Evaluating the Wide Attack

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1 Analysis Scope & Methods

Data: Tracking data and event data of all games in WSL 2023-2024

Objective: Identify and evaluate actions after a player receives a pass in the Wide Attack Area.

- Wide Attack Area: outside of the box and in the attacking third.

Methods:

- Define the success of the attacking sequence following the initial pass.
- Use game context to evaluate the difficulty of success.
- Evaluate and rank players in different circumstances

1.1 Define Candidate Sequences and Success Metrics

Identify Candidate Sequences: Use both tracking data and event data to find receive frame and receiver location of each pass. Then extract passes that receiver location is outside of the box and in the attacking third.

- Receive frame: The frame when the distance between the ball and the receiving player first becomes less than 2 meters.
- Start of sequence: The receive frame.
- End of sequence: When the second pass or shot event occurs after the sequence starts.

Define Success: A sequence is considered successful if it meets the following criteria:

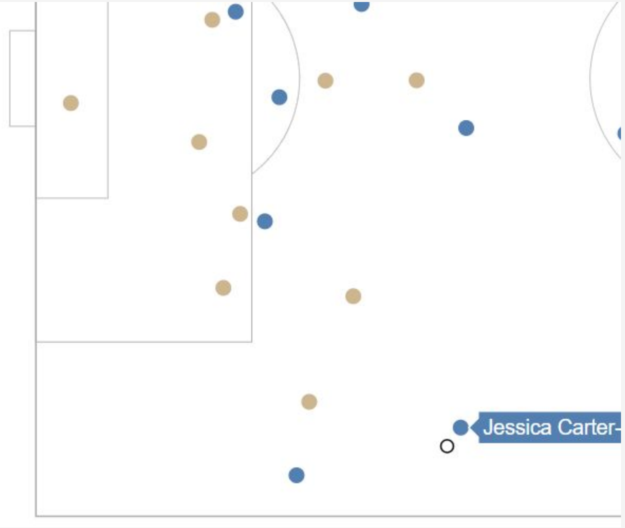
- The ball's new location is at least 2 meters closer to the goal compared to its position at the start of the sequence.
- The attacking team maintains continuous possession of the ball until it reaches the specified location.

During this project, the location of possessing player was used to indicate the ball location, as event frames were marked during the passes at which the ball was away from where the player last possessed it.

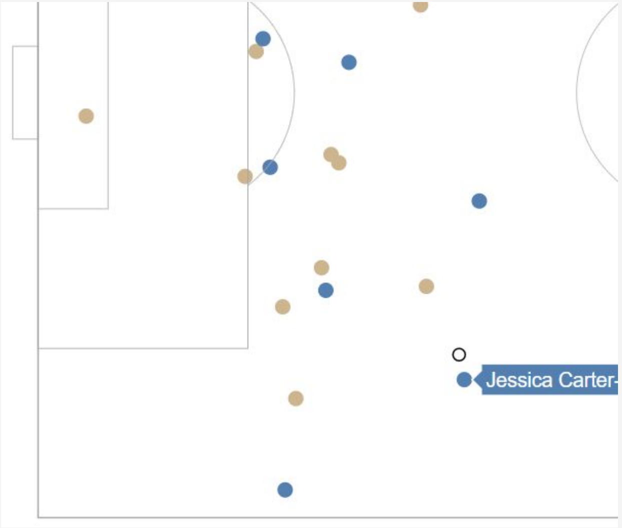
1.2 Example of a Sequence

Here is an example of a sequence which meets the criteria of success at the 2nd event.

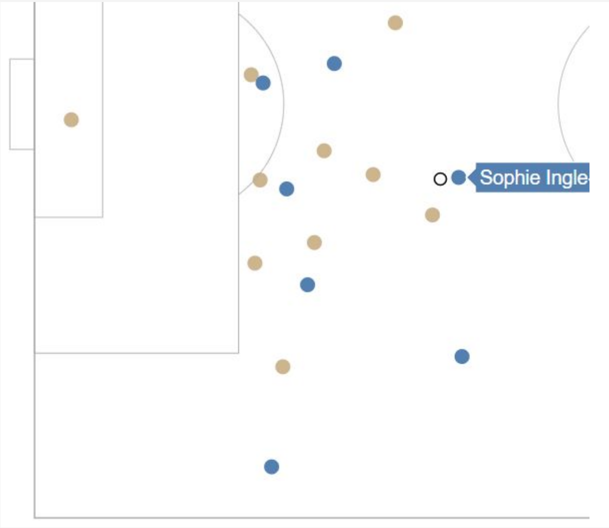
Start of sequence
Ball to goal distance: 42.04 m



