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A risk-reward assessment of passing decisions: comparison between positional roles using tracking data from professional men's soccer

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ABSTRACT

Introduction: Performance assessment in professional soccer often focusses on notational assessment like assists or pass accuracy. However, rather than statistics, performance is more about making the best possible tactical decision, in the context of aplayer's positional role and the available options at the time. With the current paper, we aim to construct an improved model for the assessment of pass risk and reward across different positional roles, and validate that model by studying differences in decision-making between players with different positional roles.
Methods: To achieve our aim, we collected position tracking data from an entire season of Dutch Eredivisie matches, containing 286.151 passes of 336 players. From that data, we derived several features on risk and reward, both for the pass that has been played, as well as for the pass options that were available at the time of passing.
Results: Our findings indicate that we could adequately model risk and reward, outperforming previously published models, and that there were large differences in decision-making between players with different positional roles.
Discussion: Our model can be used to assess player performance based on what could have happened, rather than solely based on what did happen in amatch.

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KEYWORDS
football; time-motion analysis; tactical behaviour; spatiotemporal behaviour; risk-taking behaviour

Introduction

Performance assessment in professional soccer often entails notational assesment (Goes et al., 2020) focussed on statistics like assists, expected goals or pass accuracy. However, rather than achieving good statistics, performance is about making the best possible tactical decision (Kannekens et al., 2009), in the context of the options available to a player. So far, the study of in-play decision-making has mainly been based on observational and post-match interviews (Kermarrec and Bossard, 2014), retrospectively analysing decisions. However, one could argue that assessment of decision-making requires the identification of alternative options, as well as a quantitative analysis of (alternative) outcomes. Furthermore, such an analysis should account for the time constraints of decision-making, as well as the differences per positional role when it comes to the desired decision outcomes, all things which can only be achieved on a larger scale using tracking data (Cervone et al., 2014).

A typical example of tactical decision-making in soccer is passing. Passes are amongst the most frequent actions in a soccer game (Goes et al., 2019), and are the preferred way of a team to move the ball up the field, disrupt the opponent, and create scoring opportunities (Goes et al., 2021a). Traditional notational analysis only assesses basic attributes like accuracy or number of assists. However, as a player could theoretically attempt a pass to every teammate, the key is not only to assess what has happened but to assess what also could have happened. The use of position-tracking data of all players and the ball enables the identification of alternative pass options by modelling the likelihood of a pass arriving at a given teammate (risk), as well as the quantification of associated outcomes, such as gaining territory, outplaying opponents, or creating space (reward).

In general, risk can be defined as the probability of failure associated with a given action (Power et al., 2017). For passing, this is typically operationalized as the chance of a pass resulting in an interception (Power et al., 2017; Spearman et al., 2017). The probability of an interception can be assumed to be related to the field position, pass length, technical difficulty, pressure on the passer and coverage of the receiver, and other similar factors (Power et al., 2017; Spearman et al., 2017; Chawla et al., 2017). Previous studies that modelled pass risk based on the probability of failure illustrate the potential of such an analysis. However, these models leave considerable room for improvement, as the reported prediction accuracy errors range from 0.20 to 0.35 on a scale of 0– 1 (Power et al., 2017; Spearman et al., 2017; Chawla et al., 2017).

While the definition of risk is straightforward, the definition of reward is more ambiguous. Reward is typically modelled based on metrics related to goal-scoring (Power et al., 2017; Link et al., 2016), thereby typically attributing success to the offensive players. Although scoring is essential in soccer, not every pass can be an assist, and most passes not even intend to be one (Goes et al., 2019). As has been demonstrated in previous work, the two football teams in a match can be considered as two tightly coupled interacting complex dynamical

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systems (Low et al., 2020; Balague et al., 2013; Goes et al., 2021b). While the ultimate goal of these teams is to create a scoring opportunity, doing so first requires them to create space by disrupting the coupling with the opponent (Goes et al., 2019; Goes et al., 2021b). This disruption can be assessed on the level of individual players making a dribble or passing action (Goes et al., 2019; Corrêa, 2016), or on the level of subgroups of players responding to an on ball action (Goes et al., 2019; Goes et al., 2021a), and has been shown to be a key factor in ultimately gaining offensive success. Therefore, one could argue that reward is pluriform and context-dependent, and that as goal scoring is not the only crucial type of reward to be gained from passing, players of different positional roles can seek different types of rewards (Goes et al., 2019). Recent work has resulted in an increased ability to quantify various aspects of risk and reward in more detail, and with greater accuracy, using position-tracking data (Goes et al., 2020; Goes et al., 2019; Herold et al., 2019). Therefore, with the current work, we aim to overcome the limitations of previous studies by an accurate assessment of risk, combined with a multifaceted assessment of reward that – in contrast to previous work (Power et al., 2017; Link et al., 2016) – not only accounts for the creation of scoring opportunities but also for gaining and losing space, outplaying opponents and endangering your own goal (Goes et al., 2021a), thereby providing an opportunity for a fair judgment across different positional roles.

