A model-based risk-impact analysis of dribble actions in women's soccer

Competition Track: Soccer
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1. Introduction

In soccer, offensive actions can mainly be split into three: shots, passes and dribbles. Interestingly, numerous research and model development has been done to quantify the value of shots (Anzer and Bauer 2021; Baron et al. 2023) and passes (Rein, Raabe, and Memmert 2017; Forcher et al. 2021; Anzer and Bauer 2022). In contrast, comprehensive studies on dribbles (Magdaci 2022) are rare to be seen, although dribbling in soccer is a crucial dimension of offensive play. These actions not only serve as a tactical element for overcoming compact defensive lines and creating new attacking options, but also enable the creation of space and force the defense to shift. Hence, more emphasize should be put on analyzing dribbles in the context of individual ball handling and decision-making skills in 1v1 situations.

To fill this gap in the scientific literature, we introduce a new model-based approach to quantify individual dribbles in this work. In addition, acknowledging the limited study of women's soccer so far, we have applied our models to dribbles in the Women's World Cup 2023, while the approach and model are also applicable to men's soccer. We use event data as it is more widely available than positional data in practice - especially in women's soccer, where tracking data coverage is still relatively low.

In our approach, we undertake a comprehensive analysis of dribbles, in which both the risk and impact factors are considered. First, a distinct risk variable is developed to reflect the probability of success of a dribble. Therefore, following the model presented by (Forcher et al. 2023), we formulate a model to forecast the success of a dribble based on event data. Second, we derive a superior Expected Threat model (Singh 2018), which also accounts for the effects of adversary pressure, to quantify the impact of a dribble. In contrast to different previous approaches to quantify the value of dribbles, such as VAEP (Decroos et al. 2019) or Expected Possession (Fernández et al. 2019), an Expected Threat model has the advantage that it is risk independent. This is useful within our approach as it allows us to analyze the risk and the impact dimensions of a dribble separately respectively complementary.

By combining our two model approaches, significant insights are generated for soccer clubs. For instance, we demonstrate which players consistently surpass expectations in their dribbling during the World Cup. Furthermore, we dissect which positions are more prone to risky dribbling. Lastly, we unveil how individual teams' playing philosophy can be disclosed by presenting the peril of their dribbling in a visual format. The results have an immediate impact for coaches and players for individual and team development as well as opponent preparation and for scouts and recruiters in assessing new hires for their teams.

The remainder of the paper is structured as follows. Section 2 presents the data as well as our novel model to quantify the risk and reward of a dribbling for an offensive team. The latter part of this Section is divided into two parts: first, we introduce a new machine-learning approach to estimate

the success probability of a dribbling. Second, we develop an advanced pressure-dependent Expected Threat (xT) model, which allows us to measure the impact of a dribbling in an offensive attack in different pressure statuses. In Section 3, we present various use-cases, in which the derived model from the previous Section is applied in contexts like scouting or match analysis. Section 4 offers concluding remarks.

2. Methods

2.1. Data

We use Stats Bomb's 360 event stream data (StatsBomb 2023), which is extracted from broadcast video and consists of the regular human-annotated event stream data enhanced with snapshots of player positioning. Those snapshots capture the location and relationship of the ball carrier to all other players (teammates as well as opponents) visible in the video during each on-the-ball action. To ensure a meaningful Expected Threat model, we trained the model on all 509 publicly available women games from the StatsBomb data. For the risk analysis and the final use cases in Section 3, we use all 64 matches of the women's world cup 2023.

In contrast to StatsBomb, we use the terms dribbles and carries interchangeably as we aim to evaluate all actions in which female players carry the ball, regardless of whether they aim to gain space or bypass.

2.2. Quantitative estimation of dribbling success

To accurately assess a player's dribbling ability, it is crucial to consider not only the success rate but also the expected success rate. Dribbling past several opponents towards the opponent's penalty area poses significantly greater difficulty than advancing the ball down the sidelines in a one-on-one situation. To assess the dribbling skills of players objectively, we have developed a model that calculates the probability of successful dribbling.

