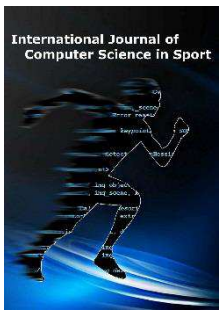
International Journal of Computer Science in Sport

Volume 23, Issue 1, 2024

Journal homepage: http://iacss.org/index.php?id=30

sciendo

DOI: 10.2478/ijcss-2024-0004



The Success-Score in Professional Football: a metric of playing style or a metric of match outcome?

David Brinkjans, Yannik Paul, Jürgen Perl, & Daniel Memmert

German Sports University Cologne

Abstract

In the growing field of data analysis in soccer tracking data is analyzed utilizing increasingly complex methods to account for the dynamic, multifactorial nature of the game. One promising approach is the Success-Score combining ball control and space control. The resulting metric is hypothesized to indicate performance levels and to distinguish performance from playing style. Position datasets from one season of the German Bundesliga were analyzed by calculating Success-Scores based on different interval lengths for two different areas. The relative goalscoring frequency above resp. below the 80^{th} percentile and the rank order correlation between goals and Success-Scores was used to assess the relevance of the Success-Score for goalscoring. The influence of the Success-Score on match outcome, accounting for possession and opponent quality was analyzed via mixed linear models. Results indicated a relation between goalscoring and the Success-Scores, as well as a considerable influence of the Success-Scores on match outcome. The mixed linear models allowed to conclude that Success-Scores capture performance rather than just playing style. The results highlight the potential of the general concept of the Success-Score, combining space and ball control. However, the practical value of the Success-Score in its current implementation appears limited and requires further development.

KEYWORDS: KEY PERFORMANCE INDICATOR, BALL POSSESSION, DOMINANT REGIONS, FOOTBALL, MIXED LINEAR MODELS

Introduction

Soccer is one of the world's most popular sports. At the same time, it also involves some of the highest financial stakes across the sporting landscape. With the British Championship play-off final, commonly referred to as the most lucrative match in football, offering a reward of up to 176 million Pounds in revenue for the winner (O'Connor-Simpson, 2022) and roughly two billion Euros being distributed across all competitors in the UEFA Champions League in the 2022/23 season (Bonn, 2023), it is obvious that there is a lot to play for even when putting emotions and glory aside. This inevitably coincides with a large degree of professionalization. One area that has experienced a considerable degree of professionalization relatively recently is match and more specifically data analysis (James, 2006; Lord et al., 2020; Memmert, 2021; Memmert & Raabe, 2023; Rein & Memmert, 2016) allowing teams to potentially gain a competitive advantage (Fernández et al., 2021). This development is not unique to Soccer. On the contrary, some of the major American sports like Basketball, Baseball and American football can be considered pioneers in this regard (Gudmundsson & Horton, 2018; Horvat & Job, 2020; Mackenzie & Cushion, 2013).

For large parts of the last decades, the use of event data and the search for key performance indicators (KPIs), variables related to success, has dominated soccer match analysis research (Coutts, 2014; Hewitt et al., 2016; James, 2006; Jamil, Liu, et al., 2021; Mackenzie & Cushion, 2013; Sarmento et al., 2014). The drawbacks of this mostly one-dimensional view on soccer have been addressed repeatedly, highlighting the necessity of considering the dynamic, interactive and multifactorial nature of soccer (Goes et al., 2021; Lord et al., 2020; Phatak et al., 2022; Rein & Memmert, 2016; Sarmento et al., 2014). Despite the acknowledged need for a changed approach, much of the practical work in the field (Herold et al., 2021) and the research conducted (Lord et al., 2020) was still mainly focused on less complex KPIs as recently as the beginning of the decade. Nevertheless, increasing availability of tracking data and knowledge transfer from other scientific fields such as computer science (see Memmert, 2024) and data science have led to a shift towards the understanding of soccer as a complex system (Low et al., 2020; Perl & Memmert, 2018) and the use of advanced analysis techniques (Goes et al., 2021; Low et al., 2020; Memmert et al., 2017; Rein & Memmert, 2016). Among other approaches, like increased use of machine learning techniques (Goes et al., 2021; Horvat & Job, 2020; Jamil, Phatak, et al., 2021), the analysis of the dynamic behavioral interaction between teams in multivariate approaches resulted from this development (Low et al., 2020; Memmert et al., 2017; Nieto et al., 2022). Major concepts under this umbrella include team centroids, the team surface (area) or convex hull, the ratio of the length and width of a team and stretch indices. These concepts have proven insightful as they can be used to describe and analyze teams' collective movement behavior as well as the interaction between teams (Low et al., 2020; Nieto et al., 2022).

Another relevant concept related to those measures of collective movement behavior is the concept of space control. Initially, space control was based on so-called dominant regions which model the area to which any player can get before any other player based on their current position (Fujimura & Sugihara, 2005; Kim, 2004; Low et al., 2020; Nakanishi et al., 2008; Rein et al., 2017; Rein & Memmert, 2016; Taki & Hasegawa, 2000). Recent works have introduced more complex modeling approaches that incorporate the kinematics of each player and the time it takes to control the ball to more accurately represent the spaces that a player can reach first, and thus control (Caetano et al., 2021; Fernandez & Bornn, 2018; Martens et al., 2021; Spearman et al., 2017). Findings suggest that space control is a relevant performance indicator (Fernandez & Bornn, 2018; Rein et al., 2016; Rein & Memmert, 2016). A connection between space control in the final third and goalscoring has been established (Rein et al., 2017) and another investigation highlighted that teams tend to try to control space close to their own goal by

maintaining numerical superiority in these areas (Vilar et al., 2013).

From the first scientific work conducted on match analysis in soccer (Reep & Benjamin, 1968) to the present (Fernández et al., 2021; Hewitt et al., 2016; Hughes & Franks, 2005; Jones et al., 2004; Pratas et al., 2018; Tenga, Ronglan, et al., 2010; Tenga & Sigmundstad, 2011) possession, and the underlying success mechanisms for individual phases of possession have been a cornerstone of the field. Results clearly confirm a certain relevance of possession for success. But this relationship between success and possession has proven complex. For one, a distinction between within- and between-team effects is necessary. While better teams tend to have more possession and win more games (between-team effect; Bradley et al., 2014; Collet, 2013; Lago, 2007; Lago-Ballesteros & Lago-Peñas, 2010; Liu et al., 2015; Yang et al., 2018; Yi et al., 2019), a higher possession percentage compared to a team's average tends to be related to a negative match outcome (within-team effect; Liu et al., 2016). This phenomenon might be explained by the necessity for teams to become more proactive when behind. A different study also indicated that top teams are more likely to win with a higher percentage of possession compared to their individual baseline, while worse teams are less likely to win with higher possession percentages, indicating an interaction between possession and team quality (Mao et al., 2016). These results and the fact that the usefulness of possession theoretically and evidently varies between different areas (Casal et al., 2019; Gonzalez Rodenas et al., 2020; Ruiz-Ruiz et al., 2013; Tenga, Holme, et al., 2010) suggests that possession reveals relevant insights only when appropriately put into context.

In an attempt to identify mechanism of successful attacks the Success-Score was developed (Perl & Memmert, 2017), a dynamic KPI based on the software tool SOCCER© by Jürgen Perl (for further information see Perl et al., 2013; Perl & Memmert, 2011). Under the assumption that neither space control nor ball control (i.e., possession) on their own are particularly useful but when occurring in combination could relate to potential attacking success, these two variables were implemented in the Success-Score (Brinkjans et al., 2022, 2023; Perl & Memmert, 2017). The Success-Score is always calculated over a certain interval length and can be applied to different areas, analyzing the events and movements within those. By combining the fluctuations in ball and space control over time, this KPI represents the dynamic and interactive gameplay of a match. Earlier studies have validated the Success-Score by identifying a relationship between the Success-Score and goalscoring, as well existing differences in the Success-Score between teams (Brinkjans et al., 2022, 2023). Moreover, results revealed that the choice of area and interval length used in the calculation have substantial influence on the resulting Success-Scores. Interval lengths between 100 and 500 seconds analyzing the penalty area and the last 30 meters in front of the opponent's goal have been identified as the optimal choices for these parameters (Brinkjans et al., 2023). Unfortunately, up to this point all investigations focused on the matches of two specific teams and included only 45 goals in the analysis. Given the influence of chance on goalscoring, previous results have to interpreted carefully (Wunderlich et al., 2021). On a related note, the inclusion of set-pieces (e.g. corner kicks) into the analysis can be questioned. The determination of ball control on position data alone is limited, relying on proximity to the ball. Hence it does not translate well to set-pieces, where several players tend to mingle in tight spaces (Brinkjans et al., 2023). Furthermore, the comparison of Success-Scores between two teams allows no conclusion on the mechanisms causing observed differences). Differences could, as intended, be representative for performances differences. However, they could just as well be the result of differences in playing style or any number of differences between the two teams analyzed. Moreover, the quality of opponents for these two teams in the analyzed dataset was not matched. As studies have shown, the quality of opponent influences performance and hence should be considered as a possible confounding factor (Fernandez-Navarro et al., 2019; Gonzalez Rodenas et al., 2020; Kempe et al., 2014; Liu, Gomez, et al., 2015). Hence, the aim of

this investigation was to assess the influence of different Success-Score versions on goalscoring and match outcome, accounting for possession and opponent quality to distinguish between variance caused by performance and variance caused by playing style and other team characteristics.

