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SCIENCE OF WINNING SOCCER: EMERGENT PATTERN-FORMING DYNAMICS IN ASSOCIATION FOOTBALL*

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Abstract Quantitative analysis is increasingly being used in team sports to better understand performance in these stylized, delineated, complex social systems. Here, the authors provide a first step toward understanding the pattern-forming dynamics that emerge from collective offensive and defensive behavior in team sports. The authors propose a novel method of analysis that captures how teams occupy sub-areas of the field as the ball changes location. The authors use this method to analyze a game of association football (soccer) based upon a hypothesis that local player numerical dominance is key to defensive stability and offensive opportunity. The authors find that the teams consistently allocated more players than their opponents in sub-areas of play closer to their own goal. This is consistent with a predominantly defensive strategy intended to prevent yielding even a single goal. The authors also find differences between the two teams' strategies: while both adopted the same distribution of defensive, midfield, and attacking players (a 4 : 3 : 3 system of play), one team was significantly more effective in maintaining both defensive and offensive numerical dominance for defensive stability and offensive opportunity. That team indeed won the match with an advantage of one goal (2 to 1) but the analysis shows the advantage in play was more pervasive than the single goal victory would indicate. The proposed focus on the local dynamics of team collective behavior is distinct from the traditional focus on individual player capability. It supports a broader view in which specific player abilities contribute within the context of the dynamics of multiplayer team coordination and coaching strategy. By applying this complex system analysis to association football, the authors can understand how players' and teams' strategies result in successful and unsuccessful relationships between teammates and opponents in the area of play.

Key words Collective behavior, performance analysis, team sports.

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1 Introduction

An important aim of sports science is to improve understanding of strategic performance and success in team competition[1]. Quantitative analyses can provide feedback to players and coaches, allowing them to enhance their performance and interpretation of the activity beyond what can be achieved by personal observation[2−4]. Traditional analysis of performance in team sports has examined behavior through reporting cumulative data on discrete actions in a Who [did]-What-Where-When fashion[5]. However, in team sports, each player's behavior is dependent on the locations and interactions of other players (both teammates and opponents), and the locations of the ball and the goal. Therefore, research should consider the behavior of multiple players and the emergent nature of performance. The performance depends on pattern-forming dynamics, i.e., on the dynamic physical relationships each player establishes with his/her teammates and opponents[6−9].

Quantitative analysis of interpersonal coordination has largely been limited to the spatio-temporal patterns of coordination between attacker and defender in one versus one (henceforth 1v1) dyadic system sub-phases of team sports[9−13]. These studies have considered how one attacker carrying the ball breaks local symmetry with the immediate defender to perform a successful pass, dribble or shot. In team sports it is reasonable to expect that an analysis of such 1v1 dynamics is not sufficient because multiplayer interactions are important in determining success and failure. Nevertheless, analyses that go beyond considering the players' 1v1 interactions in many multiplayer team competitions, including basketball, rugby-union and association football (commonly known as soccer), are limited in number.

Here, we consider team defense and offense within a general framework that characterizes the dynamic stability and instability of team interactions. When sequences of offensive and defensive actions and reactions maintain stability, no advantage results. Opportunities for scoring arise when offensive players engage in actions that destabilize the defensive response. In order to destabilize defensive systems, offensive teams displace their players and the ball irregularly to promote a cascade of local instabilities in their opponents' defense. Rather than considering how this might be done by individual player actions and responses, we consider measures of collective action. We hypothesize that team advantage in defense and offense can be quantified, at a first approximation, by the relative advantage in the number of players in a local area. In particular, we expect that instability is likely when the offensive team establishes local offensive numerical superiority (e.g., 2v1 or 3v2, so that there is one more attacker than defender) near the ball's location. Conversely, the defending team could attempt to maintain stability in local sub-systems by, for example, increasing the presence of defenders adjacent to the ball. This framework suggests that we can simply analyze dynamic stability or instability of the offensive and defensive sub-phases of the game to identify effective or ineffective performance. An analysis of the pattern-forming dynamics in different sub-areas of play in team sports may explain how the players coordinate their actions to maintain or disrupt system stability.