Unlike the expected threat model, we are not considering the value of a dribble, but the target variable is purely to maintain possession of the ball in one's own team, which we call dribble success. When discussing dribble risk, we refer to the probability of the opposite:

$$Dribble\ success\ probability\ =\ 1 - dribble\ risk$$

2.2.1. Factors influencing dribbling risk

Several factors impact the success of dribbling. Initially, we considered opponents and their effect on the likelihood of losing the ball. Thus, we evaluated the distance of the nearest opponents ("opponents_within_5m", "opponents_within_10m"), the numerical superiority of opponents near the ball ("numerical_superiority_5m", "numerical_superiority_10m") and the pressure given by them ("tagged_pressure", "calculated_pressure"). Additionally, we formulated Key Performance Indicators (KPIs) based on the locations ("x", "y", "y_symm") and consider the direction of the dribble ("dribblings_towards_opponent_goal"), because our analysis shows that the starting point of the dribble has a major influence on success (see Figure 1). The appendix contains a description of all KPIs.

The available data is considerably limited as it only displays the positions of the players visible in the video, thereby impeding a comprehensive analysis of all player positions. Still, as the camera is usually focused on the ball, information about the surrounding players is often captured, allowing for the correct calculation of the Pressure Metric and numerical superiority in many cases.
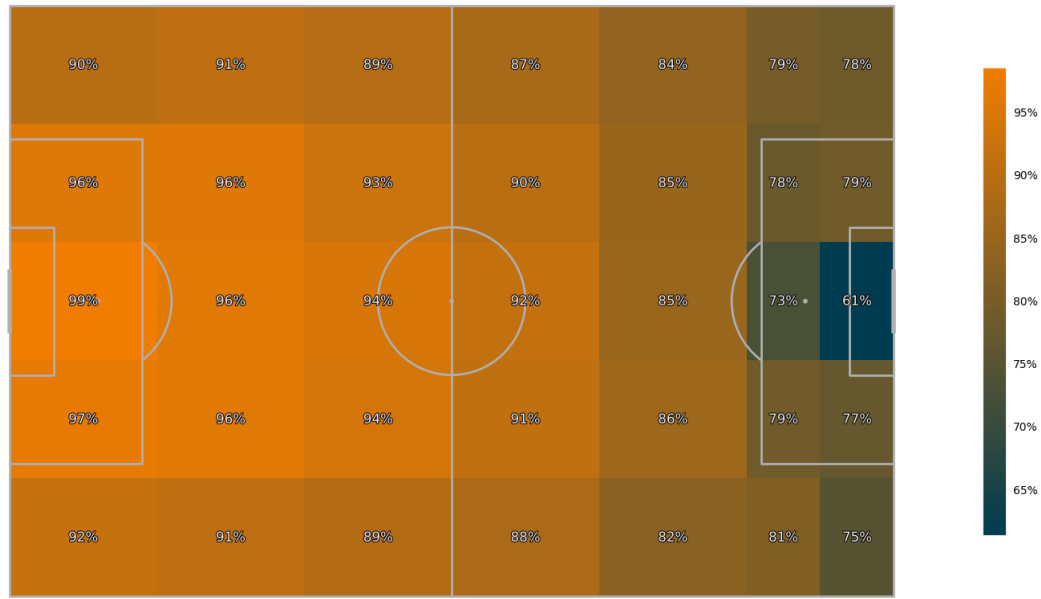
Figure 1 Dribbling success rates in different areas of the pitch.

2.2.2. Model design

Before training a prediction model, we evaluated mutual correlations between the features and eliminated those correlated features with the least predictive value, which were opponents_within_5m, opponents_within_10m, numerical_superiority_5m and y value (see appendix). Subsequently, we trained various models - Logistic Regression, XGBoost and Random Forest Classifier. From these, we chose the best model based on a test set (30% of all data), which was XGBoost. Finally, we calculated SHAP values for the ultimate model to clarify what constitutes a high success probability of a dribble.

2.2.3. Results

The evaluation is based on the test set, which consists of a total of 13,999 out of 46,663 actions (30%) where female players carried the ball. From these, the players maintained possession of the ball in 12,518 (89,4%) situations. Our model predicted a ball retention in 41,805 (90,85%) situations. The F1 score is 0,92. For a complete evaluation including the confusion matrix, refer to Figure 2.

Ground Truth	Precision	Recall	F1-Score	Support
0	0.26	0.22	0.24	1481
1	0.91	0.92	0.92	12518

Confusion Matrix		Prediction	
		0	1
Ground Truth	0	331	1150
	1	950	11568

Figure 2 Evaluation of the risk model on out-of-sample test data.

