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A data-driven analysis of the technical and tactical evolution of elite women's football

Lotte Bransen[1] and Jesse Davis[1]

Abstract

Currently, most research into the evolution of player performance in women's football has focused on physical performance. In contrast, we lack data-driven research into the technical and tactical developments of the women's game. This paper aims to fill this research gap by analysing an extensive longitudinal dataset containing event data for 3510 matches over eight years in the game's top leagues. It uses analytics techniques to assess changes in technical skills and tactical behaviours in the women's game. Tactically, we observe longer possession sequences and fewer long-distance shots. Technically, we observe that players are completing more difficult and valuable passes at a higher rate, and putting a higher percentage of shots on target, with a particular emphasis on aiming for the corners of the goal. These findings could aid football practitioners to account for the developments of the game.

Keywords

Ball possession, passing accuracy, shooting skills, soccer

Introduction

Between the 1920s and 1970s many European football federations forbid women from playing.[1] Even once federations began sanctioning matches, opportunities remained limited, particularly with the women's game largely consisting of amateurs. However, the establishment of the FIFA Women's World Cup has coincided with an increased interest and professionalisation of the women's game: many countries have established professional leagues and UEFA started a women's version of the Champions League.[2]

Money is slowly beginning to flow into the women's game.[3] The increased opportunities and investment suggest that there may be evolutions in player performance in women's football. While research on the women's game has grown, it still receives less attention than the men's game.[4] Currently, most research studies the physical aspects of women's football.[5,6]

In addition to physical skills, tactical and technical skills are also essential for football players.[7] Tactical behaviour refers to the short-term actions performed by players when adapting to the changing game situation.[8] Tactics are often summarised by defining metrics that capture the (relative) frequencies that specific behaviours arise in matches. For example, some works focus on possession such as its length (e.g. number of actions, duration)[9] and zones of the pitch where a team possesses the ball.[10] More recently, ball possessions specifically in the women's game have been analysed, focusing on goalkeeper distribution (i.e. where goalkeepers move the ball to),[11] possessions that lead to goal scoring opportunities,[12] and complete ball possessions.[4,13]

Other works perform locational analysis such as whether players are positioned higher or lower up the pitch[14] or how the prevalence and directionality (e.g. backwards, sidelines, forward) of passes depends on the location.[15] More recently, De Jong et al.[16] performed a network analysis on data from 694 matches from the women's game. They concluded that successful teams are highly connected and centralise the distribution of ball possession. They identified the lack of dependency on key players for the total ball flow as a unique characteristic of women's football.

Reviewers: Iván Iván-Baragño (European University of Madrid, Spain)
László Csató (Corvinus University of Budapest, Hungary)

[1]Department of Computer Science & Leuven.AI, KU Leuven, Leuven, Belgium

Corresponding author:
Lotte Bransen, Department of Computer Science & Leuven.AI, KU Leuven, Leuven, Belgium.
Email: lotte.bransen@kuleuven.be

Similarly, shooting behaviour such as where shots are taken and how their conversion rates depend on contextual factors (e.g. length of preceding possession, shot characteristics) has been extensively studied.[17–19] However, such research on extensive datasets has largely focused on men's football. Two more recent studies analyse goal scoring opportunities in the women's game. Scanlan et al.[20] analysed 52 matches from the 2015 FIFA Women's World Cup and found that the average time needed to create a goal scoring opportunity was 12 seconds. Mesquita et al.[21] analysed 174 goals and concluded that goal scoring opportunities in women's football are more often created through the offensive organisation than in the men's game.

Technical skills such as ball control, passing, and shooting are crucial in football performance.[22] Several studies have shown that more successful teams show better technical performance.[23,24] Accurate passing[25] and accurate shooting[22] are key football skills. Such technical skills are often evaluated by analysing the accuracy of execution[26,27] such as pass accuracies, although it is also important to consider the difficulty of executing the pass.[25] Similarly, shooting skills can be assessed by looking at the ability to generate shots and convert them to goals.[19,28]

Finally, other research uses statistics and machine learning techniques to analyse various technical and tactical aspects of football.[29–32] Typically such techniques are applied to large datasets of detailed event data that describe all on-the-ball events. The few papers that study the women's game using machine learning primarily focus on contrasting it to the men's game by looking at metrics such as pass accuracy, possession length, and shot conversions.[33,34] Pappalardo et al.[35] used machine learning techniques (logistic regression, decision trees, tree ensembles) to predict whether a match involved a men's or women's team based on technical indicators such as the number of shots and passing accuracy. Garnica-Caparrós and Memmert[36] used logistic regression, decision trees, and neural networks to find performance factors (e.g. ground duels won, shots on target, successful passes) that help differentiate between female and male football players. Both studies only considered a small set of matches (108 matches and 82 matches, respectively).

