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ORIGINAL ARTICLE

Not Every Pass Can Be an Assist: A Data-Driven Model to Measure Pass Effectiveness in Professional Soccer Matches

Floris R. Goes,^{1,*} Matthias Kempe,¹ Laurentius A. Meerhoff,² and Koen A.P.M. Lemmink¹

Abstract

In professional soccer, nowadays almost every team employs tracking technology to monitor performance during trainings and matches. Over the recent years, there has been a rapid increase in both the quality and quantity of data collected in soccer resulting in large amounts of data collected by teams every single day. The sheer amount of available data provides opportunities as well as challenges to both science and practice. Traditional experimental and statistical methods used in sport science do not seem fully capable to exploit the possibilities of the large amounts of data in modern soccer. As a result, tracking data are mainly used to monitor player loading and physical performance. However, an interesting opportunity exists at the intersection of data science and sport science. By means of tracking data, we could gain valuable insights in the how and why of tactical performance during a soccer match. One of the most interesting and most frequently occurring elements of tactical performance is the pass. Every team has around 500 passing interactions during a single game. Yet, we mainly judge the quality and effectiveness of a pass by means of observational analysis, and whether the pass reaches a teammate. In this article, we present a new approach to quantify pass effectiveness by means of tracking data. We introduce two new measures that quantify the effectiveness of a pass by means of how well a pass disrupts the opposing defense. We demonstrate that our measures are sensitive and valid in the differentiation between effective and less effective passes, as well as between the effective and less effective players. Furthermore, we use this method to study the characteristics of the most effective passes in our data set. The presented approach is the first quantitative model to measure pass effectiveness based on tracking data that are not linked directly to goal-scoring opportunities. As a result, this is the first model that does not overvalue forward passes. Therefore, our model can be used to study the complex dynamics of build-up and space creation in soccer.

Keywords: football; tracking data; performance indicators; spatiotemporal data; sports analytics; player evaluation

Introduction

Tracking technologies are a constant companion in our daily lives. Both normal persons and athletes are used to wearing microensors to track their lifestyle and habits. In soccer, every player in the top leagues is currently monitored during each training and match.^{1,2} Rein and Memmert² even characterized the current circumstances as exciting times for team sports performance analysis. The amount of available data is increasing every day

as one regular match produces roughly 3,100,000 data points. The extensive amounts of automatically registered data open up many opportunities to get a better understanding of how to analyze team tactics, evaluate players, or manage training processes,^{2,3} also referred to as sport analytics. Currently, research in soccer still struggles to handle and incorporate those big data sets.² Data science approaches, such as machine learning, are considered the most promising method to

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achieve those new insights, especially in tactical performance.⁴ It is even proposed that by incorporating data science, we will see a revolution in soccer.³

To this day, the evaluation of tactical performance is usually based on (“old-fashioned”) notational data using standardized coded notes.⁵ Outcome measures typically consist of frequencies, proportions, and other accumulated performance indicators of events happening during the course of a match. The most common of these events are passing, shooting, tackling, crossing, and—the most crucial—goals.^{6–8} However, tactical performance in team sports should not just be seen as a chain of events but rather as the management of space, time, and individual actions.⁹ Using tracking data in combination with event data is considered the most promising way to provide more insights into tactical performance.^{2,3} This might be especially true for evaluating the influence of specific actions or tactics regarding spacing and timing of teammates and opponents.

Passes are one of the most frequent events in soccer. During the last World Cup, for example, most teams performed more than 500 passes during a single game.¹⁰ Within the literature, passing parameters such as the number of passes, pass completion rate, or the numbers of passes forward are considered as some of the most important predictors for success.^{11–13} Furthermore, because some teams try to create opportunities by long direct passes, whereas other teams have a more elaborate possession-style type of play, passing parameters are key variables to distinguish different tactical approaches,^{7,14} and in creating goal scoring opportunities.¹⁵ However, there are two major concerns regarding the evaluation of passes and passing behavior using event and/or tracking data.

The main weakness of current approaches to evaluate passing, and tactical behavior in general, is that they seldom include contextual variables and the interaction with the opponent.⁵ A primary example of the need to include those parameters is given by Tenga et al.,¹⁵ who showed that a direct counter-attacking tactical approach is efficient against imbalanced (disrupted) defenses, but not against balanced ones. To account for this, several approaches have been developed to quantify the quality of a pass, mostly using tracking data, taking the opposition (partly) into account. However, they solely use evaluation strategies based on the probability of goal scoring.^{16,17} This means a pass is classified as a “good pass” if it produces a goal-scoring opportunity within a set frame of seconds¹⁸ or increases the

probability of a shot on goal.¹⁹ Therefore, in most cases, only forward passes are seen as good passes, even though a sideways or a backward pass might provide more value. Although these passes might not directly result in scoring opportunities, they might disrupt the defensive organization of the opponent creating space for scoring opportunities.

Based on these assumptions, we believe that tactical performance measures should not be directly related to the probability of goal scoring. Instead of linking large-scale tracking data with this rare event, we expect new insights into tactical performance by using spatiotemporal aggregates. Therefore, the aim of the current study was to develop and introduce a new approach to evaluate successful passes (passes reaching a teammate) based on the analysis of tracking data of competitive professional league soccer matches. This approach, using basic data science methods, values successful passes by calculating changes in the positioning of the defensive team and its subunits following a pass. The rationale behind our approach is based on the assumption that teams have to create space and disrupt the defensive organization to create scoring opportunities. In recent work by Fernandez and Bornn, it was stated that “creating space and disordering the defense” is among the most important strategies in modern elite soccer.²⁰ Our assumption is further substantiated by previous findings that possessions are more likely to produce goal-scoring opportunities if they were performed against an imbalanced moving defense.^{15,21} Therefore, we assume that passes leading to increased movement within a defending team (ultimately) result in constellations that favor the attacking team. This approach is in line with research in other team sports, focusing on and evaluating the process of a game rather than being solely goal related.²²

To provide a better understanding of the idea of the defensive disruptiveness, we will introduce the underlying spatiotemporal parameters in the next section. In addition, four recent data science approaches to evaluate passing are briefly discussed to demonstrate the possibilities of using data science techniques. Furthermore, the major differences between the measures taken so far and defensive disruptiveness will be discussed.

