A mathematical model of self-organisation in football

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The theory of self-organising systems was used to analyse the factors that play a key role in a football teams’ performance. The resulting mathematical model revealed that passing was the most central component to team’s performance. The current study aimed to introduce a spatial component into the model by exploring passing data from different spatial zones of the pitch (defence, midfield and attack). This analysis helped understand the organisation which underpins the dynamics at the core of team performance when in possession of the ball. The amended Spatial Integrated Model of Self-Organisation in Football Teams (SIMSOFT) considers seven parameters of which six relate to passing frequency and accuracy. SIMSOFT outputs a team play index which, when applied to the results from Barclays Premier League on the complete 760 games of season 2012-2013, accounts for 57% of the variance in football team performance, measured as the number of goals scored per minute of possession. We conclude that the self-organising theoretical framework is a useful theoretical approach to examine the performance of football teams. These findings may have potential implications for coaches’ looking to develop footballers in the most efficient way to maximise performance outcome.

**Keywords:** Passing, Football, Soccer, Team Sports, Performance Analysis

# Introduction

Self-organisation refers to systems made of a collection of agents that develop a structure in absence of controlled supervision (Jensen, 1998). In biological systems, it occurs in groups of organisms when the efforts of the individual are not able to achieve all the tasks required by the group. In these situations, the coordination of the constituent members becomes necessary in order to achieve larger goals. Interestingly, whilst this high-level organisation appears to be the result of a pre-set design, research has shown that this is an illusion (Bonabeau, Theraulaz, Deneubourg, Aron, & Camazine, 1997). Instead, what appears to be a supervised coordination of potentially thousands of individuals is simply the result of each individual animal responding to local patterns in their environment (Camazine, 1991). In a biological self-organised system, the system’s organisation emerges from behavioural rules applicable at the individual level. Recently it has showed that the notion of dynamical self-organising system can be applied to sports (McGarry, Anderson, & Wallace, 2002; Passos, Araújo, & Davids, 2013). Similar to animals that adjust their relative position to fit the purpose of the swarm, we reason that self-organisation in team sports refers to the ability of the players to adjust their position as a function of both the location of the ball and other players. These adjustments take place within a few seconds and stem from expert intuition (Chassy & Gobet, 2011). The players in possession need to constantly change their spatial configuration on the pitch so as to progress without losing the ball.

In football, possession has been taken as the core factor underpinning performance with most research thus focusing on the various factors that enhance or moderate possession (Jones, James, & Mellalieu, 2004; Lago-Peñas & Dellal, 2010; Lago, 2009; Morgans, Adams, Mullen, & Williams, 2014; Shafizadeh, Gray, Sproule, & McMorris, 2012). Yet, recent questioning of the central role of possession has revealed that other factors contribute largely to success (Collet, 2013; Davids, Araújo, & Shuttleworth, 2005; Travassos, Araújo, Vilar, & McGarry, 2011). Mathematical approaches integrate findings into unified theories of football (Miyamoto, Kaneki, & Misumi, 2017; Sarmento et al., 2014). The dynamical approach has enabled showing that football exhibits complex and multidimensional properties (Silva, Chung, Carvalho, Cardoso, Davids, Araújo, & Garganta, 2016). In this context, one factor identified as such is passing (Chassy, 2013). The ability to transmit the football is the only action in football that makes a team a dynamical group of interacting individuals. This paper examines the central role of passing in performance. It is important that coaches and players understand how behaviour at the player’s level influences the team performance and its tactics.