This paper represents the first large-scale analysis of women's event data which providers have only recently started collecting. Uniquely, we will perform a data-driven analysis of data from matches played in the six top domestic leagues and the Champions League between 2013 and 2022. We hypothesise that there has been an evolution and improvement in tactical and technical skills of players. These can be developed during training sessions,[37] which may be more accessible and of higher quality with increased professionalisation. Tactically, we will analyse possession lengths and shooting strategies. We expect the game to have evolved tactically in a similar manner to the men's game with a stronger emphasis on retaining possession,[38] more high-quality opportunities and fewer long-distance shots.[18] Technically, we focus on the passing and shooting skills. For passing, we will evaluate whether players are more likely to complete difficult but valuable passes such as ones that increase the chance of scoring. To evaluate shooting skill, we consider shot conversion and shot placement.

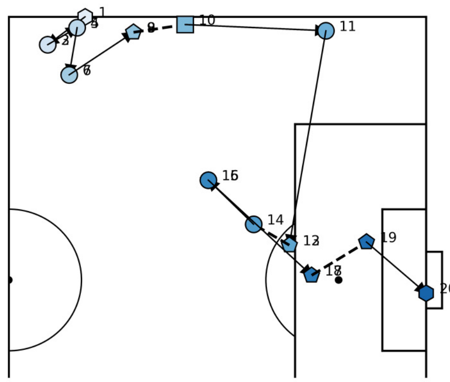
Materials and methods

Data

This work analyses an extensive match event dataset containing 8.5 million actions from 3510 matches in the top leagues and UEFA Women's Champions League (Table 1). The data was provided by SciSports in the SPADL format.[31] The data is typically recorded by human annotators watching video footage and describes all on-the-ball actions that took place in a match by recording the action's start and end location, which players were involved, the action type, and a time stamp (Figure 1). Our goal is to evaluate general differences over time. Moreover, we need a sufficient amount of data to train the machine learning models. Therefore, instead of considering a season-by-season analysis, we chronologically partition the data into two similarly sized datasets: an OLD and NEW dataset.

Table 1. The number of matches per season for each of the leagues in our dataset.

	'13 (/14)	'14 (/15)	'15 (/16)	'16 (/17)	'17 (/18)	'18 (/19)	'19 (/20)	'20 (/21)	'21 (/22)
Swedish Damallsvenskan	0	6	3	7	8	6	132	132	0
German Frauen Bundesliga	0	1	9	12	124	131	131	129	101
French Division Féminine 1	0	3	6	12	101	129	93	131	102
American NWSL	0	6	2	35	115	108	111	1	118
Spanish Primera división	0	0	2	3	86	99	116	280	175
English Women's Super League	0	0	0	1	34	97	87	131	98
Champions League	2	2	2	1	5	17	71	79	117
Total	2	18	24	71	473	587	741	883	711



#	time	player_name	type_name	x	y	dx	dy
1	18m38s	Leila Ouahabi	throw_in	62.1	68.0	-4.7	-3.6
2	18m38s	Alexia Putellas	receival	57.4	64.4	0.0	0.0
3	18m39s	Alexia Putellas	pass	57.4	64.4	3.7	2.2
4	18m39s	Leila Ouahabi	receival	61.1	66.6	0.0	0.0
5	18m40s	Leila Ouahabi	pass	61.1	66.6	-1.0	-6.1
6	18m40s	Alexia Putellas	receival	60.1	60.5	0.0	0.0
7	18m40s	Alexia Putellas	pass	60.1	60.5	8.1	5.5
8	18m41s	Lieke Martens	receival	68.2	66.0	0.0	0.0
9	18m42s	Lieke Martens	dribble	68.2	66.0	6.5	1.0
10	18m43s	Lieke Martens	take_on	74.7	67.0	17.7	-0.8
11	18m47s	Lieke Martens	pass	92.4	66.2	-4.6	-27.7
12	18m48s	Jennifer Hermoso	receival	87.8	38.5	0.0	0.0
13	18m49s	Jennifer Hermoso	dribble	87.8	38.5	-4.5	2.7
14	18m49s	Jennifer Hermoso	pass	83.3	41.2	-5.7	5.7
15	18m50s	Alexia Putellas	receival	77.6	46.9	0.0	0.0
16	18m50s	Alexia Putellas	pass	77.6	46.9	13.0	-12.3
17	18m51s	Aitana Bonmati	receival	90.6	34.6	0.0	0.0
18	18m52s	Aitana Bonmati	dribble	90.6	34.6	6.9	4.3
19	18m52s	Aitana Bonmati	shot	97.5	38.9	7.5	-6.6
20	18m52s	Aitana Bonmati	goal	105.0	32.3	0.0	0.0

Figure 1. The sequence leading to Aitana Bonmati's goal in the 2021 Champions League final. For each action, the data records its type, the player and team performing the action, the *x* and *y* coordinate of the action's start and end location, and the time in the match the action was executed.