To comprehend the model's prediction, SHAP values were analyzed (see Figure 3). These indicate that the model focuses primarily on the calculated pressure. High pressure at the beginning of a dribble greatly diminishes the chance of success. The position on the field is also a crucial factor, with dribbling in the opposing half and along the sidelines having lower chances of success (for further reference see Figure 1). Furthermore, it is crucial to maintain numerical superiority when dribbling near the ball, as ball losses are expected to increase due to opponent doubling efforts. Interestingly, the direction of the dribble is not of paramount importance, although dribbling towards one's own goal at least promises a slightly higher chance of success.
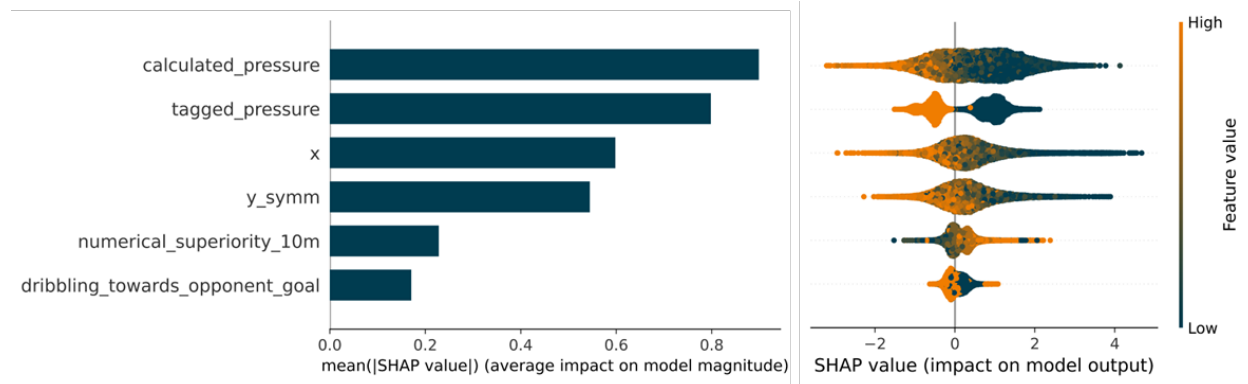

Figure 3 The SHAP values illustrate the significance and impact of the various variables.

2.3. Expected Threat with and without pressure

To calculate the contribution of a dribble to an offensive attack, we rely on an Expected Threat (xT) model (Singh 2018). In simple terms, an xT model divides the field into a grid G and calculates a scoring probability in the next couple of actions for each cell *(x,y)* of the grid (Soccerment.com 2021) . The xT value for each cell is defined as the sum of the shot threat (shot probability *s(x,y)* multiplied with the scoring probability *g(x,y)*) in the respective cell and the expected payoff of moving the ball (the sum of the xT values of all cells, weighted with the corresponding transition probabilities from the respective cell).

$$\text{xT}(x,y) = \underbrace{s(x,y) \cdot g(x,y)}_{\text{shot threat}} + \underbrace{(1 - s(x,y)) \cdot \sum_{(z,w) \in G} T_{(x,y) \to (z,w)} \cdot \text{xT(z,w)}}_{\text{move threat}}$$

Equation 1 The Expected Threat (xT) Model

The value gained by an action (like a pass or dribble) is the difference between the xT value at the end cell and at the start cell of the action. Compared to expected Goal (*xG*) or expected Assist (*xA*) models, which rely on shots or respectively passes, this approach has the advantage that the value of dribbles can also be analyzed. Furthermore, actions that do not lead directly to goal scoring opportunities but have a high value in the offensive build-up by progressing the ball to more dangerous areas on the pitch, can be measured and assigned to individual players (Soccerment.com 2021).

In contrast to other studies using xT, we expand the model by calculating advanced xT values, which also consider the pressure the ball carrier is facing. This is necessary in our point of view, as xT measures the probability of scoring a goal in the next couple of actions and this value is not only dependent on the location of an event, but also on the pressure on the current ball carrier. For

example, shot, pass and dribbles success rates are highly correlated with pressure, so that pressure should be considered in a xT model as an additional input variable.

To calculate pressure-dependent xT values, we use event-data from all matches in women's competitions in the open-source StatsBomb library (509 matches). First, we compute conventional xT*(x,y; general)* for each cell in our 30x20 grid, considering all relevant events in the dataset (see Equation 1). We use these xT values later to refer to events, in which pressure is not observable or unknown.

