



29 **Exploring the determinants of success in different clusters of ball**  
30 **possession sequences in soccer**

31  
32 **ABSTRACT**

33 The purpose of this study was two-step: classify ball possession (BP) according  
34 to the duration and number of passes; identify which tactical variables most  
35 discriminate the different BP. We obtained 527 BPs from four official matches of  
36 the Brazilian Soccer Championship 2016. Forty-one 'notational', 'space  
37 occupation', and 'displacement synchronization' predictor variables were used.  
38 The BPs were classified into three groups: short ( $11.07 \pm 4.49s$ ,  $1.93 \pm 0.99$   
39 passes), medium ( $26.83 \pm 7.33s$ ,  $5.41 \pm 1.84$  passes), long ( $55.50 \pm 14.97s$ ,  $12.11$   
40  $\pm 4.61$  passes). Discriminant analysis identified the five most relevant variables to  
41 describe each group: coefficient of variation (CV) of the defensive team's  
42 synchronization-Y, CV defensive team's synchronization-X, successful pass last  
43 third, CV distance between offensive team's centroid and target, mean of the  
44 offensive team's width. The approach highlights important variables and could  
45 benefit the description of offensive and defensive game sequences to provide  
46 precise knowledge on the process.

47 **Keywords:** ball possession; tactical; multivariate; soccer

## 58 **Introduction**

59           Ball possession (BP) is the consequence of interactions determined by  
60 contextual factors, such as quality of opponent, tactical configuration, match status, or  
61 venue of the match (Link, Hoernig, Nassis, Laughlin, & Witt, 2017). Tactically,  
62 controlling the ball possession as much possible consists of a substantial set of on-ball  
63 and off-ball actions to generate scoring chances. Some of these actions are associated  
64 with game principles like creating numerical superiority or promoting disorder on the  
65 opponents' defense, but most importantly, generating and occupying spaces (Fernandez  
66 & Bornn, 2018).

67           Although BP is a complex phenomenon whose success depends on the  
68 combination of many variables, most research insist in an attempt to establish a cause-  
69 effect relationship, ie, how BP's time influences performance indicators such as shots  
70 and goals or performance across the season (Collet, 2013; Hughes & Franks, 2005).  
71 Besides that, literature studies have explored others properties of BP, considering  
72 aspects such as passing frequency, pitch zones where the ball moves, passing  
73 characteristics and match status (Cintia, Giannotti et al., 2015; Lago & Martín, 2007; P.  
74 D. Jones, 2004; Paixão et al., 2015a).

75           In our viewpoint, more important that to relate BP's properties to performance  
76 indicators, is identify and describe collective behaviors that help to maintain BP and  
77 perform passes, considering their relevance to the match.

78           For this topic, recent research has proposed several variables that compose  
79 collective movement behaviour (Memmert, Lemmink, & Sampaio, 2016). When the  
80 analysis is focused on the dynamics of space occupation, variables such as the coverage  
81 area or effective playing space (Moura et al., 2012), length, width, and measures around

82 the centroid (Folgado, Lemmink, Frencken, & Sampaio, 2014; Coutinho et al., 2019)  
83 are widely used. Besides that, several non-linear processing techniques have been used  
84 to improve the performance analysis process. For example, approximate entropy (ApEn)  
85 appears to provide information about the regularity of certain behaviour in soccer games  
86 and seems to be associated with adaptation during training interventions (Sampaio &  
87 Maçãs, 2012), critical moments of the game (Aguiar, Gonçalves, Botelho, Duarte, &  
88 Sampaio, 2017), or interpersonal game distances (Gonçalves et al., 2016).  
89 Complementarily to this structure of variability, the coefficient of variation (CV) has  
90 also been used to measure the magnitude of the variability of a given behaviour across  
91 time (Gonçalves et al., 2017; Lorenzo-Martínez et al., 2019; Castillo, et al., 2019).

92 Non-linear processing techniques have also been used to identify coordination  
93 patterns in tactical behaviour analyses. Several studies have shown that movement  
94 synchronization is linked to tactical performance (Folgado, Duarte, Fernandes, &  
95 Sampaio, 2014; Folgado, Gonçalves, Sampaio, Folgado, & Gonçalves, 2017), with  
96 consequences on the external and internal workload demands (Folgado, Duarte,  
97 Marques, Gonçalves, & Sampaio, 2018).