While every soccer player can be expected to aim for a minimal chance of failure, players typically have to make decisions under time-constraints in a highly dynamic environment, while the consequences of failure differ substantially across positional roles. Attacking players, for example, are typically instructed by their coach to take more risk and look for difficult but potentially rewarding options, while defensive players are typically instructed to be more conservative and avoid high-risk options, given the greater impact of losing the ball close to the own goal. Literature on information processing and decision-making suggests that such decisions, and the risk associated with them, could be influenced by a number of factors, with experience being one of the most important (Kermarrec and Bossard, 2014; Maule et al., 2000). Under time-constraints, humans tend to make decisions based on previous experience with comparable situations, instead of rational deduction (Kermarrec and Bossard, 2014), making the context a person is most familiar with one of the most important factors in relation to interpersonal differences in decision-making (De Craen et al., 2011; Deakin et al., 2004). As the positional role of a player determines the context he is most familiar with, and the type of reward he typically seeks, one can assume players with different positional roles will display differences in decision-making and associated risk-taking behaviour (Wiemeyer, 2003).

To summarize, the main aim of this study is to construct an improved model for the assessment of pass risk and reward across different positional roles, and validate that model by studying differences in decision-making between players with different positional roles. Based on the presented literature, we hypothesize that higher risk is associated with higher probability of failure, but also with higher reward. Furthermore, we hypothesize that defensive players are more orientated at avoiding negative rewards and will therefore display less risk-taking behaviour, while it would be the other way around in offensive players.

As performance analysis in soccer is currently centred around offensive contributions like assists, key passes and goals, success is typically attributed to the most offensively oriented players. Furthermore, one could argue that the performance of even the most creative mastermind will only be judged as good if the receivers of their passes actually convert their opportunities, as otherwise those genius passes will never become a key pass or assist. This illustrates how performance analysis in soccer typically overlooks the best players, and often wrongfully attributes success to players with the best notational statistics. Our contribution is aimed at resolving these issues, by providing a performance analysis model that not necessarily analyses a player in terms of the stats he achieved, but rather in terms of how optimal the decisions were that he made, in the context of the positional role that he is playing in. Achieving our aim ideally results in a system that teams can use for the purpose of performance optimization on the individual and team level, as well as for the purpose of recruiting the best players for a given positional role and talent identification and development.

Methods

Data

For the construction of the features required for our analysis we retrospectively collected position-tracking data and notational event data from 299 matches between 18 teams played during the 2018–2019 Dutch Eredivisie season (play-offs excluded). In total, data on 336 players were included in our study (see Table 1 for characteristics). Seven matches from that season (2.3%) were missing because of erroneous or missing data. Position-tracking data was generated through a league-wide employed optical tracking system (ChyronHego, New York, USA) that captures the X and Y coordinates of all players and the ball at 25 Hz, with an accuracy of ± 0.09 m (Linke, Link & Lames, 2020). Notational event data were routinely collected from Opta Sports (STATS LLC, Chicago, USA) as part of the league-wide tracking system employed in the Dutch Eredivisie.

Before the analysis, position-tracking data were first pre-processed with ImoClient software (Inmotiotec Object Tracking B.V., Zeist, The Netherlands). Pre-processing consisted of filtering the data with a weighted Gaussian algorithm (100% sensitivity), down sampling to 10 Hz, and detection of

Table 1. Dataset Characteristics.

Dataset Characteristics*	
Number of players	336
Number of successful passes	213.853
Number of interceptions	72.298
Mean pass accuracy	74.7%
Positional roles	
Defenders	136 (40.5%)
Midfielders	107 (31.8%)
Forwards	93 (27.7%)

*Only players who played at least 75 successful passes were included. All goalkeepers were excluded from the analysis. The total sample before filtering consisted of 445 players.

possession and ball events based on the synchronization of notational event data with position tracking data. Furthermore, all data were mapped to the same standard field size (105 m × 68 m), with the longitudinal (x-)axis running from goal to goal (–52.5 m to +52.5 m) and the lateral (y-) axis running along the middle-line (–34.0 m to +34.0 m). All further processing and analysis were programmed in Python 3.7.

Quantifying pass risk & reward

To be able to analyse pass decisions, we first selected all passes from the current dataset, by identifying all annotated passes from the event data and subsequently synchronizing those passes in terms of time and location using the position tracking data. This resulted in a dataset of 286,151 labelled (successful or non-successful) passes (Table 1).