Related Work

Spatiotemporal analysis of tactical behavior in soccer

Although tracking data are still predominantly used to monitor and study a player’s physiological and physical

loading,^{6,23} the field of spatiotemporal tactical analysis has recently gained popularity among both sports scientists as well as computer scientists.^{2,4,24} Within the sports science domain, multiple aggregate variables such as the team centroid,²⁵ line centroid,⁴ stretch index,²⁶ team surface area,²⁵ and team spread²⁷ have been developed to summarize the raw tracking data and capture the complex spatiotemporal dynamics of soccer. These aggregate variables have previously been used to study the flow of the game in small-sided games²⁸ (SSGs), Champions League soccer,⁴ and Brazilian professional soccer games²⁹ to study the effect of manipulations and instructions on SSGs^{30,31} and to compare tactical behavior in different populations.³² It was demonstrated that the aforementioned aggregate variables can adequately describe the tactical dynamics of soccer on a team and subunit level. By reducing the size and complexity of the tracking data, from 22 relatively noisy data points every 0.04 seconds into consistent aggregates, these variables provide the opportunity to study tactical behavior based on data of the full match as opposed to data from methods relying on specific match events.³³ However, these spatiotemporal aggregates have mainly been used in experimental settings such as SSGs, and a single spatial aggregate might not be representative of the complex dynamics of tactical performance in competitive 11 versus 11 matches.

On the one hand, the spatiotemporal aggregates described above can help to provide insights into tactical behavior. On the other hand, developments within the data science domain have provided us with increasingly advanced techniques to study large quantities of tracking data.^{2,24} These techniques enable scientists to discover hidden coordination patterns,^{34,35} model game situations,¹⁷ classify,¹⁹ and predict³⁶ events based on large quantities of data. Implementation of techniques from data science can provide an advanced understanding in the complex spatiotemporal aspects of soccer tactics.

By combining methods from data science and sports science, new areas of interest regarding the study of tactical behavior in soccer are emerging. The main part of the research on tactical behavior is dedicated to the study of passing. Traditionally passing studies have mainly been based on notational analysis,³⁷ and although advanced methods based on event data exist,³⁷ they can only take the passer and the receiver into account. The availability of tracking data of all players and the ball allows for designs that are more complex. For example, incorporating the interactions

between two teams. Multiple authors have already used tracking data in their analysis to model pass options,³⁸ or objectively quantify pass effectiveness,^{16,18,39} that way increasing our insight into passing performance.

Quantifying pass effectiveness

Link et al. developed a model that quantifies pass effectiveness based on the change in goal-scoring probability as the result of a pass.¹⁷ The model has not specifically been developed to study passes but rather to evaluate all individual ball actions at every time frame. The probability of a goal being scored—called dangerousity—is quantified based on field position, individual ball control, defensive pressure, and opposing player density in the near surroundings. Dangerousity is then used to calculate the so-called action value of a ball action. The action value of a pass could then be defined as the change in dangerousity between the pass and the subsequent reception.¹⁷ The model provides an interesting continuous and quantitative measure to rate ball actions such as a pass. However, this model strongly links pass effectiveness to goal-scoring opportunities, while one could argue not every pass aims to be an assist. For example, passes to the back or to the side could aim to create space on the field or relieve defensive pressure. The most important downside of the dangerousity model is therefore that these passes would all have a neutral or even negative action value and would thus be rated as ineffective passes.

Power et al. used a similar approach to assess the effectiveness of a pass.¹⁸ Their model is based on an objective quantification of the risk and reward of a pass. The pass risk was defined as the difficulty of a pass based on the speed of the passer and receiver, speed, distance and angle of the nearest defender, ball control, and the time since gaining possession. Pass reward was defined as the likelihood that a goal would occur in the next 10 seconds.¹⁸ This 10 seconds window could be regarded as one of the limitations of this model. During the 10 seconds after a pass, multiple other passes or events might occur, and the final reward (a shot on goal) 10 seconds after a pass can, thus, be viewed as the result of a chain of events rather than that of a single pass. Furthermore, because—like in the dangerousity model¹⁷—the effectiveness of a pass is tied to the probability of a scoring opportunity, the majority of passes would still be qualified as ineffective because scoring opportunities are relatively rare events in soccer games. Passes aimed at creating space for an attack would therefore often be regarded as ineffective.

Rein et al.¹⁶ have tried to solve this issue by using space control in their model to quantify pass effectiveness. They computed pass effectiveness based on the change in space control in the final third of the field between the moment of the pass and the moment of the subsequent reception using Voronoi diagrams.⁴⁰ Furthermore, they added a second measure that uses the amount of outplayed defenders as a measure of pass effectiveness.¹⁶ Opposite to the dangerousity,¹⁷ and risk-reward model,¹⁸ the space control model¹⁶ does not directly link the effectiveness of a pass to the creation of goal-scoring opportunities. However, by focusing on space control in the final third and outplayed defenders, the model still heavily favors passes forward and will probably quantify every sideways or backward pass as an ineffective pass.

The pass classification model by Chawla et al.¹⁹ is, in fact, the only model that can be used to automatically assess the effectiveness of all passes on the field without linking it to goal scoring. Based on an extensive set of predictor variables incorporating among other things all the aforementioned aspects of pass risk and pass rewards, they developed a machine learning classification algorithm to automatically give classifier ratings to every pass.¹⁹ The biggest downside of this model is that it has been developed to replicate the subjective pass ratings (“Good,” “OK,” or “Bad”) given by human observers. Although the model performs accurate automatic classifications, it does not provide a continuous quantitative measure of pass effectiveness, and thus, it does not provide benefits over subjective human ratings if we wish to objectively rank the effectiveness of passes or players.