In a second step, we calculate shot probabilities *s(x,y)*, shot success rates *g(x,y)* and transition matrices *T(x,y)* with different pressure status values (*Pressure* and *no Pressure*) for each cell in our grid *G*. This allows us to solve the following Equation 2.

$$\text{xT}(x, y; Pressure\ Status) = \underbrace{s(x, y; Pressure\ Status) \cdot g(x, y,\ Pressure\ Status)}_{shot\ threat}$$

$$\underbrace{+ (1 - s(x, y;\ Pressure\ Status)) \cdot \sum_{(z,w) \in G} T_{(x,y) \to (z,w)}(Pressure\ Status) \cdot xT(z,w; general)}_{move\ threat}$$

Equation 2 The pressure-dependent Expected Threat (xT) Model

Note that these two models also rely on the *xT(x,y; general)* values, as they quantify game situations after a transition to a new cell, when the status of pressure is unknown. With this model approach, we get two additional xT values for each cell *(x, y)* on the pitch: one with pressure *xT(x, y; Pressure)* and one without pressure *xT(x, y; no Pressure)* on the ball carrier (see Figure 4 for the results).
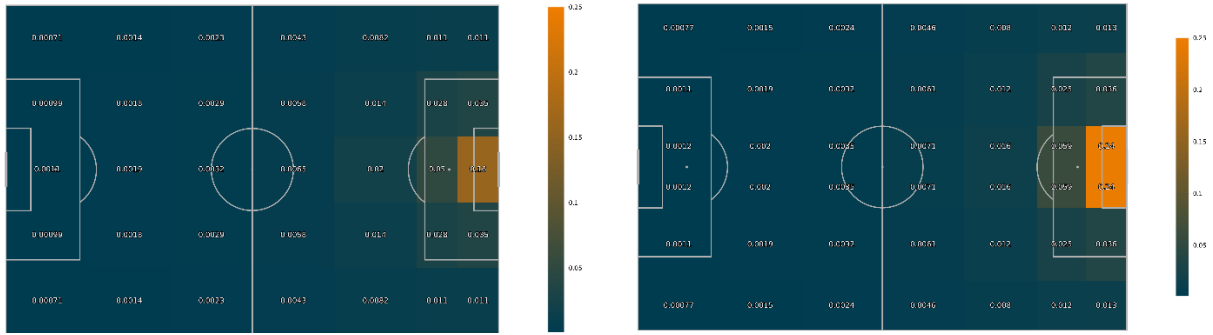

Figure 4 Expected Threat xT with pressure (left) and without pressure (right).

Our approach has the advantage, that a successful dribble with pressure on the ball carrier is not only rewarded by the movement of the ball to a new cell *(a, b)* (like in standard xT models), but also by the dissolving of the pressure situation:

$$\text{xT}_{Gain}(x, y) = \text{xT}(a, b; no\ Pressure) - xT(x, y; Pressure)$$

$$= \underbrace{xT(a, b; no\ Pressure) - xT(a, b; Pressure)}_{Dissolving\ pressure\ situation} + \underbrace{xT(a, b; Pressure) - xT(x, y; Pressure)}_{Movement\ to\ a\ new\ location}$$

We can also calculate xT_{Loss} values for unsuccessful dribbles, which do not only take into account the loss of possession, but also the change in possession.

$$xT_{Loss}(x,y) = \underbrace{- \text{xT}(x, y; \: Pressure \: Status)}_{Loss \: of \: Possession} \underbrace{- xT(Pitch \: Length \: - \: x, y; \: Pressure)}_{Change \: in \: Possession}$$

In addition, we can estimate (ex-ante) values xT_{Gain} for unsuccessful dribbles (where we assume that the dribble would have ended in the neighboring cell nearest to the goal) as well (ex-ante) values xT_{Loss} for successful dribbles, so that we have outcome-independent values for xT_{Gain} and xT_{Loss} for each carry. Following this approach in combination with the estimation of dribbling success, these two variables xT_{Gain} and xT_{Loss} allow us to calculate an expected value of xT_{Gain}, which is basically the sum of both variables, weighted with the dribble success probability p (introduced in the previous Section 2.2):

$$E(xT_{Gain}) = \: p \: * \: xT_{Gain} \: + \: (1-p) * xT_{Loss}$$

This metric enables us to identify locations on the pitch, where dribbles generate (ex-ante) the most (or the least) value for a team as well as players, who take valuable (or invaluable) decisions by choosing to dribble (instead of passing or shooting).

3. Use Cases

By comparing the determined success probability, the expected threat, and the actual success of dribbles, a multitude of questions can now be answered. A comparison of success probability and dribbling success allows for an evaluation of technical abilities, while the combined analysis of success probability and value quantifies the decision-making process of the players.

