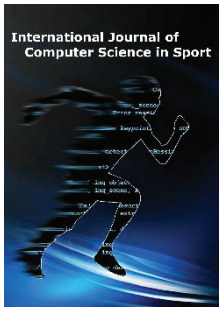
International Journal of Computer Science in Sport

Volume 21, Issue 2, 2022

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

sciendo

DOI: 10.2478/ijcss-2022-0009



Success-Score in Professional Soccer – Validation of a Dynamic Key Performance Indicator Combining Space Control and Ball Control within Goalscoring Opportunities

David Brinkjans, Daniel Memmert, Jonas Imkamp, & Jürgen Perl

German Sports University Cologne

Abstract

Typical performance indicators in professional quantitative soccer analysis simplify complex matters, resulting in loss of information. Hence, a novel approach to characterize the performance of soccer teams was investigated: Success-Scores, combining space control with ball control and the correlation between the two.

Success-Score Profiles were calculated for 14 games from the German Bundesliga. The dataset was split into two groups: all data points above resp. below the 80th percentile of Success-Scores. Subsequently, the relative goalscoring frequency in those two groups was compared. All data points were sorted according to their Success-Score and split into equally sized eighths. These groups were tested for a rank order correlation with the number of scored goals. Finally, the Success-Scores of two teams with different success levels as well as their opponents' Success-Scores were compared.

Results indicated significantly higher goalscoring frequencies above the 80th percentile for Success-Scores and a statistically significant rank order correlation between the Success-Scores and the number of scored goals, $r_s(6) = 0.73$, $p = .04$. The more successful team showed significantly higher Success-Scores.

This novel performance indicator shows significant connections to success defined as scoring goals and final ranking in elite soccer and therefore shows potential in reconizing underlying performance.

KEYWORDS: KPI, BALL POSSESSION, DOMINANT REGIONS, FOOTBALL, EFFICIENCY

Introduction

Dominant soccer teams in history like AC Milan, FC Barcelona, Real Madrid, or FC Bayern Munich were all playing different styles but still dominated national and international soccer. The one thing they have in common is success. Key Performance Indicators (KPIs) are used – not only in soccer (see also team handball: Hassan et al., 2017a, 2017b; Schrapf et al., 2017) – to scale, rank, and rate systems or system-components (Jamil et al., 2021; Perl & Memmert, 2017; Raabe et al., 2022) to identify success factors. Some match actions have been used as singular traditional KPI values and as such have been linked to success (Sarmento et al., 2014; Memmert & Raabe, 2018; Memmert et al., 2017). However, the attempt to evaluate complex, tactical team sports like soccer and its interactive nature with KPIs, where performance depends on a large variety of attributes and multiple individuals, is especially difficult (Biermann et al., 2021; Perl & Memmert, 2018). This is partially because these values neglect most contextual information (Mackenzie & Cushion, 2013; Rein & Memmert, 2016; Sarmento et al., 2014).

A typical example illustrating the limitations of KPIs in soccer would be a game between a team that plays with ball control heavy tactics against a team that uses fast counterattacks as primary strategy. Even if "the counter-attack-team" could clearly be identified as the superior team by experts, performance indicators such as ball control, space control or the number of passes might very well favor their opponent. Memmert and Rein (2018) explained that KPIs need to be carefully interpreted within the right context and with acknowledgment of their limitations. Due to these limitations and the fact that goals often are just a product of chance (Wunderlich et al., 2021), KPIs are not able to predict the outcome of games accurately. Nevertheless, a recent review showed that the majority of studies on performance analysis in soccer and in other invasion sports focus on such simple KPIs (Lord et al., 2020).