Positioning of our work

The four introduced approaches to evaluate passes based on the combination of event and tracking data illustrate the potential of data science approaches in classifying tactical performance. By using large sample sizes and evaluating different tactical behaviors, they are able to provide a more detailed picture of player and team performance than just goals and assists. Yet, these approaches strongly link pass effectiveness with creating goal-scoring opportunities (a variable determined by human observers) and tend to overvalue forward passes and passes in the final third of the field.^{16–18} To overcome the limitations of previous work, the aim of the current study was to introduce a new defensive disruptiveness (D-Def) score and to validate our approach by demonstrating its ability to differentiate between players. To measure changes in defensive organization, we use a principle component analysis to merge spatiotemporal aggregates that repre-

sent the organization of a team and its subunits. These aggregates previously demonstrated to adequately describe the tactical dynamics of soccer. To prove the validity of the D-Def score, we show that it is highly connected to the overall movement of the players of the defending team. In addition, we examine whether the D-Def score is able to differentiate the performance of different passes and players. In the last step, we calculate the predictive values of different passing parameters such as passing velocity, passing length, and passing angle on defensive disruptiveness. This allows us to examine which passes cause high defensive disruptiveness and whether the direction of a pass is an important factor in D-Def score. Using these three steps, we will show that the Def-D score is a valid measure to evaluate passing, without overvaluing forward passes.

Preliminaries

Input data

As input data for our model we used the tracking data of all players and the ball. These data were obtained through a semi-automatic optical tracking system (SportVU; STATS LLC, Chicago, IL) that captures the X and Y coordinates of all players and the ball in meters at 10 Hz. All pitches are interpolated to the same size. The X-axis runs longitudinally from goal to goal with coordinates from -55 to 55 m, and the Y-axis runs laterally from side to side with coordinates from -35 to 35 m. The data of every single match were first preprocessed with ImoClient software (Inmotiotec GmbH, Austria). Preprocessing consisted of filtering the data with a weighted Gaussian algorithm (85% sensitivity) and automatic detection of ball possessions and ball events based on the tracking data. Both the tracking data and the ball event data were then imported as individual data frames in Python 3.6.⁴¹ All data processing, data analysis, visualization, and statistical analysis after initial preprocessing were conducted using the NumPy,⁴² Pandas,⁴³ SciPy,⁴⁴ Scikit-learn,⁴⁵ StatsModels, Matplotlib,⁴⁶ and Seaborn⁴⁷ libraries. Tables 1 (tracking data) and 2 (ball event data) provide a graphic representation of how the preprocessed data frames were organized.

Experimental data

We collected tracking and pass data for 18 competitive professional soccer matches of 1 team against 13 different teams during the 2017–2018 Dutch premier league (Eredivisie). The full data set consisted of 16,943 passes, of which 10,481 were received by a teammate, resulting in an average pass completion rate

Table 1. Schematic representation of tracking data on $t = 100$ imported as a DataFrame in Python

Time stamp (ms)	Object ID	X (m)	Y (m)	Velocity (m/s)	Acceleration (m/s) ²
100	Ball	35.6	-20.3	10.1	3.2
100	HomePlayer ₁	20.7	-10.6	5.0	-1.5
100	...	...	...	...	...
100	HomePlayer _n	39.5	15.3	1.2	-2.6
100	AwayPlayer ₁	15.8	35.0	6.3	0.3
100	...	...	...	...	...
100	AwayPlayer _n	-5.1	-35.0	3.2	2.0

of 61.8%. For our model, we preselected time-windows of the game without any missing or erroneous data, and we then selected completed passes with a passing length of >2 and <90 m and a passing velocity of <40 m/s. These criteria were chosen to filter erroneous data and because the pass detection algorithm is not able to differentiate between intentional passes and unintentional ball contacts. Passes with a length of >90 m or a velocity of >40 m/s could indicate corrupted data, and passes with a length of <2 m can be the result of unintentional ball contact. Using those thresholds, 6460 passes were extracted and used for further analysis.

Pass parameters

To determine pass characteristics, we first transformed the ball event data coordinates to only positive coordinates (+55 in the X-axis and +35 in Y-axis) and accounted for playing direction. For any given pass from A to B (Fig. 1), we used the distance between the passer and the receiver on the X-axis (X_{pass}) and Y-axis (Y_{pass}) to compute the passing length L in meters [Eq. (1)], and the passing angle in relation to the Y-axis α in degrees [Eq. (2)].

$$L = \sqrt{X_{pass}^2 + Y_{pass}^2}. \quad (1)$$

$$\alpha = \tan^{-1} \frac{X_{pass}}{|Y_{pass}|}. \quad (2)$$

Table 2. Schematic representation of ball event data imported as a DataFrame in Python

Start (ms)	End (ms)	X (m)	Y (m)	Player	Target	Label
100	1100	20.2	15.3	HomePlayer ₁	HomePlayer ₅	Pass
1100	1100	35.3	17.9	HomePlayer ₅		Reception
1300	1900	35.3	17.9	HomePlayer ₅	HomePlayer ₇	Pass
1900	1900	40.7	-15.1	AwayPlayer ₉		Interception
1900	3100	40.7	-15.1	AwayPlayer ₈		Running with ball

Based on the time stamp of the pass (t_{pass}) and the time stamp of the subsequent reception ($t_{reception}$), we also computed the passing velocity V_{pass} in m/s [Eq. (3)].

$$V_{pass} = L / (t_{reception} - t_{pass}). \quad (3)$$

To classify passes as backward, sideways, or forward, passing angles were divided into 90° bins. All pass parameters are shown in Figure 1.

Ethical considerations

For our study, we collected data from professional soccer clubs. The data we used were previously collected by the clubs for performance purposes and not collected for experimental purposes. All involved players are professional players whom provided consent to their clubs to collect, share, and store their data. For privacy reasons, all personal data were made anonymous before the analysis. The participating clubs provided written informed consent for the use of their data, and the principles in the Declaration of Helsinki were followed during the entire study.