Next, for every pass in our dataset, we identified all alternative pass options. To identify alternative pass options, we trained a LightGBM machine learning classifier to predict pass outcome (successful or non-successful) at the moment of passing, using the passes from our dataset in combination with a set of features related to the length and angle of the pass, position on the field and direction of movement of the passer and receiver, number of opposing players in the passing lane, pressure on the passer and coverage of the receiver (Andrienko et al., 2017), computed for every pass. All features were computed using custom routines programmed in Python 3.7, using the position-tracking data. For a complete overview of our classifier model and its underlying features, see Table 2.

Our classifier was trained using a training-set of 80% of the passes, and subsequently evaluated over a fivefold cross-validation using a test-set with 20% of the passes. Cross-validated evaluation showed we were able to correctly predict successful passes with an average accuracy of 84.5% over a fivefold cross-validation in a test-set in which the average pass accuracy was 74.8%. The classifier outputs a predicted probability (between 0 and 1) of a pass successfully arriving at the intended teammate, in which 1 represents a 100% chance of the pass arriving at the intended teammate, and 0 represents a 0% chance. The decision boundary was set at 50%. Using the trained classifier, we then identified alternative pass options by computing the features required by the classifier for every potential receiver (all team-mates that did not actually receive the original pass), and subsequently predicting the chance of a pass to a given player being successful using our trained classifier. The resulting probability that a pass is successful is considered the *pass quality* (PQ) of a pass or pass option in our analysis, and only receivers with a predicted probability >50% were considered to be realistic alternative options.

Following the identification of alternative pass options, we constructed a set of features quantifying the risk of the played pass in the context of the alternative options. For every pass, we computed the following variables:

- PQ = the predicted probability of the pass being successful.
- $N_{options}$ = the number of pass options with a predicted probability >50%.
- N_{safer} = the number of pass options with a higher PQ than the played pass.
- $RMSD_{safer}$ = the mean difference between the PQ of the played pass and that of all safer options.

Finally, after the identification of pass options and quantification of pass risk, we constructed a set of features to quantify pass reward. As different passes have different objectives (some passes are aimed at gaining territory, while others are aimed at outplaying opponents or creating a goal-scoring opportunity), and reward can also be negative if the ball is turned-over (i.e., losing territory, 'outplaying' teammates or conceding a scoring opportunity), we constructed a pluriform set of reward features that map to the different pass objectives, and allow for positive (in case of a successful pass) and negative (in case of a non-successful pass) rewards. This resulted in the following variables being computed for every played pass:

- RW_{pot+} = the potential of a successful pass to result in scoring opportunity, as previously defined in Goes et al. (2021a), scored in a range from 0– to 1.
- RW_{pot-} = the potential of a non-successful pass to result in scoring opportunity by the opponent, adapted from Goes et al. (2021b), scored in a range from 0– to 1.
- RW_{OPO+} = the number of longitudinally outplayed opponents by a successful pass(Goes et al., 2021b).

Table 2. Pass Classifier.

Independent Variables (X)	
Pass Length (m)	Euclidean distance between pass and reception.
Pass Angle (°)	Angle between pass and reception (negative angles equal backward passes)
Path Density	Number of opponents in the passing lane.
Passer Direction (°)	Direction of movement of the passer relative to its own goal.
Receiver Direction (°)	Direction of movement of the receiver relative to its own goal.
Forward Displacement (m)	Forward (goal to goal) displacement of a pass.
Goal Distance Pass (m)	Distance between the passer and opposing goal.
Goal Angle Pass (°)	Angle between the passer and opposing goal.
Goal Distance Reception (m)	Distance between the receiver and opposing goal.
Goal Angle Reception (°)	Angle between the receiver and opposing goal.
Pressure on Pass (%)	Pressure on the passer, adapted from Andrienko's model (Andrienko et al., 2017).
Pressure on Receiver (%)	Pressure on the receiver, adapted from Andrienko's model (Andrienkoet al., 2017).
Dependent Variable (y)	
Pass Result	1: Successful (reception) 0: Non-successful (interception)

- RW_{OPO-} = the number of longitudinally outplayed teammates by a non-successful pass.
- RW_{goal+} = the Euclidean distance gained to the opposing goal by a successful pass.
- RW_{goal-} = the Euclidean distance conceded to the own goal by a non-successful pass.

We previously showed that achieving a higher RW_{pot+} score has a strong relation to successful performance in Dutch Eredivisie matches (Goes et al., 2021a), and that achieving higher RW_{OPO+} values has also been linked to successful performance in earlier studies (Goes et al., 2021b; Rein et al., 2017).