Ball possession takes a special place in this field of research and has done so for quite some time (e. g. Jones et al., 2004). As possession of the ball is a precondition of scoring goals (ignoring own goals for the sake of argument) it seems reasonable to assume that there might be a relationship between time in possession and goals scored or even overarching success. Results are nevertheless mixed and inconclusive. Findings indicate that long-term success (higher ranked teams) tends to be positively related to ball possession (e. g. Collet, 2013; Liu, Yi, et al., 2015; Vogelbein et al., 2014) while short-term success (match status and match outcome) is sometimes linked to higher possession percentages (Lago-Peñas et al., 2011; Liu, Gomez, et al., 2015), other times no differences (Alves et al., 2019; Liu, Yi, et al., 2015), or even a negative relationship is found (Collet, 2013). These discrepancies might be explainable by distinguishing between intra- and inter-team differences in possession. On the one hand, better teams (teams that win more games) tend to play a more possession-based style (Gollan et al., 2018; Kempe et al., 2014; Ruan et al., 2022; Zhou et al., 2021). On the other hand, all teams have to get more proactive when trailing, which leads to higher ball possession percentages (Liu et al., 2016; Mao et al., 2016). Another reason for these inconclusive findings could be the complex nature of soccer with many interacting factors influencing performance and outcome. Possession clearly plays a role in success but it is no condition for it and has limited predictive value (Memmert & Rein, 2018). If ball possession in itself is not clearly linked to success, maybe possession in certain areas could be? Again, a reasonable assumption would be that possession closer to the opponents' goal is more likely to lead to a scoring opportunity and hence more valuable than more distant ball possessions. In fact, Tenga et al. (2010) found score box possession, possession in an extended penalty area of 30m, to be a valid surrogate for goals scored. Other studies linked entries into the penalty area with a positive match outcome (Liu et al., 2021; Ruiz-Ruiz et al., 2013) and a recent review showed the offensive midfield area to be the most important area for goalscoring (Caicedo-Parada et al., 2020).

Nevertheless, it is still relevant how possession time is utilized (Schulze et al., 2022; Winter & Pfeiffer, 2016). One attempt to quantify performance is space control. In this framework, models estimate the regions that each player can get to before any other, so-called dominant regions (Fujimura & Sugihara, 2005; Taki & Hasegawa, 2000). The usefulness of dominant regions has been described before (Rein et al., 2017; Rein & Memmert, 2016) and space control was found to be linked to goalscoring and the probability to win a match (Rein et al., 2017). Nonetheless, no matter how much space is controlled by a team, they won't be able to score a goal without ball possession.

Based on these considerations and due to the lack of predictive KPIs in a complex sport like soccer a novel approach based on the software tool SOCCER© by Jürgen Perl (for further information see: Perl et al., 2013; Perl & Memmert, 2011) was developed (Perl & Memmert, 2017) and subsequently named Success-Scores. In general, the intention is to identify a KPI that captures performance linked to success which at the same time is not as influenced by chance as goals scored (Castellano & Pic, 2019; Wunderlich et al., 2021). This approach specifically aims to maximize the expressiveness of quantitative indicators by combining space control and ball control in certain areas under the assumption that the combination facilitates or even preconditions goalscoring opportunities (Perl & Memmert, 2017). The main purpose is to validate this new dynamic KPI in professional soccer matches by demonstrating that more successful team show significantly higher Success-Scores.

Methods

Success-Score

The idea of this new approach is to calculate the efficiency and effort of a team over a certain time interval. Since efficiency is generally defined as the relation between useful output (which we call "success") and input (which we call "effort"), we can rewrite that equation in order to calculate success for a given time interval (1):

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

Efficiency and effort of a team over a time interval of an arbitrary number of seconds can be calculated by SOCCER and therefore enables to calculate *success* as our ultimate parameter of interest.

Effort was defined as the sum of space control and possession events within 30 meters in front of the opponent's goal. Efficiency is calculated as the correlation between space control and ball control. Neither ball control nor space control indicates a goal threat on their own, but only if they correspond with each other.

$$Success(t_{start}, t_{end}) = r(S,B)_{t_{start}}^{t_{end}} * \sum_{t=\,t_{start}}^{t_{end}} \big(S(t) + B(t)\big) \tag{2}$$

In a mathematical context, function (2) describes the calculation of the Success-Score. The value for a given time interval is calculated as the sum of ball control (B) and controlled space (S), times the correlation (r) of the two. For a detailed description check Perl & Memmert (2017). According to its formula, the Success-Score should be high if high numbers of space control and ball control are combined by a team including occurrences of quick counter attacks whose high

efficiency leads to a high Success-Score. Whereas high numbers of space control without ball control or a long period of ball control without high space control lead to low Success-Score values.