Association football is a game played between 11-player teams on an approximately 105m by 65m field, with teams attacking in opposite directions. Each team attempts to kick the ball into the opposing team's goal, while preventing the ball from entering its own goal. Only one player on each team, the goalkeeper, is allowed to use hands to intercept the ball and then only inside the (defended) goal-area. Compared with team sports in which all players use their hands to control the ball and the field is significantly smaller (40m by 20m), such as basketball or handball, association football is a defensive game characterized by a low number of goals scored. The low scoring constrains the strategic adoption of different systems of play, and arises from the chosen systems self-consistently. The systems of play are generally defined by the starting formations of play: the number of players in the team's back, midfield and front lines (e.g., $4:4:2$, $4:3:3$, etc.)[14]. However, systems of play only describe the global organization of each team. During the game, players move and interact with one another, constantly changing the team's spatial structure. Coordination between players to achieve performance objectives (i.e., scoring or preventing goals) through dribbling, passing, and tackling arise under spatial organization constraints that affect those actions[9].

In this paper we investigate collective pattern-forming dynamics in association football by examining how team coordination emerges in one actual competitive match. The study of only a single match suggests our analysis has limited claim to generality. However, a single match is considered adequate as a measure of the relative strength of two teams, as evidenced by single match playoffs. Thus, the measures we observe that consistently distinguish the winning from losing team may indeed reflect team capability. We will show that it is possible to perform an analysis of stability and instability consistent with our intuitive hypothesis and game outcome.

In order to focus on the offensive and defensive actions we consider a new definition of the area of play. Rather than considering the entire field, we define the area of play as that area circumscribed by the location of the 20 outfield (non-goalkeeper) players. We then identify the offensive and defensive sub-areas within this area of play to characterize how the teams organize themselves dynamically during the game. In order to do this, we dynamically track a spatial frame that moves with the players. We use this novel method to follow the game dynamics as a first step toward understanding collective offensive and defensive risk and security in team game performance. We show how a strategy emerges from teams' interactions and results in arrangements of players across the field which create local stabilities and instabilities in specific sub-areas. We find that teams allocate more players than their opponents in sub-areas closer to their own goal to ensure higher security. The focus on security is consistent with the defensive nature of low scoring games where conceding even a single goal could easily result in losing the game. By analyzing the unpredictability of teams' numerical relationships in each sub-area of play, we identify the regions where more transitions between stable and unstable modes of coordination occur, enabling us to describe each team's competitive performance profiles. We also observe differences between team strategies: for example, while both adopted a $4:3:3$ distribution of backfield, midfield and front field players, significant differences are observable.

The analysis shows greater scoring opportunities for Team A due to more frequent dominance in the key offensive areas. Equivalently, Team A was more successful in maintaining defensive stability near its goal areas. Consistent with our analysis as well as expectations that a single goal advantage could well determine the winner, Team A won the match examined here by a score of 2 to 1.

2 Methods

2.1 Data Collection

Twenty-eight male professional players participated in an association football match in the English Premier League in October 2010. The total duration of the match was 95 minutes and 29 seconds. The performance of all participants was monitored using a multiple-camera match analysis system [ProZone3®, ProZone Holdings Ltd, Leeds, UK]. Movements of twenty outfield players (goalkeepers were excluded) from the two competing teams were recorded during the entire game, using eight cameras positioned at the top of the stadium. Video files were synchronized and 10Hz frames were obtained by automated processing[15,16]. This procedure yielded two-dimensional player displacement coordinates. Excluding the out-of-bound locations to which players went during play, the effective playing area was 68m wide (from $x = -34$m to $x = 34$m) and 105m long (from $y = -52.5$m to $y = 52.5$m). Teams switch sides of the field halfway through the game. To facilitate visualization, we inverted player displacements for the second half of the game, so Team A would always attack toward positive coordinate values and Team B would always attack toward negative coordinate values (see Figure 1).