98 Considering the previous arguments, a multivariate approach based on metrics  
99 that describe collective behaviors in BP sequences could provide a more holistic model  
100 of this phenomenon in soccer matches. Within this topic, the outcomes would benefit  
101 from descriptions of the offensive and defensive game sequences to provide precise  
102 knowledge on the process. In addition, there are few studies on ball possession that  
103 describe collective tactical behaviours that determine the team ability to maintain ball  
104 possession. Thus, the purpose of this study was two-step: i) classify ball possession  
105 sequences according to the duration and number of passes; ii) identify which tactical

106 variables most discriminate the different ball possession sequences, as classified in the  
107 previous step.

## 108 **Methods**

### 109 *Data collection and sample*

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111 The Ethics Committee of the Campinas State University approved this research. The  
112 sample of this study corresponds to 527 ball possession (BP) sequences obtained from  
113 four first division official matches of the Brazilian Soccer Championship 2016.

114 The matches were recorded by two digital cameras (HDR-CX405, Sony), HD  
115 resolution, acquisition frequency of 15Hz, commonly used in collective tactical analysis  
116 (Rico-gonzález, Arcos, Nakamura, Arruda, & Pino-ortega, 2019). Subsequently, a  
117 semiautomatic tracking system was used to obtain the players' 2D positional data using  
118 the software DVideo (Pascual, Leite, & Barros, 2002; Figueroa, Leite, & Barros, 2006).  
119 The 2D coordinates of each player were defined as  $X_p(t)$  and  $Y_p(t)$ , where  $t$  represents  
120 each instant of time. The X and Y axes represent length and width of the pitch  
121 respectively. A Butterworth third-order low-pass digital filter with a cut-off frequency  
122 of 0.4 Hz was used as an external filter according to previous study recommendations  
123 (Barros et al., 2007). DVideo software has an automatic tracking rate of 94% of the  
124 processed frames, an average error of 0.3 m for the determination of player position,  
125 and an average error of 1.4% for the distance covered (Figueroa, Leite, & Barros, 2006).  
126 Notational analysis was performed by an experienced operator to register the technical  
127 actions of each player, synchronized with the positioning data.

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132 ***Ball possession sequences***

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134 Each ball possession started when any player controlled the ball through the successful  
135 execution of a technical action, such as a pass, interception or tackle, and restarting  
136 play, such as a free kick, throw-in, corner kick, and goal kick. When the game stopped  
137 for less than 15 seconds and the ball remained with the same team, it was considered the  
138 same BP sequence. This decision was made since the match dynamics of player  
139 positioning were not influenced. BP sequences of less than four seconds were excluded  
140 (to fulfil the nonlinear computation requirements). BP that did not contain at least one  
141 successful pass were also excluded.

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143 ***Variables***

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145 Forty-one variables were computed and classified into three groups: notational, space  
146 occupation, and displacement synchronization (Table 1). Dynamic variables were  
147 analysed using the absolute values (mean), normalized approximate entropy (ApEn),  
148 and coefficient of variation (CV). ApEn is a nonlinear measure that quantifies the  
149 regularity in complex system behaviors (Pincus, 1991). For this study, we decided to  
150 compute the normalized entropy, a non-modified measure of regularity derived from the  
151 original ApEn, which is less dependent on time series length (Fonseca, Milho, Passos,  
152 Araújo, & Davids, 2012). Coefficient of variation (CV) values ((standard  
153 deviation/mean)×100) were used to verify the magnitude of variability of the time  
154 series.