1st event
Ball to goal distance: 40.38 m



2nd event
Ball to goal distance: 34.68 m - **Success**



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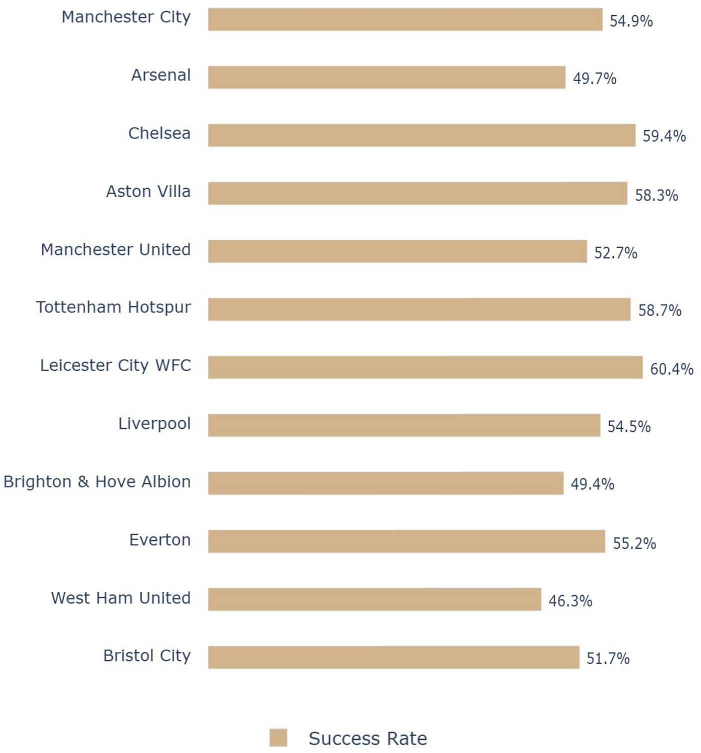
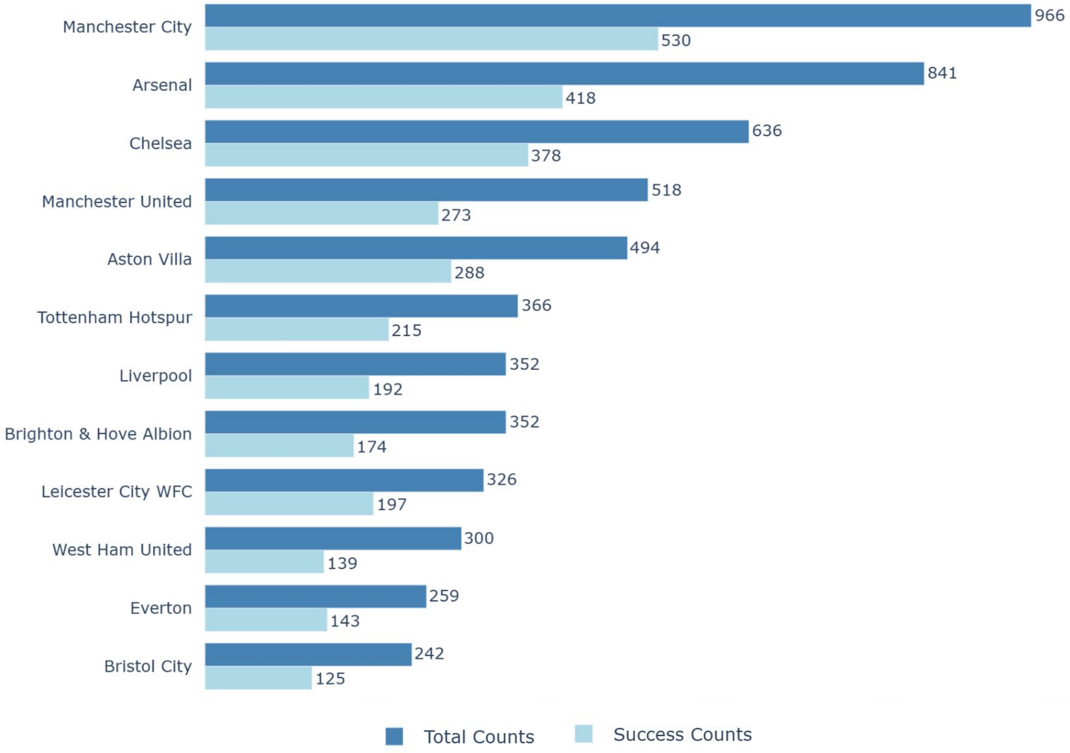
1.3 Team Performance

Manchester City and Arsenal lead in the total number of successful sequences. However, some teams with much lower counts achieve impressive success rates—for instance, Leicester City succeeded in 60.4% of all their wide attack sequences, top of all teams..