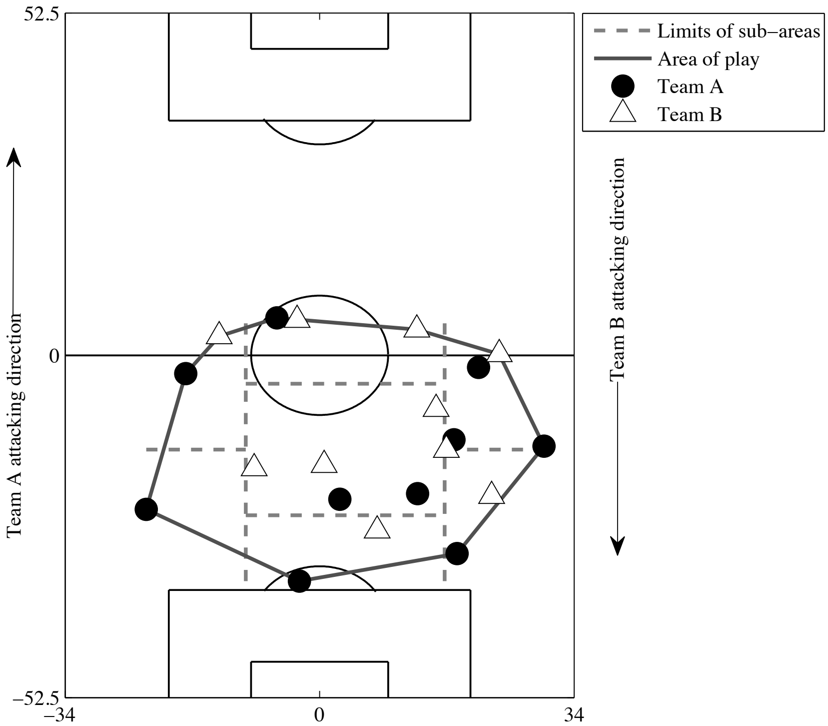

Figure 1 The association football field and the locations of the 20 outfield players, area of play, and sub-areas of play in one exemplar moment

2.2 Data Analysis

We excluded the time the game was stopped and the players abandoned their standard positions, such as for injuries (8 minutes 52 seconds), goal celebrations (2 minutes 41 seconds), or substitutions (1 minutes 35 seconds). From the location of the 20 outfield players in each increment of time (recorded frame), we calculated the area of play using a convex hull computation (i.e., the minimal convex area containing all outfield players). The analysis considered the distribution of players in this dynamically adaptive area of play, changing from frame to frame during the game time.

We calculated two longitudinal (goal to goal) vectors that divided the area of play into three channels: right (0% to 25%), center (26% to 74%), and left channels (75% to 100%). We also calculated three lateral (side line to side line) vectors that divided the area of play into two segments for the right and left channels: back (0% to 50%) and front segments (51% to 100%); and three segments for the center channel: back (0% to 25%), midfield (26% to 74%), and front segments (75% to 100%). The interaction of channels and segments led to the construction of seven sub-areas of play[17]: right-back (RB), center-back (CB), and left-back (LB); center-middle (CM); right-front (RF), center-front (CF), and left-front (LF) (see Figure 1). Only the center-middle sub-area was the same for Team A and Team B. The remaining performance sub-areas of each team had an opposing relationship: the center-back sub-area of Team A was the center-front sub-area of Team B (and vice-versa); the right-back and left-back sub-areas of play of Team A were left-front and right-front sub-areas of play of Team B, respectively (and vice-versa).

In each frame we calculated the number of players from each team inside the different sub-areas of play and the difference between the players of Team A and Team B, or the net team numerical advantage (a disadvantage for negative values). Frequency histograms were plotted for both of these variables. We also computed the uncertainty of the team numerical advantage across sub-areas using Shannon's entropy, H:

$$H(x) = -\sum_i p(x_i) \log_2 p(x_i), \tag{1}$$

where $p(x_i)$ is the probability over time of each team's numerical distribution. This measure characterizes the variability of number of players in each region.

3 Results

We begin by considering the coordination between players of opposing teams based on the numerical relationships established in opposing sub-areas of play. Second, we explore the uncertainty in numbers across sub-areas of play. Finally, we compare directly the spatial patterns of the two teams. The results reveal aspects of team behavior that may give rise to distinct performance profiles.

3.1 Inter-Team Coordination Tendencies

The numerical advantage in every sub-area is shown in Figure 2. There is a notational symmetry between opposite sub-areas of play for the two teams. For example, a +1-player advantage in the left-back sub-area for Team A means that Team A had one player more in its left-back sub-area of play than Team B had in its right-front.

Results show a pattern of focus on defensive stability. For example, the most likely team numerical advantage in center defensive areas is +1. This defensively stable pattern of one more defender than attacker in the center-back sub-areas is present for nearly half of the playing time (47% of match time in the CB of Team A, and 44% of match time in CB of Team B). Each team tries to secure those regions against dominance by the opposition. Considering the adjacent possibilities of 0 or +2, we see that Team A has a higher likelihood of +2 than 0 defenders, while Team B has a nearly an equal number. This suggests that Team B is either not as defensively oriented, or not as successful in achieving defensive stability, consistent with the victory of Team A in the match. We can also frame this advantage of numbers as an offensive superiority. For Team A an equal 0-player and +1-player pattern occurred in its center-front region (CF vs CB) with a frequency of 21% and 6%, respectively, while for Team B a 0-player and +1-player patterns occurred in its own CF region (CB vs CF) with a frequency of only 13% and 2%, respectively. The longer time during which Team A had numerical equality or superiority in its center-front areas suggests the occurrence of instabilities in the center-back sub-area of play of Team B, and a winning offensive advantage for Team A.