155         The displacement synchronization variables consisted of the percentage of time  
156 that inter-player displacements were synchronized, calculated using the vector coding  
157 technique (Sparrow, Donovan, Van Emmerik, & Barry, 1987) and recently applied to

158 investigate player behaviour during tennis matches (Pereira, van Emmerik, Misuta,  
159 Barros, & Moura, 2017). The technique consists of calculating the angle ( $\theta$ ) formed by  
160 the relative motion between two oscillators in two consecutive coordinates of a given  
161 time series. The coupling angle represents an instantaneous spatial relationship between  
162 two players (dyad) in relation to the axes (X and Y). The coupling was considered as in-  
163 phase when the angle was at  $45^\circ$  or  $225^\circ$  (positive diagonal). Thus, the intervals  $22.5^\circ$   
164  $\leq \theta < 67.5^\circ$  and  $202.5^\circ \leq \theta < 247.5^\circ$  were chosen to assume an in-phase synchronization  
165 between two players. The synchronization percentage for each dyad was calculated for  
166 each team (in possession and without possession), in each ball possession sequence. The  
167 mean values of the percentage (% mean) of all the dyads were used to represent the  
168 mean of team synchronization and the CV (based on the % mean of all dyads) was  
169 calculated to indicate the variability between the dyads, i.e., if there was homogeneous  
170 behaviour of the team. All these procedures were performed for the X (longitudinal) and  
171 Y (lateral) axes of the pitch reference. Space occupation and synchronization variables  
172 are shown in Figures 1a and 1b, respectively. Data processing was performed in  
173 Matlab<sup>®</sup>2017(Mathworks Inc., Natick, MA, USA).

#### 174 *Statistical analysis*

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176 A two-step cluster with log-likelihood as the distances measure and the Schwartz's  
177 Bayesian criterion was used to classify the ball possession sequences into the different  
178 groups, according to the time of possession and number of successful passes.  
179 Afterwards, a stepwise fisher's discriminant analysis (FDA) was conducted to identify  
180 which variables best discriminate the previously obtained clusters. At each step, the  
181 variable that minimized the overall Wilks' Lambda was entered in the model. A  
182 minimum partial F (Fisher) value (3.84) to enter and maximum partial F value (2.71) to  
183 remove was used. Validation of discriminant models was conducted using the leave-

184 one-out method of cross-validation. Was applied One-way ANOVA was used to  
185 compare the twelve selected variables into different groups (short, medium, and long  
186 ball possession sequences). Subsequently, the Bonferroni post-hoc test was utilized to  
187 identify pairwise differences. Statistical significance was set at 0.05 and the statistical  
188 analysis was carried out in IBM SPSS Statistics for Windows (Armonk, NY: IBM  
189 Corp). Complementarily, was observed the standardized mean differences and  
190 respective 95% confidence limits (CL), were also computed as magnitude of observed  
191 differences, effect size (Cohen's *d*) and thresholds were: <0.2, trivial; 0.6, small; 1.20,  
192 moderate; 2.0, large; and >2.0, very large (Hopkins et al., 2009).

### 193 **Results**

194 The 527 ball possession sequences (BP) were classified into three different groups  
195 according to the time duration and number of successful passes: cluster 1 (short  
196 possessions  $n=295$  or 55.8%,  $11.07 \pm 4.49s$ ,  $1.93 \pm 0.99$  successful passes), cluster 2  
197 (medium possessions  $n=179$  or 34%,  $26.83 \pm 7.33s$ ,  $5.41 \pm 1.84$  successful passes), and  
198 cluster 3 (long possessions  $n=53$  or 10.3%,  $55.50 \pm 14.97s$ ,  $12.11 \pm 4.61$  successful  
199 passes).

200 The stepwise fisher's discriminant analysis (FDA) identified the most relevant  
201 variables to describe each cluster. The model consisted of two discriminant functions,  
202 with function 1 representing 95.8% of the total variance and function 2 representing  
203 4.2%. The canonical correlations of functions 1 and 2 were, respectively, 0.83 and 0.30,  
204 with both functions being statistically significant ( $p < 0.0001$ ), (Wilks' Lambda = 0.27  
205 and 0.91 for functions 1 and 2, respectively). The model presented a total of 81.6% of  
206 the original grouped cases classified correctly. Table 2 presents the descriptive analysis  
207 for each variable, for the three clusters, as well as the structure coefficients (SC) for  
208 each function.