Using these pluriform reward variables, we computed a negative reward composite score for both the played pass (RW^{-}) as well as for all alternative pass options (Option RW^{+}) using eq. 1 (negative reward) and eq. 2 (positive reward). We based the coefficients in both equations on the differences in scale between features and relative importance of the reward based on their relation with match outcome (Goes et al., 2021a).

$$\text{(Option) } RW^{-} = 0.5\, RW_{goal-} + RW_{OPO-} + 10 * (1 + RW_{pot-}) \quad (1)$$

$$\text{(Option) } RW^{+} = 0.5\, RW_{goal+} + RW_{OPO+} + 10 * (1 + RW_{pot+}) \quad (2)$$

Statistical analysis

We conducted a statistical analysis with a two-fold purpose. First, we wanted to validate our assumptions that (1) higher risk is related to a higher probability of failure (lower accuracy), and (2) that higher risk is related to higher rewards. To achieve this, we compared successful and unsuccessful passes by computing average pass risk features per player in successful and unsuccessful passes using within-subject *t-tests*. Furthermore, we computed the *Pearson* correlation *r* between all risk and reward features ($r < .1$ = weak, $.1 < r < .3$ = medium, $r > .5$ = large effect) (Cohen, 1988).

Second, we wanted to analyse the effect of positional role on the risk and reward of passing decisions. To achieve this, we statically compared the positional groups on all average risk and reward features using MANOVA tests, with planned post-hoc testing using pairwise Tukey HSD tests. Effect sizes were computed using partial η^2, where values >0.01 were considered to represent small effect sizes, values >0.06 medium effect sizes and values >0.14 large effect sizes (Richardson, 2011). As we expected high risk to be associated with higher changes of failure, we also expected the biggest differences in risk and potential reward in unsuccessful passes, and we therefore conduct a separate analysis for successful and unsuccessful passes.

Results

Risk in relation to pass accuracy

To validate our model, we determined if higher risk is related to higher probability of failure and compared risk between successful and unsuccessful passes. During successful passes, players had more options (Mean $N_{options}$ = 7.2 ± 0.6 vs. 7.0 ± 0.5), though fewer safer options (Mean N_{safer} = 4.6 ± 0.9 vs. 7.7 ± 0.5), a higher pass quality (Mean PQ = 0.76 ± 0.07 vs. 0.37 ± 0.05), and a smaller mean difference to safer options (Mean $RMSD_{safer}$ = 0.17 ± 0.05 vs. 0.42 ± 0.04). All differences were significant at a p-level of $p < .0001$.

Table 3. Pearson's r correlations between player pass risk and pass reward features.

		Pass Reward			
		Pass RW^{+}	Pass RW^{-}	Option RW^{+}	Option RW^{-}
Pass Reward	$N_{options}$	0.01	−0.13*	−0.93**	0.92**
	N_{safer}	−0.01	0.03	−0.89**	0.86**
	PQ	−0.01	−0.04	0.72**	−0.68**
	$RMSD_{safer}$	0.01	0.03	−0.71**	0.67**

*p < .05, ** p < .01. RW = Reward, Option = predicted outcomes averaged over all alternative pass options. $N_{options}$ = number of realistic pass options, N_{safer} = Number of safer pass options, PQ = Pass Quality, $RMSD_{safer}$ = the mean difference between the predicted probability of the played pass and all safer alternatives.

Risk in relation to reward

To validate our second assumption that higher risk is related to higher reward, we studied the correlation between risk and reward per player on all features. We found no correlations between risk and reward, with exception of the weak correlation between the $N_{options}$ and Pass RW^{-} (*r* = −0.13: Table 3). However, $RMSD_{safer}$, $N_{options}$ and N_{safer} all had large negative correlations with the avg. positive reward score (Option RW^{+}), of all options with correlations ranging from *r* = −0.71 to −0.93 (Table 3), while PQ had a large positive correlation with Option RW^{+} and Option RW^{-} (*r* = 0.72 and −0.68: Table 3). These correlations indicate higher risk was correlated with higher potential positive rewards, and lower potential negative rewards (Table 3).