While Team A had greater defensive dominance than B in the center, when we consider the two wings we see that Team A had only a slightly greater numerical advantage in its RB area

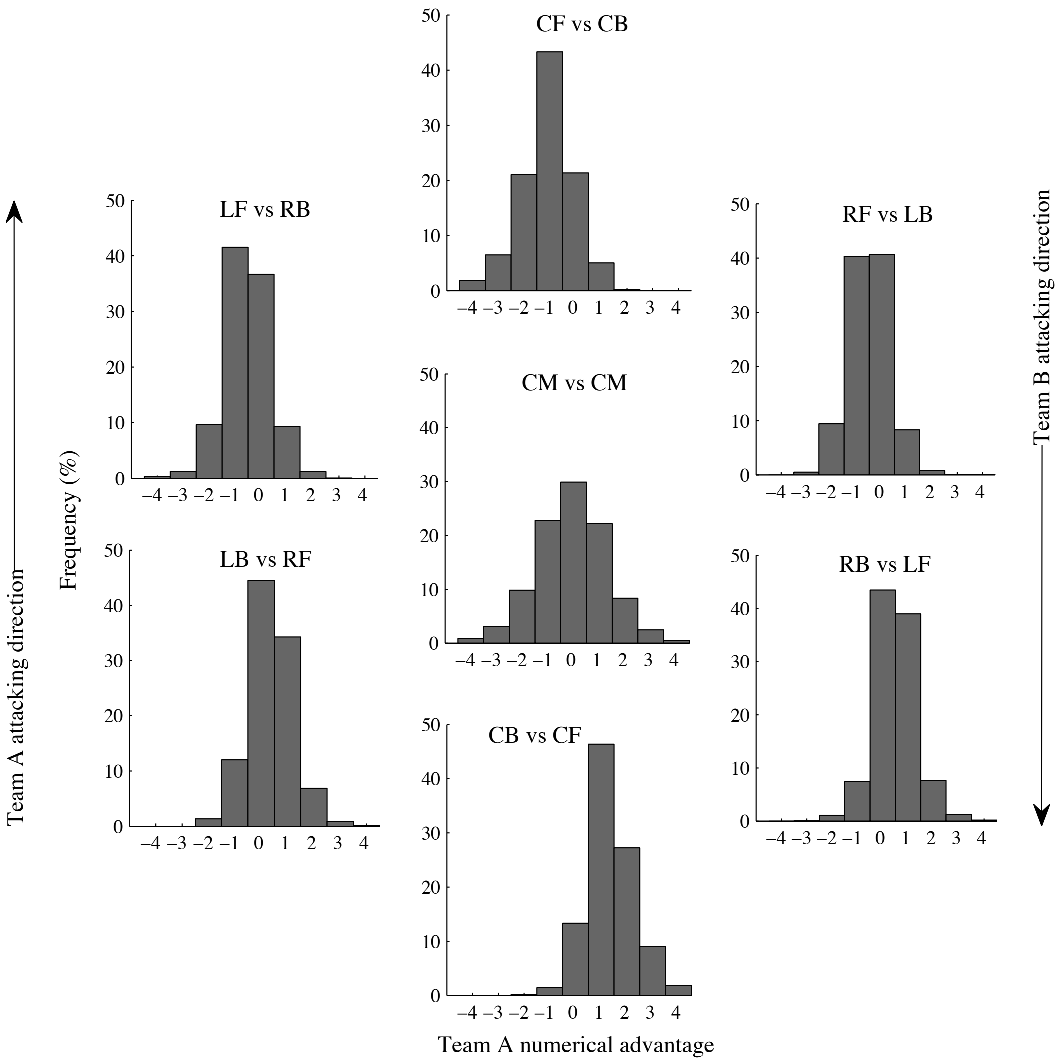

Figure 2 Frequency histogram of Team A numerical advantage (disadvantage for negative values) in each sub-area of play, over the entire match. Teams are represented as attacking in opposite directions. Each sub-plot represents the opposite sub-areas of play of Team A and Team B, respectively. The center-back (CB) sub-area of Team A is the center-front (CF) sub-area of Team B (and vice-versa); the right-back (RB) and left-back (LB) sub-areas of Team A are the left-front (LF) and right-front (RF) sub-areas of Team B. We omitted bins with frequencies lower than 1%. Note the symmetry of the center sub-plot

than Team B did in its own RB area, if any, and Team A had less of an advantage in its LB area than Team B had in its own LB area. Numerically, the +1 defender pattern was held by Team A in its RB area (RB vs LF) 43% of the time, while it was held by Team B in its RB area (LF vs RB) for almost the same percentage of the time, 42%. In the left channel, the