209           The variables that contributed most to the classification of the BP into function  
210 1, in order of importance were: CV of the defensive synchronization-Y (SC = 0.58), CV  
211 of the defensive synchronization-X (SC = 0.42), successful pass last third, CV of the  
212 distance between offensive centroid and target (SC = 0.34), and mean of the offensive  
213 width (SC = 0.33). The remaining seven variables were: centroid progression, % mean  
214 of the offensive synchronization-X, CV of the offensive synchronization-X, % mean of  
215 the defensive synchronization-X, mean of the defensive length, and mean of the  
216 distance between offensive centroid and target.

217           Figure 2 represents the canonical discriminant function by distribution of the  
218 possession linked to cluster centroids, based on the discriminant scores represented by  
219 the X axis (function 1) and the Y axis (function 2).

## 220 **Discussion**

221           The purpose of this study was two-step: i) classify ball possession sequences  
222 according to the duration and number of passes; ii) identify which tactical variables  
223 most discriminate the different ball possession sequences, as classified in the previous  
224 step. In the first step, the cluster analysis classified the ball possession (BP) into three  
225 groups, short, medium and long duration. This classification allowed identify, describe  
226 and compare the collective tactical behavior to both teams, in offensive and defensive  
227 phase. For this, in the second step we use FDA to highlight, between forty-one tactical  
228 variables, the most relevant that better describe these three clusters. Five variables were  
229 highlighted: coefficient of variation (CV) of the defensive team's synchronization-Y,  
230 CV defensive team's synchronization-X, successful pass last third, CV distance  
231 between offensive team's centroid and target, mean of the offensive team's width. The  
232 findings provided accurate tactical characterization to offensive and defensive team's in  
233 the short, medium and long BP sequences and therefore suggest collective behaviors

234 that help to maintain BP and perform passes, which is one of the challenges of the  
235 offensive phase of the matches.

236 In relation to the ball possession clusters identified, Aguiar et al. (2017) also  
237 classified BP using cluster analysis, however found two distinct groups, short and long,  
238 and the criterion for separation was based on centroid approximate entropy  
239 measurements. Jones et al. (2004) proposed three categories of ball possession  
240 durations, 3-10s, 10-20s, and more than 20s to investigate the relation with match status.  
241 Other studies with BP did not review the time duration or the number of passes and  
242 usually compared short and long sequences (Collet, 2013; da Mota et al., 2015;  
243 Yiannakos & Armatas, 2017).

244 In the present study, the short ball possession duration was characterized by  
245 lower successful passes in the last third, high CV of defensive team's synchronization in  
246 relation to X-axis and Y-axis, lower CV of distance between offensive team's centroid  
247 and target, and lower mean offensive team width. On the other hand, when we analysed  
248 the long ball possession duration, we observed more successful passes in the last third  
249 of the pitch, smaller CV of defensive team's synchronization in relation to X-axis and  
250 Y-axis, higher CV of distance between offensive team's centroid and target, and higher  
251 mean of the offensive team width. The medium ball possession duration presented  
252 intermediate values for the five variables.

253 The successful passes in the last third was the only notational variable  
254 highlighted. Displacement synchronization variables demonstrated importance for  
255 classification of the cluster, especially through the CV values of the defending team.  
256 These variables represent the variability of the percentage values of all team dyads. That  
257 is, the higher the CV, the more heterogenic the behaviour of the dyadic relations during  
258 the time series, as observed in short ball possessions. Otherwise, when dyads present

259 similar behaviours between them, the CV values decrease, characterized in longer ball  
260 possessions. It is probable this behaviour is associated with the transition phases and  
261 stabilization in the possessions, i.e., when there is loss of the ball, the defensive team  
262 reorganizes strategically into its new tactical functions, changing the dynamics of space  
263 occupation during this transition. In short ball possessions, characterized as a mean of  
264 11.7 s duration, there is no stabilization moment, or the transition phase is predominant,  
265 reflecting in the high CV of synchronization in relation to the X and Y axes. In the long  
266 possessions, there is also a transition phase, following a long period of stabilization,  
267 which probably explains the lower CV. These behaviours were conceptually identified  
268 by Hewitt et al. (2016), who generally describe the game as moments of frenetic attack  
269 to create imbalances in the opponent and moments of homeostasis, with rapid  
270 reorganization towards control and stability between the teams. Moura et al. (2013) also  
271 describe similar behaviour, but through the dynamics of the team occupying area,  
272 assigning higher values, based on spectral analysis, at the moment of the game where  
273 teams change ball possession rapidly, i.e., short possessions.