Methods

Success-Score

An in-depth description of the development of the Success-Score can be found in Perl and Memmert (2017). The basic idea of capturing ball and space control in compound was implemented via the correlation of the two, thereby representing how strongly a team combines these two performance parameters. This correlation of space control rate (SR, relative to the complete area) and ball control events (B) within the set area was defined as *Efficiency*. A team is efficient if they tend to control space whenever they control the ball and vice versa. A possession phase in which little space is controlled, or phases in which a team controls space but not the ball, are considered inefficient. *Effort* was defined as attacking attempts made. This was conceptualized as the or-sum of ball control and space control events (S) within the same area and time interval. Space control events are defined by a space control rate of at least 20%. Based on the common definition of efficiency as the ratio of useful output ("Success") and input ("Effort") this allows us to derive *Success*:

$$\begin{gathered}\text{Efficiency} = \text{Success} / \text{Effort} \\ \textit{is equivalent to} \\ \text{Success} = \text{Efficiency} * \text{Effort}\end{gathered} \tag{1}$$

Equation 2 formalizes the described concept mathematically:

$$Success(t_{start}, t_{end}) = r(SR, B)_{t_{start}}^{t_{end}} * \left(\sum_{t=t_{start}}^{t_{end}} \left(S(t) \oplus B(t) \right) \right) / IL \tag{2}$$

In principle, the correlation coefficient (Efficiency) can be between -1 and 1. The or-sum of efforts is scaled by the interval length and therefore the Effort can take values between 0 and 1. Negative correlation between ball control and space control tend to be very rare. From a tactical perspective, negative correlations are considered no worse than no correlation at all. Therefore, all negative Success-Scores are subsequently set to 0. Hence, Success-Scores can take values between 0 and 1 and are finally rescaled to a percentage range of 0 to 100.

One Success-Score is calculated for every second (t_{end}), representing the team's performance in a set time interval up until that second. If $\Delta t = t_{end} - t_{start} = 300$ is the set interval length and $t_{end} = 600$, then the Success-Score at $t_{end} = 600$ is based on the interval from $t_{start} = 300$ seconds to $t_{end} = 600$ seconds. This rolling calculation of Success-Scores for both teams in a match creates dynamic and interactive profiles (Brinkjans et al., 2022, 2023; Perl & Memmert, 2017).

Data Analysis

DFL position and Opta event data from the 2016/17 Bundesliga season formed the sample for this study. Four matches had to be excluded as either event or position data was incomplete, leaving data for 302 matches. Possession percentages for both teams in each match were accessed from FBref.com (FBref, 2023b). FBref data is provided by Opta which has been reported to be a reliable source (FBref, 2023a; Liu et al., 2013). Data processing was conducted

with Python 3.10.11 (Van Rossum & Drake, 2009) and relied on functions provided in the floodlight package (Raabe et al., 2022). All scripts can be accessed via a dedicated GitHub repository (link in the appendix). Event data was used to determine the timepoints, location and game phase associated with each goal scored. Moreover, event data was used to identify any cases where a team finished the match with less than eleven players (injuries and red cards). Any such match was excluded from the following analysis, as the effects of numerical imbalances on all variables of interest cannot be accounted for in the context of this investigation (Badiella et al., 2023). This left 253 matches in which 864 goals were scored. Of these goals, 605 goals were scored from open play and 528 from open play and within the penalty area. In another step, position data had to be parsed into the format required by SOCCER©. Both the width (previously -34 to 34) and the length (-52.5 to 52.5) was rescaled to a range of 0 to 10. The coordinate-columns of players subbed off and on were combined into singular columns covering the entire match and the framerate was reduced to the requirements of SOCCER© (1 Hz). Eventually, the preprocessed position datasets were fed to SOCCER© and six versions of the Success-Score were computed. Success-Scores were computed for both the penalty area and the 30-meter-zone. 100, 300 and 500 seconds were chosen as interval lengths based on previous findings (Brinkjans et al., 2022, 2023; Perl & Memmert, 2017). An option provided by the Software to exclude set-pieces from the analysis was selected. Occasionally, the exclusion of set-pieces caused Success-Scores in the theoretically implausible range > 100. The influence of these values was tested and determined irrelevant due to the small frequency of these extremes (< 0.1%). None of these extremes was linked to a goal. Finally, it was deemed tidiest to exclude these values.

The analysis of the link between goalscoring and Success-Scores was done in concordance with the first two investigations to ensure comparability (Brinkjans et al., 2022, 2023). For each of the 605 goals scored from open play in the 253 matches, the timestamp was matched to the associated Success-Score. Subsequently, two separate analyses were conducted to test for a connection between the Success-Scores in all six versions and goalscoring. On the one hand, the relative goal scoring frequency above and below the 80th Success-Score percentile was compared using a Chi-squared test of independence (Kirkwood et al., 2003). On the other hand, the correlation between Success-Scores and goalscoring was tested via Kendall's Tau-b rank correlation coefficient. For this purpose, the Success-Scores were split into eight percentile groups, each spanning 12.5% of the Success-Score distributions. The correlation was then calculated between the number of goals in each percentile group and the rank of that group. Some Success-Score values spanned across multiple percentile groups. Therefore, some goals had to be multiplied by the share of the associated Success-Score value that fell into every percentile group and the result was then assigned to the respective percentile group. Kendall's tau was chosen over Spearman's rank correlation coefficient since it has been reported to be a better estimate of correlation in cases of small sample sizes and large numbers of tied ranks (Field et al., 2012; Prematunga, 2012). For the analysis of the 30-meter-zone, all 605 goals from open play were used. Only the goals scored from within the penalty area were included in the analysis on Success-Scores for the penalty area. Linear mixed effects models (LMMs) were used to model match outcome. Model building and evaluation was conducted in R Version 4.2.2 (R Core Team, 2022; RStudio Team, 2022) using the lme4 package (Bates et al., 2015) to build the model and the sjPlot package (Lüdecke et al., 2023) for diagnostics (Harrison et al., 2018). The variance inflation factor (VIF) was used to test predictors for collinearity and revealed no issues (< 2.5; Harrison et al., 2018). LMMs with random intercepts for team identity were chosen to account for the hierarchical dependence structure of interdependent match outcomes within each team (Brown, 2021; Faraway, 2006; Harrison et al., 2018; Hoffman & Walters, 2022). Match outcome, defined as the goal difference between two opposing teams for each match from both teams' perspective, was modelled with the difference in both teams' match-specific average Success-Score, the opponent's team quality and the team's possession percentage in that match

as fixed effects. Please note that Success-Scores were averaged for each match and the difference in average of the two competing teams was calculated. This results in two Success-Scores-differences per match, one the additive inverse of the other. These Success-Score-differences are not to be confused with the initial Success-Scores with one score per second used for the goalscoring analysis. Even though team quality is commonly defined by competition rankings (Fernandez-Navarro et al., 2019; Lago, 2009; Liu, Yi, et al., 2015; Vogelbein et al., 2014) and should optimally be assessed dynamically (Koning, 2017; Ley et al., 2019; Wunderlich & Memmert, 2018), team quality was defined as a team's end of the season goal differential. Dynamic modeling of team quality would have exceeded the scope of this research project, so goal differential was chosen over season ranking as it discards less information. The possession variable was deducted by 50 (e.g., 40% = -10%) and thus centered at the mean to ensure interpretable intercepts (Harrison et al., 2018). The initial model included random slopes for possession since previous results indicated that better teams tend to profit more from increased possession percentages (Mao et al., 2016). In contrast, the authors saw no reason to assume that the effect of opponent quality and Success-Score-difference should vary across teams. The general initial model for all six Success-Score versions therefore looks as shown in equation 3. The random effects of all models were evaluated using likelihood-ratio tests comparing models with and without the random effect (Brown, 2021; Faraway, 2006). Therefore, for each Success-Score version three models were created. Apart from the initial model, also referred to as full model (FM), this included two models, each of which did not include one of the two random effects, while being identical in all other aspects. The random intercept model (RI) did not include a random intercept for team identity and was hence used to assess the relevance of said random intercept. Equivalently, the possession slope model (PS) did not include a random slope for possession. By comparing this model with the full model, the relevance of random slopes of possession across all teams was evaluated.

$$MO = (\beta_0 + u_{0t}) + \beta_{ass} ASS_{it} + \beta_{oq} OQ_{it} + (\beta_p + u_{pt}) P_{it} \quad (3)$$

Where:

MO = match outcome

β_0 = overall intercept

u_{0t} = the random intercept, the team specific deviation from overall intercept

β = the slope for each predictor (fixed effects)

u_{pt} = the random slope of team t for possession / team t's deviation from overall slope

ASS = Difference in average Success-Scores

OQ = opponent quality

P = possession

i = the match

t = the team

Results

Descriptive statistics for all six Success-Score versions are displayed in Table 1. The distributions differed considerably. Larger numbers of the Success-Score value zero were found for the Success-Score versions of the penalty area and for shorter interval lengths. This coincides with smaller estimates of central tendency. The maximum Success-Scores found on the other hand were higher for shorter interval lengths.

Table 1: Descriptive statistics for the six Success-Score distributions

Success-Score	N	Min	Max	Mean	Median	SD	0-share
SuSc_16_100	2857632	0	99.7	3.51	0.1	5.95	49.69%
SuSc_16_300	2858073	0	85.8	3.56	2.3	4.18	19.99%
SuSc_16_500	2858096	0	56.5	3.36	2.5	3.33	12.87%
SuSc_30_100	2855495	0	100	13.88	9.8	14.71	21.71%
SuSc_30_300	2858067	0	100	14.42	12.8	10.48	5.46%
SuSc_30_500	2858098	0	64	14.06	13	9.05	4.10%

Note. N: number of data points (i.e., seconds); Min: minimum; Max: maximum; SD: standard deviation; 0-share: frequency of zeros as a percentage of the distribution; Mean, standard deviation and 0-share are rounded to two decimal places.