This indicator always refers to the time interval prior to a given t_{end}. Hence, if e.g. the current point of success calculation is t = 500 seconds (i.e. t_{end} = 500), and $\Delta t = t_{end} - t_{start}$ = 100 seconds, then the calculated Success-Score of Team A at t_{end}=500 represents the performance of the team between the 400th and 500th second of the game. By moving Δt one second at a time, a Success-Score can be calculated for each second of the game for each team, eventually leading to a Success-Score Profile of a dynamic KPI, reflecting the interaction of both teams' attacking efforts. In this study, the interval length is defined as $\Delta t = t_{end} - t_{start}$ = 300 seconds.

Data

N=56 position-datasets from 28 halftimes of 14 Bundesliga matches were processed by SOCCER© (Perl & Memmert, 2011; Perl et al., 2013). In all of the investigated games, at least one of the following two teams was involved: Team A– a specific team with 43% average ball possession and a final table position in the lower midrange of the 18 teams – and Team B, a specific team with 55% ball possession average over the season and a final table position in the top 4. The software calculated the Success-Scores at the frequency of 1Hz for a 300-second interval length and a defined space control area of 30 meters in front of the opponent's goal.

The exact timecode of each scored goal in the dataset was determined by experts (ICC > .80) through video data and linked to one specific data point. The timecode of goals scored from penalty or freekick was set back to the second of the foul that lead to the set-piece to calculate values of an in-play situation. The movement of players from the time between the foul and the execution of the set-piece and the difference in the players' position would otherwise heavily distort the Success-Score. To ensure exclusively positive values an offset in the magnitude of the smallest value was added so that the most negative Success-Score became zero. In this case, 18.7 was added resulting in the data subsequently analyzed.

Each dataset was split into two groups: all data points above resp. below the 80th percentile of Success-Score. The data was scaled nominally (goal/no goal). The Chi-squared test, an adequate option when comparing proportions of a categorical outcome (Kirkwood et al., 2003) was used to assess the independence of the number of goals scored from the success score percentile . The significance level was set to 0.05 a priori, which in the present dataset corresponds to a critical Chi-square value of 3.81. For further calculation, the dataset was sorted according to the Success-Score of each data point and split into equally sized eighths. Subsequently, the number of goals for each eighth was counted and the coefficient of the correlation between groups and scored goals, as well as the corresponding significance level, was calculated using Spearman´s Rank-Order correlation coefficient.

The mean values of Success-Scores for Team A and Team B as well as for their opposing teams were calculated. Subsequently, an independent t-test was used to assess the significance of differences in mean values. The significance level was set to 0.05 a priori. Additionally, the effect size was assessed, using Cohen´s d for which 0.2, 0.5, and 0.8 were considered to represent small, medium, and large differences respectively (Rice & Harris, 2005). Due to the enormous sample sizes and the obvious Gaussian shape of the plotted data, no test for normal distribution was conducted.

Results

The maximum value of the Success-Score (S_{gmax}) was 76.8 with the 80th percentile threshold at

38.5. The average Success-Score was 30.9. representing approximately the 58th percentile. The average Success-Score for when a goal was scored was 34.6 representing approximately the 70th percentile. 156606 Success-Scores were analyzed as well as 45 goals scored during all investigated games. Of those 45 goals, 30 were scored within the group under the 80th percentile, resulting in a relative scoring frequency of 0.024%. 15 goals were scored within the group over the 80th percentile. The resulting relative goalscoring frequency was 0.048% and statistically significantly larger than for the group under the 80th percentile with X^2 (1, N = 156606) = 4.8. Figure 1 illustrates the frequency distribution of Success-Scores for the dataset.