However, splitting the data is challenging. We do not want matches played in the same time window (year/season) to appear in both datasets. Moreover, because we want to test differences over time and not differences across leagues, we want a similar number of matches per league in both datasets. This is complicated because the number of matches per league varies per season for two reasons: (a) due to COVID-19 some matches were cancelled (e.g. NWSL 2020 season) or rescheduled, and (b) some league structures changed resulting in more teams participating (e.g. Champions League, Spanish Primera División).

Given these desiderata, the NEW dataset contains all matches ($N = 1594$) played in the 2020, 2020/2021, 2021 and 2021/2022 (until 23th March, 2022) seasons, whereas the OLD dataset contains all matches ($N = 1916$) played before these seasons.

Methods

We present the methods and metrics used to assess tactical and technical evolutions.

Tactical behaviour. We analyse tactical behaviour by studying ball possession and shooting behaviour.

Ball possession. A possession sequence is a sequence of consecutive actions performed by one team without an interruption by the opposing team.[39] Longer possession sequences are an indicator of success.[9,39] Possession sequences are extracted by identifying moments of ball loss (e.g. pass intercepted by opponent, ball out event, foul) which signify the end of the ongoing sequence. We only consider sequences where the team has executed at least two consecutive actions to avoid having the results unduly influenced by short possessions (e.g. being immediately dispossessed after getting the ball). We report the duration and distance travelled for possession sequences. The duration is the time in seconds between the first and last action.[39] Distance travelled is the metres travelled by the ball throughout the sequence (i.e. the sum of the metres travelled between each pair of consecutive actions in the sequence).

Goal attempts. We report the number of shots in a match as well as the number of shots from in and outside the penalty box. We use an expected goals model (xG)[17,19,40,41] to measure the quality for a specific shot. xG models use machine learning to find patterns in historical shots that relate the characteristics of the shot (e.g. where the shot was taken from, scoreline, etc.) to its outcome (goal vs. no goal). Specifically, given a shot the xG model computes the probability that it will yield a goal. We train xG models to compare the xG distributions for shots in- and outside the box to get an understanding of the difference in the quality of shots taken in both datasets.

Measuring chance quality. To train our xG models, we first collect all shots from open play in our datasets. Hence shots directly from set pieces such as penalty kicks and free kicks are excluded. Shots directly following a set piece such as a corner or throw in are included. We also remove all own goals from our dataset. This results in a total of 45,606 shots in the OLD dataset and a total of 36,256 shots in the NEW dataset. The average number of shots per match in the OLD and NEW dataset are 23.8 ± 6.1 and 22.8 ± 6.4, respectively.

Training an xG model can be framed as a binary classification problem: each shot either results in a goal (positive label) or not (negative label). Our dataset is imbalanced due to the fact that around 1 out of 10 open play shots result in a goal. We want the probabilities that the model assigns to each shot yielding a goal to be as accurate as possible and will therefore focus on optimising the Brier loss[42] of our xG models. This is an evaluation metric that looks at how well-calibrated probabilistic predictions are. A well-calibrated model means that predicted probabilities match the definition of a probability. For example, if all shots with an xG value of 0.13 are considered, in a well-calibrated model 13% of those shots will yield a goal.

We use the publicly available XGBoost Python package (https://xgboost.readthedocs.io/en/) to train XGBoost classifiers[43] on different sets of our datasets. As shown by Robberechts and Davis,[44] XGBoost classifiers show good performance for xG models. We will use the same feature set as they used which can be constructed using the open source xG-soccer Python package (https://github.com/ML-KULeuven/soccer_xg). Appendix C1 describes the features used for our xG models.

Typically when training and evaluating a machine learning model, one splits that data set in three sets: a training set, a validation set and a test set (hold-out set). The model learns the patterns using the data in the training set, the hyperparameters are tuned using the validation set and the analysis is performed on the test set. As we want to compare the xG distributions over time, we will not use such a static split with one held-out set. Therefore, we train six models on the OLD dataset and six models on the NEW dataset: one for each of the domestic leagues. We use the shots from the Champions League as a comparison set to analyse the performance of our models on. Each model is trained on five leagues and the model is used to make predictions for the shots in the held-out league. In that way we can fairly use these values for our analysis on the differences over time. For each model, we use the same set of features and use 5-fold cross validation on the training set to optimise the number of trees and the tree depth as those are important hyperparameters to avoid overfitting.[43] Appendix C1 describes the performance of our models.

Technical skills. We investigate passing and shooting skills because they are important indicators of higher technical performance.[45] As we expect technical skills to have improved, we use one-sided t-tests to test whether we observe positive improvements in passing and shooting skills amongst players.