Goalscoring analysis

Statistically significant rank-order-correlations were found between the Success-Scores of all six versions and the number of goals scored (Table 2). The correlation was strongest for the Success-Score version of the penalty area over 300 seconds. The only Success-Score version showing no strong, but a still statistically significant correlation, is the one over 100 seconds of the penalty area. The relative goalscoring frequency was found to be statistically significantly higher over the 80th percentile in all Success-Scores versions as well (Table 3). The extent of the difference was similar for both the penalty area and the 30-meter-zone over 300 and 500 seconds. Both Success-Scores versions over 100 seconds showed substantially larger differences in the relative goalscoring frequency above and below the 80th percentile though.

Table 2: Number of goals in percentile groups and associated results for Kendall's tau

	SuSc_16_100	SuSc_16_300	SuSc_16_500	SuSc_30_100	SuSc_30_300	SuSc_30_500
1	20.88	23.14	24.28	10.94	26.89	33.00
2	20.88	23.71	53.73	9.94	47.97	60.40
3	20.88	54.28	52.58	53.11	61.03	57.04
4	20.77	66.38	49.28	86.32	70.17	56.38
5	71.18	62.03	56.44	78.67	62.92	70.09
6	116.60	68.46	62.83	89.86	77.88	75.48
7	99.98	73.00	61.28	88.02	90.15	72.47
8	78.83	79.00	89.59	99.13	79.00	91.14
τ	0.4914	0.9286	0.7143	0.7857	0.8571	0.7143
p-value	.0489	.0002	.0071	.0028	.0009	.0071

Note. 1-8: percentile groups starting with 0-12.5% (1) and ending with 87.5-100% (8); τ: Kendall's tau; τ and p-values are rounded to four decimal places; number of goals is rounded to two decimal places.

Table 3: Number of goals over and under the 80th percentile and results for associated chi-squared test

	G>80th	G<80th	χ2	p	%>80th	%<80th
SuSc_16_100	136.73	313.27	30.33	< .0001	0.0239	0.0137
SuSc_16_300	124.00	326.00	16.06	.0001	0.0217	0.0143
SuSc_16_500	123.22	326.78	15.33	.0001	0.0216	0.0143
SuSc_30_100	154.22	361.78	31.53	< .0001	0.0270	0.0158
SuSc_30_300	139.00	377.00	15.52	.0001	0.0243	0.0165
SuSc_30_500	131.19	384.81	9.49	.0021	0.0230	0.0168

Note. G>80th & G<80th: number of goals over and under the 80th percentile (rounded to two decimal places); χ2: chi-squared statistic (rounded to two decimal places); p: associated p-value (rounded to four decimal places); %>80th & %<80th: relative goal scoring frequency above and below the 80th percentile in percentage of all seconds (rounded to four decimal places).

Match outcome modeling

Descriptive statistics for the Success-Score-differences per match can be found in Table 4. These statistics refer to only the positive share of the distribution by excluding the additive inverses. Differences between two teams tended to be higher in the Success-Scores versions of the 30-meter-zone which coincides with the general tendency of higher Success-Score values for the 30-meter-zone (Table 1). Diagnostics revealed no concerns regarding the distribution of residuals. Despite significant correlations between all predictor variables, the variance inflation factors suggested no reason for concern (<2.5). Even still the correlations should be kept in mind for the interpretation. A moderate, negative correlation was found between opponent quality and possession ($r(504) \approx -0.4823$, $p < 0001$ 95% CI [-0.55, -0.41]). The correlations between the Success-Scores and opponent quality were also negative and of constant moderate size. Correlations between the Success-Score and possession were strong and positive across all Success-Scores versions but higher for the Success-Score versions of the 30-meter-zone.

Table 4: Descriptive statistic for the Success-Score average differences per game

	N	Mean	Median	SD	Min	Max	P25	P75
SuSc_16_100	253	1.92	1.48	1.54	0.01	7.37	0.72	2.87
SuSc_16_300	253	1.92	1.57	1.60	0.01	10.15	0.69	2.74
SuSc_16_500	253	1.83	1.47	1.51	0.01	8.00	0.63	2.54
SuSc_30_100	253	5.80	4.67	4.53	0.04	19.05	2.05	8.10
SuSc_30_300	253	5.96	4.90	4.61	0.02	18.68	2.12	8.32
SuSc_30_500	253	5.72	4.83	4.41	0.02	17.23	2.10	8.20

Note. N: number of data points (i.e., seconds); Min: minimum; Max: maximum; SD: standard deviation; P25: 25th percentile; P75: 75th percentile; all values are rounded to two decimal places.

The fixed and random effects of all models can be found in Tables 5a to 10a. The associated likelihood-ratio test model comparisons are depicted in Tables 5b to 10b. In these Tables, the model statistics refer to the respective model, while the inference statistics refer to the comparison of the adapted model to the full model. Modelling results for all six Success-Score versions vary only in details. The likelihood-ratio tests revealed that FMs had a statistically significant better fit compared to the RI-models in all Success-Score versions. The exclusion of the random effect of possession did not result in any statistically detectable decrease in model fit for any of the FMs. Therefore, the PS-models were deemed the optimal and therefore final models. Thus, the final models were at the center of the remaining analysis. Nevertheless, the other two models for each Success-Score version were consulted for comparisons to derive insights into the interacting nature of predictors. Possession was found to be a highly significant predictor of match outcome in all six final models. The coefficient of gradient (β) varied only

minimally between the PSs. The negative coefficient indicated a change in expected match outcome by 0.56 to 0.63 goals to the worse with an increase of possession by ten percentage points (e.g., a match with 60-40 possession compared to 50-50). Similar, yet minimally smaller effects of possession were found in the full models, while a considerable decrease of the effect was detectable when random intercepts were not included. For these models, the same difference in possession percentage changes the predicted match outcome by only roughly half as many goals (-0.32 to -0.23). Similarly, the coefficient of gradient for the opponent quality was constant across all Success-Score versions, indicating an unfavorable change in match outcome with an increase in opponent quality. An increase of roughly +28 goals in the opponent's goal difference is predicted to worsen the expected match outcome by one goal. The fixed effect of opponent quality was found to be almost identical in the full model but slightly smaller when random intercepts were excluded from the model. The fixed effect of the Success-Score was found to be statistically significant and positive in all PS-models. To compare the effect between Success-Score versions, one cannot simply check the coefficients of gradient since ranges of the Success-Scores vary. To enable a comparison, a calculation example (Table 11) was used to illustrate the expected change in match outcome if the Success-Score difference changes by one inter-quartile-range (Table 4). Resulting changes in expected match outcome vary around 0.3 goals without substantial differences between the six PSs. Strikingly, the coefficient of gradient was smaller when the random intercept for team identity was excluded in the three models on the 30-meter-zone, but in contrast increased in the RI-models for the penalty area. When extrapolating these effects to the smallest and largest difference in Success-Scores captured in this dataset, the maximum influence of the Success-Score can be estimated to a range of roughly 0.72 to 1.39 goals (Table 11). Only small differences between the PSs and the associated models were found within the random effects. In all six Success-Score versions, the random intercept contributed considerably to the explained variance which was confirmed by the likelihood ratio tests. When excluding the random slopes for possession only very little of the explained variance is lost. This was also reflected in the statistical insignificance of the likelihood ratio test comparing the full model with the final model which did not include random slopes.

Discussion

The characteristics of the Success-Score distributions match those observed in previous investigations and thereby strengthen the conclusions drawn previously (Brinkjans et al., 2022, 2023). Higher maximal Success-Scores were observed for Success-Scores versions covering shorter intervals, indicating that controlling possession and space in attacking areas is hardly possible for periods as long as 300 or even 500 seconds. Another contributing factor might be that perfect or very high correlation coefficients are just more likely to occur if the calculation includes fewer values (i.e., seconds). Similarly, higher maximal Success-Scores in the 30-meter-zone compared to the penalty area show that teams are more likely to control possession and at least 20% of the space (i.e., space control events) within the 30-meter-zone than in the penalty area. The penalty area with its proximity to the goal tends to be more intensely defended by the opponent and hence progression into the penalty area tends to be much more challenging and not as long lasting (Tenga, Holme, et al., 2010; Vilar et al., 2013).

Table 5a: Model overview for SuSc_16_100

			FM	RI	**PS**
Fixed effects	possession	β	-0.0578	-0.0324	**-0.0588**
		SE	0.0097	0.0119	**0.0095**
		df	219.4	49.1	**504.8**
		t	-5.94	-2.73	**-6.18**
		p	<.0001	.0088	**<.0001**
	opponent quality	β	-0.0351	-0.0307	**-0.0351**
		SE	0.0034	0.0034	**0.0034**
		df	500.0	502.0	**499.9**
		t	-10.48	-8.95	**-10.47**
		p	<.0001	<.0001	**<.0001**
	Success-Score	β	0.1531	0.1570	**0.1545**
		SE	0.0416	0.0425	**0.0416**
		df	496.5	501.2	**496.7**
		t	3.68	3.69	**3.71**
		p	.0003	.0002	**.0002**
Random effects		$\sigma_{Intercept}$	0.7688		**0.8289**
		σ_{slopeP}	0.009	0.0324	
		$\sigma_{residual}$	1.5472	1.6288	**1.5463**

Note. FM: full model (see equation 3); RI: full model without random intercept; PS: full model excluding random effect for possession; β: fixed-effect slope; SE: standard error; df: degrees of freedom; t: t-value; p: p-value; $\sigma_{Intercept}$: standard deviation of random intercept; σ_{slopeP}: standard deviation of random slope for possession; $\sigma_{residual}$: standard deviation of residuals; all effects, standard errors and p-values are rounded to four decimal places; t and df are rounded to two decimal places.