274         The other two highlighted variables belong to the 'space occupation' group. The  
275 CV of the distance between the offensive team's centroid and target indicated greater  
276 variability in longer ball possessions. It is probable the greater mobility of the team in  
277 possession exploring the pitch favoured the passes performed and control of the ball, as  
278 well as the width of the offensive team, which was higher in long ball possessions. It  
279 seems clear that teams adopting wider pitch space occupation and mobility favoured  
280 BP. Mobility and width are two of the five most important offensive principles  
281 proposed by Ouellette (2004). According to Clemente et al. (2013), the movements of  
282 players should extend to use the effective playing space by increasing the dispersion of  
283 players during the offensive phase. This behaviour makes it easier to attract defensive

284 players to non-vital zones (e.g., lateral zones), thereby removing them from the vital  
285 zones (i.e., the middle zones). Clearly, it is essential to analyse offensive and defensive  
286 behaviour from the interaction between teams, not just from a single perspective, as  
287 proposed by Fernandez-Navarro et al. (2016).

288         In summary, ball possession sequences were classified into three clusters based  
289 on the time possession and number of successful passes: short, medium and long  
290 duration. The discriminant analysis highlighted five most important variables to  
291 describe each cluster, and thus, these should be observed with more attention by  
292 coaches and sports scientists. Long ball possessions durations were characterized by  
293 more homogeneous behavior of the defending team in relation to displacements in  
294 lateral and longitudinal directions. There are few studies related to this phenomenon and  
295 therefore, their association with the micro-level relations among teammates should be  
296 further explored. Completely, higher width and mobility of the offensive team in long  
297 ball possession reinforcing some principles of offensive game advocated by experts,  
298 with the advantage of having been quantified and not only subjectively identified. This  
299 study used a limited sample based on Brazilian Soccer Championship and therefore  
300 should not be conclusive. The approach based on a multivariate model, using metrics  
301 recently proposed by research in performance analysis, allowed holistic analysis of the  
302 phenomena and provided accurate knowledge.

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458 Table 1. Tactical variables used separated by groups.

Groups	Variables	Values
<b>Notational</b>	Time of possession	absolute value
	Successful pass	frequency
	Successful pass last third	frequency
	Shots	frequency
	Goal	frequency
<b>Space occupation</b>	Offensive team's effective playing space	mean, CV, ApEn
	Defensive team's effective playing space	mean, CV, ApEn
	Offensive team's length	mean, CV, ApEn
	Defensive team's length	mean, CV, ApEn
	Offensive team's width	mean, CV, ApEn
	Defensive team's width	mean, CV, ApEn
	Distance between offensive team's centroid and target	mean, CV, ApEn
	Distance between defensive team's centroid and target	mean, CV, ApEn
<b>Displacement synchronization</b>	Distance between team's centroid	mean, CV, ApEn
	Centroid Progression	absolute value
	Offensive team's synchronization X-axis	% mean, CV
	Defensive team's synchronization X-axis	% mean, CV
<b>Displacement synchronization</b>	Offensive team's synchronization Y-axis	% mean, CV
	Defensive team's synchronization Y-axis	% mean, CV

459 Forty-one variables were classified into three groups; notational (five variables), space  
 460 occupation (twenty-eight variables), displacement synchronization (eight variables).  
 461 Notational variables represent the total occurrence of the offensive team's ball  
 462 possession, except time of possession. All continuous space occupation variables are  
 463 calculated as mean, coefficient of variation (CV), and approximate entropy (ApEn) per  
 464 ball possession per each team, except centroid progression that represents the difference  
 465 between offensive team's centroid position in the last ball possession moment and the  
 466 beginning of ball possession. For all displacement synchronization variables mean  
 467 values of the percentage (% mean) of all the dyads were calculated to represent the  
 468 mean of team synchronization and the CV was calculated to indicate the variability  
 469 between the dyads. Abbreviations: CV = coefficient of variation; ApEn = approximate  
 470 entropy; % mean = mean of the percentage.