Passing skills. While pass completion percentage is a common metric, it can be misleading because it can be increased by favouring safer passes (e.g. backpasses) over more risky, yet valuable, ones (e.g. through balls).[25] Therefore, we investigate the success rates on two other types of passes. First, we consider deep completions which are defined by SciSports as forward passes (passing angle of 45 degrees) that travel at least 15 m and end in the final third of the pitch. Such passes are harder to complete as the final third is typically more crowded and forward passes are harder to complete than backward passes. Furthermore, passes towards crowded areas have been related to technical skills and team success.[46]

Second, we use a pass' xT value[47,48] to assess the impact of the pass. Simply put, a pass' xT value measures the difference in the chances of scoring a goal in the near future of locations where the pass a) ended and b) started. A key difference between xT and xG is that xT values ball progression actions (passes, carries) whereas xG only considers shots, which is beneficial since there are many more ball progression actions than shots in a match.

Formally, xT is a discrete Markov Decision Process, in which the game of football is modelled as a system with transitions between states. In each state, the system has a certain probability of transitioning to another state. xT represents states by overlaying a 32×24 grid on the pitch. The current state is given by the location of the player possessing the ball. For each state, the model specifies the probability that a player will (a) shoot or (b) move the ball to every other zone on the pitch. Moreover, it specifies the probability that the action is successful (e.g. shot results in a goal). Second, a value is assigned to each state. Intuitively, the value represents the probability that a team will score before losing possession of the ball if they possess the ball in a specific location (i.e. state). Consequently, xT takes a longer-term perspective when assessing value as it considers what is likely to happen after multiple subsequent actions. In contrast, xG only considers the chance of directly scoring from the shot.

We use the publicly available soccer action Python package (https://github.com/ML-KULeuven/socceraction) to learn the xT models separately on the OLD and NEW dataset. For example, Putellas' pass to Bonmati in Figure 1 has an xT value of 0.075 indicating that her pass increased her team's chance of scoring by 7.5 percentage points. Valuable passes with the highest expected reward are often also the riskiest ones. Hence, we report the accuracy on the passes that would be in the top 5% of xT value if they were completed. Such passes increase the scoring chances by at least 2 percentage points.

Shooting skills. Shot conversion rate and percentage of shots on target are common metrics. However, neither are necessarily proxies for shooting skill as their values are affected by the type of shots taken. Distance to goal is the most predictive feature for both metrics.[19] Therefore, we look at shooting skill in two ways. First, we report conversion rate and percent of shots on target inside and outside the penalty box. Conversion rates and the number of shots on target from different locations have been related to player abilities.[22,28] Second, we look at the placement of the shots in terms of percentage of shots that are within a certain distance of the posts.

Sensitivity analysis. We perform a sensitivity analysis to check the robustness of our findings. For this, we repeat our analysis on an alternative partition of the data. As the amount of data across the leagues is not equal for the older seasons, we introduce an alternative OLD dataset OLD_ALT in which we exclude all matches played in the '13(/14), '14(/15), '16(/17) and '17(/18) seasons. Similarly, we introduce NEW_ALT in which we exclude the matches played in the 20/21 season and the single match played in the 2020 NWSL season. Due to the Covid pandemic, the NWSL 2020 season was cancelled, and the matches in the 20/21 season were played under different circumstances. Note that some matches in the 19/20 season were played behind closed doors. However, we do not know which matches were affected so we only excluded the 20/21 season matches. We investigate whether excluding these matches has an impact on our main findings. The OLD_ALT dataset contains data from 1670 matches and the NEW_ALT dataset contains data from 711 matches.

Results

Evolution in tactical behaviour

Ball possession. Possession sequences have become significantly longer, both in time and distance travelled. The duration of possession sequences has increased from 13.0 ± 11.7 seconds in the OLD dataset to 13.5 ± 13.0 seconds ($p < 0.001$) in the NEW dataset, whereas the distance travelled has increased from 84.1 ± 65.5 m to 85.6 ± 69.2 m ($p < 0.001$). The same holds for sequences that lead to a shot on target (17.9 ± 14.3 seconds to 19.3 ± 16.0 seconds ($p < 0.001$) and 121.8 ± 79.3 m to 123.8 ± 86.9 m ($p < 0.001$)).

Goal attempts. The number of shots from outside the penalty box and the proportion of shots taken with the foot have decreased (Table 2). Furthermore, the average xG per shot outside the box has increased, whereas the average xG for shots inside the box has decreased (Table 2).

Evolution in technical skill

Evolution in passing skill. While the number of passes per match did not significantly change, success percentages have risen significantly from $77.1 \pm 0.034\%$ in the OLD dataset to $78.2 \pm 0.037\%$ ($p < 0.001$) in the NEW dataset for all passes. The number of deep passes has dropped from 50.3 ± 10.5 to 48.4 ± 11.3 ($p < 0.001$) deep passes per match, whereas the success percentage has increased from $48.5 \pm 0.16\%$ to $51.5 \pm 0.18\%$ ($p < 0.001$). Also, the success percentage of passes with high (top 5%) xT values has risen from $39.8 \pm 0.18\%$ to $42.5 \pm 0.20\%$ ($p < 0.001$). Moreover, a year-on-year analysis shows a steady increase in the success percentage for deep passes (Figure 2) and passes with a high xT value (Figure 3).