Table 5b: Model comparison for SuSc_16_100

Model	npar	AIC	BIC	logLik	deviance	χ^2	df	p-value
FM	8	1931.1	1964.9	-957.53	1915.1			
RI	6	1958.9	1984.3	-973.46	1946.9	31.87	2	<.0001
PS	6	1928.7	1954.1	-958.36	1916.7	1.67	2	0.4349

Note. FM: full model (see equation 3); RI: full model without random intercept; PS: full model excluding random effect for possession; npar: number of model parameters; AIC: Akaike information criterion; BIC: Bayesian information criterion; logLik: log-likelihood; χ2: Chi-squared statistic; df: degrees of freedom; AIC, BIC and deviance are rounded to one decimal place; logLik and χ2 are rounded to two decimal places; p-values are rounded to four decimal places.

Table 6a: Model overview for SuSc_16_300

			FM	RI	**PS**
Fixed effects	possession	β	-0.0545	-0.0304	**-0.0554**
		SE	0.0094	0.0116	**0.0091**
		df	190.8	44.0	**503.6**
		t	-5.81	-2.61	**-6.06**
		p	<.0001	.0122	**<.0001**
	opponent quality	β	-0.0351	-0.0307	**-0.0352**
		SE	0.0034	0.0034	**0.0034**
		df	500.1	501.8	**499.9**
		t	-10.47	-8.95	**-10.47**
		p	<.0001	<.0001	**<.0001**
	Success-Score	β	0.1365	0.1485	**0.1368**
		SE	0.0383	0.0394	**0.0382**
		df	493.9	501.6	**494.5**
		t	3.57	3.77	**3.58**
		p	.0004	.0002	**.0004**
Random effects		$\sigma_{Intercept}$	0.7618		**0.8273**
		σ_{slopeP}	0.0093	0.0328	
		$\sigma_{residual}$	1.5489	1.6275	**1.548**

Note. FM: full model (see equation 3); RI: full model without random intercept; PS: full model excluding random effect for possession; β: fixed-effect slope; SE: standard error; df: degrees of freedom; t: t-value; p: p-value; $\sigma_{Intercept}$: standard deviation of random intercept; σ_{slopeP}: standard deviation of random slope for possession; $\sigma_{residual}$: standard deviation of residuals; all effects, standard errors and p-values are rounded to four decimal places; t and df are rounded to two decimal places.

Table 6b: Model comparison for SuSc_16_300

Model	npar	AIC	BIC	logLik	deviance	χ^2	df	p-value
FM	8	1931.8	1965.6	-957.91	1915.8			
RI	6	1958.3	1983.7	-973.18	1946.3	30.65	2	<.0001
PS	6	1929.7	1955	-958.84	1917.7	1.85	2	0.3972

Note. FM: full model (see equation 3); RI: full model without random intercept; PS: full model excluding random effect for possession; npar: number of model parameters; AIC: Akaike information criterion; BIC: Bayesian information criterion; logLik: log-likelihood; χ2: Chi-squared statistic; df: degrees of freedom; AIC, BIC and deviance are rounded to one decimal place; logLik and χ2 are rounded to two decimal places; p-values are rounded to four decimal places.

Table 7a: Model overview for SuSc_16_500

			FM	RI	**PS**
Fixed effects	possession	β	-0.0553	-0.0316	**-0.0562**
		SE	0.0093	0.0115	**0.0090**
		df	191.1	43.5	**503.4**
		t	-5.96	-2.75	**-6.22**
		p	<.0001	.0086	**<.0001**
	opponent quality	β	-0.0347	-0.0303	**-0.0347**
		SE	0.0034	0.0034	**0.0034**
		df	500.4	502.1	**500.3**
		t	-10.35	-8.84	**-10.34**
		p	<.0001	<.0001	**<.0001**
	Success-Score	β	0.1573	0.1720	**0.1578**
		SE	0.0402	0.0412	**0.0402**
		df	495.3	501.7	**495.8**
		t	3.91	4.18	**3.93**
		p	.0001	<.0001	**.0001**
Random effects		$\sigma_{Intercept}$	0.7542		**0.8181**
		σ_{slopeP}	0.0092	0.0324	
		$\sigma_{residual}$	1.5454	1.6228	**1.5444**

Note. FM: full model (see equation 3); RI: full model without random intercept; PS: full model excluding random effect for possession; β: fixed-effect slope; SE: standard error; df: degrees of freedom; t: t-value; p: p-value; $\sigma_{Intercept}$: standard deviation of random intercept; σ_{slopeP}: standard deviation of random slope for possession; $\sigma_{residual}$: standard deviation of residuals; all effects, standard errors and p-values are rounded to four decimal places; t and df are rounded to two decimal places.

Table 7b: Model comparison for SuSc_16_500

Model	npar	AIC	BIC	logLik	deviance	χ^2	df	p-value
FM	8	1929.3	1963.1	-956.66	1913.3			
RI	6	1955.2	1980.6	-971.61	1943.2	30.52	2	<.0001
PS	6	1927.1	1952.5	-957.56	1915.1	1.80	2	0.4061

Note. FM: full model (see equation 3); RI: full model without random intercept; PS: full model excluding random effect for possession; npar: number of model parameters; AIC: Akaike information criterion; BIC: Bayesian information criterion; logLik: log-likelihood; $\chi 2$: Chi-squared statistic; df: degrees of freedom; AIC, BIC and deviance are rounded to one decimal place; logLik and $\chi 2$ are rounded to two decimal places; p-values are rounded to four decimal places.

Table 8a: Model overview for SuSc_30_100

			FM	RI	**PS**
Fixed effects	possession	β	-0.0593	-0.0259	**-0.0606**
		SE	0.0106	0.0124	**0.0104**
		df	60.8	58.5	**505.2**
		t	-5.58	-2.09	**-5.83**
		p	<.0001	.0410	**<.0001**
	opponent quality	β	-0.0358	-0.0312	**-0.0358**
		SE	0.0034	0.0035	**0.0034**
		df	492.8	502.2	**499.4**
		t	-10.66	-9.03	**-10.65**
		p	<.0001	<.0001	**<.0001**
	Success-Score	β	0.0474	0.0338	**0.0492**
		SE	0.0156	0.0157	**0.0156**
		df	490.4	505.1	**501.5**
		t	3.04	2.15	**3.15**
		p	.0025	.0321	**.0017**
Random effects		$\sigma_{Intercept}$	0.7991		**0.8489**
		σ_{slopeP}	0.0091	0.0320	
		$\sigma_{residual}$	1.5512	1.6439	**1.5510**

Note. FM: full model (see equation 3); RI: full model without random intercept; PS: full model excluding random effect for possession; β: fixed-effect slope; SE: standard error; df: degrees of freedom; t: t-value; p: p-value; $\sigma_{Intercept}$: standard deviation of random intercept; σ_{slopeP}: standard deviation of random slope for possession; $\sigma_{residual}$: standard deviation of residuals; all effects, standard errors and p-values are rounded to four decimal places; t and df are rounded to two decimal places.

Table8b: Model comparison for SuSc_30_100

Model	npar	AIC	BIC	logLik	deviance	χ^2	df	p-value
FM	8	1935.5	1969.3	-959.73	1919.5			
RI	6	1967.8	1993.2	-977.9	1955.8	36.35	2	<.0001
PS	6	1932.5	1957.8	-960.24	1920.5	1.02	2	0.5996

Note. FM: full model (see equation 3); RI: full model without random intercept; PS: full model excluding random effect for possession; npar: number of model parameters; AIC: Akaike information criterion; BIC: Bayesian information criterion; logLik: log-likelihood; $\chi 2$: Chi-squared statistic; df: degrees of freedom; AIC, BIC and deviance are rounded to one decimal place; logLik and $\chi 2$ are rounded to two decimal places; p-values are rounded to four decimal places.

Table 9a: Model overview for SuSc_30_300

			FM	RI	**PS**
Fixed effects	possession	β	-0.0619	-0.0292	**-0.0631**
		SE	0.0103	0.0122	**0.0102**
		df	303.2	55.7	**505.1**
		t	-6.02	-2.40	**-6.21**
		p	<.0001	.0198	**<.0001**
	opponent quality	β	-0.0357	-0.0311	**-0.0357**
		SE	0.0033	0.0035	**0.0033**
		df	499.3	502.3	**499.3**
		t	-10.66	-9.01	**-10.66**
		p	<.0001	<.0001	**<.0001**
	Success-Score	β	0.0531	0.0416	**0.0546**
		SE	0.0147	0.0149	**0.0147**
		df	498.0	504.3	**500.2**
		t	3.61	2.79	**3.71**
		p	.0003	.0055	**.0002**
Random effects		$\sigma_{Intercept}$	0.8042		**0.8489**
		σ_{slopeP}	0.0069	0.032	
		$\sigma_{residual}$	1.5462	1.6390	**1.5451**

Note. FM: full model (see equation 3); RI: full model without random intercept; PS: full model excluding random effect for possession; β: fixed-effect slope; SE: standard error; df: degrees of freedom; t: t-value; p: p-value; $\sigma_{Intercept}$: standard deviation of random intercept; σ_{slopeP}: standard deviation of random slope for possession; $\sigma_{residual}$: standard deviation of residuals; all effects, standard errors and p-values are rounded to four decimal places; t and df are rounded to two decimal places.

Table 9b: Model comparison for SuSc_30_300

Model	npar	AIC	BIC	logLik	deviance	χ^2	df	p-value
FM	8	1931.8	1965.6	-957.88	1915.8			
RI	6	1964.7	1990	-976.34	1952.7	36.94	2	<.0001
PS	6	1928.7	1954.1	-958.36	1916.7	0.97	2	0.6156

Note. FM: full model (see equation 3); RI: full model without random intercept; PS: full model excluding random effect for possession; npar: number of model parameters; AIC: Akaike information criterion; BIC: Bayesian information criterion; logLik: log-likelihood; $\chi 2$: Chi-squared statistic; df: degrees of freedom; AIC, BIC and deviance are rounded to one decimal place; logLik and $\chi 2$ are rounded to two decimal places; p-values are rounded to four decimal places.