Positional role

In successful (Figure 1) and unsuccessful passes (Figure 2), we found significant differences between positional roles on all risk features. We found significant effects of positional role on the number of pass options in successful passes (*F* (324, 2) = 219.3, $p < .0001$, $\eta^2 = 0.56$), and unsuccessful passes (*F* (324, 2) = 64.2, $p < .0001$, $\eta^2 = 0.28$), as well as the number of safer options in successful passes (*F* (324, 2) = 218.5, $p < .0001$, $\eta^2 = 0.57$), and unsuccessful passes (*F* (324, 2) = 153.2, $p < .0001$, $\eta^2 = 0.48$). Furthermore, we found significant effects of positional role on pass quality (PQ) in both successful (*F* (324, 2) = 115.0, $p < .0001$, $\eta^2 = 0.41$) and unsuccessful passes (*F* (324, 2) = 123.2, $p < .0001$, $\eta^2 = 0.43$). Finally, we found significant effects of positional role on $RMSD_{safer}$ in successful passes (*F* (324, 2) = 109.06, $p < .0001$, $\eta^2 = 0.39$), and unsuccessful passes (*F* (324, 2) = 110.2, $p < .0001$, $\eta^2 = 0.40$). Post-hoc testing revealed defenders had the least options while forwards had the most options (Figure 1A & Figure 2A), while defenders also had the fewest safer alternatives and forwards the most (Figure 1B & Figure 2B). Furthermore, results also indicated forwards took the most risk, and defenders the least (Figure 1 C/D & Figure 2 C/D).

In both successful (Figure 3) and unsuccessful passes (Figure 4), no differences were found between positional roles in achieved positive (RW^{+}) or negative (RW^{-}) reward. However, we found significant differences between positional roles on

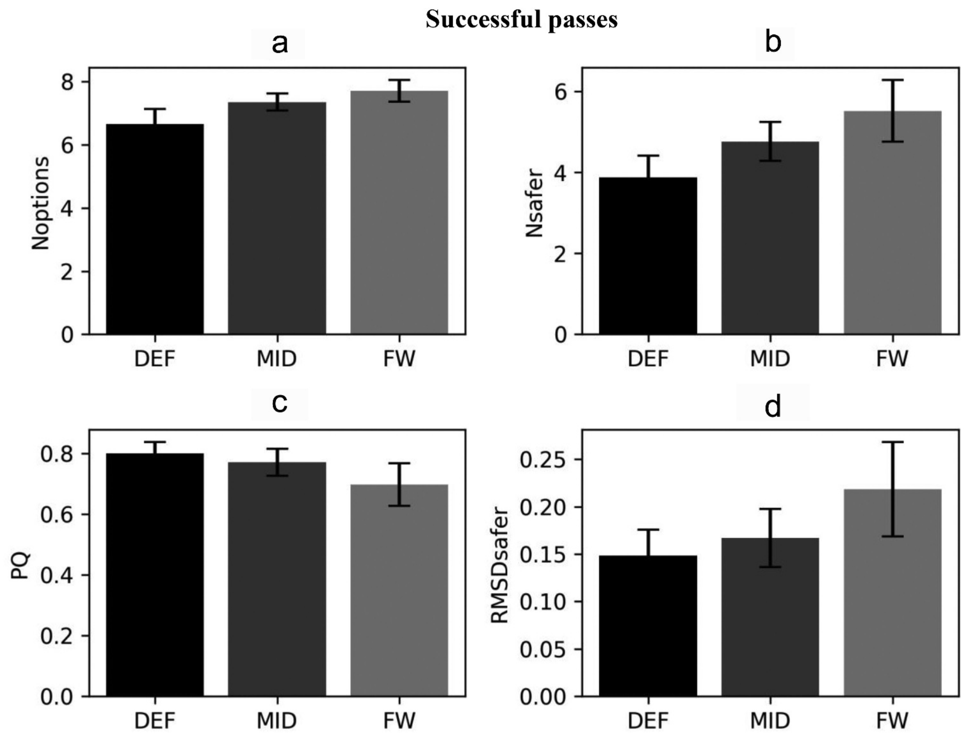

Figure 1. A-D Comparison between Positional role and Pass Risk in Successful Passes. DEF = Defenders, MID = Midfielders, FW = Forwards. Black bars represent standard deviations. $N_{options}$ = number of realistic pass options, N_{safer} = Number of safer pass options, PQ = Pass Quality, $RMSD_{safer}$ = the mean difference between the predicted probability of the played pass and all safer alternatives.