A Model of Defensive Disruptiveness

Defensive movement

For our model, we constructed two measures of defensive movement. The first represents the total individual movement of the defensive players (I-Mov) on the field, and the second represents the disruption of the defensive organization (D-Def). We assumed that an important aim of passing is to move the defense to disrupt the organization, thus creating space. Yet, movement alone does not necessarily result in space creation. For that reason, we developed separate measures for movement (I-Mov) and disruption (D-Def).

Individual movement

Our measure of total individual movement is constructed out of two components: absolute displacement (m) in the longitudinal (X-axis) and absolute displacement (m) in the lateral (Y-axis). We first calculated the sum of absolute displacement in the X-position [X_c —Eq. (4)] and Y-position [Y_c —Eq. (5)] for all defending players between the moment the pass was given (t_0) and 3 seconds later ($t_0 + 3$). Second, we concatenated the sums of displacement on the X-axis and Y-axis to construct I-Mov [Eq. (6)].

$$X_c = \sum_{i=1}^n |(X_1^{t_0+3} - X_1^{t_0})| + |(X_2^{t_0+3} - X_2^{t_0})| + \dots + |(X_{11}^{t_0+3} - X_{11}^{t_0})|, \quad (4)$$

FIG. 1. Schematic representation of a pass from player 1 (center dot) to player 2 (right dot) with a representation of the pass characteristics length and angle. X-pass denotes the displacement of the ball on the X-axis, and Y-pass denotes the displacement of the ball on the Y-axis.

$$Y_c = \sum_{i=1}^n |(Y_1^{t_0+3} - Y_1^{t_0})| + |(Y_2^{t_0+3} - Y_2^{t_0})| + \dots + |(Y_{11}^{t_0+3} - Y_{11}^{t_0})|, \quad (5)$$

$$I\text{-Mov} = X_c + Y_c. \quad (6)$$

When analyzing the game events in soccer, a 3-second window is commonly used as it was suggested by coaches to be a critical window.⁴⁸ Furthermore, the average duration of a pass is roughly 2 seconds in our data set; Windows <3 seconds might miss the effect of the pass, whereas windows >3 seconds might include the effect of the next pass.

Disruption of the defense

To objectively quantify the defensive organization, we computed the displacement of the average X and Y positions (or centroids) for the full team [C_X , C_Y in m—Eqs. (7) and (8)], the defensive (C_{DEFX} , C_{DEFY} in m), midfield (C_{MIDX} , C_{MIDY} in m), and attacking [C_{ATTX} , C_{ATTY} in m—Eqs. (9) and (10)] lines between the moment a pass was given (t_0) and 3 seconds later ($t_0 + 3$). Line formations were based on the starting formations

of the teams as provided by coaches before a match, and we accounted for substitutions.

$$C_x = \left(\sum_{i=1}^n X_1^{t_0+3} + X_2^{t_0+3} + \dots + X_n^{t_0+3} \right) / n - \left(\sum_{i=1}^n X_1^{t_0} + X_2^{t_0} + \dots + X_n^{t_0} \right) / n, \quad (7)$$

$$C_y = \left(\sum_{i=1}^n Y_1^{t_0+3} + Y_2^{t_0+3} + \dots + Y_n^{t_0+3} \right) / n - \left(\sum_{i=1}^n Y_1^{t_0} + Y_2^{t_0} + \dots + Y_n^{t_0} \right) / n, \quad (8)$$

$$C_{line_x} = \left(\sum_{i=1}^n X_1^{t_0+3} + X_2^{t_0+3} + \dots + X_n^{t_0+3} \right) / n - \left(\sum_{i=1}^n X_1^{t_0} + X_2^{t_0} + \dots + X_n^{t_0} \right) / n, \quad (9)$$

$$C_{line_y} = \left(\sum_{i=1}^n Y_1^{t_0+3} + Y_2^{t_0+3} + \dots + Y_n^{t_0+3} \right) / n - \left(\sum_{i=1}^n Y_1^{t_0} + Y_2^{t_0} + \dots + Y_n^{t_0} \right) / n. \quad (10)$$

Table 3. Inter-item correlation of all 10 (centroids, surface, and spread measures) pass effect variables

	C_X	C_Y	C_{XDEF}	C_{YDEF}	C_{XMID}	C_{YMID}	C_{XATT}	C_{YATT}	S_{area}	S_F
C_X	1.00									
C_Y	-0.03	1.00								
C_{XDEF}	0.94	-0.04	1.00							
C_{YDEF}	-0.02	0.92	-0.03	1.00						
C_{XMID}	0.94	-0.02	0.85	-0.01	1.00					
C_{YMID}	-0.02	0.92	-0.03	0.78	-0.02	1.00				
C_{XATT}	0.90	-0.02	0.75	-0.01	0.79	-0.01	1.00			
C_{YATT}	-0.05	0.87	-0.06	0.69	-0.04	0.71	-0.04	1.00		
S_{area}	0.01	0.03	0.01	0.01	0.02	0.03	0.01	0.03	1.00	
S_F	-0.01	0.00	-0.01	-0.01	0.00	0.00	-0.00	0.01	0.29	1.00

We also computed the change in surface area [S_{AREA} in m^2 —Eq. (11)] and the change in spread [S_F in m —Eq. (12)] of the full team. The surface area at a given time stamp t was equal to the smallest convex hull area of a matrix P_t containing positions of all players on the team.²⁷ The spread of the team on t is calculated as the Frobenius norm of the position of all players⁴⁹ in matrix P_t . Both the convex hull and spread variables were computed using specific functions in the SciPy⁴⁴ library.

$$S_{AREA} = \text{ConvexHull}||P_t||, \quad (11)$$

$$S_F = \text{FrobeniusNorm}||P_t||. \quad (12)$$

To create an overall composite measure for the disruptiveness of the defensive organization, we then conducted a principal component analysis using the Scikit-learn⁴⁵ library in Python based on the displacement measures of all passes in our data set.