Table 10a: Model overview for SuSc_30_500

			FM	RI	**PS**
Fixed effects	possession	β	-0.0549	-0.0227	**-0.0566**
		SE	0.0105	0.0123	**0.0103**
		df	55.4	56.3	**504.9**
		t	-5.22	-1.85	**-5.50**
		p	<.0001	.0699	**<.0001**
	opponent quality	β	-0.0357	-0.0312	**-0.0358**
		SE	0.0034	0.0035	**0.0034**
		df	492.2	502.3	**499.5**
		t	-10.60	-9.01	**-10.61**
		p	<.0001	<.0001	**<.0001**
	Success-Score	β	0.0396	0.0273	**0.0416**
		SE	0.0157	0.0158	**0.0157**
		df	496.1	504.8	**501.7**
		t	2.52	1.73	**2.65**
		p	.0120	.0840	**.0082**
Random effects		$\sigma_{Intercept}$	0.7819		**0.8462**
		σ_{slopeP}	0.0095	0.0321	
		$\sigma_{residual}$	1.5565	1.6465	**1.5557**

Note. FM: full model (see equation 3); RI: full model without random intercept; PS: full model excluding random effect for possession; β: fixed-effect slope; SE: standard error; df: degrees of freedom; t: t-value; p: p-value; $\sigma_{Intercept}$: standard deviation of random intercept; σ_{slopeP}: standard deviation of random slope for possession; $\sigma_{residual}$: standard deviation of residuals; all effects, standard errors and p-values are rounded to four decimal places; t and df are rounded to two decimal places.

Table 10b: Model comparison for SuSc_30_500

Model	npar	AIC	BIC	logLik	deviance	χ^2	df	p-value
FM	8	1938.2	1972	-961.11	1922.2			
RI	6	1969.4	1994.8	-978.7	1957.4	35.18	2	<0.0001
PS	6	1935.3	1960.7	-961.66	1923.3	1.10	2	0.5771

Note. FM: full model (see equation 3); RI: full model without random intercept; PS: full model excluding random effect for possession; npar: number of model parameters; AIC: Akaike information criterion; BIC: Bayesian information criterion; logLik: log-likelihood; $\chi 2$: Chi-squared statistic; df: degrees of freedom; AIC, BIC and deviance are rounded to one decimal place; logLik and $\chi 2$ are rounded to two decimal places; p-values are rounded to four decimal places.

Table 11: Sample effect calculation for the Success-Score predictors

	β	IQR	$Effect_{IQR}$	Range	$Effect_{range}$
SuSc_16_100	0.15	2.15	0.33	7.36	1.14
SuSc_16_300	0.14	2.05	0.28	10.14	1.39
SuSc_16_500	0.16	1.91	0.30	7.99	1.26
SuSc_30_100	0.05	6.05	0.30	19.01	0.93
SuSc_30_300	0.05	6.20	0.34	18.66	1.02
SuSc_30_500	0.04	6.10	0.25	17.21	0.72

Note. β: coefficient of gradients for the Success-Scores in the PS-models; IQR: interquartile range; $Effect_{IQR}$: the expected change in match outcome for a change of one IQR of that Success-Score; $Effect_{range}$: the expected change in match outcome for a change from minimum to maximum and vice versa of that Success-Score version; all values are rounded to two decimal places.

Goalscoring analysis

As hypothesized and previously observed (Brinkjans et al., 2022, 2023), both the correlational analysis and the chi-square tests indicated a connection between the Success-Scores and goals. Based on the increase in the number of goals analyzed compared to the previous studies with 45 goals, the result can be considered far more robust and appear to strengthen the link between the Success-Scores and goalscoring. The higher goalscoring frequencies above the 80th percentile suggest that the highest values of Success-Scores indicate some form of attacking danger. The significant correlations between the Success-Score ranks and the number of goals scored, in turn, seem to suggest that with increasing Success-Scores, the chance of scoring a goal increases simultaneously. However, looking at the number of goals in each percentile group (Table 2), this interpretation must be revised. While the highest number of goals is scored within either percentile group 7 or 8 for all but one Success-Score version (SuSc_16_100), no consistent linear trend of increasing numbers of goals being scored at higher Success-Score values can be observed. Instead, the number of goals is relatively constant within the mid-range of Success-Score values and considerable differences are only observable between the lowest Success-Score ranges and the rest. More specifically, those percentile group that consist mostly or entirely of zeros contain substantially fewer goals than all other groups (Table 1). For all Success-Score versions, we find that the point in the distribution where the Success-Score values raise above zero coincides perfectly with a jump in the number of goals scored. Consequentially, the argument can be made, that a Success-Score of zero in most cases just indicates the absence of attacking efforts (e.g., defending in the own half) and hence smaller goalscoring frequencies for these Success-Score values are hardly surprising, as goal scoring logically depends on possession and is evidently also linked to possession and occupation of space in specific attacking areas (Caicedo-Parada et al., 2020; Fernández et al., 2021; González-Ródenas et al., 2019). This not only weakens the relevance of the correlational effects but also to a lesser extent also compromises the effects found in the chi-square tests. This follows from the fact that the range below the 80th percentile includes a varying number of zero-values as well, which can be considered less relevant for the question at hand. The important question is whether the Success-Score can differentiate promising from unpromising attacking sequences. This would require a connection between Success-Scores and goalscoring within a sample of attacking sequences, or in other words between goalscoring and Success-Scores > 0. Unfortunately, this was not explicitly tested. While the limited relevance of Success-Score values of zero is apparent in this sample, previous findings suggested, that depending on the parameters of the Success-Score,

values of zero can in fact be relevant (Brinkjans et al., 2022, 2023). On a purely descriptive level, some small trends can be observed in Table 2. However, the practical relevance appears questionable.

The few substantial differences existing between the Success-Scores versions regarding goalscoring are easily explainable. The weaker correlation for SuSc_16_100 results from the almost 50% of zeros in the Success-Score distribution. These cause a lot of tied ranks and hence a weaker correlation. That being sad, the remaining four percentile groups show no trend either. The differences between the remaining five Success-Scores versions are relatively small given the substantial effect of individual changes in ranking order in a rank correlation with as few ranks as eight. For both Success-Score versions over 100 seconds, the relative goalscoring frequency is twice as high above than below the 80th percentile. In contrast, the remaining four Success-Score versions show a much smaller difference between these two sections of roughly 50%. This, in large part, will also be a consequence of the larger number of zeros in the Success-Score versions over 100 seconds, which as discussed before, are naturally linked to fewer goals. The lack of differences between the Success-Scores versions goes against prior hypotheses to a certain extent. The findings do not support the supposed increased relevance of the penalty area compared to the 30-meter-zone based on previous findings (Gonzalez Rodenas et al., 2020; Michailidis et al., 2013; Ruiz-Ruiz et al., 2013; Tenga, Holme, et al., 2010; Wright et al., 2011; Wunderlich et al., 2021). Neither do they indicate that shorter intervals are more closely linked to goalscoring than longer intervals (Brinkjans et al., 2022, 2023). While the effects of the zero-share might contribute to the lack of differences between the Success-Score versions, one might still interpret them as a sign, that the parameter selection has limited influence on the practical relevance of the Success-Score within the range of values tested. For the penalty area this could imply, that while most goals are scored from within the penalty area (Gonzalez Rodenas et al., 2020; Wright et al., 2011; Wunderlich et al., 2021) and progression into the penalty has consequently be identified as a crucial performance characteristics (Ruiz-Ruiz et al., 2013; Tenga, Ronglan, et al., 2010), this does not imply the necessity of controlling a large degree of space in the penalty area or long phases of ball control within the penalty area. Controlling certain spaces in front of the penalty area and a small corridor of space within the penalty area for a split second might be enough to progress into a dangerous position in the box. This line of thought is supported by studies that described the relevance of spaces in the final third including spaces in front of the penalty area (Caicedo-Parada et al., 2020; Fernandez & Bornn, 2018). The absence of clear differences between interval lengths within the tested range could potentially hint at what the Success-Score represents. One possible interpretation would be that it reflects attacking progression and phases of attacking pressure, as intended in the development (Perl & Memmert, 2017), rather than individual goal scoring opportunities. This would explain why intervals as long as seven minutes work just as well as shorter intervals.

Match outcome modeling

Random effects

Based on the variances and the model statistics (Table 5-10), it appears that none of the models is fit to predict match outcome accurately. This was never the aim and cannot be surprising considering the simplicity of the model, the complexity of the game and the influence of randomness (Wunderlich et al., 2021). Nevertheless, the models clearly identify factors contributing to match outcome. Since the only difference between the six PSs is the Success-Score version used, it is not surprising that the random effects, which do not include the Success-Scores, are very similar. Most variance in match outcome was explained when including a random intercept for team identity, providing evidence for inherent differences in match outcome baselines between teams and therefore the necessity to use mixed effects model in the

analysis. The inclusion of the random possession slope did not improve any of the models and hence, there is no evidence supporting previous observations that teams of higher quality profit from possession more than weaker teams do (Mao et al., 2016).

Fixed effects

In line with previous findings (Liu et al., 2016), the mixed effect models provide evidence for the distinction between within- and between-team effects for possession. Due to the random intercept for team identity, the fixed effect for possession can be interpreted as a within-team effect (Enders & Tofighi, 2007; Hoffman & Walters, 2022). It indicates the influence of possession excluding given match outcome differences between teams. Therefore, it follows that based on the derived models, one would expect the match outcome to get worse with higher possession percentages for the same team. With a swing of more than 0.5 goals predicted in case of a 10-point change of the possession percentage, this effect can be considered very relevant. If, in fact, there is a positive between-team effect (Liu et al., 2016), the possession effect should invert or at least approach zero when excluding the random intercept for team identity. In these models, the fixed effect for possession combines the theoretical between- and within-team effects of possession. Therefore, the reduction of the coefficient of gradient by roughly 50% in all six RI-models hints at the existence of a positive between-team effect.