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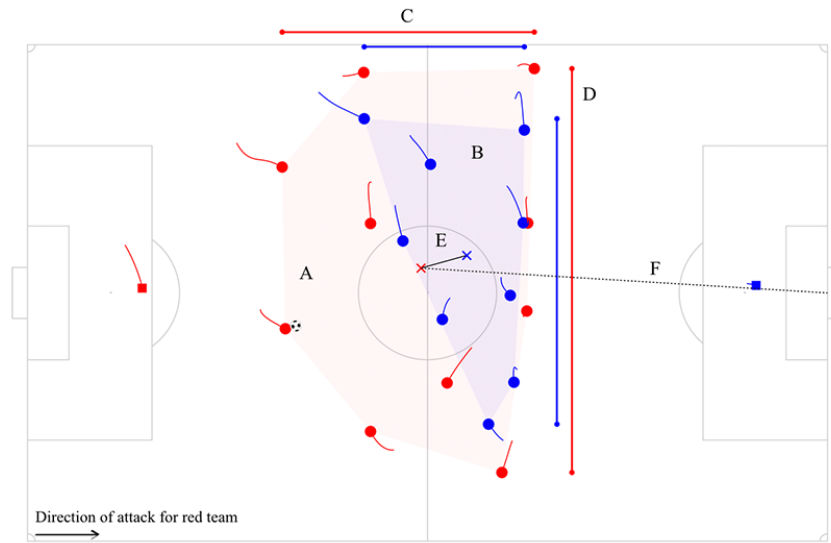
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477 Table 2. Descriptive and inferential statistics of different clusters of ball possession sequences.