2 Context Variables

As the team performance differs, each sequence faces difference attacking difficulties. Here are a few variables considered to have influences on the sequence result.

- **Score difference**
  The scoring situation at the start of sequence can affect players' aggressive levels. It may also reflect the skill disparity between the teams.

- **Count of defenders in the box**
  With a sufficient number of defenders in the box, the main defender of the sequence has more freedom to leave space behind and press hard, thereby increasing the attacking difficulty.

- **Count of attacker** (beyond the attacking point)
  From the 2 meters behind ball location to the goal line, all the attackers within this zone are considered as potential helpers to assist the sequence.

- **Home vs Away**
  Playing at a home stadium is often believed to impact a team's performance positively.

- **Sum of Freedom**
  The available space where an attacker can move with minimal threat. This is calculated using a Voronoi diagram, as detailed on the next page.

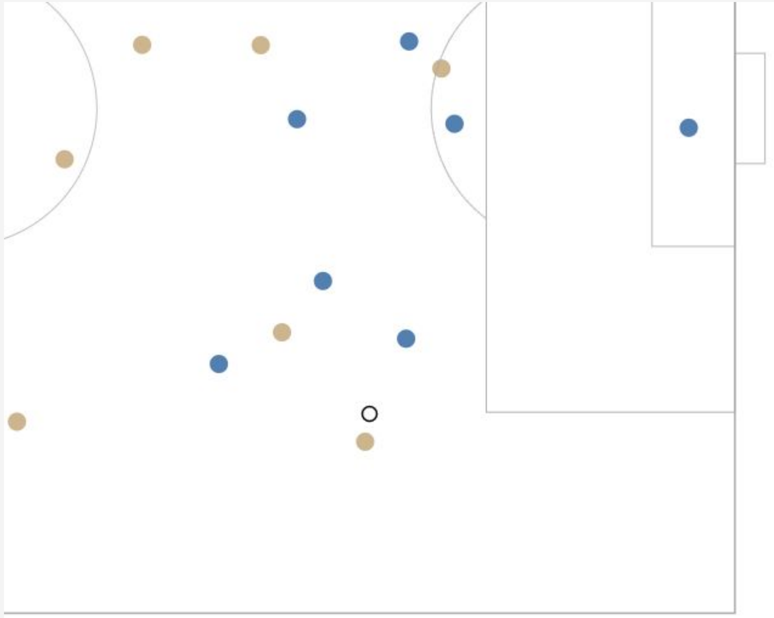
2.1 Sum of Freedom

For each sequence, a Voronoi site is generated for the ball and nearby defenders. The site is divided by a line perpendicular to the line connecting the ball and the center of the goal. The Sum of Freedom is defined as the sum of the site areas closer to and farther from the goal, with a heavier weight applied to the area closer to the goal

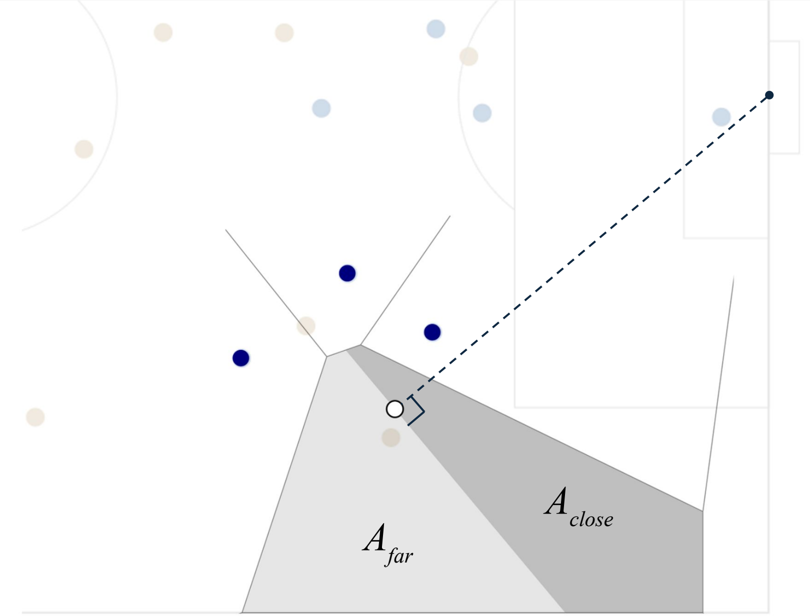
The boundary of the Voronoi diagram was the sidelines, the goal lines, and 20 m away from the ball to four directions.