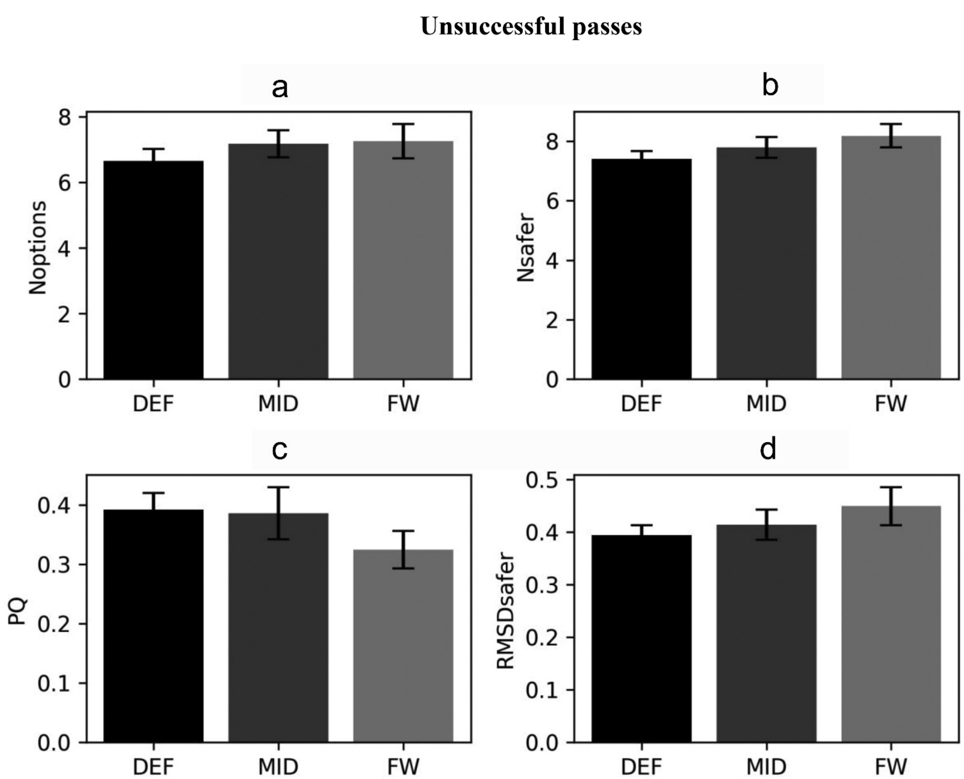

Figure 2. A-D Comparison between Positional role and Pass Risk in Unsuccessful Passes. DEF = Defenders, MID = Midfielders, FW = Forwards. Black bars represent standard deviations. $N_{options}$ = number of realistic pass options, N_{safer} = Number of safer pass options, PQ = Pass Quality, $RMSD_{safer}$ = the mean difference between the predicted probability of the played pass and all safer alternatives.

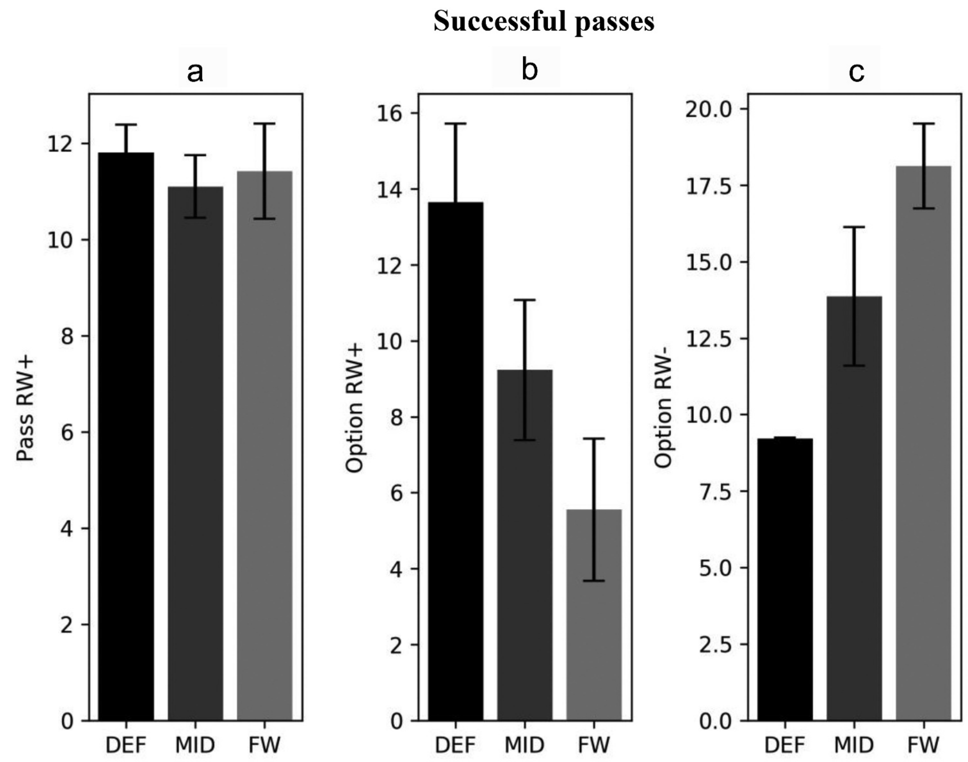

Figure 3. A-C Comparison between Positional role and Pass Reward in Successful Passes. DEF = Defenders, MID = Midfielders, FW = Forwards. Black bars represent standard deviations.