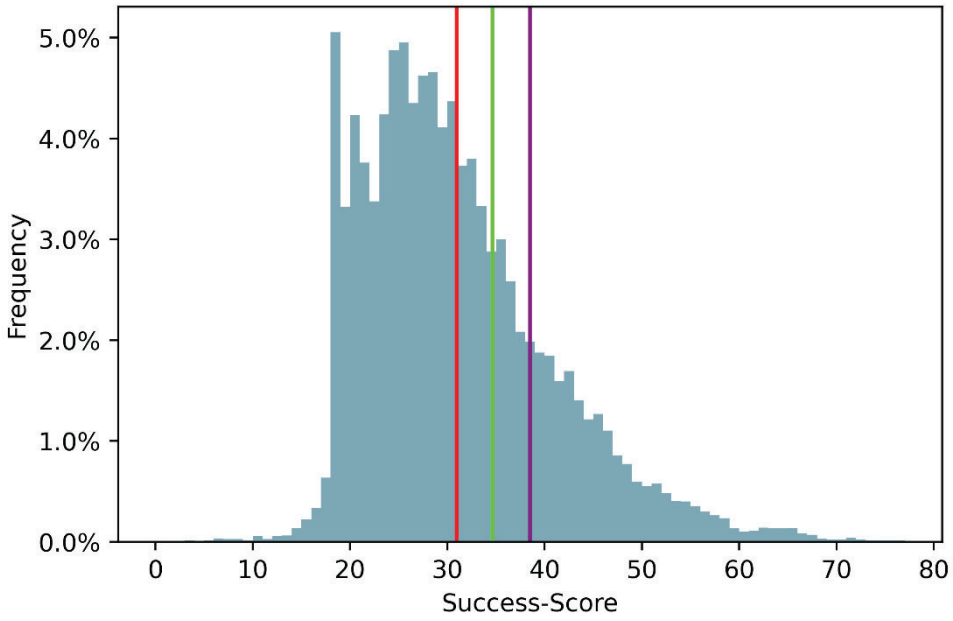


Figure 1: Frequency distribution, mean (red), 80th percentile (purple) and mean Success-Scores for scored goals (green) of the Dataset.

Table 1 divides all data points into eight equally large groups according to their Success-Score. This means Group 1 contains all data points from percentile zero to 12.5, Group 2 contains all data points from percentile 12.5 to 25, and so on until Group 8, which contains the percentiles 87.5 to 100. Since some Success-Scores occur at very high frequencies, the same score can be part of two neighboring groups.

Table 1: The dataset split into equally sized eighth and to which Success-Scores those eighth correspond.

Groups	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	Group 8
Percentiles	0 -12.5%	12.5% - 25%	25% - 37.5%	37.5% - 50%	50% - 62.5%	62.5% - 75%	75% - 87.5%	87.5% - 100%
Success-Scores	0 - 20.5	20.5 - 23.8	23.8 - 26.4	26.4 - 29.2	29.2 - 32.3	32.3 - 36.2	36.3 - 42.6	42.6 - 76.8

Based on this principle, Figure 2 provides an overview of how many goals were scored in each group. Additionally, it shows that there is a strong and statistically significant correlation

between the groups and the goals scored within them.