Principal component analysis:

disruption of the defensive organization

Before the principal component analysis, standardized versions of all variables were created. The correlation matrix (Table 3) revealed 8 of 10 standardized variables correlated at least 0.3 with another variable, suggesting reasonable factorability. With a ratio of more than 600 cases per variable, sample size requirements were met,⁵⁰ and Bartlett's test of sphericity was significant ($\chi^2(6459) = 276274.23$, $p < 0.01$), so factor analysis was deemed suitable with all 10 variables.

The first three factors had eigenvalues >1 and fulfilled Kaiser's criterion.⁵¹ These three factors together explained 83.3% of the variance. Based on the individual factor loadings (Table 4), composite scores were computed for every factor [Eqs. (13–15)].

$$\begin{aligned} PC1 = & -0.46 C_X + 0.26 C_Y - 0.43 C_{XDEF} \\ & + 0.24 C_{YDEF} - 0.43 C_{XMID} + 0.24 C_{YMID} \\ & - 0.41 C_{XATT} + 0.24 C_{YATT}, \end{aligned} \quad (13)$$

$$\begin{aligned} PC2 = & -0.26 C_X - 0.47 C_Y - 0.24 C_{XDEF} \\ & - 0.43 C_{YDEF} - 0.25 C_{XMID} - 0.43 C_{YMID} \\ & - 0.24 C_{XATT} - 0.40 C_{YATT}, \end{aligned} \quad (14)$$

$$PC3 = 0.71 S_{AREA} + 0.71 S_F. \quad (15)$$

As a measure of disruption of the defensive organization, we then took the cumulative sum of the three absolute factor scores [Eq. (16)].

$$D - \text{Def} = |PC1| + |PC2| + |PC3|. \quad (16)$$

We took the absolute scores to account for the differences between forward and backward, and left side and right side movement. The resulting D-Def score is a unit less score based on the absolute standardized variables multiplied by the factor loadings. The theoretical range of the D-Def score is 0 to 20. A score of 0 represents no disruption of the defensive organization at all, whereas a score of 20 would represent the maximal amount of achievable disruption on all components at the same time.

Relation between individual movement and defensive disruption

We previously hypothesized that individual movement would result in disruption of the collective organization. Because individual movement does not necessarily have to result in disruption (e.g., if two players in the same line change position), we wanted to know to what extent an increase in total individual movement after a pass results in a disruption of the defensive organization. The Pearson correlation between I-Mov and

Table 4. Factor loadings computed in the principal component analysis (values <0.20 are suppressed)

	PC1 (longitudinal movement)	PC2 (lateral movement)	PC3 (surface and spread)
C _X	−0.46	−0.26	
C _Y	0.26	−0.47	
C _{XDEF}	−0.43	−0.24	
C _{YDEF}	0.24	−0.43	
C _{XMID}	−0.43	−0.25	
C _{YMID}	0.24	−0.43	
C _{XATT}	−0.41	−0.24	
C _{YATT}	0.24	−0.40	
S _{area}			0.71
S _F			0.71

D-Def was computed (Fig. 2). With $R^2 = 0.74$, a relatively strong correlation between both variables was observed, confirming our initial hypothesis.

Experimental Results

Ranking passes and players

To demonstrate the sensitivity of the I-Mov and D-Def measures, we ranked all 6460 passes in our data set both on the I-Mov measure and on the D-Def measure. The two pass rankings were then used to compare the effectiveness and pass characteristics of the 10% most effective passes ($n=646$), the 80% average effective passes ($n=5168$), and the 10% least effective passes ($n=646$). To evaluate the pass effectiveness of individual players and demonstrate the sensitivity of the I-Mov and D-Def measures to identify effective passers, players were ranked on their average I-Mov score and on their average D-Def score. In order for scores

to be representative of average pass effectiveness, we choose to rank only players with >25 passes ($n=59$). The two player rankings (Tables 5 and 6) were then used to compare average player pass effectiveness and average pass characteristics of the 10% most effective players ($n=5$), the 80% average effective players ($n=49$), and the 10% least effective players ($n=5$). The average I-Mov and D-Def scores for the ranked pass groups are displayed in Figure 3, and the average I-Mov and D-Def scores for the ranked player groups are displayed in Figure 4. All scores, pass characteristics, and between-group differences of the ranked passes and ranked players are displayed in Table 7.

Passes ranked on I-Mov

A one-way ANOVA was conducted to compare the I-Mov, D-Def, pass length, pass angle, and pass velocity in the top 10%, average 80%, and bottom 10% passes ranked on I-Mov. Between-group differences (Table 7) were tested using Tukey's *post hoc* tests with a Bonferroni correction. Results of the one-way ANOVA tests showed that there was a significant effect of ranking group on I-Mov [$F(2, 6456) = 5213.388, p < 0.000, \eta^2 = 0.62$], a significant effect on D-Def score [$F(2, 6456) = 2399.340, p < 0.000, \eta^2 = 0.43$], a significant effect on pass length [$F(2, 6456) = 5.329, p < 0.01, \eta^2 = 0.002$], a significant effect on pass velocity [$F(2, 6456) = 14.835, p < 0.000, \eta^2 = 0.005$], but no significant effect of ranking group on pass angle.

Passes ranked on D-Def

A one-way ANOVA was conducted to compare the I-Mov, D-Def, pass length, pass angle, and pass velocity in the top 10%, average 80%, and bottom 10% passes

FIG. 2. Scatterplot of I-Mov (m) scores versus D-Def scores of all passes in the data set.

Table 5. Player ranking based on the average I-Mov score of individual players

	Player	I-mov (m)	X displacement (m)	Y displacement (m)
1	Player 21 (DEF)	100.78	50.35	50.44
2	Player 16 (DEF)	96.98	51.26	45.72
3	Player 1 (MID)	94.51	62.47	33.68
4	Player 19 (DEF)	92.46	54.16	38.30
5	Player 9 (GK)	91.60	52.05	39.55
...	...	...	...	...
55	Player 70 (GK)	70.38	43.44	27.94
56	Player 34 (ATT)	70.40	36.33	34.07
57	Player 26 (DEF)	69.54	33.29	36.25
58	Player 85 (MID)	65.53	32.95	32.58
59	Player 42 (ATT)	61.69	37.44	24.25

The two components associated with the I-Mov score (X and Y displacement) of the players are shown. Only the best and worst scoring five players are shown in the table.