It is easy to see why the quality of opponent would impact performance and match outcome. Hence, it is no surprise, that based on the models too, one would expect the opponent quality to have a substantial effect on match outcome. This is in line with previous studies reporting opponent quality to influence performance and success (Fernandez-Navarro et al., 2019; González Rodenas et al., 2020; Kempe et al., 2014; Liu, Yi, et al., 2015). According to the fitted models, it would take a change of the opponent season goal differential by almost 30 goals to cause a change of one goal in the expected match outcome. 30 goals can be the difference between a top team and a team from the lower regions of the table. Therefore, while not extreme, this effect seems substantial. Compared to all six PSs, the effect of opponent quality decreases slightly when no random intercept is included for team identity (RI). This might be a consequence of a few individual differences in each team's list of opponents caused by the matches that had to be excluded. Regardless, the differences appear practically irrelevant. For both possession and opponent quality, just as observed, one would not anticipate any big differences between the six models, as only the Success-Score version differentiates these models.

The relevance of asking the question whether the Success-Score reflects only playing style or performance as well is highlighted by the positive correlation between possession and the Success-Score. A certain degree of overlap is inevitable, as ball control is a prerequisite for Success-Scores values over zero as well as goalscoring. The explicit modeling of confounding factors such as possession and the incorporation of random intercepts for team identity allows to mostly isolate the influence of the Success-Score from innate differences between teams. Hence, the statistically significant impact of the fixed effect of the Success-Score provides evidence that the Success-Score captures success-related performance characteristics independent of playing style or pure dominance. A hypothetical change in the difference in Success-Scores between two opposing teams by one interquartile range was chosen to visualize the strength of the Success-Scores' influence. One interquartile range represents a reasonably common delta in the Success-Score difference while also representing a meaningful delta which might for instance be interpreted as the change from a balanced match (based on the Success-Score) to a match in which one team shows a considerably better Success-Score-performance than the other (Table 4). The change of roughly 0.3 goals associated with such a change in the Success-Score-difference is not as large as expected based on the established relevance of the

Success-Score (Table 11, Brinkjans et al., 2022, 2023). Taking the change in expected match outcome of roughly one goal following an extreme difference in Success-Score performance into account, the impact of the Success-Score undoubtedly exceeds that of possession, nonetheless. The practical relevance of this influence can be questioned though, as these extreme differences in match outcome are rare cases.

Contradictory to prior assumptions, no clear differences between the different Success-Score versions was detectable. The influence of the Success-Scores in different versions within their most common range of values appears very consistent. Moreover, the vastly different influence in extreme cases can be easily explained. The maximum values for the Success-Scores on the penalty area are, relative to mean and standard deviation (i.e., z-score), much more extreme than those for the Success-Score on the 30-meter-zone. This small number of outliers causes the larger effects for the penalty area. The results thus provide little evidence that longer intervals or the 30-meter-zone are more susceptible to reflect dominance and playing style rather than attacking danger. Instead, the results suggest that controlling space and the ball in the last 30 meters is just as crucial as doing the same in the penalty area. In combination with the goalscoring results, this could hint at the relevance of controlling spaces around the penalty area which might allow to generate the essential penalty area entries (Liu et al., 2021; Ruiz-Ruiz et al., 2013). Furthermore, this strengthens the argument made that potentially, space control and ball control in the penalty area are only really advantageous up to a certain degree. At the top level, multiple seconds within plenty of space and in control of the ball in the penalty area are a rarity. Most goals rather follow a short instance of ball control within a small amount of space. At the highest level, this tends to be and has to be enough to score a goal (Gonzalez Rodenas et al., 2020). At the rare instance where a larger amount of space and the ball is controlled within the opponent's penalty area, the chance of scoring a goal might very well still increase considerably. But the occurrence of comparable situations might just be too infrequent to detect such an effect in the data. The only objection to this line of argumentation is the conspicuous difference between the effects of the Success-Score versions in the penalty area and the 30-meter-zone in the model without a random intercept. The fact, that the effect increases for the penalty area and decreases for 30-meter-zone when the random intercept is excluded (RI) hints at a minor case of Simpson's paradox (Kievit et al., 2013). The random intercepts of team identity show a slightly weaker correlation with the teams' Success-Scores in the models on the 30-meter zone than in the models analyzing the penalty area-Success-Score versions. In combination with the other fixed effects this is enough to cause the random intercept to affect the Success-Scores' fixed effects in different directions. This is no reason for concern but emphasizes the relevance of the random intercepts (Kievit et al., 2013).

Both the goalscoring analysis and the match outcome modeling did not result in the hypothesized effects. The lack of a clear connection between the Success-Score and goalscoring beyond recognizing attacking sequences, and the absence of clear differences between the Success-Score versions regarding match outcome prediction, could be the consequence of some drawbacks associated with the way in which the general concept of the Success-Score is currently implemented. One point of concern is the implementation of space control via Voronoi-cells. In areas where milliseconds and centimeters are crucial for the outcome, like in and around the penalty area, the simplifications made in Voronoi-cells might cause too much inaccuracy. Instead, more complex models that incorporate player kinematics might be required (Caetano et al., 2021; Fernandez & Bornn, 2018; Martens et al., 2021; Spearman et al., 2017). Furthermore, arguments can be made that a distinction between the values of different spaces would add insight to the model and therefore to the Success-Score (Fernández et al., 2019; Rudd, 2011; Singh, 2019). Similar concerns apply to the definition of ball control purely based on position data. The actual degree of control a player holds over the ball cannot be determined by position

data and proximity-based definitions alone. This is especially problematic whenever players are moving in tight spaces, or first touch scoring opportunities occur. Additionally, the cut-off value of 20% used for the definition of space control events can be discussed in light of the fact that the amount of space a team can feasibly control varies between different areas.

Conclusion

In summary, the results of this study clearly highlight the potential in combining space and ball control to estimate attacking efficiency and success. Nonetheless, the practical applicability is put into question by the limited size of the effects. Therefore, the results warrant future attempts to improve the Success-Scores' expressiveness. Despite the increase in complexity and effort it would cause, the implementation of more detailed space control models and the use of notational data to identify ball control can be considered primary options to improve the Success-Score.

References

Badiella, L., Puig, P., Lago-Peñas, C., & Casals, M. (2023). Influence of Red and Yellow cards on team performance in elite soccer. *Annals of Operations Research*, *325*(1), 149–165. https://doi.org/10.1007/s10479-022-04733-0

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software*, *67*(1), 1–48. https://doi.org/10.18637/jss.v067.i01

Bonn, K. (2023, June 5). *Champions League prize money breakdown 2022/2023: How much do the UCL winners get from UEFA? | Sporting News United Kingdom*. Sportingnews.Com. https://www.sportingnews.com/uk/football/news/champions-league-prize-money-2022-2023-ucl-winners-uefa/axbbtipavsvy1howxwj6vanp

Bradley, P. S., Lago-Peñas, C., Rey, E., & Sampaio, J. (2014). The influence of situational variables on ball possession in the English Premier League. *Journal of Sports Sciences*, *32*(20), 1867–1873. https://doi.org/10.1080/02640414.2014.887850

Brinkjans, D., Memmert, D., Imkamp, J., & Perl, J. (2022). Success-Score in Professional Soccer – Validation of a Dynamic Key Performance Indicator Combining Space Control and Ball Control within Goalscoring Opportunities. *International Journal of Computer Science in Sport*, *21*(2), 32–42. https://doi.org/10.2478/ijcss-2022-0009

Brinkjans, D., Memmert, D., Paul, Y., & Perl, J. (2023). Success-Score in Professional Soccer – Is there a sweet spot in the analysis of space and ball control? *International Journal of Computer Science in Sport*, *22*(2), 77–97. https://doi.org/10.2478/ijcss-2023-0013

Brown, V. A. (2021). An Introduction to Linear Mixed-Effects Modeling in R. *Advances in Methods and Practices in Psychological Science*, *4*(1), 251524592096035. https://doi.org/10.1177/2515245920960351

Caetano, F. G., Barbon Junior, S., Torres, R. da S., Cunha, S. A., Ruffino, P. R. C., Martins, L. E. B., & Moura, F. A. (2021). Football player dominant region determined by a novel model based on instantaneous kinematics variables. *Scientific Reports*, *11*(1), 18209. https://doi.org/10.1038/s41598-021-97537-4

Caicedo-Parada, S., Lago-Peñas, C., & Ortega-Toro, E. (2020). Passing Networks and Tactical Action in Football: A Systematic Review. *International Journal of Environmental Research and Public Health*, *17*(18), 6649. https://doi.org/10.3390/ijerph17186649

Casal, C. A., Anguera, M. T., Maneiro, R., & Losada, J. L. (2019). Possession in Football: More Than a Quantitative Aspect – A Mixed Method Study. *Frontiers in Psychology*, *10*, 501. https://doi.org/10.3389/fpsyg.2019.00501

Collet, C. (2013). The possession game? A comparative analysis of ball retention and team success in European and international football, 2007–2010. *Journal of Sports Sciences*, *31*(2), 123–136. https://doi.org/10.1080/02640414.2012.727455

Coutts, A. J. (2014). Evolution of football match analysis research. *Journal of Sports Sciences*, *32*(20), 1829–1830. https://doi.org/10.1080/02640414.2014.985450

Enders, C. K., & Tofighi, D. (2007). Centering predictor variables in cross-sectional multilevel models: A new look at an old issue. *Psychological Methods*, *12*(2), 121–138. https://doi.org/10.1037/1082-989X.12.2.121

Faraway, J. J. (2006). *Extending the linear model with R: Generalized linear, mixed effects and nonparametric regression models*. Chapman & Hall/CRC.