Evolution in shooting skill. Overall shot conversion rates have remained relatively stable ($11.9 \pm 0.15\%$ in the OLD dataset and $12.2 \pm 0.17\%$ in the NEW dataset, $p = 0.188$), whereas the proportion of shots on target has increased significantly from $39.1 \pm 0.23\%$ in the OLD dataset to $41.2 \pm 0.26\%$ in the NEW dataset ($p < 0.001$). This is driven by an increase in shots on target from outside of the penalty box, which have risen from $30.1 \pm 0.34\%$ in the OLD dataset to $32.8 \pm 0.41\%$ in the NEW dataset ($p < 0.001$).

There has been large significant increases in the percentage of shots placed near the posts (Table 3 and Figure 4). We observe these increases across all leagues, with an average increase per league of $57.7 \pm 8.4\%$ for the proportion of shots placed within 0.5 metres of the posts. Furthermore, we observe a clear upward trend for the

Table 2. The average number of shots per match, the proportion of all shots and the average xG value per shot for all shots, shots taken with a foot, shots from outside the box, and shots from inside the box.

		OLD	NEW	*p*-Value
All shots	Number per match	23.90 ± 6.07	22.85 ± 6.43	<0.001
	xG per shot	0.117 ± 0.138	0.120 ± 0.142	0.0015
Shots by foot	Number per match	20.55 ± 5.52	19.51 ± 5.77	<0.001
	Proportion of shots	$86.0 \pm 0.16\%$	$85.4 \pm 0.19\%$	0.014
	xG per shot	0.111 ± 0.136	0.114 ± 0.139	0.0026
Outside box	Number per match	9.57 ± 3.67	8.34 ± 3.45	<0.001
	Proportion of shots	$40.1 \pm 0.23\%$	$36.5 \pm 0.25\%$	<0.001
	xG per shot	0.035 ± 0.033	0.039 ± 0.040	<0.001
Inside box	Number per match	14.23 ± 4.8	14.41 ± 4.98	0.28
	Proportion of shots	$59.9 \pm 0.23\%$	$63.5 \pm 0.25\%$	<0.001
	xG per shot	0.173 ± 0.154	0.167 ± 0.158	<0.001

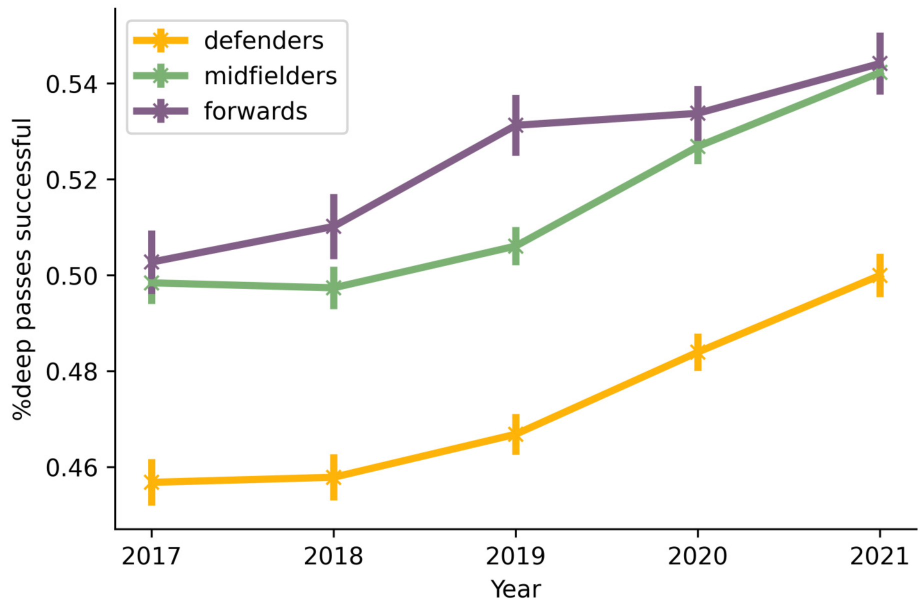


Figure 2. The accuracy on deep passes for each position line as a function of time. The accuracy of these passes has increased for all position groups over time.