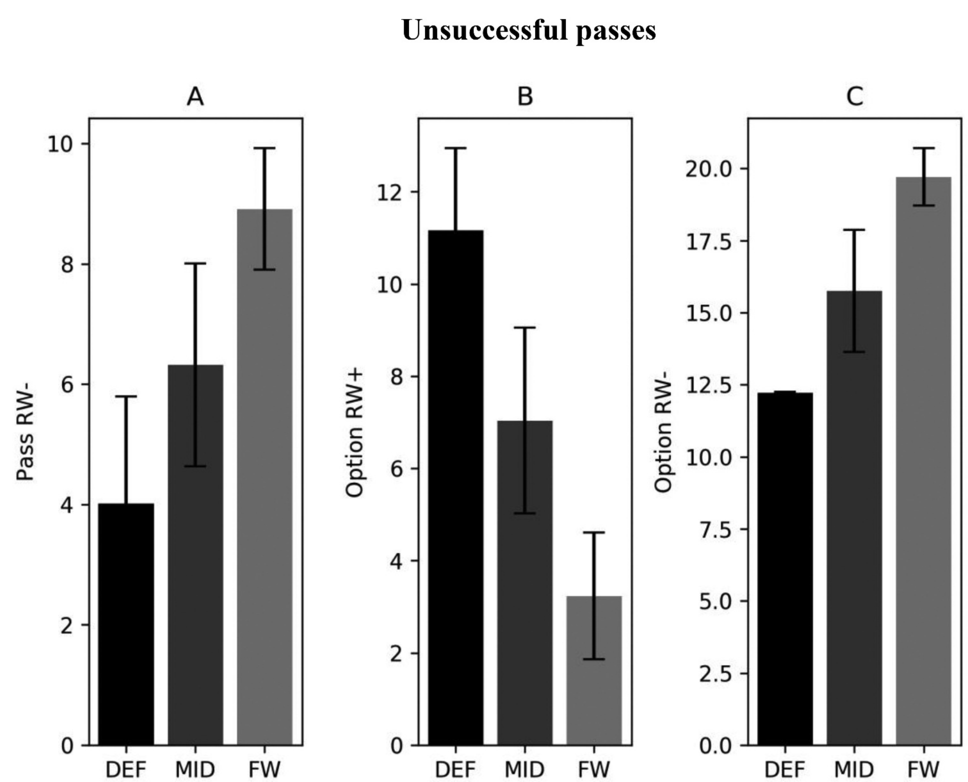

Figure 4. A-C Comparison between Positional role and Pass Reward in Unsuccessful Passes. DEF = Defenders, MID = Midfielders, FW = Forwards. Black bars represent standard deviations.

potential rewards of pass options. Option RW^+ (F (324, 2) = 496.2, p < .0001, η^2 = 0.74) and Option RW^- (F (324, 2) = 377.1, p < .0001, η^2 = 0.69) in successful passes (Figure 3B & Figure 3 C), as well as Option RW^+ (F (324, 2) = 565.8, p < .0001, η^2 = 0.77) and Option RW^- (F (324, 2) = 394.4, p < .0001, η^2 = 0.70) in unsuccessful passes (Figure 4B & Figure 4 C) were significantly different across positional roles. Post-hoc comparisons revealed the options of midfielders had lower positive rewards and significantly higher negative rewards in comparison to defenders, while the same was found for the comparison between forwards and midfielders (p < 0.05).

Discussion

The current study aimed to construct an improved model for the assessment of pass risk and reward, and validate that model by studying differences in decision-making between players with different positional roles. To achieve this, we studied the risk and reward of pass decisions using position tracking data from a sample of 336 players over the span of an entire season. Our findings indicate we could adequately model risk and reward, and large differences in decision-making between players with different positional roles were found.

The results of our model are in line with those of previous literature. Spearman et al. (2017) mathematically modelled the probability of a pass being successful (Spearman et al., 2017). They achieved a prediction accuracy of 80.5% in a test-set with a 78.5% passing accuracy. In another study by Power et al. (2017), the authors mention a mean prediction error of 24.4–36.2% in predicting pass accuracy in different sets of passes (Power et al., 2017), suggesting comparably poorer performance. In the current study, we managed to achieve a prediction accuracy of 84.5% in a test-set with a 74.8% passing accuracy, indicating we managed to outperform both models. Reward, on the other hand, is less straightforward to put into perspective. In the only apparent comparable study to date (Power et al., 2017) reward was only studied in relation to goal-scoring. In line with our findings, high performing teams were found to have a lower pass risk but achieve higher rewards (Power et al., 2017).