Teams are dynamical systems that constantly try outdoing each other (Gréhaigne & Godbout, 2014). In line with the realisation that football can be analysed through the self-organising principles (McGarry, Anderson, Wallace, Hughes, & Franks, 2002), positional data is becoming a new standard to exam dynamical patterns of play (Memmert, Lemmink, & Sampaio, 2017). Tactics, defined as predetermined patterns of the spatial distribution of players, underpin spatial control and thus team performance (Moura, Martins, Anido, Ruffino, Barros, & Cunha, 2013; Rein & Memmert, 2016). Different teams adopt different, yet specific, tactical schemes to outdo the opponent (Bialkowski, Lucey, Carr, Yue, Sridharan, & Matthews, 2014). The idea behind tactical schemes is that a shared mental map of positions will facilitate dynamical exchanges of the ball. Yet, because of the opponents’ efforts to stop progression (Andrienko, Andrienko, Budziak, Dykes, Fuchs, von Landesberger, & Weber, 2017), the spatial configuration of the players is constantly changing. It is their ability to form a unit that constitutes the source of efficiency (Duarte, Araújo, Correia, Davids, Marques, & Richardson, 2013).

Previous studies have applied the self-organisation framework within football, focusing on goal scoring (Grehaigne, Bouthier, & David, 1997; McGarry et al., 2002, ; Passos et al., 2013; Travassos et al., 2011) and the role of passing (Chassy, 2013; Tenga, Holme, & Ronglan, 2010). The analysis of sequences has demonstrated that passing is a crucial component in scoring goals regardless of possession time (Hughes & Franks, 2005; Redwood-Brown, 2008). The team as a whole can progress only if the players stay connected all along. The distance between the players has been highlighted as a key component of successful passing (Travassos et al., 2011). The coordination of moving players on the pitch is thus the crucial factor. It is evidently underpinned by the players knowledge of the tactics, their physical ability to be in the correct position and their technical skills to execute the appropriate motor actions. It remains true that the last player touching the ball should have the technical capacity to score. In line with this, much research has been dedicated in understanding the importance of accurate shooting collet (Collet, 2013; Marques et al., 2011). However, it is often forgotten that shooting opportunities arise because of good passing. Tenga and colleagues (2010) have shown that longer possessions are more likely to produce a goal when the possession includes a longer passing sequence. The question that can be asked is how much of a team performance can be predicted based upon shooting and passing parameters. Should self-organisation hold true for football, a mathematical model that would integrate passing should be an accurate indicator of the level of swarm intelligence displayed by a team.

Chassy (2013) employed the self-organisation framework to develop a mathematical model of team performance based upon passing, shooting, and possession. Passing and shooting abilities were selected to develop the initial model as they provide a proxy measure of the self-organisational ability of a team. Many factors play a role in a team’s progress towards the goal (Lago-Ballesteros, Lago-Peñas, & Rey, 2012) but passing constitutes the one process that involves a cooperative interaction (Hughes & Franks, 2005; Rein, Raabe, & Memmert, 2017). The importance of passing is illustrated by the fact that its rate has increased over time at the highest level of practice (Barnes, Archer, Hogg, Bush, & Bradley, 2014; Wallace & Norton, 2014). This trend of increasing passing can also be seen at the player level, where the passing requirements have dramatically increased for specific positions (Bush, Barnes, Archer, Hogg, & Bradley, 2015). Whilst passing restricts the measure of self-organisation to two players, the multiplicity of measures, averaged across all players and over 90 minutes of play provides a measure of coordinated actions for the whole team. Shooting is obviously a key skill but it usually arises usually after series of passes (Barreira, Vendite, & Vendite, 2016; Hughes & Franks, 2005; Wright, Atkins, Polman, Jones, & Sargeson, 2011); and thus constitutes only another proxy of the ability of the team to deliver an outcome. These two variables together have the advantage of providing a multidimensional scale to measure interactions between players. Chassy’s (2013) study revealed that three parameters play a key role in performance: the average number of passes per minute of possession (pass density), proportion of successfully completed passes (pass precision), and number of goals scored divided by the number of shots taken (hit ratio). Pass density and precision were introduced to integrate the role of passing in a team’s performance. The parameters were used to compute two factors, self-organisation and offensive power, which combined, produced a general index of performance: team play (TP). While the factor self-organization was heavily loaded with passing parameters, the factor offensive power was dominated by shooting. This split in weights between the two factors is indicative that two aspects standing at the core to team performance: Passing ability and shooting skills. The primary aim was to introduce the idea that passing is more important than mere possession. In this respect, the model was successful: both passing density and pass precision were both strong predictors of possession (99.85%) and shooting opportunities (94.92%).