The results can be aggregated at the player level for scouting purposes to identify players with desired skills. Aggregation at the team level provides insights for game analysis, both in preparation for the upcoming opponent's playstyle and in optimizing one's own tactics. By considering the analyses based on players' positions on the field, actionable instructions for female players can be derived and incorporated into their training.

The following section presents selected application cases. To ensure comparable results, all analyses were normalized to a game duration of 90 minutes. To prevent outliers, we only considered players who played at least 60 minutes in the tournament. This excludes players who achieve a high value through a few actions in an extremely short amount of playing time.

3.1. Frequent Overperformers
Looking only at the risk dimension, it can be inferred that certain players are capable of performing successful dribbles much more consistently than others. To assess a player's skill, we calculate the predicted success rate for each individual dribble and compare it with the actual outcome. By adding up all of a player's dribbles and standardizing them to 90 minutes of playtime, we can determine their ability to exceed expectations and therefore evaluate their overall skill level. Figure 5 displays players who have the highest median in dribbling more successful than predicted. The boxplot shows the

outcome for all individual dribbles of the players, meaning that if a player dribbles successfully although the prediction was only 20%, it achieves a value of 0.8 for that dribble.
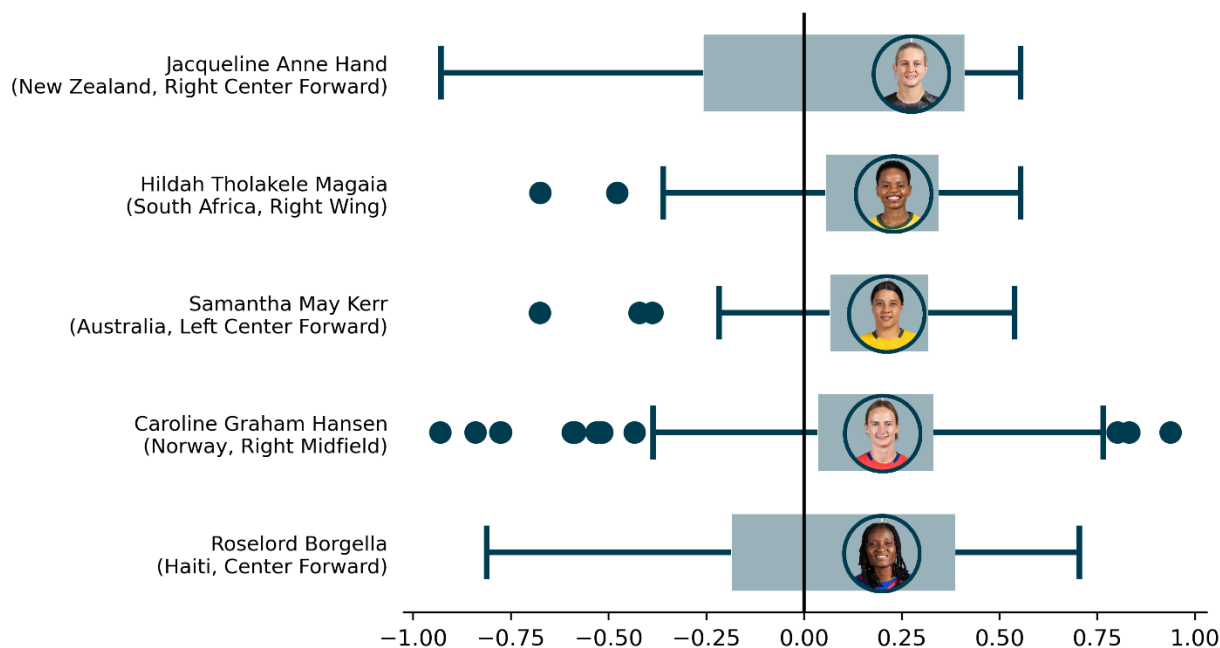

Figure 5 Overview how much the dribble outcomes of the best performers (highest median) exceeded the expectation. Player photos taken from fifa.com.