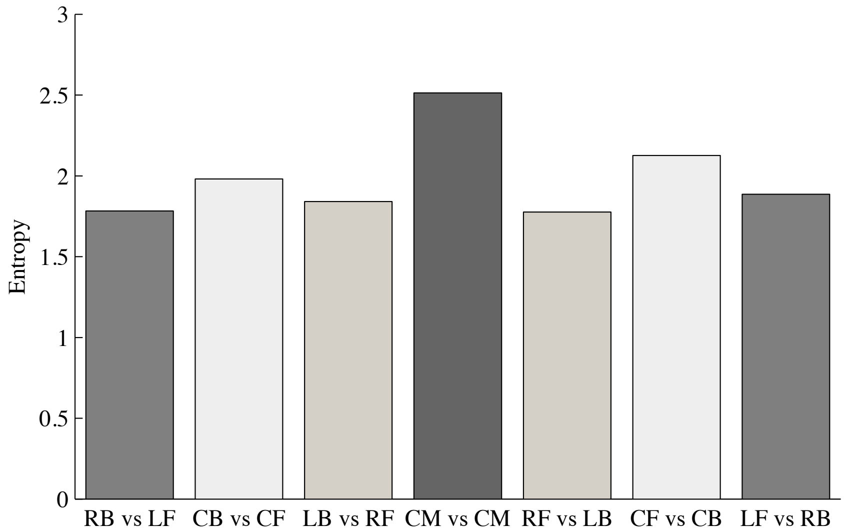

Figure 3 Uncertainty of team numerical advantage in each sub-area of play during the match. The x axis contains the opposite sub-areas of play of Team A and Team B, respectively: the center-back (CB) sub-area of Team A is the center-front (CF) sub-area of Team B (and vice-versa); the right-back (RB) and left-back (LB) sub-areas of play of Team A are the left-front (LF) and right-front (RF) sub-areas of play of Team B (and vice-versa). Opposing sub-areas are shaded with the same colors

advantage is to Team B; the +1 defender pattern was held by Team A in its LB area (LB vs RF) for 35% of match time, while it was held by Team B in its LB area (RF vs LB) for 42% of match time. Team A's prevalence of defensive security in the center areas rather than the wings suggests a slightly lower importance assigned to wing defense than center defense. This small difference in prioritization may have contributed to the successful strategy of Team A.

3.2 Unpredictability of Inter-Team Coordination

Figure 3 shows the uncertainty/variability of team numerical relationships in each sub-area of play during the match. The highest uncertainty is in the center-middle sub-areas of play with a value of 2.51. The uncertainty reflects a flatter distribution in the team numerical advantage. Such a distribution reflects dynamic shifts of players into and out of the sub-area from adjacent sub-areas that change the relative number of players of the teams over time. The center-middle area has boundaries to all other sub-areas, and can be both the origin and target of shifting player movements. Changes in this sub-area have less significance for either offense or defense than other sub-areas, which are more likely to be the source of attacks on the goal. Therefore, teams may choose not to maintain as close control over the balance of players in this area. Instead, they can use the center-middle sub-area as a reservoir of players to move to the locations of greatest need, allowing the variability in that area to enable the higher priority stabilization of the other areas.

The next highest uncertainty areas are the two symmetrically defined center-front and center-back areas. These areas are the primary attack and defense areas. From Figure 2 we can see that this uncertainty is primarily a variation of the number of excess defenders. Rarely does a team dominate its CF area, though according to our hypothesis about stability and instability such an advantage is likely to be a major tactical objective.

We can compare the uncertainty between the two teams in their corresponding sub-areas. The largest difference is the lower uncertainty in Team A's CB (Team B's CF), 1.98, in comparison to Team B's CB (Team A's CF), 2.13. This shows Team A in the center-back sub-area of play was more predictable in its defensive dominance than Team B was in its defensive area. From Figure 2, we see that indeed, Team A was better at limiting times in which Team B had an offensive advantage in this area or even an equal number of players. Correspondingly, Team A had more occasions with a greater than or equal number of players in its primary offensive area. This would predict that Team A would be more successful due to a greater reliability of its defensive pattern than Team B, and indeed, Team A is the victor in this match.

Team A's right-back sub-area uncertainty is 1.78, which is more predictable than Team B's at 1.89. The only pair of corresponding defensive (back) zones for which uncertainty predicts an advantage for Team B is each team's LB zone. Uncertainty in A's LB (B's RF) was 1.84, while uncertainty in B's LB (A's RF) was 1.78.