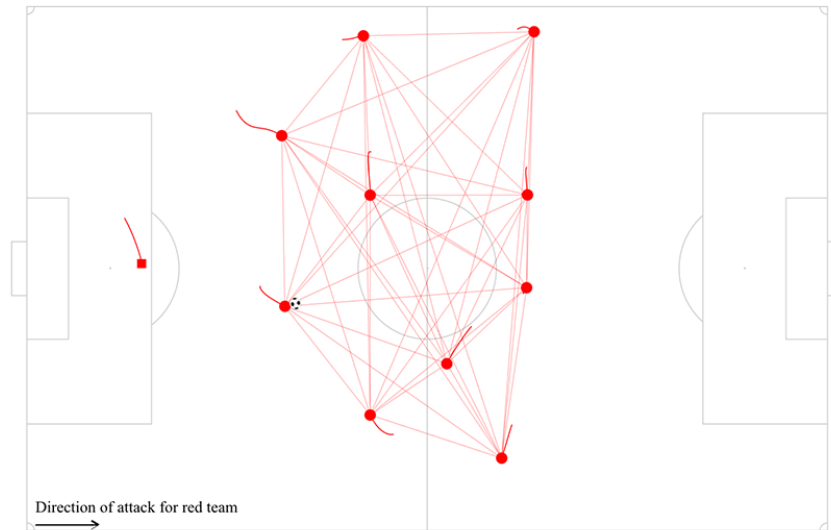
Variables	Short	Medium	Long	Short vs Medium	Short vs Long	Medium vs Long	F1 95.8%	F2 4.2%
	(Mean ± SD)	(Mean ± SD)	(Mean ± SD)	(Mean difference ± CL) Effect size	(Mean difference ± CL) Effect size	(Mean difference ± CL) Effect size		
Time possession	11.07 <sup>ab</sup> ± 4.49	26.83 <sup>c</sup> ± 7.33	55.50 ± 14.97	15.76 ± 1.07 very large	44.43 ± 2.09 very large	28.67 ± 2.96 very large	-	-
Successful pass	1.93 <sup>ab</sup> ± 0.99	5.41 <sup>c</sup> ± 1.84	12.11 ± 4.61	3.49; ± 0.26 very large	10.19; ± 0.59 very large	6.70; ± 0.84 very large	-	-
CV DEF-SynY	47.25 <sup>ab</sup> ± 13.55	30.11 <sup>c</sup> ± 8.10	20.89 ± 4.51	-17.14; ± 2,19 large	-26.37; ± 3.70 very large	-9.23; ± 2.29 large	.577*	.244
CV DEF-SynX	40.60 <sup>ab</sup> ± 14.43	27.00 <sup>c</sup> ± 8.44	20.77 ± 5.64	-13.60; ± 2.33 moderate	-19.84; ± 3.95 large	-6.24; ± 2.43 moderate	.418*	.246
CV OFF-DCT	9.39 <sup>ab</sup> ± 7.90	18.11 <sup>c</sup> ± 9.83	20.55 ± 8.99	8.72; ± 1.62 moderate	11.16; ± 2.37 large	2.44; ± 2.97 small	-.346*	-.343
mean OFF-WID	40.41 <sup>ab</sup> ± 6.84	45.97 <sup>c</sup> ± 6.13	49.21 ± 4.62	5.56; ± 1.22 moderate	8.80; ± 1.92 large	3.24; ± 1.80 small	-.335*	-.112
CV OFF-SynX	44.99 <sup>ab</sup> ± 16.03	35.10 <sup>c</sup> ± 11.30	27.81 ± 7.64	-9.88; ± 2.69 moderate	-17.18; ± 4.42 moderate	-7.30; ± 3.26 moderate	.289*	.014
CProgress	12.72 <sup>b</sup> ± 14.44 <sup>a</sup>	22.02 <sup>c</sup> ± 17.63	26.16 ± 13.07	9.30; ± 2.92 small	13.44; ± 4.18 moderate	4.13; ± 5.15 small	-.221*	-.136
mean OFF-DCT	55.00 <sup>ab</sup> ± 14.63	47.56 ± 9.48	44.97 ± 8.51	-7.44; ± 2.41 small	-10.03; ± 4.08 moderate	-2.59; ± 2.86 small	.210*	.174
mean DEF-LEN	34.34 <sup>ab</sup> ± 7.55	31.53 <sup>c</sup> ± 7.00	27.58 ± 6.85	-2.80; ± 1.37 small	-6.75; ± 2.19 moderate	-3.95; ± 2.15 small	.190*	-.174
% mean OFF-SynX	47.37 <sup>ab</sup> ± 15.85	42.52 <sup>c</sup> ± 9.84	36.56 ± 6.20	-4.85; ± 2.58 small	-10.81; ± 4.35 moderate	-5.96; ± 2.82 moderate	.172*	-.119
% mean DEF-SynX	47.84 <sup>ab</sup> ± 13.90	44.84 ± 10.47	42.85 ± 7.51	-3.00; ± 2.37 small	-4.99; ± 3.85 small	-4.03; ± 3.30 small	.097*	.018
Successful pass-LT	0.46 <sup>ab</sup> ± 0.83	1.58 <sup>c</sup> ± 1.68	3.38 ± 3.19	1.11; ± 0.22 moderate	2.92; ± 0.43 large	1.80; ± 0.65 moderate	-.381	.436*
% mean DEF-SynY	37.65 ± 11.62	37.16 ± 7.82	40.20 ± 6.57	-0.49; ± 1.92 trivial	2.54; ± 3.23 small	3.03; ± 2.33 small	-.025	.239*

478 Mean ± Standard deviation (SD), mean difference and respective 95% confidence limit (CL), effect size based on Cohen's *d*, structure coefficient  
479 (SC) of 12 variables selected by the FDA model, and 2 variables used to separate the clusters (time of possession and successful pass). \*variable  
480 better explained by function 1 or 2. One-way ANOVA and the Bonferroni post hoc to differentiate between groups (a = difference between  
481 clusters 1 and 2; b = difference between clusters 1 and 3; c = difference between clusters 2 and 3; p<0.05). Abbreviations: Short = Short ball  
482 possession sequences; Medium = Medium ball possession sequences; Long = Long ball possession sequences; F1 = Function 1; F2 = Function 2.