3.2. Dangerous dribbles in the opponent's half

Looking at all dribbles from all players in general, we can see that the distribution of dribbles is roughly symmetrical, i.e., that roughly the same number of dribbles take place in both halves of the pitch. Going one step further, two important findings can be confirmed with the help of our metrics: Firstly, dribbles in the own half are mainly about overcoming space and do not generate much immediate threat. They are mainly taken in situations with much less risk. On the other hand, dribbles in the opponents' half are used to create scoring chances. Dribbling that starts just outside the penalty area produces the highest xT_{Gain}.
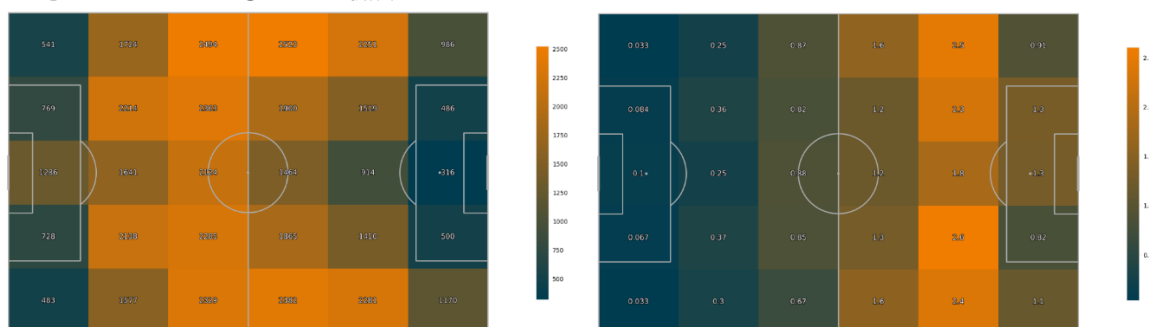

Figure 6 Amount of carries and dribbles (left), Sum of expected threat (xT) from successful dribbles (right).

3.3. The teams' playing philosophy: Germany, England and Spain

Building on the general distribution of xT, one can analyze how individual teams play. Clear and concise overviews permit match analysts to gain insights rapidly. For instance, Germany is especially dangerous on the very left lane and the half right lane of the pitch. A comparison of the two finalists,

Spain and England, indicates that the Spanish are creating much more goalscoring threat through dribbling.
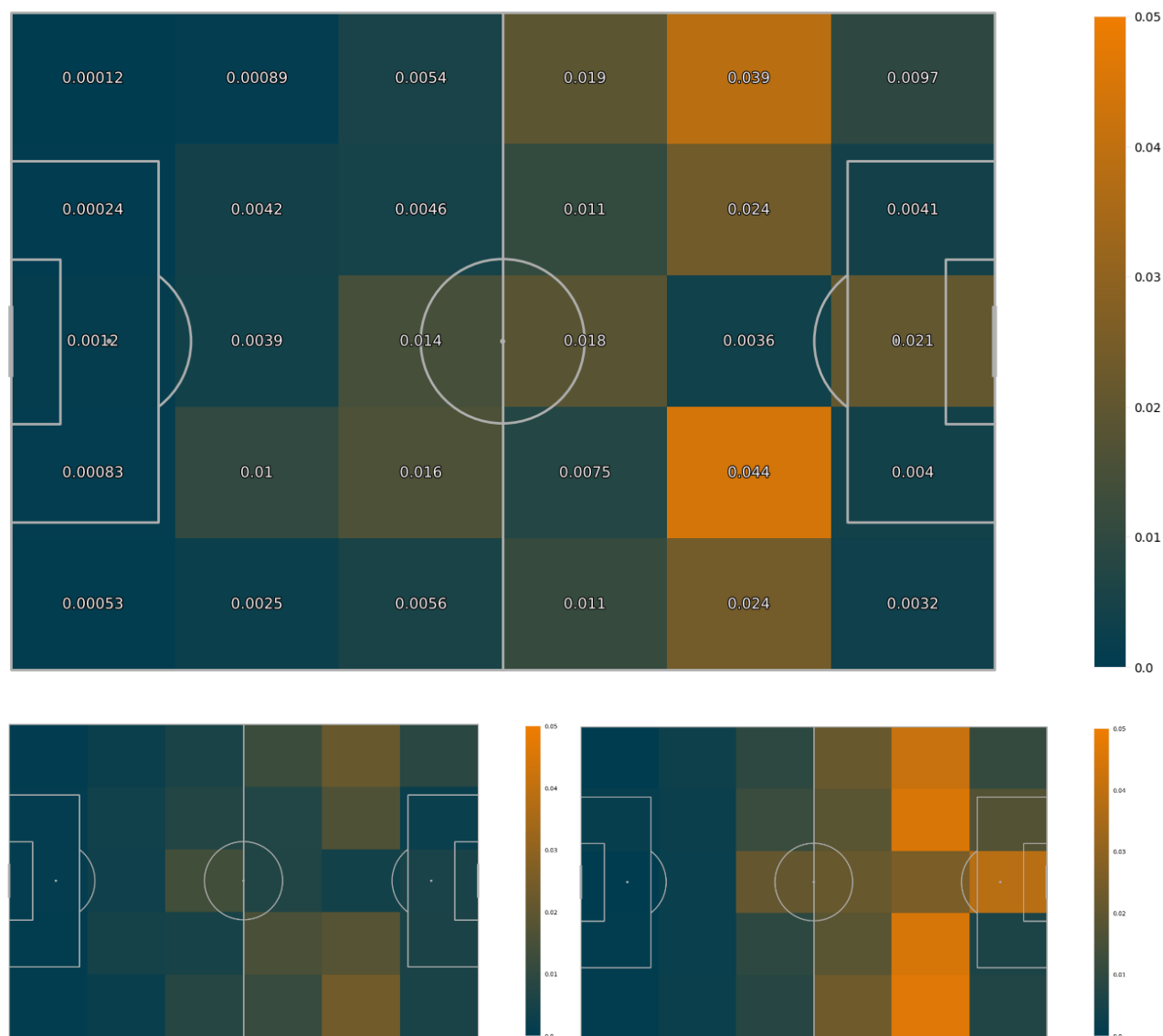