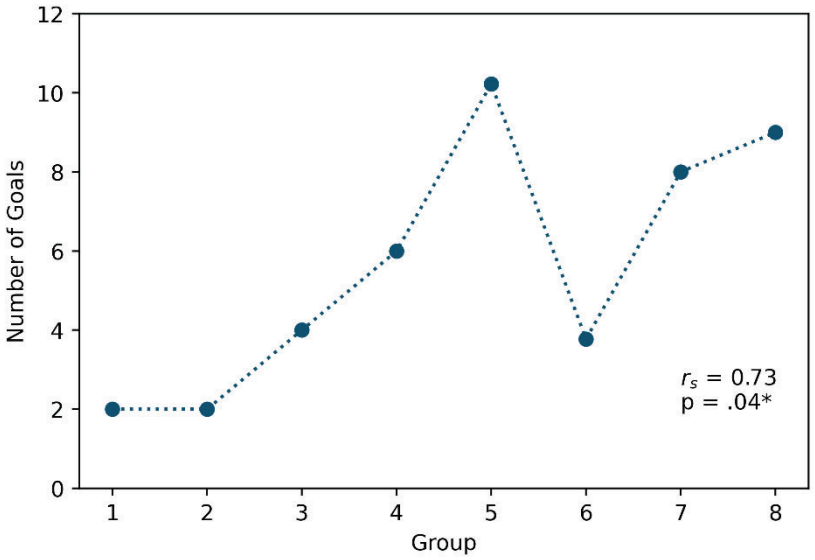


Figure 2: Spearman's Rank-Order Correlation between eight equally sized groups (sorted by Success-Scores) and the amount of scored goals within those groups. A correlation is found statistically significant (*) if $p < 0.05$

Figure 3 shows the Success-Score distribution of both teams for all games in the dataset. Team B seems to achieve higher Success-Scores more frequently. The mean Success-Score for Team B ($M = 32.6$, $SD = 10.6$) was statistically significantly higher than for Team A ($M = 28.7$, $SD = 8.1$), $t(156604) = -60.6$, $p < .001$. The effect size was small with $d = 0.4$.

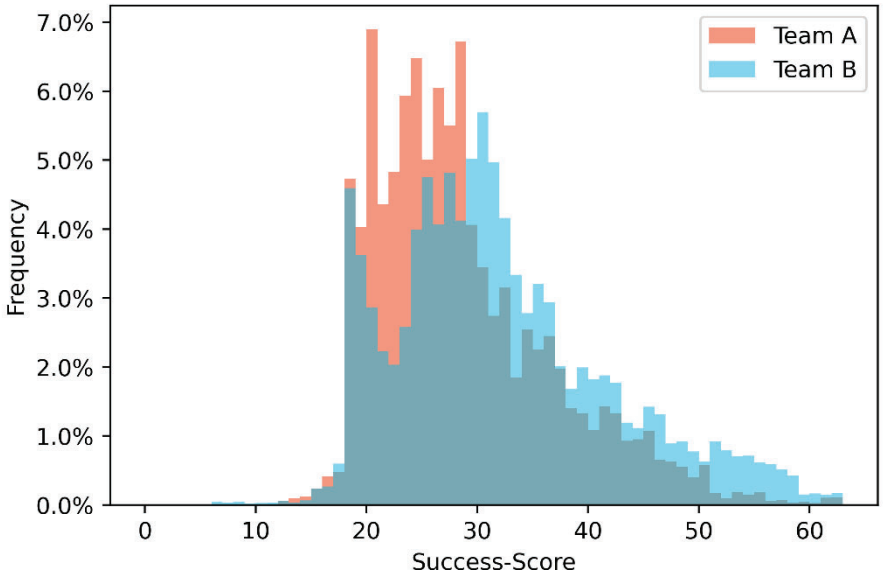


Figure 3: Compared frequency distribution of Success-Scores for the two investigated teams.

Figures 4 visualizes the frequency distributions of both teams' opponents. The opposing teams of Team A appear to achieve higher Success-Scores more frequently than the opponents of Team B. The differrence in mean Success-Scores of their respective opponents between Team A (*M*=

33.5, *SD* = 10.2), and Team B (*M* = 29.6, *SD* = 9.0) was statistically significant, $t(156604) = 60$, $p < .001$ representing a small effect ($d = 0.4$).