Table 6. Player ranking based on the average D-Def score of individual players

	Player	D-Def	PC1	PC2	PC3
1	Player 1 (MID)	2.70	-1.63	-0.86	0.10
2	Player 2 (DEF)	1.88	-0.88	0.93	0.08
3	Player 3 (DEF)	1.66	-0.64	0.49	0.53
4	Player 4 (MID)	1.64	0.70	0.40	-0.54
5	Player 5 (DEF)	1.41	0.93	0.29	-0.20
...	...	...	...	...	...
55	Player 30 (MID/ATT)	0.17	0.13	0.02	0.02
56	Player 40 (MID/ATT)	0.16	0.03	0.12	0.01
57	Player 27 (DEF)	0.14	-0.02	0.10	-0.02
58	Player 42 (MID/ATT)	0.13	0.00	0.10	-0.03
59	Player 64 (DEF)	0.08	0.02	-0.05	-0.01

The three components associated with the D-Def score (PC1, PC2, and PC3) of the players are shown. Only the best and worst scoring five players are shown in the table.

ranked on D-Def score. Between-group differences (Table 7) were tested using Tukey's *post hoc* tests with a Bonferroni correction. Results of the one-way ANOVA tests showed that there was a significant effect of ranking group on I-Mov [$F(2, 6456) = 2451.022$, $p < 0.000$, $\eta^2 = 0.43$], a significant effect on D-Def score [$F(2, 6456) = 4935.191$, $p < 0.000$, $\eta^2 = 0.60$], a significant effect on pass length [$F(2, 6456) = 4.762$,

$p < 0.01$, $\eta^2 = 0.001$], a significant effect on pass velocity [$F(2, 6456) = 9.96$, $p < 0.000$, $\eta^2 = 0.003$], but no significant effect of ranking group on pass angle.

Players ranked on average I-Mov

A one-way ANOVA was conducted to compare the I-Mov, D-Def, pass length, pass angle, and pass velocity in the top 10%, average 80%, and bottom 10% players ranked on the average I-Mov. Between-group differences (Table 7) were tested using Tukey's *post hoc* tests with a Bonferroni correction. Results of the one-way ANOVA tests showed that there was a significant effect of ranking group on the average I-Mov [$F(2, 55) = 50.857$, $p < 0.000$, $\eta^2 = 0.65$], but no significant effect on the average D-Def score, average pass length, average pass velocity, or average pass angle.

Players ranked on average D-Def score

A one-way ANOVA was conducted to compare the I-Mov, D-Def, pass length, pass angle, and pass velocity in the top 10%, average 80%, and bottom 10% players ranked on the average D-Def. Between-group differences (Table 7) were tested using Tukey's *post hoc* tests with a

FIG. 3. Box plots of the top 10% ($n = 646$), average 80% ($n = 5168$), and bottom 10% ($n = 646$) passes ranked on I-Mov score (left) or D-Def score (right). *Depicts significant between-group differences ($p < 0.01$).

FIG. 4. Box plots of the top 10% most effective ($n=5$), average 80% ($n=49$), and bottom 10% least effective ($N=5$) players ranked on their average I-Mov score (left) and their average D-Def score (right). *Depicts significant between-group differences ($p < 0.01$).

Bonferroni correction. Results of the one-way ANOVA tests showed that there was a significant effect of ranking group on the average D-Def score [$F(2, 55) = 43.992$, $p < 0.000$, $\eta^2 = 0.61$], but no significant effect on the average I-Mov, average pass length, average pass velocity, or average pass angle.

Predicting the effectiveness of a pass based on pass characteristics

The results demonstrated that there were differences in the pass characteristics between the most and least effective passes. As a final step in our analysis, we used a multiple linear regression model to predict the I-Mov and D-Def scores based on the pass characteristics: length, velocity, angle, X and Y pass locations.

For I-Mov, a significant regression equation was found [$F(5, 5016) = 3993.0$, $p < 0.001$], with an R^2 of 0.799. The predicted total individual movement [I-Mov] is equal to 0.6467 (X location) $+0.3984$ (Y Location) $+0.6585$ (Passing length) $+0.0525$ (Passing angle) $+2.2131$ (Passing velocity).

For D-Def, a significant regression equation was also found [$F(5, 5016) = 2998.0$, $p < 0.001$], with an R^2 of

0.749. The predicted disruption of the defensive organization [D-Def] is equal to 0.0289 (X location) $+0.0148$ (Y Location) $+0.0322$ (Passing length) $+0.0028$ (Passing angle) $+0.1117$ (Passing velocity).

In both regression equations, the effect of velocity and length stood out. An increase of passing velocity with 1 m/s would result in an increase in total individual movement of 2.2 m and an increase in D-Def score of 0.11 points. Furthermore, an increase in pass length of 10 m resulted in an increase in total individual movement of 6.5 m and an increase in D-Def score of 0.3 points.

Discussion

Evaluating tactical performance on an individual and a team level is one of the main challenges in sports analytics.² This task is especially complex in soccer, where valid performance outcomes (goals or shots on goal) are rare in relation to the amount of actions performed in one game. Therefore, we introduced a new model of “passing disruptiveness” to evaluate passing, the most frequent action by a team during offense. The basic idea behind the model is that a good pass will lead to

Table 7. Effectiveness scores and pass characteristics of all passes and players ranked on either I-Mov or D-Def score