Figure 7 Comparison of the xT_{Gain} per match by successful dribbles of Germany (top), England (left) and Spain (right).

3.4. Combined analysis of risk and expected threat

Combining both models, one can gain additional insights. Figure 8 shows the average expected threat gain of successful dribbles in relation to the taken risk that players achieved during 90 minutes of playing time, where the bubble size shows the averaged normalized number of carries per player. This analysis compares different field positions, including the outer and inner lanes, to assess the risk and return associated with each. In practice, analysts can filter this diagram for particular teams, allowing for direct conclusions to be made about their playing style.
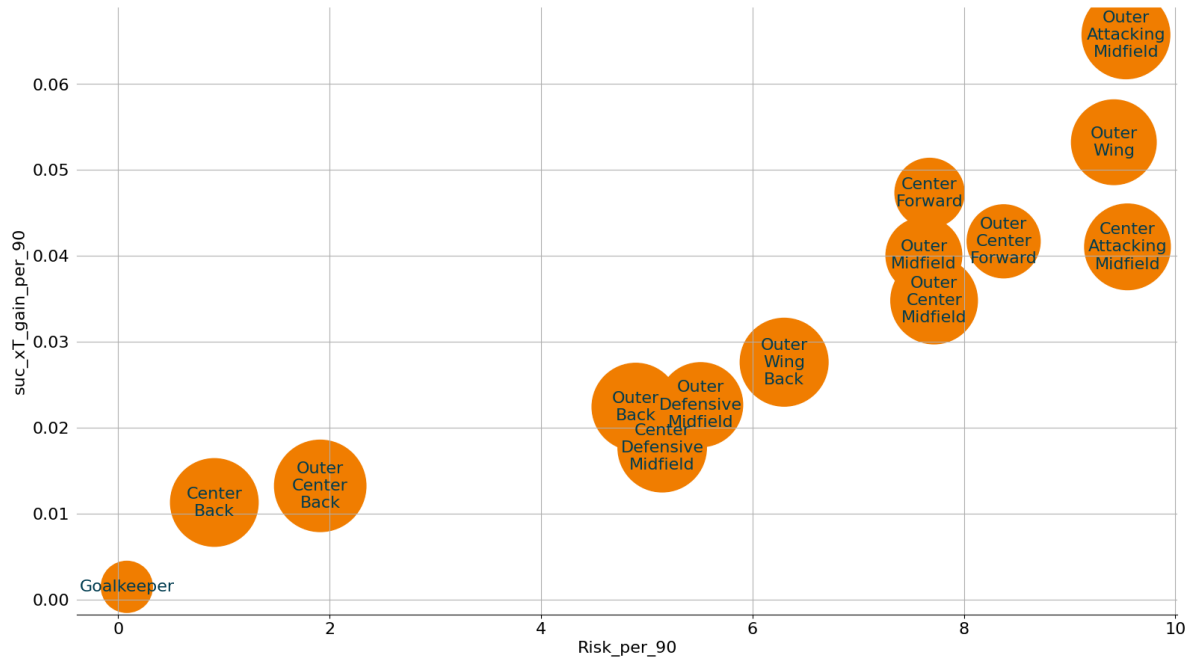
Figure 8 Comparing risk and successful xT gain of players normalized to 90 minutes of playing time.