FBref. (2023a, July 14). *All About FBref.com*. FBref.Com. https://fbref.com/en/about/

FBref. (2023b, July 14). *Football Statistics and History*. FBref.Com. https://fbref.com/en/

Fernandez, J., & Bornn, L. (2018). *Wide Open Spaces: A statistical technique for measuring space creation in professional soccer*.

Fernández, J., Bornn, L., & Cervone, D. (2021). A framework for the fine-grained evaluation of the instantaneous expected value of soccer possessions. *Machine Learning*, *110*(6), 1389–1427. https://doi.org/10.1007/s10994-021-05989-6

Fernández, J., Bornn, L., & Cervone, D. (2019). *Decomposing the Immeasurable Sport: A deep learning expected possession value framework for soccer*. MIT Sloan Sports Analytics Conference, Boston.

Fernandez-Navarro, J., Fradua, L., Zubillaga, A., & McRobert, A. P. (2019). Evaluating the effectiveness of styles of play in elite soccer. *International Journal of Sports Science & Coaching*, *14*(4), 514–527. https://doi.org/10.1177/1747954119855361

Field, A. P., Miles, J., & Field, Z. (2012). *Discovering statistics using R*. Sage. http://catalog.hathitrust.org/api/volumes/oclc/760970657.html

Fujimura, A., & Sugihara, K. (2005). Geometric analysis and quantitative evaluation of sport teamwork. *Systems and Computers in Japan*, *36*(6), 49–58. https://doi.org/10.1002/scj.20254

Goes, F. R., Meerhoff, L. A., Bueno, M. J. O., Rodrigues, D. M., Moura, F. A., Brink, M. S., Elferink-Gemser, M. T., Knobbe, A. J., Cunha, S. A., Torres, R. S., & Lemmink, K. A. P. M. (2021). Unlocking the potential of big data to support tactical performance analysis in professional soccer: A systematic review. *European Journal of Sport Science*, *21*(4), 481–496. https://doi.org/10.1080/17461391.2020.1747552

Gonzalez Rodenas, J., Aranda Malaves, R., Tudela Desantes, A., Sanz Ramirez, E., Crespo Hervas, J., & Aranda Malaves, R. (2020). Past, present and future of goal scoring analysis in professional soccer (Pasado, presente y futuro del análisis de goles en el fútbol profesional). *Retos*, *37*, 774–785. https://doi.org/10.47197/retos.v37i37.69837

González Rodenas, J. G., Malavés, R. A., Desantes, A. T., Ramírez, E. S., Hervás, J. C., & Malavés, R. A. (2020). Past, present and future of goal scoring analysis in professional soccer. *Retos: Nuevas Tendencias En Educación Física, Deporte y Recreación*, *37*, 774–785.

González-Ródenas, J., López-Bondia, I., Aranda-Malavés, R., Tudela Desantes, A., Sanz-Ramírez, E., & Aranda Malaves, R. (2019). Technical, tactical and spatial indicators related to goal scoring in European elite soccer. *Journal of Human Sport and Exercise*, *15*(1). https://doi.org/10.14198/jhse.2020.151.17

Gudmundsson, J., & Horton, M. (2018). Spatio-Temporal Analysis of Team Sports. *ACM Computing Surveys*, *50*(2), 1–34. https://doi.org/10.1145/3054132

Harrison, X. A., Donaldson, L., Correa-Cano, M. E., Evans, J., Fisher, D. N., Goodwin, C. E. D., Robinson, B. S., Hodgson, D. J., & Inger, R. (2018). A brief introduction to mixed effects modelling and multi-model inference in ecology. *PeerJ*, *6*, e4794. https://doi.org/10.7717/peerj.4794

Herold, M., Kempe, M., Bauer, P., & Meyer, T. (2021). Attacking Key Performance Indicators in Soccer: Current Practice and Perceptions from the Elite to Youth Academy Level. *Journal of Sports Science and Medicine*, 158–169. https://doi.org/10.52082/jssm.2021.158

Hewitt, A., Greenham, G., & Norton, K. (2016). Game style in soccer: What is it and can we quantify it? *International Journal of Performance Analysis in Sport*, *16*(1), 355–372. https://doi.org/10.1080/24748668.2016.11868892

Hoffman, L., & Walters, R. W. (2022). Catching Up on Multilevel Modeling. *Annual Review of Psychology*, *73*(1), 659–689. https://doi.org/10.1146/annurev-psych-020821-103525

Horvat, T., & Job, J. (2020). The use of machine learning in sport outcome prediction: A review. *WIREs Data Mining and Knowledge Discovery*, *10*(5). https://doi.org/10.1002/widm.1380

Hughes, M., & Franks, I. (2005). Analysis of passing sequences, shots and goals in soccer. *Journal of Sports Sciences*, *23*(5), 509–514. https://doi.org/10.1080/02640410410001716779

James, N. (2006). Notational analysis in soccer: Past, present and future. *International Journal of Performance Analysis in Sport*, *6*(2), 67–81. https://doi.org/10.1080/24748668.2006.11868373

Jamil, M., Liu, H., Phatak, A., & Memmert, D. (2021). An investigation identifying which key performance indicators influence the chances of promotion to the elite leagues in professional European football. *International Journal of Performance Analysis in Sport*, *21*(4), 641–650. https://doi.org/10.1080/24748668.2021.1933845

Jamil, M., Phatak, A., Mehta, S., Beato, M., Memmert, D., & Connor, M. (2021). Using multiple machine learning algorithms to classify elite and sub-elite goalkeepers in professional men's football. *Scientific Reports*, *11*(1), 22703. https://doi.org/10.1038/s41598-021-01187-5

Jones, P. D., James, N., & Mellalieu, S. D. (2004). Possession as a performance indicator in soccer. *International Journal of Performance Analysis in Sport*, *4*(1), 98–102. https://doi.org/10.1080/24748668.2004.11868295

Kempe, M., Vogelbein, M., Memmert, D., & Nopp, S. (2014). Possession vs. Direct Play: Evaluating Tactical Behavior in Elite Soccer. *International Journal of Sports Science*, *4*(6A), 35–41. http://dx.doi.org/10.5923/s.sports.201401.05

Kievit, R. A., Frankenhuis, W. E., Waldorp, L. J., & Borsboom, D. (2013). Simpson's paradox in psychological science: A practical guide. *Frontiers in Psychology*, *4*. https://doi.org/10.3389/fpsyg.2013.00513

Kim, S. (2004). Voronoi Analysis of a Soccer Game. *Nonlinear Analysis: Modelling and Control*, *9*(3), 233–240. https://doi.org/10.15388/NA.2004.9.3.15154

Kirkwood, B. R., Sterne, J. A. C., & Kirkwood, B. R. (2003). *Essential medical statistics* (2nd ed). Blackwell Science.

Koning, R. H. (2017). Rating of Team Abilities in Soccer. In J. Albert, *Handbook of statistical methods and analyses in sports* (Vol. 1). CRC Press, Taylor & Francis.

Lago, C. (2007). Are winners different from losers? Performance and chance in the FIFA World Cup Germany 2006. *International Journal of Performance Analysis in Sport*, *7*(2), 36–47. https://doi.org/10.1080/24748668.2007.11868395

Lago, C. (2009). The influence of match location, quality of opposition, and match status on possession strategies in professional association football. *Journal of Sports Sciences*, *27*(13), 1463–1469. https://doi.org/10.1080/02640410903131681

Lago-Ballesteros, J., & Lago-Peñas, C. (2010). Performance in Team Sports: Identifying the Keys to Success in Soccer. *Journal of Human Kinetics*, *25*(2010), 85–91. https://doi.org/10.2478/v10078-010-0035-0

Ley, C., Wiele, T. V. D., & Eetvelde, H. V. (2019). Ranking soccer teams on the basis of their current strength: A comparison of maximum likelihood approaches. *Statistical Modelling*, *19*(1), 55–73. https://doi.org/10.1177/1471082X18817650

Liu, H., Gomez, M.-Á., Lago-Peñas, C., & Sampaio, J. (2015). Match statistics related to winning in the group stage of 2014 Brazil FIFA World Cup. *Journal of Sports Sciences*, *33*(12), 1205–1213. https://doi.org/10.1080/02640414.2015.1022578

Liu, H., Hopkins, W. G., & Gómez, M.-A. (2016). Modelling relationships between match events and match outcome in elite football. *European Journal of Sport Science*, *16*(5), 516–525. https://doi.org/10.1080/17461391.2015.1042527

Liu, H., Hopkins, W., Gómez, A. M., & Molinuevo, S. J. (2013). Inter-operator reliability of live football match statistics from OPTA Sportsdata. *International Journal of Performance Analysis in Sport*, *13*(3), 803–821. https://doi.org/10.1080/24748668.2013.11868690

Liu, H., Yi, Q., Giménez, J.-V., Gómez, M.-A., & Lago-Peñas, C. (2015). Performance profiles of football teams in the UEFA Champions League considering situational efficiency. *International Journal of Performance Analysis in Sport*, *15*(1), 371–390. https://doi.org/10.1080/24748668.2015.11868799

Lord, F., Pyne, D. B., Welvaert, M., & Mara, J. K. (2020). Methods of performance analysis in team invasion sports: A systematic review. *Journal of Sports Sciences*, *38*(20), 2338–2349. https://doi.org/10.1080/02640414.2020.1785185

Low, B., Coutinho, D., Gonçalves, B., Rein, R., Memmert, D., & Sampaio, J. (2020). A Systematic Review of Collective Tactical Behaviours in Football Using Positional Data. *Sports Medicine*, *50*(2), 343–385. https://doi.org/10.1007/s40279-019-01194-7

Lüdecke, D., Bartel, A., Schwemmer, C., Powell, C., Djalovski, A., & Titz, J. (2023). *sjPlot: Data Visualization for Statistics in Social Science* (2.8.14) [R Package]. https://cran.r-project.org/package=sjPlot

Mackenzie, R., & Cushion, C. (2013). Performance analysis in football: A critical review and implications for future research. *Journal of Sports Sciences*, *31*(6), 639–676. https://doi.org/10.1080/02640414.2012.746720

Mao, L., Peng, Z., Liu, H., & Gómez, M.-A. (2016). Identifying keys to win in the Chinese professional soccer league. *International Journal of Performance Analysis in Sport*, *16*(3), 935–947. https://doi.org/10.1080/24748668.2016.11868940

Martens, F., Dick, U., & Brefeld, U. (2021). Space and Control in Soccer. *Frontiers in Sports and Active Living*, *3*, 676179. https://doi.org/10.3389/fspor.2021.676179

Memmert, (Ed.) (2024). *Computer Science in Sport: Modeling, Simulation, Data Analysis and Visualization of Sports-Related Data.* Berlin: Springer-Verlag.