The model has two key limitations that call for further research. One, key limitation of the model was the fact that all passes were considered of equal value. For example, it is evident that the consequences of imprecise passing in front of one’s goal can lead to more damaging consequences than a missed passed on the opposing side of the pitch. This spatially-dependent aspect of football requires consideration for a more accurate view of self-organising systems, and thus of efficiency in football. In addition, the model was only applied to a knockout competition (UEFA Champions League) rather than a league competition where teams play against opposition both home and away across a longitudinal period. The purpose of the present study was to further determine which match variables are key to a football team’s performance across a competitive season. In order to investigate the influence of zonal position on the pitch, match performance variables were explored in three equal sized subsections of the pitch: the attacking zone, the midfield zone, and the defensive zone.

# Methods

## Match Data

In this prospective study, match data were collected during the 2013-14 Barclays Premier League season from the database provided by Opta (London, UK). We recorded 760 entries with the following parameters: home team, away team, result, possession percentage, successful passes and total passes for the defensive zone, the middle zone and the attacking zone of the pitch, and number of shots for the home and away team. Pass density is calculated as the ratio of passes over possession time. Pass precision is calculated as the ratio of correct passes over the total passes. Efficiency, finally, is the ratio between goals and total shots. For each team and each game, we standardised the parameters of interest. The data were then averaged across games to generate mean estimates for each team. While the data collected arose as a condition of employment for the players involved, approval for the study from the Liverpool Hope University ethics board was obtained.

## Spatial integrated model of self-organisation in football teams (SIMSOFT)

Chassy’s original mathematical model (Chassy, 2013) was developed upon pass density (PD), pass precision (PP) and hit ratio (HR). Based upon these parameters, two factors were calculated. First and foremost was Self organisation = .79PD + .81PP + -.04HR wherein the weight of shooting performance is negligible. In the second factor, Offensive power (OP), the relative weights of the parameters emphasise the importance of shooting but also highlight that passing still plays a role: OP = .33PD - .29 PP + .94 HR (i.e. there is no shooting opportunity without passing). Team play (TP) was calculated by summing the two factors. To integrate spatiality into the model, we divided the pitch into three zones of play (defensive, midfield and attacking thirds) of equal area and used principal component analysis (PCA) to integrate the weight of passing density and accuracy in each third. PCA is a mathematical technique that reduces a series of measures, which potentially highly correlate, to a number of independent factors. Factors are recursively selected according to the variance that they account for until a criterion of acceptance is reached (i.e. values less than 1, (Stevens, 1996)). Prior to being performed, PCA analysis requires a set of conditions to be met (Kaiser, 1960; Tabachnick, Fidell, & Osterlind, 2001). To evaluate the suitability of the 2013-2014 Premier league data set to be submitted to PCA analysis, we carried out the Kaiser-Meyer-Olkin (KMO) test and Bartlett’s test. A KMO value equal or superior to 0.5 indicates that PCA is suitable for the data set. Both tests have been shown to be good indicators of the suitability of data for factor reduction (Kaiser, 1960; Tabachnick et al., 2001). The KMO value for our data set was .64. The KMO test indicates that the variables in our set do not correlate highly with one another. Similarly, Bartlett's test of sphericity was highly significant χ²(15, n = 20) = 85.87, P < .01. Both KMO and Bartlett’s tests support the use of PCA to reduce the number of factors.

Following this methodological precaution, PCA was conducted on the pass precision and density of all three zones of play (defence, midfield, and attack) to determine the relative weight and contribution of each component to self-organisation. The new mathematical model, called the spatial integrated model of self-organisation in football teams (SIMSOFT), enables the examination of how teams reorganise in different spatial zones (defence, midfield, attack).

## Ecological validity of the model

SIMFSOFT is a mathematical model of team play when in possession of the ball. Such capability should reflect on the performance on the team and, under the assumption of a football team being a self-organised system, should actually be predictive of performance. We tested three predictions that demonstrate the model’s ecological validity and thus highlight the practical impact of SIMSOFT.