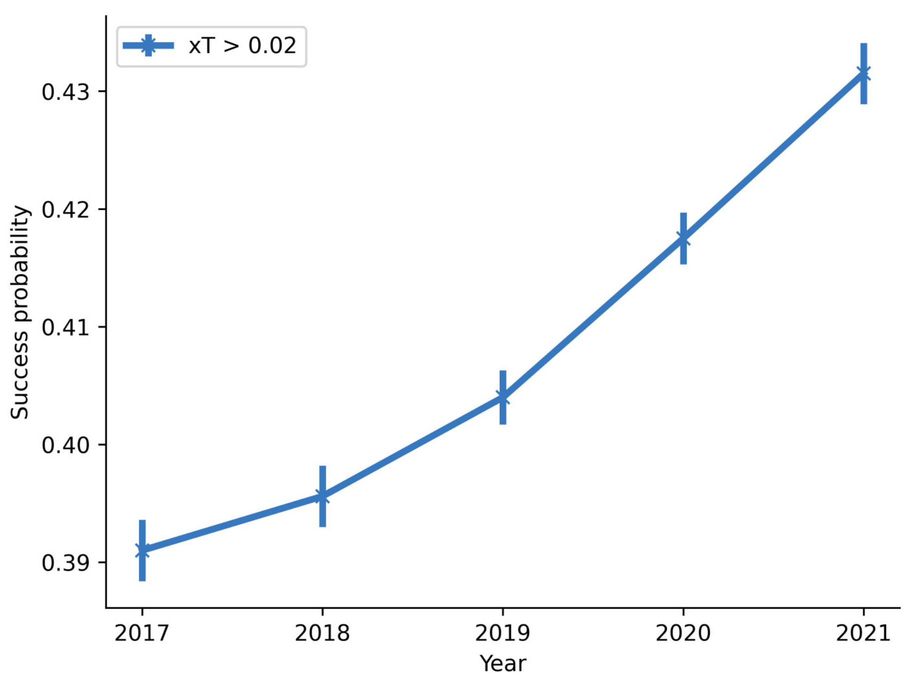


Figure 3. The success probability for passes that would be in the top 5% of xt value if they were completed. The accuracy of these passes has increased over time.

proportion of shots placed within 0.5 metres of the posts increasing from 4.9% in 2017, to 5.4% in 2018, 5.3% in 2019, 7.7% in 2020 to 8.6% in 2021.

Sensitivity analysis. Table 4 shows the results of our sensitivity analysis for our main findings.

Discussion

Using standard metrics and machine learning techniques, we have observed changes in tactical behaviour and improvements in proxies for technical skills in an analysis of data from 3510 matches from top women's leagues plus the UEFA Women's Champions League.

Table 3. Proportion of shots that fall within various interval distances of one of the posts.

Distance to posts	Proportion shots from	OLD	NEW	*p*-Value
3–3.5m	All shots	6.0 ± 0.11% (2723)	5.3 ± 0.12% (1931)	0.030
	Inside box shots	6.2 ± 0.15% (1700)	5.4 ± 0.15% (1248)	0.009
	Outside box shots	5.6 ± 0.17% (1023)	5.1 ± 0.19% (683)	0.0861
2.5–3m	All shots	4.4 ± 0.10% (2027)	3.9 ± 0.10% (1371)	<0.001
	Inside box shots	5.1 ± 0.13% (1397)	4.2 ± 0.13% (965)	<0.001
	Outside box shots	3.4 ± 0.13% (630)	3.1 ± 0.15% (406)	0.596
2–2.5m	All shots	4.9 ± 0.10% (2216)	4.2 ± 0.11% (1541)	<0.001
	Inside box shots	5.7 ± 0.14% (1562)	4.9 ± 0.14% (1114)	<0.001
	Outside box shots	3.6 ± 0.14% (654)	3.2 ± 0.15% (427)	0.0864
1.5–2m	All shots	5.0 ± 0.10% (2270)	4.2 ± 0.11% (1537)	<0.001
	Inside box shots	6.2 ± 0.15% (1684)	5.0 ± 0.14% (1141)	<0.001
	Outside box shots	3.2 ± 0.13% (586)	3.0 ± 0.15% (396)	0.272
1–1.5m	All shots	5.6 ± 0.11% (2551)	5.2 ± 0.12% (1901)	0.028
	Inside box shots	6.8 ± 0.15% (1853)	6.1 ± 0.16% (1408)	0.0026
	Outside box shots	3.8 ± 0.14% (698)	3.7 ± 0.16% (493)	0.650
0.5–1 m	All shots	6.3 ± 0.11% (2882)	7.2 ± 0.14% (2605)	<0.001
	Inside box shots	7.5 ± 0.16% (2049)	8.4 ± 0.18% (1921)	<0.001
	Outside box shots	4.5 ± 0.15% (833)	5.1 ± 0.19% (684)	0.0134
0–0.5 m	All shots	5.2 ± 0.10% (2371) to (p =< 0.001)	8.1 ± 0.14% (2938)	<0.001
	Inside box shots	5.8 ± 0.14% (1579)	9.2 ± 0.19% (2111)	<0.001
	Outside box shots	4.3 ± 0.15% (792)	6.2 ± 0.21% (827)	<0.001

The goal width is 7.32 metres. There has been large significant increases in the percent of shots placed near the posts. For example, there have been 1.9 (outside the box) and 3.4 (inside the box) percentage point increases in the proportion of shots within 0.5 m of the post.