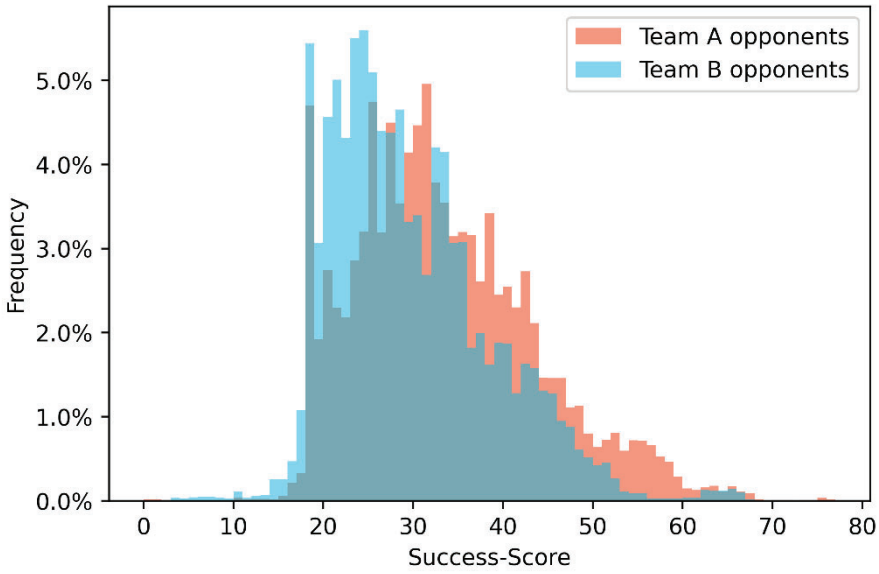


Figure 4: Compared frequency distribution of Success-Scores for the opponents of the two investigated teams

Discussion

The main aim of this paper was to evaluate a new dynamic parameter named Success-Score as a new KPI to analyze tactics and performance in professional soccer. No previous studies have investigated the newly developed Success-Score and its link to long-term success as well as goalscoring up to this point. The results indicated a clear link between the developed Success-Score and the scored goals with a relative goalscoring frequency for the top 20% of Success-Score twice as high as for the rest of the data points. The correlation between the groups and the scored goals within them gives further merit to that interpretation. Considering, that possession was more consistently linked to long-term success than short-term (i. e. goals) in previous investigations (Liu et al., 2016; Mao et al., 2016), these results highlight the importance of adding space control to ball possession when analyzing attacking efficiency and success. Particularly striking is the fact that Group 6 is clearly exempt from the trend of more goals being scored with higher Success-Scores and that in Groups 7 and 8 fewer goals were scored than in Group 5. One possible interpretation is a decrease in added benefit with Success-Scores above a certain level. Perhaps, elite teams and players need a certain amount of space control combined with ball control for a certain amount of time to create scoring opportunities while longer periods of ball control with higher rates of space control might be helpful but not required. Since the occurrence of goals is highly affected by chance and the number of goals in the data is relatively small these conspicuities might also be a product of chance.

The statistically significant differences between Teams A and B and between the respective opposing teams though small show that the Success-Score captures differences between teams of different levels and playing styles. Remarkably, the Success-Score distribution of Team A resembles that of the opponents of Team B and vice versa. This emphasizes the dynamic interaction included in the Success-Score. When one team achieves high Success-Scores in a match, the other team tends to achieve smaller Success-Scores. Looking at the respective distributions it seems like the vast amount of Succes-Scores in the midrange somewhat conceals the differences in the frequency of high and low Success-Scores, thereby possibly explaining the small effect size. Perhaps teams differ mainly in the frequency of high and low Success-Scores.

Phases where neither of the two teams combines substantial space control and ball control in the attacking areas appear to account for much of the play of both teams. No clear conclusions can be drawn about its usefulness in predicting match outcomes since the intra-team difference was not tested on a game-to-game basis. But considering the solid link to goalscoring, it might very well be a better predictor of match outcome than ball possession on its own. As mixed results in previous studies (e. g. Collet, 2013; Liu et al., 2016) on ball possession have highlighted it can be difficult to determine whether differences in a KPI are linked to playing style or playing success as successful teams more often than not adopt an possession based playing style (Gollan et al., 2018; Zhou et al., 2021). A successful team that on average had more ball possession than its opponents was compared with a less successful team that on average had less ball possession than their opponents. Differences between the two could be related to either success, playing style, or both. Whether the Success-Score overcomes the shortcomings of other KPIs in that regard and allows us to sufficiently distinguish between auspicious performances and characteristics of playing styles requires further investigation. To bridge that gap intra-team comparisons and comparisons between teams with different playing styles within the groups of successful and less successful teams are in order.