The first prediction stands at the team level. A properly self-organised system should be delivering an output (i.e. goals) in spite of constant changes in the layout of the opposite team. SIMSOFT predicts team’s performance as evaluated by the number of goals per minute of possession. To test this prediction, team play indexes were correlated with the number of goals per minute of possession.

The second prediction stands at the match level. We tested whether SIMSOFT is able to account for individual games outcomes. To predict the outcome of a game we compared the team play index of the two teams and assigned the team with the best team play a theoretical win. This method does not allow predicting draws (78 games out of 360) as none of the team play’s indices are equal but it provides a proxy regarding the importance of team play in performance.

The third prediction stands at the league level. Should passing play a key role in performance then the self-organising theory should account for the final ranking of a team. We examined whether SIMSOFT predicts team ranking in the League. To this purpose, teams were ranked according to their team play index. Such theoretical ranking was correlated to the actual ranking in the league tables.

# Results

### SIMSOFT

Table 1 reports the parameters of interest for each team. The standardised parameters already offer some insight into a team’s structure by highlighting the differences in passing abilities across all the 20 teams in the premier league. It is striking to see that teams within the Premier league and thus the best possible football in the UK can differ from one another by several standard deviations in their ability to make passes.

**\*\*\*Insert Table 1 Around Here\*\***

The correlation matrix (Table 2) indicates the degree of association between the variables. As the correlation matrix shows, density tends to correlate negatively across the three zones of the field. Precision on the other hand correlates positively across the three zones. The correlation between density and precision is apparent only in the midfield with all r² > .19.

**\*\*\*Insert Table 2 Around Here\*\*\***

Principal components extraction identified two main components, a result that supports the previous study identifying also two components to a team’s performance (Chassy, 2013). Table 3 details the relative loading of each component. Component 1 alone accounts for 55% of the variance, with the second component accounting for 26%. The sum of both components accounts for 81% of the sum of squares.

**\*\*\*Insert Table 3 Around Here\*\*\***

The results of the PCA were integrated into the initial Chassy’s model (Chassy, 2013) with the Efficiency parameter being left unchanged. The resulting mathematical model, SIMSOFT, is presented in Equation 1. It is interesting to note that the Efficiency factor, the only factor not relating to passing, influences the performance of the team at one stage only. Hence, out of 14 factors, shooting is relevant once; Its weight cumulated over the two components is very small as compared to passing parameters (0.94 < 3.17). Equation 1 below is the full model that predicts team play as a function of standardised passing and shooting parameters. A regression of the TP index over team’s performance shows that SIMFOT has a significant predictive power (r = .76, P < .001, 95% CI [179.14-437.95]). Performance = 0.002 \* Team Play + 0.030) and that a team performance linearly increases with team play.

SIMSOFT model, Equation 1. Team Play = .33 DD + .863 DP + .76 MD + .97 MP + .20 AD + .94 AP + -.040 E + -.80 DD + -.11 DP + -.21 MD + .12 MP + .89 AD + .23 AP + .940E, accurate to three decimal places.

## Ecological validity

All three ecological predictions received empirical support. The ecological prediction at the team level was supported. SIMSOFT’s team play index significantly predicts the number of goals per minute of possession (r = .779, 95% CI [125.44-291.91], F(1, 18) = 27, P < 0.001). Thirteen out of twenty teams fall within the confidence interval of the equation, indicating a high level of prediction. This result constitutes good evidence that passing abilities in the three thirds of the game underpin a team’s ability to create scoring opportunities.

The ecological prediction at the match level was supported. By comparing team play indexes, SIMSOFT predicts the winner in 68% of games (204 results predicted out of 302 games). A predictor capability that significantly departs from chance (χ²(1) = 37.21, N = 302, p < .001). SIMSOFT correctly predicted outcomes were 66% (118 / 180) of wins (χ²(1) = 12.90, N = 298, p < .001) for the home team and 70% (86 / 122) of wins by the away team (χ²(1) = 6.23, N = 208, p < .001). This result is supportive of the idea that passing is an essential key aspect of competition.