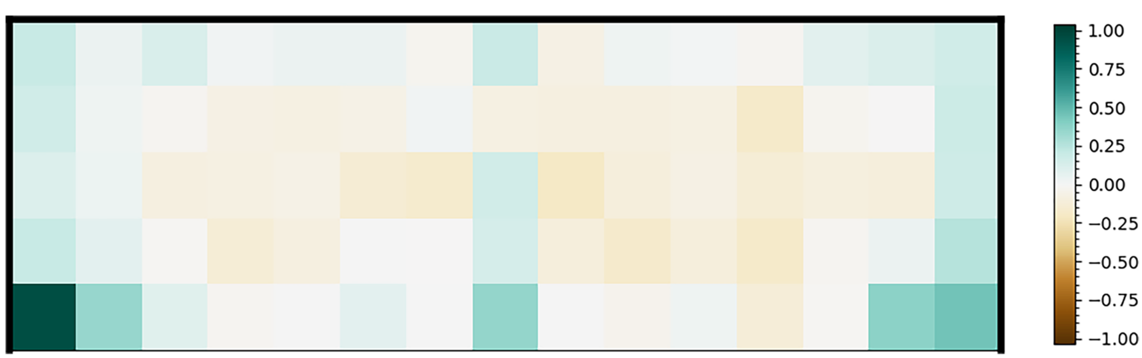


Figure 4. The difference in end locations for shots from inside the box plotted on the goal. Green (orange) indicates a higher proportion of shots end in the location in the NEW (OLD) dataset end in a location. The values in the colorbar correspond to the proportion difference between the two datasets in percentage points. We observe a higher proportion of shots aimed at the far corner in the NEW dataset.

Tactically, it seems that retaining possession has become more important. Possession sequences are longer in both duration and distance, mirroring changes in the men's game.[38] These changes follow the optimal passing characteristics for elite women's football as described by Dipple et al..[13] Furthermore, players have become more judicious about the shots they take. Mirroring the men's game, there has been a decrease in shots from outside the penalty box.[18] The average xG value of a shot outside the box has increased, as women forgo the lowest quality long shots.

Technically, there is evidence that players have improved their passing and shooting skills. Players have become more proficient at completing difficult passes. We observed an increased success percentage for two types of passes that are completed less often than a typical pass. An increased accuracy for such passes has been linked to improved technical skills.[46] However, an alternative

Table 4. Results of our sensitivity analysis for our 4 datasets.

	OLD	OLD_ALT	NEW	NEW_ALT	Difference
Possession length	84.1m	83.9m	85.6m	85.1m	Increase
Possession duration	13.0s	13.0s	13.5s	13.5s	Increase
xG per shot	0.117	0.117	0.120	0.122	Increase
xG per shot outside box	0.035	0.034	0.039	0.400	Increase
Pass accuracy	77.1%	77.2%	78.2%	78.3%	Increase
Nr deep passes per match	50.3	50.1	48.4	46.1	Decrease
Success percentage deep passes	48.5%	48.6%	51.5%	52.3%	Increase
Success percentage high xT	39.8%	40.0%	42.5%	42.9%	Increase
Shot conversion rate	11.9%	12.0%	12.2%	12.0%	No change
Shot placement within 0.5 m from post (all shots)	5.2%	5.4%	8.1%	8.6%	Increase
Shot placement within 0.5 m from post (shots inside box)	5.8%	6.0%	9.2%	9.9%	Increase
Shot placement within 0.5 m from post (shots outside box)	4.3%	4.4%	6.2%	6.4%	Increase

For all findings, except for the shot conversion rate, we observe significant differences between the OLD versus NEW_ALT datasets, OLD_ALT versus NEW datasets, and OLD_ALT versus NEW_ALT datasets. For the NEW_ALT dataset we even observe some bigger differences in shot placement values and pass accuracy values.

hypothesis is that tactical evolutions made these passes somehow easier to complete.

Regardless of whether they shoot from inside or outside the box, players nowadays are placing more shots on target. Similarly, there is a significant increase in the placement of shots near the posts. Such shots are harder to stop and are an indication of improved technical skills.[27] For shots taken inside the box, the proportion and number of on target shots placed within 0.5 metres of a post have significantly increased. There are also gains for shots outside the box. Regardless of location, the proportion and number of shots ending within 1 and 3.5 metres of posts have fallen. However, we do not observe an increased conversion rate for on target shots, which might indicate improved shot-stopping by goalkeepers. This requires further investigation.