3.3 Internal Team Coordination

Figures 4 and 5 show the frequency distribution of the number of players of Teams A and B, respectively, in each area of play. Both Team A and Team B prioritized the defensive rather than offensive sub-areas of play. The mode number of players present for each team is 2 in each team's center-back area of play (for 44% of match time for Team A and 41% for Team B), 2 in the center-middle, (39% of the time for Team A and 38% for Team B), and 1 in the center-forward (52% of the time for Team A and 50% for Team B). Results for both also show a higher importance accorded to center channels relative to the wings. Team A allocated 2 players to the center-back for 44% of match time, but allocated 2 players to the left-back and right-back only 26% of the time for each. Likewise, Team B allocated 2 players to the center-back for 41% of match time, but allocated 2 players to the left-back and right-back only 29% and 20% of match time, respectively. However, the teams differed in their left-right symmetry; Team A seems to have placed greater importance on the right-back than the left-back (with 1 player there 43% of the time versus 37%), while Team B had an approximately equal amount of time with no player in either wing. Team B did have a higher percentage of two players in its right-back sub-area, which may be a response to the larger number of players in the right-front area of Team A.

4 Discussion

In this paper we characterized the patterns emerging from player interactions in different sub-areas of the field. We also sought to provide a first step toward understanding collective offensive and defensive performance in relation to opportunity, risk and security. We lent support to a hypothesis about stability and instability originating primarily in local numerical superiority by examining how teams place their players on the field during the game. Finally, we identified sub-areas of play that appear to be key to stability and instability.

Analysis of pattern-forming dynamics between players of opposing teams (inter-team coordination) showed how teams managed offensive and defensive risk and security. Results supported the understanding of association football as primarily defensive: teams allocated more players