The ecological prediction at the league level was supported. Ranking teams as a function of team play is predictive of the final league table ranking at the end of the season (r = .76, 95% CI [0.43-1.08], F(1,18) = 23.85, P < .001).

All three ecological predictions were supported indicating that SIMSOFT is valid across levels of analysis; from team performance to final league ranking. This crucial result suggests that passing abilities constitute the core of a team’s success. The ecological tests carried out support the idea that SIMSOFT constitutes a mathematical model that, by integrating passing and shooting parameters into a spatially-structured mathematical model, can predict team performance in real world situations.

# Discussion

The main finding of the present study is that Team Play was a significant predictor of team performance; accounting for 61% of the variance. This finding provides further support for mathematical modelling of football play (Brillinger, 2007; Chassy, 2013; McGarry et al., 2002), and through it, to the hypothesis of a team behaving as a self-organised system. SIMSOFT is significantly accurate in predicting the outcome of games as well as the final ranking of a team in a round-robin tournament. It is critical to note that SIMSOFT is a compound of six passing and one shooting parameter, which highlights the fact that the relative weights of passing in three zones of play contribute to predict performance. The present findings suggest that density of passing whilst in possession is a key contributor to performance.

The introduction of zones of play in the model allows for consideration of the role of location in a team’s performance. Pass density analysis revealed that defensive play was negatively related to pass density in attack (r = -.45). This suggests that the more passes made in the defensive zone, the fewer passes are made in the attacking zone indicating a difficulty in progressing from the defensive third to the attacking third; a proper, objective measure of spatial domination by one team. A similar pattern of findings was found with the midfield zone, which was positively related to passing in defence, but also shared a negative relationship with the pass density in the attacking zone (r = -.09). This could be indicative of a lower frequency of passing in the attacking zone relating to an increased number of attempts at the goal, and subsequently a higher goal-scoring rate. Indeed, there is literature to support the idea that more goals are scored as the result of shorter passing sequences (Travassos et al., 2011). However, there is also contrasting evidence to suggest that more goals are scored from longer passing sequences (Hughes & Franks, 2005; Tenga et al., 2010). As the majority of the evidence reported here did not explore whether passing sequences originated in either the defensive, midfield, or attacking zones, it is possible that the starting point of the passing manoeuvre is influential to the length of passing sequences that lead to a shot on target.

The match data analysis indicated that the midfield zone is the most influential zone in the current model, contributing to the highest weightings for both pass density and pass precision. This interpretation is in line with the work of Tenga et al. (2010) who reported that more goals were scored from possessions that began in the midfield zone of the pitch than either the defensive or attacking zones. Our explanation for this result is that, in the attacking zone, the mean ratio between the two teams in terms of players becomes less than one for the attacking team. For example, where both teams play in 4-4-2 in the defensive third, the team in possession has a ratio of 2 (four defenders vs. two attackers), in its midfield, the ratio is 1 (four midfields vs four midfields). However, in the attacking third they have to create space in a ratio of .5 (two attackers vs. four defenders). The progressive decrease of the balance between the two teams as the attacking team progresses towards the goal is mirrored by an increasing demand in coordination and speed. According to our results, the midfield is the place to self-organise for future attacks. This approach would also explain why there is a higher proportion of play in the midfield zone, as it is where both teams have equal forces and thus are perpetually trying to create an advantage. This logic is in line with the finding that pass density increases before a goal is scored (Redwood-Brown, 2008). Taken together these results suggest that good coordination in the midfield plus an acceleration of the passing pattern, while maintaining accuracy, when progressing to the goal are key to scoring.

Our results have several practical implications. The key result is the high weight of the passing parameters in determining a team’s performance. To be performed successfully, passing requires the presence of two factors. The first is the correct positioning of the passer and the receiver on the pitch. We believe this factor to be mostly of cognitive nature. The role of cognitive skills in the acquisition of football expertise has been largely emphasised earlier (Ward, & Williams, 2003) and our study supports its centrality. Tactical schemes will guide players in how they should progress towards the goal (Gonzalez-Rodenas, Lopez-Bondia, Calabuig, Pérez-Turpin, & Aranda, 2016; Tenga, Holme, Ronglan, & Barh, 2010). Each player has knowledge of the typical positions that could be taken and the typical manoeuvres that were rehearsed at training. The ability of the players to implement, or adapt, the team’s tactical scheme is, we suggest, heavily depending upon spatial cognition. Foreseeing and anticipating the evolution of a game will create the positive conditions for a successful pass. If spatial cognition plays a role as we suggest in the present paper, then it would be beneficial to develop a sense of space awareness in players and develop their spatial skills through training drills. The second factor is the actual skill to make the pass. Like any motor skill, performance is a mere reflection of training (Ericsson, Krampe, & Tesch-Römer, 1993; Newell, & Rosenbloom, 1981); much literature has been written on the direct relationship between amount of practice and skills (Kaufman & Duckworth, 2017) even though other factors might also modulate speed of acquisition (Chassy & Gobet, 2011; Hornig, Aust, & Güllich, 2016). Considering that players occupy determined positions all along the game, they are likely to be required to make passes in the same direction. The set of motor skills acquired during training should match the passing requirements determined by the spatial location of the player.

The mathematical model, SIMSOFT, will benefit from more research. Three main avenues for improvement would be beneficial at this stage. The first is introducing parameters that modulate the effect of team play. For example, playing home (or away) is known to have an effect on the result (Nevill, Newell, & Gale, 1996). The second avenue is to develop a more sophisticated mapping of the football pitch. The spatiality of the model should be extended maybe with a continuous coordinate system in place of an arbitrary division of the pitch. Third, we have suggested that a team’s performance can be formalised by using the framework of a self-organising system; however, it is important to note that the current model only predicts performance when a team has possession of the ball. Possession is considered an important indicator of performance and there is a large body of research exploring this relationship (Hughes & Franks, 2005; Lago-Peñas & Dellal, 2010; Lago, 2009). It is clear that a team would also function as a self-organising system when they do not have possession. Otherwise, it would not be possible for players to perform defensive actions. Thus, only accounting for possession play represents a limitation of the current model which should be addressed in future research. Noticeably though, there is no equivalent behavioural measure of direct interactions, and thus self-organisation, when the team is not in possession. A potential technique that could be used is to analyse the relative motion of players (Folgado, Duarte, Marques, Gonçalves, & Sampaio, 2018). A spatial approach to self-organisation provides a proxy on the degree of coordination between players but does not reflect their ability to interact.

In conclusion, the present study has provided further evidence that the theory of self-organising systems is an appropriate and useful framework through which to explore the team play in football when a team is in possession. The study has replicated the original model (Chassy, 2013) using data from a round robin league and has developed this further, demonstrating the contribution of localised, self-organised sub-systems in three zones of play. The SIMSOFT mathematical model successfully predicts the winning team, in 68% of the games. The present results open a new avenue for analysing and integrating team performance into a single framework.