Variable	Ranking	Group (mean $\pm$ SD)			Mean difference (95% CI)		
		Top 10% (A)	Average 80% (B)	Bottom 10% (C)	B vs. A	B vs. C	A vs. C
I-Mov (m)	Passes ranked on I-Mov score	150.9 $\pm$ 18.3	79.3 $\pm$ 23.1	29.8 $\pm$ 7.6	-49.5 ^a (-51.7 to -47.2)	71.6 ^a (69.5 to 73.7)	121.1 ^a (118.3 to 124.0)
	Passes ranked on D-Def score	138.9 $\pm$ 27.8	79.8 $\pm$ 27.2	37.5 $\pm$ 15.3	-42.4 ^a (-45.0 to -39.8)	59.1 ^a (56.5 to 61.6)	101.4 ^a (98.0 to 104.9)
	Players ranked on avg. I-Mov score	95.6 $\pm$ 3.7	80.0 $\pm$ 4.5	67.7 $\pm$ 4.0	-12.3 ^a (-17.3 to -7.3)	15.6 ^a (10.6 to 20.6)	27.9 ^a (21.2 to 34.6)
	Players ranked on avg. D-Def score	85.1 $\pm$ 7.9	80.3 $\pm$ 7.1	77.3 $\pm$ 9.4	-3.0 (-11.3 to 5.4)	4.8 (-3.5 to 13.2)	7.8 (-3.5 to 19.0)
D-Def (arbitrary units)	Passes ranked on I-Mov score	7.2 $\pm$ 1.6	3.8 $\pm$ 1.6	1.3 $\pm$ 0.8	-2.5 ^a (-2.6 to -2.3)	3.4 ^a (3.2 to 3.5)	5.8 ^a (5.6 to 6.0)
	Passes ranked on D-Def score	7.8 $\pm$ 1.0	3.8 $\pm$ 1.4	0.9 $\pm$ 0.3	-2.8 ^a (-3.0 to -2.7)	4.1 ^a (3.9 to 4.2)	6.9 ^a (6.7 to 7.1)
	Players ranked on avg. I-Mov score	1.2 $\pm$ 0.8	0.7 $\pm$ 0.4	0.7 $\pm$ 0.3	0.0 (-0.5 to 0.5)	0.5 (0.0 to 1.1)	0.5 (-0.2 to 1.2)
	Players ranked on avg. D-Def score	1.9 $\pm$ 0.5	0.7 $\pm$ 0.3	0.1 $\pm$ 0.0	-0.6 ^a (-0.9 to -0.2)	1.2 ^a (0.8 to 1.5)	1.7 ^a (1.3 to 2.2)
Length (m)	Passes ranked on I-Mov score	19.0 $\pm$ 11.9	17.4 $\pm$ 12.8	18.3 $\pm$ 13.7	0.8 (-0.4 to 2.1)	1.6 ^a (0.4 to 2.9)	0.8 (-0.9 to 2.4)
	Passes ranked on D-Def score	19.0 $\pm$ 12.0	17.5 $\pm$ 12.8	17.2 $\pm$ 13.0	-0.3 (-1.5 to 1.0)	1.6 ^a (0.3 to 2.8)	1.9 ^a (0.2 to 3.5)
	Players ranked on avg. I-Mov score	20.6 $\pm$ 6.2	17.6 $\pm$ 4.2	21.5 $\pm$ 7.6	3.9 (-1.4 to 9.2)	3.0 (-2.3 to 8.3)	-0.9 (-8.0 to 6.3)
	Players ranked on avg. D-Def score	17.8 $\pm$ 1.7	18.3 $\pm$ 5.2	17.3 $\pm$ 2.0	-0.9 (-6.4 to 4.6)	-0.5 (-6.0 to 5.0)	0.5 (-7.0 to 7.9)
Velocity (m/s)	Passes ranked on I-Mov score	10.7 $\pm$ 5.2	10.0 $\pm$ 5.1	9.2 $\pm$ 5.2	-0.8 ^a (-1.3 to -0.3)	0.8 ^a (0.3 to 1.3)	1.5 ^a (0.9 to 2.2)
	Passes ranked on D-Def score	10.7 $\pm$ 5.2	10.0 $\pm$ 5.1	9.4 $\pm$ 5.3	-0.6 ^a (-1.1 to -0.1)	0.7 ^a (0.2 to 1.2)	1.3 ^a (0.6 to 1.9)
	Players ranked on avg. I-Mov score	10.5 $\pm$ 1.3	10.0 $\pm$ 1.3	9.9 $\pm$ 1.9	-0.1 (-1.6 to 1.5)	0.5 (-1.0 to 2.1)	0.6 (-1.5 to 2.7)
	Players ranked on avg. D-Def score	10.9 $\pm$ 1.0	10.0 $\pm$ 1.3	9.9 $\pm$ 1.3	-0.1 (-1.6 to 1.4)	0.8 (-0.7 to 2.3)	0.9 (-1.1 to 2.9)
Angle (°)	Passes ranked on I-Mov score	8.8 $\pm$ 51.5	5.9 $\pm$ 51.3	4.8 $\pm$ 50.6	-1.2 (6.2 to 3.8)	2.9 (-2.1 to 7.9)	4.1 (-2.6 to 10.7)
	Passes ranked on D-Def score	8.9 $\pm$ 50.6	6.0 $\pm$ 51.3	3.8 $\pm$ 51.3	-2.2 (-7.2 to 2.8)	2.8 (-2.2 to 7.8)	5.0 (-1.6 to 11.7)
	Players ranked on avg. I-Mov score	20.2 $\pm$ 24.2	6.4 $\pm$ 18.6	17.1 $\pm$ 33.1	10.7 (-12.5 to 33.8)	13.7 (-9.4 to 36.9)	3.1 (-28.1 to 34.3)
	Players ranked on avg. D-Def score	8.2 $\pm$ 12.4	9.1 $\pm$ 22.0	3.1 $\pm$ 14.1	-6.0 (-29.7 to 17.7)	0.9 (-24.6 to 22.8)	5.1 (-26.9 to 37.0)

^aRepresents significant between-group differences ($p < 0.01$).
SD, standard deviation; CI, confidence interval.

more individual movement and disruption of the opponent. As indicated by the literature, this might be a valid performance measure as a less organized, unbalanced defense is more prone to receiving goals.^{15,21} We used a spatiotemporal representation in the team centroid, spread, and surface, as well as a representation of the subunits via the attacking, midfield, and defending line centroids, which have previously been put forward as measures for defensive organization.^{4,28} As a result, we calculated the D-Def score as an index that represents the change in defensive organization via player movement as a result of a pass. To validate the index, we also calculated the sum of the movement of each player of the defensive team (I-Mov score).