As previous studies have indicated, the zone within 30 meters of the goal (Tenga et al., 2010), or more generally the attacking midfield area is highly relevant in the context of goalscoring (Caicedo-Parada et al., 2020). The results at hand reaffirm these findings and indicate that the amount of space control and ball control that teams generate within that specific area are linked to goalscoring and long-term success. Therefore, in combination with an interval length of 300 seconds, 30 meters appears to be a valid area for the calculation of the Success-Score. Other studies analyzed the relevance of the penalty area and the results emphasize the link between success and penalty area entries (Liu et al., 2021; Ruiz-Ruiz et al., 2013). Within the zone of 30 meters, different areas (i. e. in the penalty area, central areas, half spaces) are likely to be of varying importance to attacking success. Therefore, comparing the Success-Score for different areas might potentially reveal other areas resulting in a useful Success-Score.

In the development of the Success-Score Perl & Memmert (2017) stated that the optimal interval length would lay somewhere between 100 and 600 seconds, arguing that shorter intervals mainly represent dominant events while longer intervals hide phases of attacking success and the interactive nature of both teams' scores. This might in part be caused by the fact that most of the time the defense controls the majority of space around their own goal. Additionally, it seems reasonable to assume that phases combining space and ball control do not have to be as long as a couple of minutes to create scoring opportunities. At the extreme, a Success-Score over an interval of 2700 seconds would merely represent the average for an entire half and therefore a static KPI. The dynamic interaction between both teams would be lost. Our study demonstrated that 300 seconds is a valid interval length. Nevertheless, other lengths within the proposed range should be tested against the results of a 300-second interval. The interaction of the interval length and the size of the selected area is crucial in that regard. This is because in smaller areas close to the opponents' goal controlled spaces and ball control by the attacking team are less likely to occur. Future investigations should strive to increase generalizability by investigating a larger variety of teams with varying characteristics, including success and playing style while also incorporating a larger number of data points to control for the effect of chance in the occurrence of goals. A direct comparison of Success-Scores from one dataset with those from another is complicated by the fact that the offset calculation results in varying final success scores for the same raw Success-Score depending on the dataset's minimum. The range of the Success-Score is also dependent on the area and the interval length used for its calculation as elaborated on above. Hence, further investigations need to consider potential remedies enabling researchers and perspectively practioners to make comparisons across datasets (Memmert, 2021).

Conclusion

Despite its early stage in assessment, the developed Success-Score has proven to be of high potential in analyzing performance in professional Soccer as it appears to detect successful offensive performance favoring goalscoring and positive match outcome and showing higher values in more successful teams. The chosen area of 30 meters and the interval length of 300 seconds have proven to be good parameters to create an insightful Success-Score. When assessing Success-Scores with deviating parameters, results should be compared with those for 30 meters and 300 seconds.

Acknowledgements

This research was supported by a grant from the German Research Council (DFG, Deutsche Forschungsgemeinschaft) to the second author DM (grant ME 2678/26.1).