### (a) Space occupation



### (b) Displacements synchronization

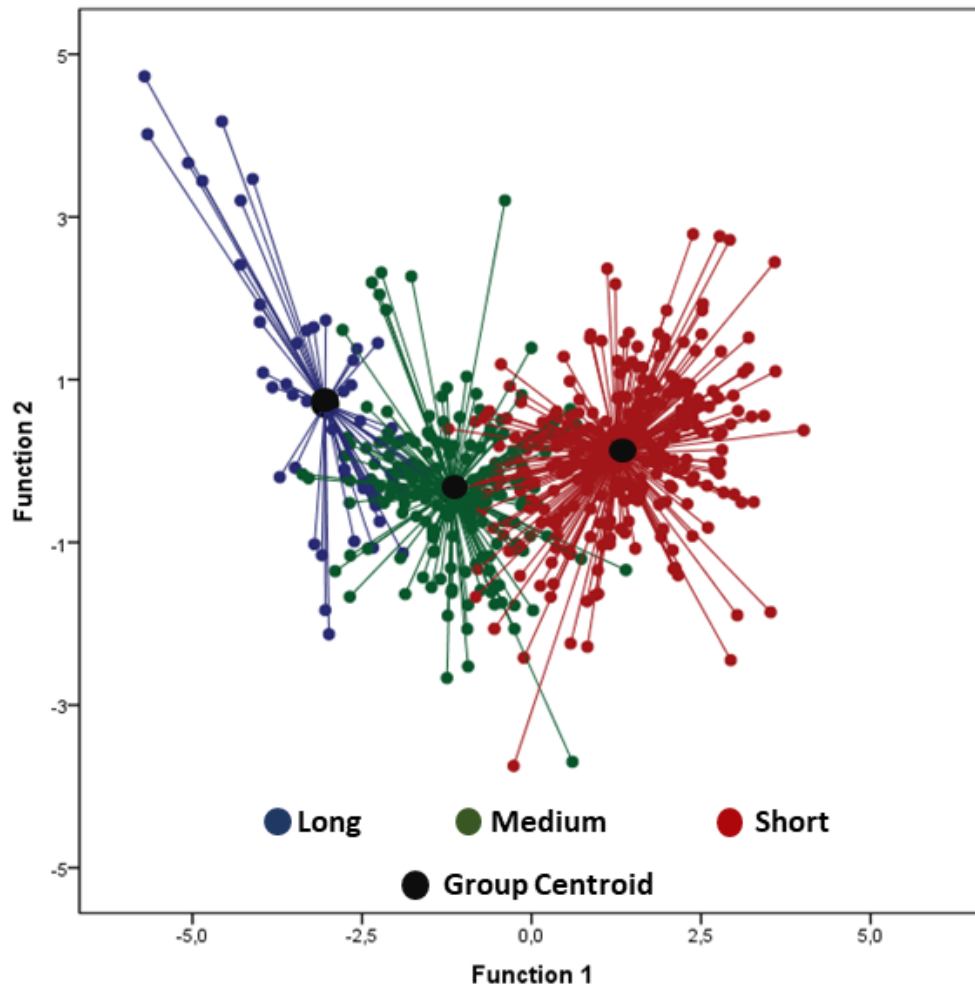


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484 **Figure 1.a)** Representation of space occupation variables. Red team in ball possession  
485 (offensive phase) versus blue team (defensive phase) during long ball possession  
486 sequence. Abbreviations: A = Effective playing space (red team); B= Effective playing  
487 space (blue team); C = length (red team); D = width (red team); E = distance between  
488 team centroids; F = distance between centroid and target (red team). b) Representation  
489 of displacements synchronization. Each edge represents a dyad. Each player is  
490 connected to nine other players, except for the goalkeeper (total of 45 dyads).

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494 **Figure 2.** Territorial maps of the cluster centroids (group centroid) and their respective  
 495 ball possession sequences (short = short ball possession; medium = medium ball  
 496 possession; long = long ball possession) based on two canonical discriminant functions.  
 497 Function 1 representing 95.8% of the total variance (0.83 of the canonical correlation)  
 498 and function 2 representing 4.2% (0.30 of the canonical correlation), both functions  
 499 being statistically significant ( $p < 0.0001$ ), (Wilks' Lambda = 0.27 and 0.91 for functions  
 500 1 and 2, respectively).

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