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**Table 1.** Standardised values used for principal component analysis.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | Defence | | Midfield | | Attack |  | |
| Team | Density | Precision | Density | Precision | Density | Precision | Efficiency |
| Arsenal | 0.50 | 0.77 | 1.29 | 1.38 | 1.93 | 1.71 | 0.40 |
| Aston Villa | -0.92 | -0.90 | -0.47 | -1.41 | -0.11 | -1.34 | 0.16 |
| Cardiff | 0.82 | -1.10 | -0.82 | -1.09 | -0.92 | -0.74 | 1.19 |
| Chelsea | -0.46 | 1.37 | -0.42 | 0.93 | 1.23 | 0.88 | -1.81 |
| Crystal Palace | -1.24 | -2.69 | -0.85 | -2.19 | 1.19 | -1.11 | -0.55 |
| Everton | 0.90 | 1.23 | -0.79 | 0.84 | 0.40 | 0.92 | -0.84 |
| Fulham | 1.31 | 0.50 | -0.10 | -0.37 | -0.87 | -0.69 | 2.48 |
| Hull | 0.29 | -0.53 | 0.36 | -0.63 | -0.52 | -1.04 | 0.17 |
| Liverpool | 1.70 | 0.88 | 0.63 | 1.04 | 0.39 | 0.95 | 0.64 |
| Man City | -1.63 | 0.89 | 1.42 | 1.54 | 1.66 | 1.75 | 0.57 |
| Manchester | -0.67 | 1.16 | 0.58 | 1.07 | 0.44 | 1.16 | -0.99 |
| Newcastle | -0.29 | 0.28 | 0.28 | 0.15 | -1.27 | -0.43 | -1.38 |
| Norwich | 0.42 | -0.54 | -0.99 | -0.65 | 0.48 | -0.73 | 0.66 |
| Southampton | 1.03 | 0.80 | 0.51 | 0.20 | -1.14 | 0.01 | -0.77 |
| Stoke | 0.07 | -0.74 | 0.15 | -0.51 | -0.90 | -0.67 | 1.41 |
| Sunderland | -0.02 | 0.06 | -0.61 | -0.78 | -0.95 | -0.20 | -0.44 |
| Swansea | 1.63 | 0.53 | 2.38 | 0.97 | -1.70 | 0.95 | 0.26 |
| Tottenham | -1.28 | -0.57 | 0.38 | 0.55 | -0.20 | 0.60 | -1.03 |
| West Bromwich | -1.15 | -0.98 | -0.67 | -0.15 | 0.66 | -0.44 | -0.21 |
| West Ham | -1.01 | -0.40 | -2.25 | -0.90 | 0.20 | -1.54 | 0.07 |

Note. The first six columns are the standardised pass density and precision for each of the three zones of play (defence, midfield, and attack). The last column reports the standardised ability to score with respect to the number of attempts. Pass density is the standardised ratio of passes made per minute of possession. Pass precision is the standardised percentage of correct passes. Efficiency is the standardised percentage of shots that scored a goal.

**Table 2.** Correlation matrix reporting all correlation coefficients between the six combinations of the two factors: pass (density and precision) per zone of play (defence, midfield, and attack)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | | Defence |  | Midfield |  | Attack |  |
|  |  | Density | Precision | Density | Precision | Density | Precision |
| Defence | Density | 1 | 0.37 | 0.29 | 0.19 | -0.45 | 0.13 |
|  | Precision | 0.37 | 1 | 0.44 | 0.85 | 0.07 | 0.73 |
| Midfield | Density | 0.29 | 0.44 | 1 | 0.66 | -0.09 | 0.68 |
|  | Precision | 0.19 | 0.85 | 0.66 | 1 | 0.26 | 0.93 |
| Attack | Density | -0.45 | 0.07 | -0.09 | 0.26 | 1 | 0.39 |
|  | Precision | 0.13 | 0.73 | 0.68 | 0.93 | 0.39 | 1 |

Note. Pass density is the standardised ratio of passes made per minute of possession. Pass precision is the standardised percentage of correct passes. Efficiency is the standardised percentage of shots that scored a goal.

**Table 3.** The relative loadings of each component (density and precision of passes) in each zone (defence, midfield and attack)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Parameters | |  | Component | |
| Location | Passes | Name | 1 | 2 |
| Defence | Density | DD | 0.33 | -0.80 |
|  | Precision | DP | 0.86 | -0.11 |
| Midfield | Density | MD | 0.76 | -0.21 |
|  | Precision | MP | 0.97 | 0.12 |
| Attack | Density | AD | 0.20 | 0.89 |
|  | Precision | AP | 0.94 | 0.23 |

Note. Pass density is the standardised ratio of passes made per minute of possession. Pass precision is the standardised percentage of correct passes. Efficiency is the standardised percentage of shots that scored a goal.