References

Alves, D. L., Osiecki, R., Palumbo, D. P., Moiano-Junior, J. V. M., Oneda, G., & Cruz, R. (2019). What variables can differentiate winning and losing teams in the group and final stages of the 2018 FIFA World Cup? *International Journal of Performance Analysis in Sport, 19*(2), 248–257. https://doi.org/10.1080/24748668.2019.1593096

Biermann, H., Theiner, J., Bassek, M., Raabe, D., Memmert, D., & Ewerth, R. (2021). A Unified Taxonomy and Multimodal Dataset for Events in Invasion Games. *In Proceedings of the 4th International Workshop on Multimedia Content Analysis in Sports.*

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

Castellano, J., & Pic, M. (2019). Identification and Preference of Game Styles in LaLiga Associated with Match Outcomes. *International Journal of Environmental Research and Public Health*, 16(24), 5090. https://doi.org/10.3390/ijerph16245090

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

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

Gollan, S., Ferrar, K., & Norton, K. (2018). Characterising game styles in the English Premier League using the "moments of play" framework. *International Journal of Performance Analysis in Sport*, 18(6), 998–1009. https://doi.org/10.1080/24748668.2018.1539383

Hassan, A., Schrapf, N., & Tilp, M. (2017a). The prediction of action positions in team handball by non-linear hybrid neural networks. *International Journal of Performance Analysis in Sport, 17*(3), 293–302.

Hassan, A., Schrapf, N., Ramadan, W., & Tilp, M. (2017b). Evaluation of tactical training in team handball by means of artificial neural networks. *Journal of Sports Sciences, 35*(7), 642–647.

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), 1-7.

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

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

Lago-Peñas, C., Lago-Ballesteros, J., & Rey, E. (2011). Differences in performance indicators between winning and losing teams in the UEFA Champions League. *Journal of Human Kinetics, 27*(2011), 135–146. https://doi.org/10.2478/v10078-011-0011-3

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., 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

Liu, T., Yang, L., Chen, H., & García-de-Alcaraz, A. (2021). Impact of Possession and Player Position on Physical and Technical-Tactical Performance Indicators in the Chinese Football Super League. *Frontiers in Psychology, 12*, 722200. https://doi.org/10.3389/fpsyg.2021.722200

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

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

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

Memmert, D., & Raabe, D. (2018). *Data Analytics in Football. Positional Data Collection, Modelling and 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.

Memmert, D., & Rein, R. (2018). Match analysis, Big Data and tactics: Current trends in elite soccer. *Deutsche Zeitschrift Für Sportmedizin, 2018*(03), 65–72. https://doi.org/10.5960/dzsm.2018.322

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* (S. 73–94). Routledge.

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.

Raabe, D., Nabben, R., & Memmert, D. (2022). Graph Representations for the Analysis of Multi-Agent Spatiotemporal Sports Data. *Applied Intelligence, 1-21.*

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

Rice, M. E., & Harris, G. T. (2005). Comparing Effect Sizes in Follow-Up Studies: ROC Area, Cohen's d, and r. *Law and Human Behavior, 29*(5), 615–620. https://doi.org/10.1007/s10979-005-6832-7

Ruan, L., Ge, H., Gómez, M.-Á., Shen, Y., Gong, B., & Cui, Y. (2022). Analysis of defensive playing styles in the professional Chinese Football Super League. Science and Medicine in Football, 1–9. https://doi.org/10.1080/24733938.2022.2099964

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

Schrapf, N., Alsaied, S., & Tilp, M. (2017). Tactical interaction of offensive and defensive teams in team handball analysed by artificial neural networks. *Mathematical and Computer Modelling of Dynamical Systems, 23*(4), 363–371.

Schulze, E., Julian, R., & Meyer, T. (2022). Exploring Factors Related to Goal Scoring Opportunities in Professional Football. Science and Medicine in Football, 6(2), 181–188. https://doi.org/10.1080/24733938.2021.1931421

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., 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

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

Winter, C., & Pfeiffer, M. (2016). Tactical metrics that discriminate winning, drawing and losing teams in UEFA Euro 2012®. *Journal of Sports Sciences, 34*(6), 486–492. https://doi.org/10.1080/02640414.2015.1099714

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

Zhou, C., Lago-Peñas, C., Lorenzo, A., & Gómez, M.-Á. (2021). Long-Term Trend Analysis of Playing Styles in the Chinese Soccer Super League. Journal of Human Kinetics, 79(1), 237–247. https://doi.org/10.2478/hukin-2021-0077