To prove our concept of defensive disruptiveness, we used a three-step approach to validate the D-Def score. In the first step, we showed that overall individual movement (I-Mov) highly correlated with disruptiveness of the defensive organization (D-Def). This result supports our assumption that the amount of movement on the defensive side is highly connected with changes in defensive organization, but also that movement *per se* does not result in defensive disruption.

In the second step, we showed that the D-Def score was able to clearly distinguish between different passes as it yielded major differences between top, average, and low performance passes via a one-way ANOVA. In addition, we could also show that the D-Def score might be a useful tool on an individual level as it was able to distinguish between good (more disruptive) and bad (less disruptive) passers. Taken together, these results demonstrated that our model of defensive disruptiveness is a useful tool to evaluate passing performance.

The main reason for introducing the D-Def score is to overcome the limitations of previous models to evaluate passing performance. In contrast to previous approaches,¹⁸ and similar to the model of Rein et al.,¹⁶ our model focuses on the interaction process of both teams (of creating an advantage) rather than on goal-scoring probabilities. Furthermore, our model is the first to not “overvalue” forward passes. In the previously introduced methods that evaluate passing behavior, all sideways or backward passes are valued with low scores by design,^{2,17–19} as it is easier to score a goal if you are closer to the goal.^{10,52} In principle, a pass that reduces the distance to the goal is crucial for success. However, to advance the ball to the attacking third or near the penalty area is oftentimes the result of the “passing process.” This means that a sideways or back-

ward pass might be as important as it actually creates space that might result in the subsequent creation of an opening for a forward pass or assist. To account for this, we created the D-Def score. This score gives an impression of the change in positioning of the defending team and therefore the likelihood of unbalancing the defense.

As expected and in contrast to the previous approaches, passing angle was not a determining factor for evaluating good or bad passes or good or bad passers using the D-Def score. The passing angle was also a weak predictor for the D-Def score in the regression model. However, passes that produce the best D-Def score are slightly more in a forward direction, but not on a significant level. This indicates that the D-Def score also values forward passes, but it is not “overvaluing” them. As the large standard deviation of 50.6° shows even sideways and backward passes can result in a high Def-D score.

To achieve a decrease in defensive organization, passing length and passing velocity were found to be the most important factors. Both variables showed a significant difference between top, average, and low scoring D-Def passes. Passing velocity was also the strongest predictor for defensive disruptiveness in the regression model. This is in line with previous findings that found out that not possession of the ball but speed and precision of passes are predictors for success.⁵³ Our results revealed that a top level pass, which leads to a significant decrease in defensive organization, was between 19 and 30 m long and was given with a passing velocity of at least 10.7 m/s.

On an individual level, good passers produced a lot of movement in the longitudinal direction. This means that the defensive side has to perform more forward and backward movements, which typically results in more space between the subunits and opens opportunities for forward passes. When taking a look at the passing characteristics of different players, there are no differences in the average passing behavior of top-level passer in comparison to average or bad passers.

On a team level, the D-Def score might be a helpful tool to validate and optimize the tactical approach of a team. For example, passes with a high D-Def score produce an overall movement in the defense up to 200 m, whereas a pass with a low D-Def score just leads to around 20 m of movement. Therefore, disruptive passes might also be very valuable to fatigue the opponent, an important factor as most goals are scored in the last quarter of a game.⁵⁴

Although the results of the model are promising, there are still some challenges that need to be addressed in the future. In our analysis, we only included successful passes. By now, we are able to evaluate the effect of a pass by a player but not the actual effectiveness. If a player has a high D-Def score but only 30% of his passes reach a teammate, he might not be characterized as a good passer. As number of passes and pass completion rate are considered as important factors for success,^{6,52} they need to be included in future steps. In addition, the relationship between the D-Def score and the ultimate success criterion in soccer (scoring goals) should be investigated to validate the relationship between defensive disruptiveness and game outcome. To achieve this, future work should include a larger number of games per player. Although our data set is relatively big in terms of passes, the size might be too small to draw reliable conclusions on a team level. Furthermore, because our current data set has a lot of data on one team, and less data on other teams, future work on team-level performance evaluation should include multiple teams to prevent bias.

Finally, in our future work, we also aim to address potential improvements to our model. One of those improvements might be the incorporation of pitch values, as space creation in certain areas of the field could be a key aspect of success. However, providing adequate pitch values is not a trivial task, as they might be dynamic²⁰ and depend on playing style and tactics. Most previous work on this topic incorporated pitch values as weakly supported constants based on the distance from the goal¹⁷ and thus results in the overvaluation of passes near the scoring area. However, methods such as the model proposed by Fernandez and Bornn²⁰ could be implemented in our model and studied in the future work.

Conclusion

The aim of this study was to develop a new approach to evaluate passing in soccer, that not overvalues forward passes, and to provide a proof of concept. This approach is based on a continuous performance measure (defensive disruptiveness), not depending on the occurrence of infrequent events (like goals or goal-scoring opportunities). Within the evaluation, we could show the validity of the D-Def score and its ability to evaluate individual plays, to describe efficiency, and compare players and teams with one another. In particular, this could be a helpful tool for scientists and practitioners to investigate playing systems or tactical

group concepts. Another advantage of our approach is that it can be implemented live during a match, as it is based exclusively on information that can be calculated real time with tracking data. Since similar approaches are based on notation data as performance outcomes, they require additional processing that is not applicable during a match. In addition, it can be helpful for teams to identify players who play an important role in the game alongside goal scoring and assisting on goals, but rather create beneficial constellations. Furthermore, this approach could be adapted to other team sports with a similar structure, such as Basketball, Handball, or Hockey.

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Abbreviations Used

SSGs = small-sided games
SD = standard deviation
CI = confidence interval