Our study has some limitations. While carefully selected, our dataset is not perfect. For some seasons, data from a number of matches is missing, particularly for older seasons, meaning the proportion of matches per league varies between our datasets. However, our sensitivity analysis shows that our results are robust and hold for different partitions of the data. However, the differences for shot placement and pass accuracy are even bigger if we exclude matches played during the Covid pandemic. Moreover, the data is annotated by humans, and both the event definitions and which events are collected can change over time. Using event data allows us to perform a broader analysis. However, on-the-ball events are mostly offensive in nature. Because we do not know the locations of the defenders, we cannot study defence or other prominent tactics such as pressing.

In the future, if more data becomes available, we would like to perform a more fine-grained analysis on the league level. Furthermore, it would be interesting to investigate developments in other aspects of the game, like goalkeeper and defensive skills. It would also be worthwhile to investigate if these trends also hold in international matches and tournaments. Finally, it would be interesting to compare and contrast these trends to the evolution in the men's game.

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ORCID iD

Lotte Bransen https://orcid.org/0000-0002-0612-7999

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Appendix A: Definitions

- **Locations.** We first transform all location values to a 105 $\times$68 metres pitch, as these are the most-used pitch sizes.
- **Own third.** First 35 metres of the pitch for the attacking team.
- **Final third.** Last 35 metres of the pitch for the attacking team.
- **Pass success percentage/pass accuracy.** The percentage of attempted passes that successfully reach a teammate.
- **Shot conversion.** The percentage of shots that yield a goal.
- **Possession sequence.** A sequence of at least two consecutive on-the-ball actions executed by the same team without being disrupted by the opposing team.
- **Deep pass.** A forward pass that travels at least 15 m and ends in the final third of the pitch. SciSports decided upon this definition after consolidation with a panel of end users.

Appendix B: SPADL

SPADL is a generic format for football match event data.[31] It describes a football match as a sequence of on-the-ball actions, with the following attributes for every action:

- Unique action ID
- Match
- Team
- Player
- Time in seconds and period (1st, 2nd, 3rd, 4th half, penalty shootout)
- Start- and end locations
- Body part (foot, head, other) used
- Result (successful, unsuccessful, offside)
- Action type

Many event stream datasets can be converted into SPADL using the publicly available socceraction package: https://github.com/ML-KULeuven/socceraction.

Our dataset consists of the following action types:

- **Pass.** Normal pass in open play
- **Cross.** Cross into the box
- **Throw-in.** Throw-in
- **Crossed free-kick.** Free kick crossed into the box
- **Short free-kick.** Short free-kick
- **Crossed corner.** Corner crossed into the box
- **Short corner.** Short corner
- **Take on.** Attempt to dribble past opponent
- **Foul.** Foul
- **Tackle.** Tackle on the ball
- **Interception.** Interception of the ball
- **Shot.** Shot attempt in open play
- **Penalty shot.** Penalty shot
- **Free-kick shot.** Direct free-kick on goal
- **Keeper save.** Keeper saves a shot on goal
- **Keeper claim.** Keeper catches a cross
- **Clearance.** Player clearance
- **Bad touch.** Player makes a bad touch and loses the ball
- **Dribble.** Player dribbles with the ball
- **Goal kick.** Goal kick
- **Reception.** Reception of the ball
- **Air challenge.** Player wins an air challenge
- **Ground challenge.** Player wins a ground challenge

Appendix C: model learning

xG

For each model, we run a gridsearch on the number of estimators and maximum tree depth with the following options:

- Number of estimators: [100, 250, 500]
- Maximum tree depth: [3, 4, 5]

To have an identical test set for all models, we report the Brier loss on the data from the Champions League for each of the six trained models. Using the same test set allows making comparisons between different models. Our model shows similar performance to the models in Robberechts & Davis[44] with Brier losses varying between 0.094 and 0.096 for all xG models on the Champions League shots in that particular dataset (OLD or NEW) (Table 4). However, we would like to caution that it is not advisable to draw conclusions about the efficacy of models that are trained and evaluated on different datasets.

We used the following features for our xG models:

Table 4. The performance of all xG models on the Champions League shots in that particular dataset (OLD or NEW).

League held out	Brier OLD dataset on CL	Brier NEW dataset on CL
English Women's Super League	0.096	0.096
American NWSL	0.094	0.095
French Division 1 Féminine	0.096	0.095
German Frauen Bundesliga	0.095	0.095
Spanish Primera división	0.094	0.095
Swedish Damallsvenskan	0.095	0.095

Distance to goal. Distance to the centre of the goal in metres.
Angle to goal. Angle to the centre of the goal.
Shot angle. Angle between the shot location and both goalposts.
Time in match. Time played so far in the match.
Foot. Indicator whether the shot was executed with a foot.
Header. Indicator whether the shot was executed with the head.
Turnover. Indicator whether the shot was following directly after recovering the ball.
From dribble. Indicator whether the shot was following a dribble by the same player.
From set piece. Indicator whether the shot was directly following a corner, free-kick or throw-in.
From cross. Indicator whether the shot was directly following a cross.
From pass. Indicator whether the shot was directly following a pass.