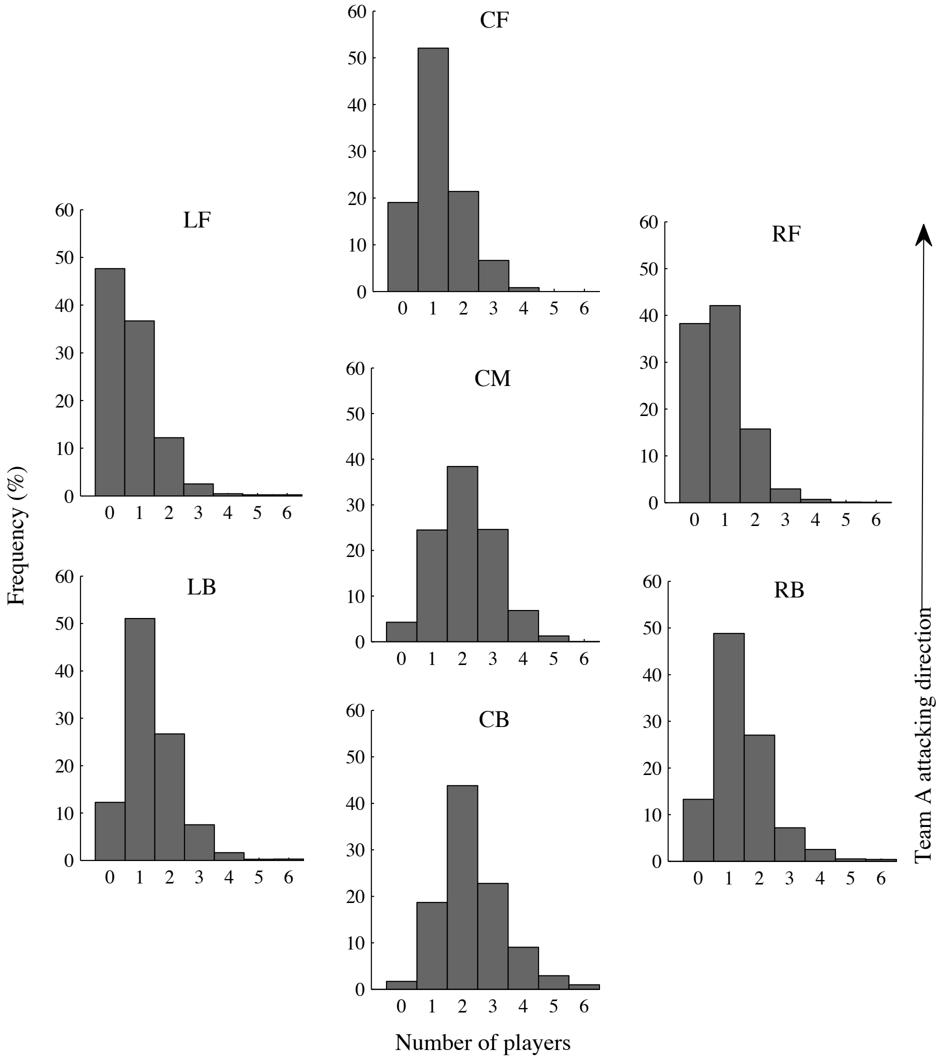

Figure 4 Frequency histogram of the number of players of Team A in the different sub-areas of play, over the entire match. Team A sub-areas are represented as attacking toward the upper part of the figure. The sub-plots represent the sub-areas of play (right-back (RB), center-back (CB), left-back (LB), right-front (RF), center-middle (CM), left-front (LF), and center-front (CF)). We excluded from representation the bins with frequencies lower than 1%

than did their opponents to sub-areas of play closer to their own goal. Conversely, in sub-areas of play more distant from their own goal, teams rarely allocated more players than their opponents. Moreover, the center channel of the field was allotted a higher level of importance than the wings. The most frequent patterns of coordination were registered in the center-back sub-areas of play with dominant patterns of +1-player advantages, revealing the perceived importance of stabilizing and securing these regions.

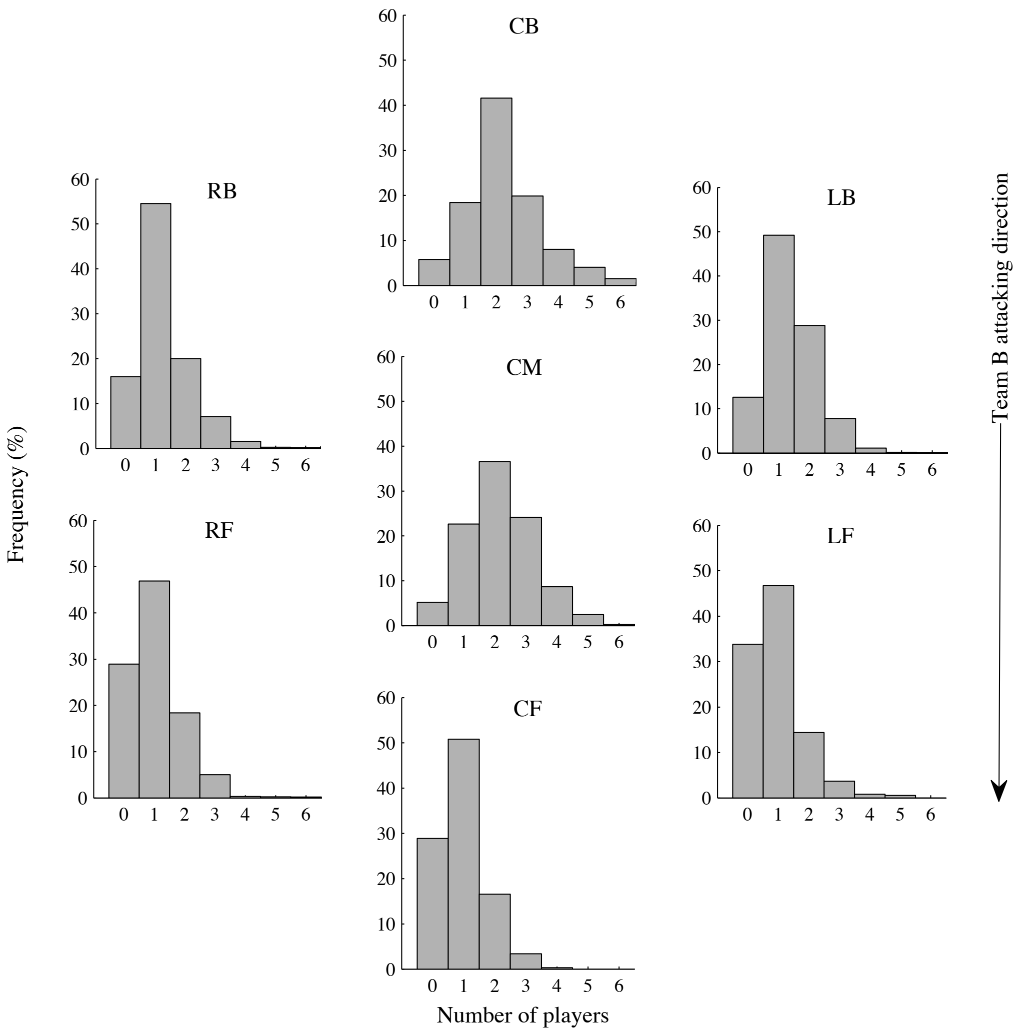

Figure 5 Frequency histogram of the number of players of Team B in its different sub-areas of play, over the entire match. Team B sub-areas are represented as attacking toward the bottom part of the figure. The sub-plots represent the sub-areas of play (right-back (RB), center-back (CB), left-back (LB), right-front (RF), center-middle (CM), left-front (LF), and center-front (CF)). We excluded from representation the bins with frequencies lower than 1%