$$SoF = log(A_{far} + 1) + A_{close}$$

Example 1 start of sequence



SoF = 166.9 m^2 Result: Success



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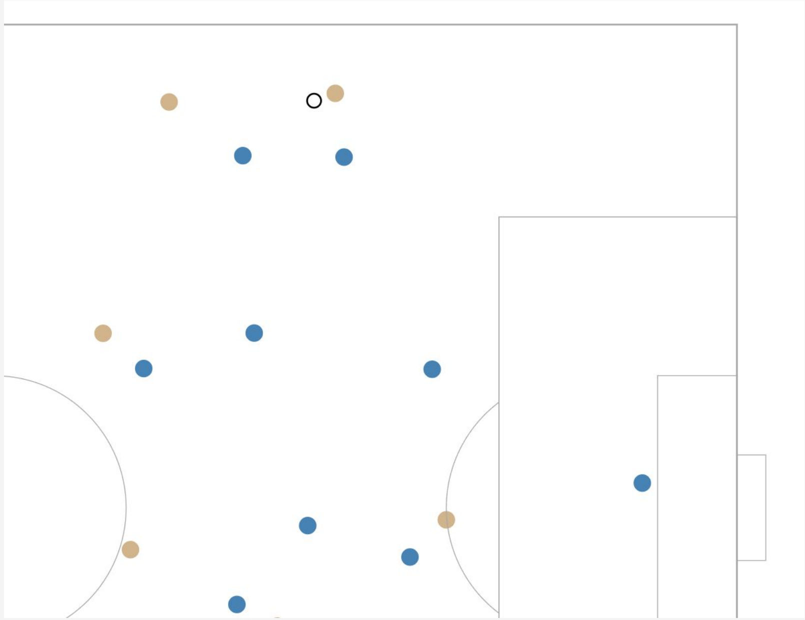
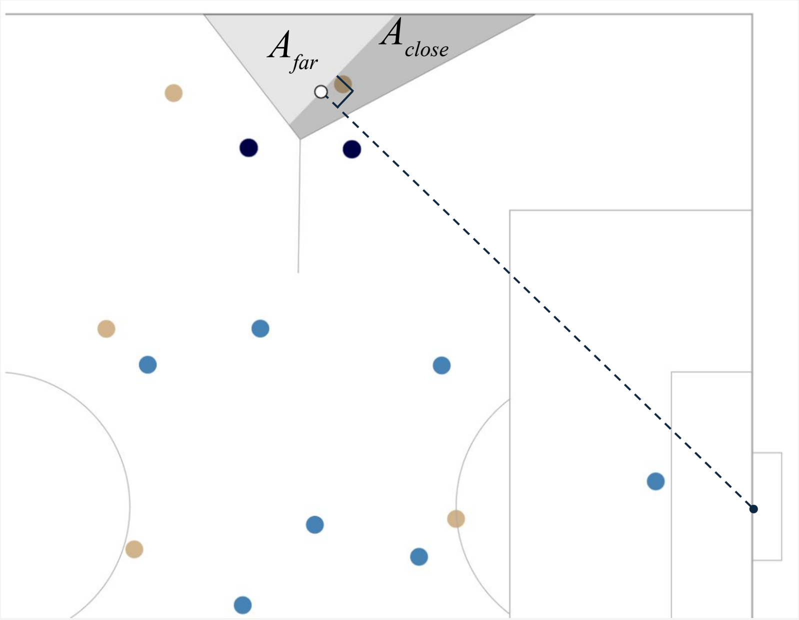
Example 2 start of sequence

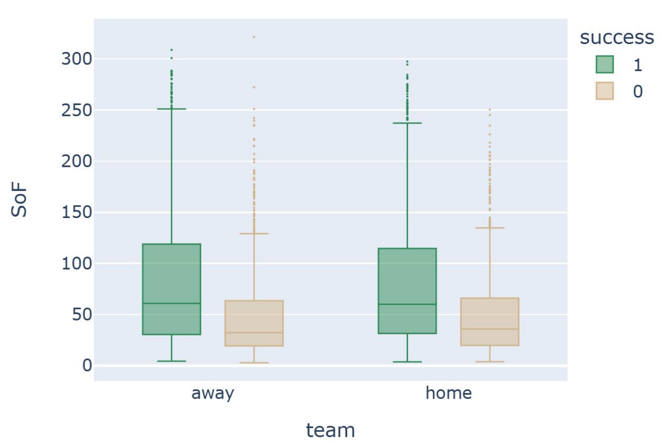


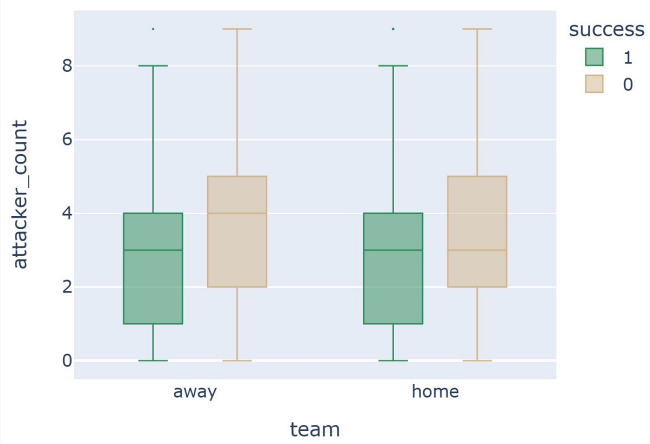
SoF = 51.3 m^2 Result: non-success

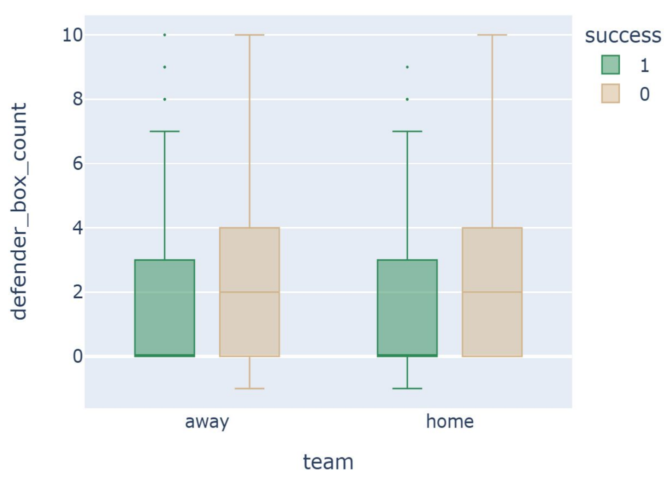


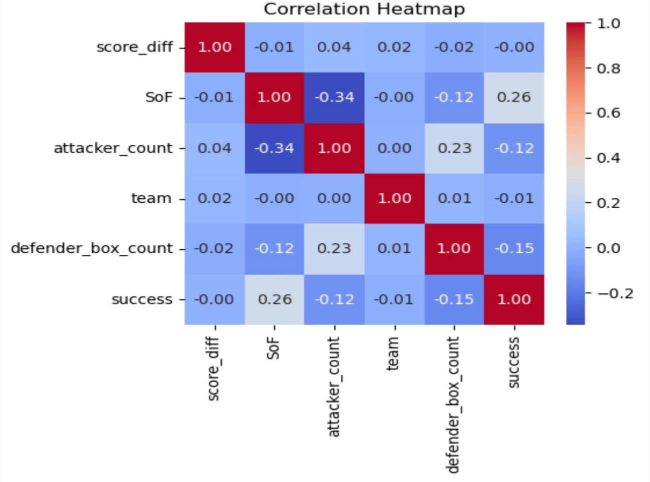
2.2 Feature Validation

A few feature exploration reveals the significance of SoF, defender_box_count, and attacker_count to the sequence result.









3 Models

Using the variables mentioned as features, a few classification models were trained to reveal how much variance of the sequence result can be explained by contextual influences.

In the report on the right, label 1 represents success, label 0 represent unsuccess.

3392 randomly selected sequences were left out before the model training and was used for player evaluation in the next section..

```
Model: RandomForest
Accuracy: 0.6438
Classification Report:
              precision    recall  f1-score   support

           0       0.59      0.67      0.63       203
           1       0.70      0.63      0.66       249

    accuracy                           0.64       452
   macro avg       0.64      0.65      0.64       452
weighted avg       0.65      0.64      0.64       452

Confusion Matrix:
[[135  68]
 [ 93 156]]
```

```
Model: GradientBoosting
Accuracy: 0.6372
Classification Report:
              precision    recall  f1-score   support

           0       0.57      0.78      0.66       203
           1       0.75      0.52      0.61       249

    accuracy                           0.64       452
   macro avg       0.66      0.65      0.64       452
weighted avg       0.67      0.64      0.63       452

Confusion Matrix:
[[159  44]
 [120 129]]
```

```
Model: LogisticRegression
Accuracy: 0.6283
Classification Report:
              precision    recall  f1-score   support

           0       0.56      0.75      0.65       203
           1       0.72      0.53      0.61       249

    accuracy                           0.63       452
   macro avg       0.64      0.64      0.63       452
weighted avg       0.65      0.63      0.63       452

Confusion Matrix:
[[153  50]
 [118 131]]
```

```
Model: KNeighbors
Accuracy: 0.5774
Classification Report:
              precision    recall  f1-score   support

           0       0.53      0.52      0.52       203
           1       0.61      0.63      0.62       249

    accuracy                           0.58       452
   macro avg       0.57      0.57      0.57       452
weighted avg       0.58      0.58      0.58       452

Confusion Matrix:
[[105  98]
 [ 93 156]]
```

4 Player Evaluation

The variance that were not explained by contextual influences should be heavily influenced by the players' capabilities:

- Outstanding attackers would succeed on scenarios which the model considered to be difficult to succeed.
- Outstanding defenders would prevent an attacking success on scenarios considered to be easy to succeed.

Among the four models, the GradientBoosting model was chosen to evaluate attacker, because of its better performance on label 0 (unsuccess), the RandomForest model chosen to evaluate defender, because of its better performance on label 1 (success).

4.1 Attacker Evaluation

Among attacker who have faced more than 15 difficult scenarios from the evaluation set, Adriana Leon, Mary Boio Fowler, and Kirsty Hanson ranked high for the percentage of difficult situation they succeeded. However, Chloe Maggie Kelly, Caitlin Jade Foord, and Lauren May Hemp made no less contribution with the total count of difficult situation they succeeded.

recipient_name	success_difficult_ratio	success_difficult	difficult_count
Adriana Leon	0.73	16	22
Mary Boio Fowler	0.63	22	35
Kirsty Hanson	0.61	17	28
Ella Toone	0.59	24	41
Chloe Maggie Kelly	0.57	53	93
Cloe Lacasse	0.55	12	22
Caitlin Jade Foord	0.54	35	65
Lauren May Hemp	0.52	27	52
Sarah Emma Mayling	0.52	14	27
Niamh Louise Charles	0.51	21	41
Lisa Catherine Evans	0.50	11	22
Lauren James	0.50	13	26
Kenza Dali	0.48	15	31
Leila Ouahabi El Ouahabi	0.47	20	43
Grace Clinton	0.43	9	21
Bethany Jane Mead	0.41	18	44

4.1 Defender Evaluation

Defender evaluation was focused on the 'paired players' who were the closest to the ball receiver at the start of sequence.

paired_player	unsuccess_easy_ratio	unsucceed_easy	easy_count	difficult_count
Ella Mae Florence Powell	0.41	22	54	36
Sarah Emma Mayling	0.39	16	41	30
Heather Payne	0.27	13	48	28
Ashleigh Neville	0.50	12	24	18
Katie Robinson	0.41	11	27	15
Ffion Morgan	0.33	11	33	31
Jamie-Lee Napier	0.30	11	37	45
Niamh Louise Charles	0.48	11	23	23
Mayumi Pacheco	0.41	11	27	30
Lisa Catherine Evans	0.52	11	21	12
Kerstin Yasmijn Casparij	0.41	9	22	6
Grace Clinton	0.50	9	18	24
Katie McCabe	0.42	8	19	11
Noelle Maritz	0.53	8	15	14
Emma Koivisto	0.25	8	32	22
Naomi Layzell	0.40	8	20	22
Jutta Rantala	0.54	7	13	11
Laura Madison Blindkilde Brown	0.54	7	13	5