Memmert, D. (Ed.) (2021). *Match Analysis.* Abingdon: Routledge.

Memmert, D., Lemmink, K. A. P. M., & Sampaio, J. (2017). Current Approaches to Tactical Performance Analyses in Soccer Using Position Data. *Sports Medicine*, *47*(1), 1–10. https://doi.org/10.1007/s40279-016-0562-5

Memmert, D., & Raabe, D. (2023). *Data Analytics in Football. Positional Data Collection, Modelling and Analysis (3. Edition).* Abingdon: Routledge.

Michailidis, Y., Michailidis, C., & Primpa, E. (2013). Analysis of goals scored in European Championship 2012. *Journal of Human Sport and Exercise*, *8*(2), 367–375. https://doi.org/10.4100/jhse.2012.82.05

Nakanishi, R., Murakami, K., & Naruse, T. (2008). Dynamic Positioning Method Based on Dominant Region Diagram to Realize Successful Cooperative Play. In U. Visser, F. Ribeiro, T. Ohashi, & F. Dellaert (Eds.), *RoboCup 2007: Robot Soccer World Cup XI* (Vol. 5001, pp. 488–495). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-68847-1_52

Nieto, S., Castellano, J., & Echeazarra, I. (2022). Description of collective behaviour in football according to the level of competence in representative tasks from positional data: Systematic review. *International Journal of Sports Science & Coaching*, *17*(6), 1553–1566. https://doi.org/10.1177/17479541221088640

O'Connor-Simpson, M. (2022, June 4). *Championship play-off final: How much is winning Premier League promotion decider worth?* 90min.Com. https://www.90min.com/posts/championship-play-off-final-how-much-premier-league-promotion-decider-worth

Perl, J., Grunz, A., & Memmert, D. (2013). Tactics Analysis in Soccer – An Advanced Approach. *International Journal of Computer Science in Sport*, *12*(1), 33–44.

Perl, J., & Memmert, D. (2011). Net-Based Game Analysis by Means of the Software Tool SOCCER. *International Journal of Computer Science in Sport*, *10*(2), 77–84.

Perl, J., & Memmert, D. (2017). A Pilot Study on Offensive Success in Soccer Based on Space and Ball Control – Key Performance Indicators and Key to Understand Game Dynamics. *International Journal of Computer Science in Sport*, *16*(1), 65–75. https://doi.org/10.1515/ijcss-2017-0005

Perl, J., & Memmert, D. (2018). Soccer: Process and interaction. In A. Baca & J. Perl, *Modelling and Simulation in Sport and Exercise* (pp. 73–94). Routledge.

Phatak, A. A., Mehta, S., Wieland, F.-G., Jamil, M., Connor, M., Bassek, M., & Memmert, D. (2022). Context is key: Normalization as a novel approach to sport specific

preprocessing of KPI's for match analysis in soccer. *Scientific Reports*, *12*(1), 1117. https://doi.org/10.1038/s41598-022-05089-y

Pratas, J. M., Volossovitch, A., & Carita, A. I. (2018). Goal scoring in elite male football: A systematic review. *Journal of Human Sport and Exercise*, *13*(1). https://doi.org/10.14198/jhse.2018.131.19

Prematunga, R. K. (2012). Correlational analysis. *Australian Critical Care*, *25*(3), 195–199. https://doi.org/10.1016/j.aucc.2012.02.003

R Core Team. (2022). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing. https://www.R-project.org/

Raabe, D., Biermann, H., Bassek, M., Wohlan, M., Komitova, R., Rein, R., Groot, T. K., & Memmert, D. (2022). floodlight—A high-level, data-driven sports analytics framework. *Journal of Open Source Software*, *7*(76), 4588. https://doi.org/10.21105/joss.04588

Reep, C., & Benjamin, B. (1968). Skill and Chance in Association Football. *Journal of the Royal Statistical Society. Series A (General)*, *131*(4), 581. https://doi.org/10.2307/2343726

Rein, R., & Brinkjans, D. (submitted). *Count games not athletes: The problem of pseudoreplication in small-sided games research*.

Rein, R., & Memmert, D. (2016). Big data and tactical analysis in elite soccer: Future challenges and opportunities for sports science. *SpringerPlus*, *5*(1), 1410. https://doi.org/10.1186/s40064-016-3108-2

Rein, R., Raabe, D., & Memmert, D. (2017). "Which pass is better?" Novel approaches to assess passing effectiveness in elite soccer. *Human Movement Science*, *55*, 172–181. https://doi.org/10.1016/j.humov.2017.07.010

RStudio Team. (2022). *RStudio: Integrated Development Environment for R* [Computer software]. RStudio, PBC. http://www.rstudio.com/

Rudd, S. (2011). *A Framework for Tactical Analysis and Individual Offensive Production Assessment in Soccer Using Markov Chains*. New England Symposium on Statistics in Sports. chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/http://www.nessis.org/nessis11/rudd.pdf

Ruiz-Ruiz, C., Fradua, L., Fernández-GarcÍa, Á., & Zubillaga, A. (2013). Analysis of entries into the penalty area as a performance indicator in soccer. *European Journal of Sport Science*, *13*(3), 241–248. https://doi.org/10.1080/17461391.2011.606834

Sarmento, H., Marcelino, R., Anguera, M. T., CampaniÇo, J., Matos, N., & LeitÃo, J. C. (2014). Match analysis in football: A systematic review. *Journal of Sports Sciences*, *32*(20), 1831–1843. https://doi.org/10.1080/02640414.2014.898852

Singh, K. (2019). Introducing Expected Threat (xT). *Karun.in/Blog*. https://karun.in/blog/expected-threat.html

Spearman, W., Basye, A., Dick, G., Hotovy, R., & Pop, P. (2017). *Physics-Based Modeling of Pass Probabilities in Soccer*. MIT Sloan Sports Analytics Conference.

Taki, T., & Hasegawa, J. (2000). Visualization of dominant region in team games and its application to teamwork analysis. *Proceedings Computer Graphics International 2000*, 227–235. https://doi.org/10.1109/CGI.2000.852338

Tenga, A., Holme, I., Ronglan, L. T., & Bahr, R. (2010). Effect of playing tactics on achieving score-box possessions in a random series of team possessions from Norwegian professional soccer matches. *Journal of Sports Sciences*, *28*(3), 245–255. https://doi.org/10.1080/02640410903502766

Tenga, A., Ronglan, L. T., & Bahr, R. (2010). Measuring the effectiveness of offensive match-play in professional soccer. *European Journal of Sport Science*, *10*(4), 269–277. https://doi.org/10.1080/17461390903515170

Tenga, A., & Sigmundstad, E. (2011). Characteristics of goal-scoring possessions in open play: Comparing the top, in-between and bottom teams from professional soccer league. *International Journal of Performance Analysis in Sport*, *11*(3), 545–552. https://doi.org/10.1080/24748668.2011.11868572

Van Rossum, G., & Drake, F. L. (2009). *Python 3 Reference Manual*. CreateSpace.

Vilar, L., Araújo, D., Davids, K., & Bar-Yam, Y. (2013). Science of winning soccer: Emergent pattern-forming dynamics in association football. *Journal of Systems Science and Complexity*, *26*(1), 73–84. https://doi.org/10.1007/s11424-013-2286-z

Vogelbein, M., Nopp, S., & Hökelmann, A. (2014). Defensive transition in soccer – are prompt possession regains a measure of success? A quantitative analysis of German Fußball-Bundesliga 2010/2011. *Journal of Sports Sciences*, *32*(11), 1076–1083. https://doi.org/10.1080/02640414.2013.879671

Wright, C., Atkins, S., Polman, R., Jones, B., & Sargeson, L. (2011). Factors Associated with Goals and Goal Scoring Opportunities in Professional Soccer. *International Journal of Performance Analysis in Sport*, *11*(3), 438–449. https://doi.org/10.1080/24748668.2011.11868563

Wunderlich, F., & Memmert, D. (2018). The Betting Odds Rating System: Using soccer forecasts to forecast soccer. *PLOS ONE*, *13*(6), e0198668. https://doi.org/10.1371/journal.pone.0198668

Wunderlich, F., Seck, A., & Memmert, D. (2021). The influence of randomness on goals in football decreases over time. An empirical analysis of randomness involved in goal scoring in the English Premier League. *Journal of Sports Sciences*, *39*(20), 2322–2337. https://doi.org/10.1080/02640414.2021.1930685

Yang, G., Leicht, A. S., Lago, C., & Gómez, M.-Á. (2018). Key team physical and technical performance indicators indicative of team quality in the soccer Chinese super league. *Research in Sports Medicine*, *26*(2), 158–167. https://doi.org/10.1080/15438627.2018.1431539

Yi, Q., Gómez, M.-Á., Liu, H., & Sampaio, J. (2019). Variation of match statistics and football teams' match performance in the group stageof the UEFA Champions League from 2010 to 2017. *Kinesiology*, *51*(2), 170–181. https://doi.org/10.26582/k.51.2.4

Appendix

Link to GitHub repository: https://github.com/DavidB1999/SOCCER23