Analysis of the unpredictability of patterns supported the importance of the center-middle sub-area of play as a reservoir of players or a transfer zone by showing higher entropy in this region. This result emphasized the role of center midfielders to explore adjacent sub-areas in order to maintain defensive stability or promote offensive instability. Moreover, the entropy in Team B's center-back sub-area of play was higher than in Team A's. Team A's ability to create uncertainty in its opponent's center-back sub-area of play, and maintain regularity in its own center-back sub-area of play, is consistent with Team A's success in the match.

Player frequency distribution analyses revealed that the underlying strategies of the two teams were very similar, and the differences we identified arose as nuances within these basic strategies. Team A generally allocated four defensive players (two in the center and one on each wing), two center midfielders and three forwards (one in the center and one on each wing). The higher entropy in the center midfield sub-area of play is consistent with the suggestion that the unaccounted for 10th outfield player may be a center midfielder that is also frequenting adjacent areas. These results suggested that Team A might have preferentially adopted what is termed a $4:3:3$ system of play. The players responsible for the wings also revealed a tendency to explore other regions. This was particularly common for Team A's left fielders, whose exploration of adjacent areas resulted in a higher likelihood of an empty left channel but may have contributed to Team A's higher defensive stability and greater offensive opportunities. The more secure patterns of play used by Team A (measured by the maximum amount of players in one specific sub-area of play) included the allocation of three or four players to the center-back sub-area of play, three or four players to the center-middle, and two to each back wing, leaving the left-front, right-front and center-front unpopulated. In contrast, the riskier patterns of play used by Team A involved the allocation of two or three players to the center-front sub-area of play, two players to each midfield wing, three or four players to the center-middle and one player to the center-back sub-area of play.

Team B showed a largely similar player allocation profile to that of Team A. Our results show a preferred allocation of four defensive players (two in the center and one on each wing), two center midfielders and three forwards (one in the center and one on each wing), as well as higher entropy in the center midfield sub-area of play, are consistent with the adoption of a $4:3:3$ system of play. Some differences between the teams can be identified when considering the specific actions of each player. More precisely, Team B's wingers did not display as much of a trend to explore other sub-areas of play, directing their efforts primarily within their original sub-areas. The riskier performance profiles of Team B included less time with two or three players in the center-front sub-area of play than Team A, and more time without any player in the center-back sub-area of play. These results suggested that Team A was able to risk more players moving to forward sub-areas while maintaining higher stability in its back regions than Team B was. An interesting question is whether these capabilities formed the basis of Team A's success in the match. These profiles may be linked to the more successful play of Team A, supporting the hypothesis that local numerical dominance plays a key role in offensive and defensive success. The conclusions emphasize the importance of describing not only individual player capability and the global structure of each team, but also how players coordinated their goal-oriented behaviors.

Our findings reinforce the general observations of previous research suggesting that specific patterns of coordination emerge from the interactions of attackers and defenders under the influence of the specific task constraints[18−20]. We provide additional understanding about how players and teams in association football make decisions about the adoption of specific systems of play (i.e., strategic decisions) and how they functionally adapt to task demands (i.e., tactical behavior). Furthermore, we extend previous research on 1v1 interactions in team sports, especially those relying upon the hands (e.g., basketball and rugby-union)[11−13] toward multiplayer defense-oriented performance environments as is found in association football, by identifying emergent pattern-forming dynamics.

We introduce a new method of quantifying the area of play using a dynamic structural analysis that follows the positions of the players. This method captures how teams explored different regions to maintain backward stability and create forward instability, in accordance with the shape and location of the area of play.

We demonstrate how complex systems science analysis can help practitioners better understand performance in association football, by quantitatively analyzing behavior at the collective scale rather than at the individual scale. We also provide insight regarding how players and teams regulate performance based on relationships with teammates and opponents, the locations of the goals and the changes in shape and location of the area of play. Further research should consider the dynamic coordination of players and teams according to the location of the ball and team possession of the ball, i.e., in offensive and defensive sub-phases of the game. Complex systems tools also offer great potential to be applied more generally in explaining multi-agent interactions in other team sports.

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