We hypothesized risk to be associated with higher probability of failure, but also with higher rewards. Our results partially confirmed this, as successful passes were characterized by higher PQ, but higher risk did not correlate with higher rewards. It seems that merely picking the riskiest pass option does not result in higher rewards, and that thus not risk itself, but rather the quality of decision-making could be the driving factor behind reward. This assumption is supported by our finding that in successful passes, players often pick one of the safer options, while the number of options available only slightly differed between successful and unsuccessful passes. Furthermore, although we did not find a relationship between risk and reward, high risk strongly correlated with high potential rewards available at the time of passing. This leads us to believe that high risk can be associated with high potential reward, but that players often fail to pick the best available option in these situations, which is in line with literature on tactical decision-making (Kannekens et al., 2009).

For positional role, we expected defensive players to be orientated at avoiding risk, while we assumed offensive players to take risks. Our results confirmed this, as defenders took the least amount of risk, and forwards the most. Interestingly, defenders had the lowest number of options available, and typically picked one of the safest options. Midfielders and especially forwards on the other hand, had more options, but often seemed to pick the riskier ones. However, there were no differences in achieved rewards between different positional roles, while the potential positive and negative rewards were larger in midfielders and forwards. These findings could be explained by the context of different positional roles. Defenders typically possess the ball with the game in front of them, resulting in a limited and homogeneous set of options. Midfielders and forwards on the other hand have options in all directions. This leads us to propose that decision-making in relation to passing is relatively easy for defenders, while being more challenging for midfielders and forwards.

Our results indicate that we have succeeded in constructing an improved model for the assessment of risk and reward in relation pass decisions. The comparably good performance of our model in predicting pass risk is one of the strong points of this study and can be explained by our ability to capture various aspects of passing in greater detail and with better accuracy using position tracking data. Another strong point is that we provide a new perspective on assessing the performance of individual players. As most studies on offensive contributions tend to focus on goal-scoring, (Power et al., 2017; Link et al., 2016; Fernandez and Bornn, 2018), offensive players are often favoured in those analyses. However, we have been able to show that with a more pluriform assessment of reward, there is no difference in achieved rewards between different positional roles, and all players can have key contributions to offensive performance.

Given the widespread availability of position tracking data in professional soccer nowadays, our proposed methodology has practical implications for performance analysis and talent identification by coaches, scouts and journalists. Our results illustrate that the most important contributions to success not always come from the player who had the final touch, but can often be found in different players. These players are typically overlooked, causing teams to buy overpriced players with good statistics but relatively poor decision-making, who might not deliver what is expected of them, and better options are often available at a cheaper price. The same could be said of the practical implications for youth academies. As players who do well in terms of their offensive statistics often stand-out, they might be promoted more easily to the first teams, while the best decision-makers remain under the radar. Finally, our findings also illustrate the need to judge a player in the context of his positional role, which is obviously an open door from an observational standpoint, but is still often neglected in data-driven performance analysis.

We identified three limitations that we would propose to solve in future research. Given the rapidly expanding set of tools to process position tracking data (Goes et al., 2020), and the ever improving accuracy of tracking data, we expect our risk-reward and pass option model to have some room for improvement. Future research, for example, could incorporate the z-coordinate of the players and ball, as well as data on the orientation of a player, to improve predictions. Furthermore, we also acknowledge that we only scratched the surface of factors that impact the decision-making process. While the current study focussed on the impact of positional role on decision-making, future research could study the impact of other factors like, for example, age, as studies on other activities like driving (De Craen et al., 2011), management (Ceschi et al., 2017) or gambling (Deakin et al., 2004) all suggest that younger adults tend to take more risk. In addition, in the current study we did not account for the inter-player coupling as a factor in decision-making. While we accounted for the proximity of opposing players to both the passers as well as the (potential) receivers, we studied these factors at a point in time, rather than analysing them from the perspective of two coupled players as a dynamical system. Literature on decision-making in dribbling suggests the interpersonal coordination timeseries play an important factor in decision-making (Corrêa et al., 2016), that could also be of relevance to our work. For future research, this could be an interesting angle to explore.

Finally, within the current study, we exclusively studied pass decisions, but one has to take into account that the decision whether or not to pass or, for example, to shoot or dribble instead is also a key decision within the process. This has previously been studied by Correa et al. (2016), who examined dribbling decisions in futsal (Corrêa et al., 2016). Their findings resembled ours in the sense that players decided to dribble not because of a lack of options, like in choosing a risking pass in our study, and they suggested that the coupling with the direct opponent and an increased variability and unpredictability of dribbling actions might explain the decision to dribble. It would be interesting for future research to widen the scope of our current analysis and not only take into account the various passing options, but also account for the alternative actions that could be taken.

Conclusion

With the current study, we proposed and validated a new model to assess the risk and reward associated with pass decisions, that can be used to assess player performance based on what could have happened, rather than solely based on what actually did happen in a match. Our results show that we can accurately model pass risk and reward, and the validity of our model is supported by our findings in relation to decision-making performance of players with different positional roles.

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