3.5. Outperforming XT

Finally, we can compare reality with the expected xT gain variable, which was introduced in Section 2.3. Players who have scored significantly more xT than can be expected by their situations demonstrate both a willingness to take risks and high technical skills. The top players of this category are shown in Figure 9.
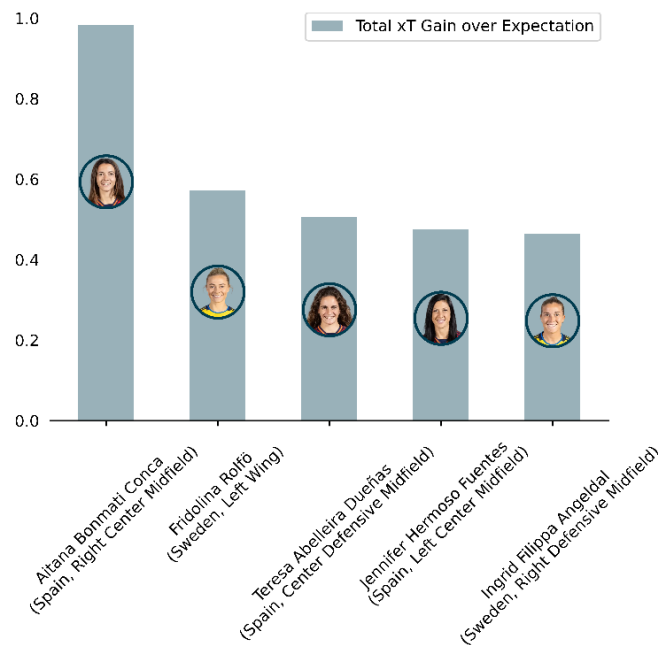

Figure 9 Comparing Risk and successful xT gain of players normalized to 90 minutes of playing time. Player photos taken from fifa.com.

4. Conclusion

Despite their obvious importance, there is a research gap in the systematic evaluation of dribbles. Closing this gap, we quantified the quality of dribbling by introducing an anticipated success rate that is dependent on the player's position and surrounding opponents. We then assessed the resulting dribbling value using an advanced expected threat model, which considers the opposition's nearby pressure since it significantly increases the threat of an action. Hence, this work allows a more comprehensive understanding of the importance of dribbles in the game of soccer.

Our model gives practical insights to analysts and scouts, which they can use to identify key skills in players and to develop training methods. To demonstrate this, we have investigated the best dribblers, positional differences and team's playing philosophy in the 2023 Women's World Championship. We therefore identified players that continuously achieve high (or low) value dribbles at an above (or below) expected success rate or weaknesses in team defenses and provided drilldowns to analyze specific game situations, areas on the pitch or also formation-dependent behavior.

In future work, further practical relevant cases relating to dribbles can be quantified. Dribbling is particularly effective in tight situations, as it allows players to get past tightly packed defenders and create dangerous situations in the penalty area. The psychological impact on opponents should not be underestimated either, as successful dribbles can boost a player's confidence and influence the morale of opponents, which can lead to more defensive behavior. Players with strong 1-on-1 dribbling skills can destabilize the opponent's defense by bringing unpredictability to the game. This helps to break tactical structures and allows the attacking team to advance into dangerous positions on the pitch.

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Appendix

Description of all calculated features:

Feature	Description
x	Start location of the dribble (x-coordinate)
y	Start location of the dribble (y-coordinate)
y_symm	Start location of the dribble (symmetric y-coordinate, measuring the distance from the center)
dribbling_towards_opponent_goal	Whether the player dribbles towards the opponent's goal (=1) or not (=0)
numerical_superiority_5m	Number of teammates subtracted by number of opponents within 5 m distance to the start location of the dribble.
numerical_superiority_10m	Number of teammates subtracted by number of opponents within 10 m distance to the start location of the dribble.
opponents_within_5m	Number of teammates within 5 m distance of the start location of the dribble.
opponents_within_10m	Number of teammates within 10 m distance of the start location of the dribble.
calculated_pressure	Own pressure calculation based on surrounding opponents at start location of a dribble: it is a piecewise linear function mapping distances to pressures, ensuring a minimum of zero and a maximum of 1, derived from specific distance-pressure pairs (0 m → 1, 2 m → 0.5, 10 m → 0).
tagged_pressure	"under_pressure" variable from StatsBomb which indicates whether a player was under pressure during an action or not.

We eliminated some highly correlated features, such as opponents within 10 meters, by observing the correlation matrix: