands of professional soccer players
16 competing in the English Championship league, to compare the effect of match location, and
17 to examine the effect of playing position on game speed outputs across the season. Twenty-
18 eight male professional soccer players were enrolled. Moving average calculations were
19 applied to the raw GNSS (STATSports) speed data of each player durations matches (home=14
20 and away=9). Positional groups were center-back (CB), full-back (FB), center-midfield (CM),
21 wing-midfield (WM) and center-forward (CF). The maximum value across each of the moving
22 average window durations was extracted and converted to units of meters per minute. Power-
23 law models were fitted to all observations ($R^2=0.64$), home only ($R^2=0.98$), and away only
24 ($R^2=0.98$). No significant effects are observed in game speed outputs when home and away
25 games were analyzed. Significant differences were seen between the following positional
26 groups; CBvs.CF ($d=-0.323$), CM ($d=-0.530$) and FB ($d=-0.350$). CM displayed positive
27 difference compared to WM ($d=0.614$). This study reported power-law model fitted game-
28 speed. Players' positional groups have significant different game-speed demands, which should
29 be considered during match analysis and training periodization. This study found that game-
30 speed is not affected by the location of the match.

31

32 **Key words: Football, Team Sports, GPS, Speed**

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34

35 Introduction

36 Soccer is a physically demanding sport where both aerobic and anaerobic systems are taxed
37 during intense activities such as sprints, accelerations, decelerations and change of directions,
38 alongside sport-specific technical actions such as tackles, headings, passes, and shots (Beato
39 & Drust, 2020; Beato & Jamil, 2018; Mohr, Krstrup, & Bangsbo, 2005). Soccer players
40 generally cover a total distance of 10-13 km during a game, which is typically associated with
41 the player' position, where external roles (*e.g.*, wings), **for tactical motivations**, cover longer
42 distances compared to internal positions (*e.g.*, central backs) (Borghini et al., 2020; Christopher
43 et al., 2016; Mohr et al., 2003; **Tierney et al., 2016**). Thus, physical conditioning is of a high
44 importance to coaches, practitioners and researchers alike in soccer (Mohr et al., 2003, 2005).

45
46 In the last years, external training load monitoring has become one of the most important
47 necessities for sport science departments (Akubat et al., 2014). External load data is used to
48 support sport science staff and coaches to make informed decisions during the training
49 microcycle and mesocycle (Gualtieri et al., 2020). For instance, coaches routinely use external
50 training load to ensure adequate recovery is provided to players between training sessions and
51 matches throughout the soccer season (Vanrenterghem et al., 2017). The correct monitoring
52 and following planification of the training load can have a key impact on the long-term
53 efficiency of the squad and for the maximization of physical and physiological adaptations
54 (Beato, Coratella, Stiff, & Dello Iacono, 2018; Chmura et al., 2019; Vanrenterghem et al.,
55 2017). This is particularly true when considering professional soccer team schedules which can
56 be very demanding and can reduce the training availability between official matches (Gualtieri
57 et al., 2020). The metrics that are generally analyzed are total distance, relative velocity, high
58 speed running, peak velocity, accelerations and decelerations (Andrzejewski et al., 2018; Beato
59 et al., 2020; Gualtieri et al., 2020; **Stevens et al., 2017**). The instrumentations usually utilized
60 to monitor external load parameters are global navigation satellite systems (GNSS) and video-
61 tracking systems (Beato & Jamil, 2018; Cummins, Orr, & Connor, 2013). Both these systems
62 give the user the possibility to evaluate external load variables, however, GNSS is currently
63 the most common instrument used in elite soccer departments because it can be used during
64 both matches and training sessions (Beato, Devereux, & Stiff, 2018; Vanrenterghem et al.,
65 2017). In this study the STATSports Apex GNSS device was used to capture match day speed
66 and displacement data. The Apex GNSS is capable of acquiring and tracking multiple satellite
67 systems (*e.g.*, global positioning systems, GLONASS, BeiDou) to provide the best possible
68 positional information (Beato, Coratella, et al., 2018) in varying environments. The validity

69 and reliability of this specific GNSS model has been previously reported (Beato & De Keijzer,
70 2019; Beato, Coratella, et al., 2018).

71

72 Recently evidence confirms that soccer matches are a critical training component of the week
73 (Anderson et al., 2016; Morgans et al., 2018). During a match, players perform, relative
74 distances (RD), high-speed running, and soccer-specific activities that can be difficult to
75 recreate during training sessions or during congested fixture micro-cycles (Gualtieri et al.,
76 2020; Jones et al., 2019). However, the majority of research analyzing match demands has
77 focused its attention on average values without considering the most intense periods (*e.g.*,
78 worst-case scenario) (Delaney et al., 2018). For this reason, training sessions and drills that
79 replicate the average match demands could underestimate the intensity of the most demanding
80 moments of the game. To overcome this issue, running intensity have been evaluated using
81 time blocks between 5 to 15 min (Bradley & Noakes, 2013). Additionally, game speed
82 (represented as RD) calculated using a moving average technique has been recently used to
83 elucidate this issue of underestimating the most intense periods of the a match in team sports
84 (Delaney et al., 2017). Previous research reported RD can be over $170 \text{ m}\cdot\text{min}^{-1}$ when analyzed
85 using short time windows (*e.g.*, 1 min) (Delaney et al., 2018). This game-speed intensity is
86 much higher than the average RD (*e.g.*, around $120 \text{ m}\cdot\text{min}^{-1}$) reported considering whole games
87 (Mohr et al., 2005; Stevens et al., 2017). Furthermore, mathematical models assessing the
88 relationship between running intensity and duration (moving average) have shown to be a valid
89 way to quantify soccer match intensity and account for true periods of maximal player output
90 (Delaney et al., 2018). Sports Scientists and coaches can use this information for training load
91 management during training microcycles in order to construct training drills of an appropriate
92 intensity and expose players to match like running conditions (Konefał et al., 2019).

93

94 Effective soccer training prescription is especially important because professional players have
95 generally a very limited time available for specific physical training because of travel
96 commitments, recovery, and the need for tactical and technical skills training (Beato, Bianchi,
97 Coratella, Merlini, & Drust, 2019). To date, information related to match day in-season external
98 load and mathematical models used to evaluate game-speed in professional soccer players is
99 limited and such information may help sports scientists and coaches to adequately prepare their
100 soccer players. Therefore, the aim of this study was, to firstly quantify and model the game
101 speed demands of professional soccer players competing in the English Championship league.
102 Secondly to compare the effect of match location on game speed outputs. Lastly to examine

103 the effect of playing position on game speed outputs across the season. The authors' hypothesis
104 was that game speed is affected by the time window being analyzed, by the location of the
105 match (home vs. away), and by the players' positional group.

106

107 **Methods**

108 **Participants**

109 Twenty-eight male professional soccer players of the same team were enrolled in this study
110 (age; 25.3 ± 4.2 years, body mass; 79.5 ± 6.3 kg, height; 1.82 ± 0.07 m). All participants and
111 the club were informed about the risk and benefits of the study and consent form was signed.
112 Inclusion criteria were the absence of any injury or illness (based on team medical staff) and
113 regular participation in soccer training and competition. Only outfield players' data were
114 analyzed in this study, while goalkeepers were excluded. Players were professional players of
115 the English championship with several years of professional experience (> 5 years). The data
116 analysis was performed during the official season 2019/20 and did not include any friendly
117 matches. Player names were anonymized before data analysis, which was performed in blind
118 by a researcher non-affiliated with the club. The Ethics Committee of the "blind" approved this
119 study. All procedures were conducted according to the Declaration of Helsinki for human
120 studies.

121

122 **Experimental design**

123 This descriptive study evaluates the game speed outputs of professional Championship players
124 using moving average windows of varying sizes and mathematical modeling techniques
125 (Delaney et al., 2018). This study also compared the effects of match location on game-speed
126 outputs. In addition, the game speed demands of different player positions during the official
127 season have been compared to determine if statistical differences exist. External training load
128 data was recorded as part of the normal monitoring routine of the team. Twenty-three matches
129 were analyzed in this study, of which fourteen were home games, and nine were away games.
130 Positional groups were defined as center back (CB), full back (FB), center midfield (CM), wing
131 midfield (WM) and center forward (CF).

132

133 ***External training load***

134 External training load parameters were recorded during matches using 10 Hz GNSS units
135 (STATSports, Apex, Northern Ireland). The GNSS units were turned on approximately 10–15
136 min before the beginning of the match. Meanwhile the subjects performed the warm-up routine

137 with the fitness coach of the team. During the matches, one GNSS unit was placed on the back
138 of each player by means of a harness at the level of the chest. The Apex GNSS model reports
139 information about the quality of the signal such as the number of satellites and dilution of
140 precision. In this study the number of satellites was 16.1 ± 1.9 and dilution of precision was
141 2.38 ± 0.60 . Players consistently wore the same GNSS unit during each match to avoid inter-
142 unit variability (Beato, Devereux, et al., 2018). Total distance in meters and relative velocity
143 calculated as the ratio between total distance and the total time were measured and analyzed
144 (Gaudino et al., 2013). GNSS data recorded by the units were downloaded and further analyzed
145 with STATSports Software (Apex version 3.0.02011). The validity and reliability of the Apex
146 GNSS unit was previously calculated during sport-specific activities. The bias reported for
147 distance was between 1.05 to 2.3% respectively (Beato, Coratella, et al., 2018). Inter-unit
148 reliability for speed was classified as *excellent* and the coefficient of variation was *good* ($< 5\%$)
149 (Beato & De Keijzer, 2019).

150

151 ***Game-speed modelling***

152 In order to model game speed data the protocol previously presented by Delaney (et al., 2018)
153 was utilized. Briefly, this involved exporting raw GNSS data at a sampling rate of 10Hz for
154 each player across all matches. A custom computer program written in the Python
155 programming language (Version 3.6.5, Anaconda Inc, New York, USA) was then used to clean
156 the raw data, removing dead time (half time, extra time) and excluding any match files **where**
157 a player had less than 60 minutes of data. Moving average calculations were then applied to
158 the GNSS Doppler speed data of each player using ten different moving average window
159 durations (1, 2, 3, ...10). The maximum value across each of the moving average window
160 durations was then extracted and converted to units of meters per minute ($\text{m}\cdot\text{min}^{-1}$) for further
161 statistical analysis (Delaney et al., 2018; Zinoubi et al., 2017).

162

163 **Statistical Analyses**

164 All statistical analyses were performed using JASP software (version 0.9.2; JASP, Amsterdam,
165 The Netherlands). Descriptive statistics are reported as mean \pm standard deviation (SD) or
166 mean \pm 95% confidence intervals (CI) unless otherwise stated. Model fitting was conducted
167 using nonlinear least squares regression, goodness-of-fit statistics are reported using the
168 coefficient of determination (R^2). Measures of goodness-of-fit summarize the discrepancy
169 between observed values and the values expected under the model in question. A multivariate
170 analysis of variance (MANOVA) was used to test for significant effects in game speed outputs

171 when games are played at home compared to away (Harrell, 2015). The total observations
172 analyzed for home and away matches was $n=96$ and $n=36$. A repeated measures analysis of
173 variance (RMANOVA) was used to test for between player positional group differences in
174 game speed outputs. Where Mauchly's test of sphericity has been found to be significant
175 Greenhouse–Geisser corrections have been applied. Post-hoc analysis was performed using
176 Bonferroni corrections (applied to the alpha value). Significance was set at $p<0.05$ and reported
177 to indicate the strength of the evidence alongside the effect size. Results are reported using p-
178 values and Omega squared (ω^2) effect sizes. Based on the Cohen's d values revised by Hopkins
179 effect sizes are interpreted as follows: *trivial* < 0.2 ; $0.2 \leq$ *small* < 0.6 ; $0.6 \leq$ *moderate* < 1.2 ;
180 $1.2 \leq$ *large* < 2.0 ; *very large* > 2.0 (Hopkins et al., 2009).

181

182 **Results**

183 All models demonstrated *acceptable* to *near perfect* fits (Harrell, 2015), Figure 1.0 displays
184 the power-law model fitted to all observations ($R^2=0.64$). Figure 2.0 displays separate models
185 fitted to the home only ($R^2=0.98$) and away only ($R^2=0.98$) observations.

186

187 **“Please, figure 1 here”**

188

189 The results of the MANOVA test detailed in Table 1.0 demonstrate that no significant effects
190 are observed in the dependent variables (game speed outputs) when the independent variables
191 (home & away games) are manipulated.

192

193 **“Please, table 1 here”**

194

195 **“Please, figure 2 here”**

196

197 The results of the RMANOVA for between subject effects are detailed in Table 2.0. Significant
198 *moderate* mean game speed output differences were found between player positional groups
199 ($p < 0.001$, $d=0.093$).

200

201 **“Please, table 2 here”**

202

203 The results of a post hoc analysis for the between subject effects are detailed in Table 3.0.
204 Significant differences are seen between the following positional groups; CB displayed *small*

205 negative differences in output compared to CF ($p=0.007$, $d=-0.323$), CM ($p<0.001$, $d=-0.530$)
206 and FB ($p=0.003$, $d=-0.350$). CF displayed a *small* positive difference compared to WM
207 ($p<0.001$, $d=-0.380$). CM displayed a *moderate* positive difference compared to WM ($p<0.001$,
208 $d=0.614$). FB displayed a *small* positive difference compared to WM ($p<0.001$, $d=0.426$).
209 Figure 3.0 shows game speed output per moving average window by player positional group.

210

211 **“Please, figure 3 here”**

212

213 **“Please, table 3 here”**

214

215 **Discussion**

216 The aim of this study was, to firstly quantify and model the game speed demands of
217 professional soccer players competing in the English Championship league. Secondly to
218 compare the effect of match location on game speed outputs. Lastly to examine the effect of
219 playing position on game speed outputs across the season. In agreement with the author’s
220 hypothesis game speed is affected by the time window being analyzed, where higher speed has
221 been found analyzing short time intervals (*e.g.*, 1-2 minutes vs. 10 minutes) and by the players'
222 positional group (*e.g.*, CM vs. WM). Contrariwise, this study found that game-speed is not
223 affected by match location (home vs. away). The findings of this study provide new
224 information related to match day game speed outputs of professional soccer players competing
225 in the English Championship running. The mathematical models fitted to the game speed
226 outputs in this study can assist in profiling the competitive running demands of Championship
227 soccer. And provide an objective anchor to design training drills that replicate match day
228 running demands.

229

230 The game speed model was fit using ten different moving average window durations (Delaney
231 et al., 2018) and reported in figure 1.0, which displays the power-law model fitted to all
232 observations ($R^2=0.64$). Game-speed is as expected higher during short window durations (*e.g.*,
233 1 min > 180 m \cdot min $^{-1}$) compared to longer window durations (*e.g.*, 10 min approximately 130
234 m \cdot min $^{-1}$). The data reported in the current study is similar to that previously reported by
235 Delaney (et al., 2018). Our study reports that English Championship players have RDs > 180
236 m \cdot min $^{-1}$ and 160 m \cdot min $^{-1}$ during short window durations (1 min and 2 min duration,
237 respectively) compared to previous research analyzing elite players of the Australian A-
238 League, who reported lower RD of around 175 m \cdot min $^{-1}$ and 155 m \cdot min $^{-1}$ using the same

239 windows durations (1 and 2 min) (Delaney et al., 2018). Conversely, game-speed differences
240 cannot be observed when longer window durations (*e.g.*, 9-10 min) are compared between the
241 two studies. Delaney (et al., 2018) reported RD between 120 and 130 m·min⁻¹, which are similar
242 to the RD reported in the current study, *e.g.*, 130 m·min⁻¹. Therefore, the current study analyzing
243 professional English Championship players presented higher RD during games compared
244 Australian A-League players only when short window durations were analyzed. This
245 comparison further highlights the utility of the modeling approach used in this study which
246 provides a more granular description of the match day running demands of competitive soccer
247 compared to traditional methodologies (Mohr et al., 2005). **Sports scientists and soccer coaches**
248 **can use these innovative findings to physically prepare their players for the demands of the**
249 **matches and determine if adjustments are required when a team is going to compete in a**
250 **different league or competition.** The differences between the game speed outputs in the two
251 studies maybe explained by the physical fitness levels of the two cohorts of players studied,
252 the higher game demands of the English Championship compared to Australian A-League, or
253 simply because of different tactical strategies used by the two teams in their respective leagues
254 (Rampinini et al., 2007; Sæterbakken et al., 2019; Wells et al., 2012; Winter & Pfeiffer, 2016).
255 Future research may compare the RD and other training load variables between the two leagues
256 to verify these hypotheses.

257

258 This study reported power-law models fitted to the home ($R^2=0.98$) and away ($R^2=0.98$)
259 observations (Figure 2.0). Therefore, both models reported in this research can be used to
260 prescribe game-speed specific intensity during drills of various durations with a high degree of
261 accuracy. However, we did not find any significant difference between home and away games
262 following MANOVA analysis (Table 1.0). This is an interesting finding which suggests that it
263 is not necessary to independently assess game-speed demands on the bases of the match
264 location, both home and away game speed values can be interpolated using the same model.
265 However, **soccer practitioners should consider that this finding is strictly related to the soccer**
266 **team analyzed in this study, therefore other teams could show some differences between home**
267 **and away games.** Furthermore, these findings have practical implications for training load
268 management during the training microcycle, where physical training does not need to be
269 differentiated on the bases of next game location since home and away games reported the
270 similar game-speed (RD) outputs on average. Future research may evaluate additional
271 independent variables to verify their effect on game-speed data. Our analysis did not analyze
272 the game-speed demands based on the score of the game, *e.g.*, win vs. lose or draw, which

273 could affect the intensity of the match (Winter & Pfeiffer, 2016). Therefore, other independent
274 variables could be taken into consideration by sports scientists and coaches to constructed
275 potentially more informative game-speed models. Future studies could also analyze how
276 players' physical, technical activities, players and team game-speed as well as contextual
277 variables may affect the match outcome (Konefał et al., 2020).

278

279 Previous research reported that game demands change on the bases of the players' position
280 (Bush et al., 2015; Carling, 2013). In this study, we confirm that game speed output assessed
281 per moving average window changes on the bases of a players' positional grouping (Figure 3).
282 Significant lower RD was reported for CB compared to CF (*small*), CM (*small*) and FB (*small*).
283 CF reported higher RD compared to WM (*small*). CM reported higher RD compared to WM
284 (*moderate*). FB reported *higher RD* compared to WM (*small*). Additionally, this study reported
285 a similar trend of decline in peak running intensity between players' positions as reported by
286 previous research (Delaney et al., 2018). These findings can have critical importance for
287 position-specific physical training in soccer. In many cases, soccer players do not receive a
288 specific physical training based on their game position but instead, they train together
289 performing similar soccer drills (*e.g.*, using small-sided games) and therefore experience
290 similar external training loads (Bianchi et al., 2019; Dello Iacono et al., 2019). This training
291 approach could underestimate the game-speed demands for some positions, as well as
292 overestimate the RD for some others, which could result in an inadequate quantification of
293 training load during the weekly microcycle or mesocycle (Duthie et al., 2018; Gualtieri et al.,
294 2020; Malone et al., 2015). This situation may be further complicated during some specific
295 periods of the season when several competitions (*e.g.*, the national cup, the national league,
296 international cup) are played in the same microcycle (Gualtieri et al., 2020; Morgans et al.,
297 2018; Thorpe et al., 2015). It has already been reported that congested fixture periods represent
298 an obstacle for players' training, injury prevention, and training load management (Dupont et
299 al., 2010; Gualtieri et al., 2020). Therefore, the current knowledge about game-speed
300 differences among players' positions could have an important role for sports scientists and
301 coaches, which should consider specific player position training load demands on the bases of
302 the findings in this study. Thus, during both congested and non-congested fixture periods,
303 positions should be taken into consideration in order to adequately prepare specific groups
304 within the team (Jones et al., 2019). Sport scientists and soccer coaches can modify soccer-
305 specific drills (*e.g.*, small and large sided games as well as soccer circuits) and adapt some
306 rules to allow higher speed intensities for specific positions (*e.g.*, FB) in order to adequately

307 load the players (Lacome et al., 2018; Stone & Kilding, 2009).

308

309 Some limitations need to be taken into considering when applying the results of this research
310 in practice. Firstly, a single team of soccer players represents a relatively low sample size.
311 However, we have considered only one club in our analysis which has made it possible to limit
312 the confounding factors associated with different types of playing and training style, which
313 could have affected the game speed demands and the ecological validity of the study.
314 Moreover, it is well known that inter-unit and inter-model variability exist between different
315 GNSS devices (Beato & De Keijzer, 2019; Beato, Coratella, et al., 2018; Thornton, Nelson,
316 Delaney, Serpiello, & Duthie, 2019), therefore the monitoring of only one soccer team has
317 allowed us to use the same GNSS device throughout the season avoiding this bias. Secondly,
318 this study analyzed the game speed demands of professional soccer players competing in the
319 English Championship league. Therefore, the results have a great applicability for teams
320 playing at the same professional level, but the same findings cannot be generalized to other
321 cohorts such as male semi-professional clubs or female professional teams. The findings
322 reported in this study may be different if another team is analyzed, therefore future research is
323 needed to verify if our results and game speed models can be applied to other clubs playing at
324 different levels and in different leagues.

325

326 **Conclusions**

327 This study presents a quantitative model describing the running intensity of English
328 Championship soccer. It reports that male soccer players game-speed demands are affected by
329 the time window analyzed. Higher game-speed has been found analyzing shorter time intervals
330 (*e.g.*, 1-2 minutes vs. 10 min). Additionally, players' positional groups have significant
331 different game-speed demands (*e.g.*, CM vs. WM), which should be considered during match
332 analysis and training load periodization. This study also found that game-speed outputs are not
333 affected by the location of the match (home vs. away), therefore sports scientists should
334 consider this new evidence during their performance analysis and the construction of effective
335 training prescriptions.

336

337 The findings of this study contribute important information related to match day game speed
338 outputs of professional soccer and presents a set of mathematical models that can be used to
339 evaluate the game-speed demands of professional soccer players. Practitioners can use the
340 approach and models presented in this study to approximate the typical demands of competition

341 and implement training interventions with the aim of replicating or overloading those demands.
342 This type of approach is particularly advantageous when performance staff are required to
343 prepare players to compete in a competition for the first time, or who are returning from an
344 injury or long absence. Having a general or specific game speed model for a playing position
345 provides a set of anchor points which can be used as objective markers in the preparation and
346 rehabilitation of players. These markers not only consider the average demands of the game
347 but also its most intense periods, forming a more complete profile of the physical demands
348 required to perform in a competition such as the English Championship. Performance staff can
349 also utilize this information as part of the long-term development of youth players who aspire
350 to compete at this level, intelligent training drill design can be developed to gradually expose
351 youth players to the physical, technical and tactical demands of senior competition across a
352 spectrum of intensities relative to game speed. Similar, as previously stated the practice of
353 game speed modelling is an effective method of assessing the relative demands of training
354 drills in comparison to match day outputs, this provides coaches and performance staff with a
355 novel method to use when selecting or designing training activities. Using the duration of a
356 training drill coaches can quickly and easily assess the running intensity relative to game
357 demands of the same duration and express those differences in terms of a percentage value.
358 This method provides an arguably more granular and controlled approach to managing the
359 volume, intensity and specificity of training activities. Therefore, we conclude that game speed
360 modeling is a highly practical method of analyzing the demands of competition and provides
361 coaches and performance staff with key information that can be used to develop players, inform
362 rehabilitation practices and manage the design and selection of training protocols with a high
363 degree of control.

364

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