Valuing the Effect of Off-Ball Runs in Increasing Dribble Success

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"Today, without players who dribble, nothing can be done. Attacking a team that is stuck in its own goal, without players who dribble, who do not get you superiority with moves into spaces, is impossible."
Pep Guardiola (2022)

"If I play with one or two touches within a second or two to you [via a pass], you know exactly what will happen. It's communication. It's talking. If a player runs and dribbles with the ball all the time, no one knows what will happen."
Jon Dahl Tomasson (2025)

INTRODUCTION

Pep Guardiola, perhaps the greatest manager of all, has spoken multiple times about the necessity of dribblers. However, dribbling in the current tactical environment tends to be discouraged or limited to certain zones or situations in favor of passing due to the greater importance of team cohesion and risk aversion. Often, dribbling is seen as an individual action, unaffected and unreadable by other players. For example, Jon Dahl Tomasson's quote above highlights the perspective of some coaches that view dribbling as a disruptive noise that cannot be readily understood by other players within the clear communication of the passing game. Martin Rafelt of Spielverlagerung, in episode 2 of the podcast The Third Circle, critiqued this view, and stressed the need for players to learn effective off-ball movement for when a teammate is dribbling and, in the same episode, co-host and coach Jamie Hamilton professed that the language of dribbling is not very obvious to players and coaches.

This research seeks to find the voices in the so-called disruptive noise of dribbling and explores connections between off-ball runs and dribbling success. Specifically, I address the following questions with the goal of increasing our understanding of ways that off-ball runs can facilitate dribbling success under different scenarios (channels, phases of play, etc.):

1. How do off-ball runs impact dribble success and how does this vary across run types, phases of play, and vertical channels?
2. How are dribble events impacted by the collective off-ball movement of teammates?

This research will advance our understanding of how off-ball movement affects dribbling outcomes and help lead to the production of actionable metrics and principles that coaches and analysts can use to quantify and improve off-ball movement during dribbles. Moreover, research highlighting relationships between dribbling and off-ball movements will further contribute to the recognition that dribbling outcomes are determined by more than a dribbler's individual skill, and that the right off-ball runs and team movement patterns at the right time, can contribute to dribbling success.

METHODS

Data Acquisition and Extraction

Data from 319 matches from the 2024 NWSL Season and the 2024/25 Women's Super League were utilized in the analyses. Of these games, 45 matches were removed from the dataset because they failed Skillcorner's quality check, and another eight failed to download after multiple attempts, resulting in a total of 266 matches included in the analyses. Using Python, dribble events from these matches were extracted from the Wyscout data (n=11,463). For the dataset provided, Wyscout defined dribbles as types of ground duels in which one player tries to move past an opposing player while trying to maintain possession of the ball. Off-ball run data from runs that occurred during these dribbles were identified based on timestamps and extracted from Skillcorner's dataset (specific details described below). Statistical analyses were conducted using JMP version 18.2.2 (JMP.com), and Python was used to generate graphs and figures to visualize results.

Objective 1: How does each off-ball run impact dribble success?
For this analysis, I focused on how individual runs influenced dribbling success. To determine success, I looked at two metrics collected by Wyscout: whether the ball was kept by the dribbler ("ball retained"; True/False), and whether the ball was progressed by the dribbler ("ball progressed"; True/False). Data from Skillcorner was used to characterize individual runs occurring during each dribble. This included: (1) the type of run made (10 types of runs: behind, coming short, cross receiver, dropping off, overlap, pulling half space, pulling wide, run ahead of ball, support, underlap), (2) vertical channel of the run (5 levels: central, near-side half space, near-side wide, far-side half-space, far-side wide), (3) the difference between the run and dribble channels ("channel difference," 5 levels: 0 (same channel), 1, 2, 3, and 4 channels away from each other), and (4) possession phase during the dribble. The possession phases included in the analysis were Build Up, Create, Finish, Quick Break, Transition, and Chaotic. The Direct, Set Play, and Disruption possession phases were excluded from the analysis due to low sample sizes in the data. This resulted in 10,638 runs analyzed. Generalized Linear Mixed Models (GLMM; binomial distribution with logit link) were utilized to test for the effects of possession phase, run type, channel, and channel difference on ball retention (True/False) and ball progression (True/False) of dribbling events. Interactions among the main effects were not included in the models due to insufficient sample sizes of certain combinations of run phases, run types, channels, and channel differences. When significant main effects were identified, pairwise comparisons were evaluated using the Tukey Kramer Method to account for unequal sample sizes to identify differences. 95% Confidence Intervals (CI) were generated associated with probabilities of success and key results were summarized in tables and figures.

Objective 2: How does collective team movement impact dribble success?
For this analysis, I evaluated how collective team off-ball movement during a dribbling event impacted dribbling success. As above, to determine success, I looked at whether the ball was retained by the dribbler (True/False) and whether the ball was progressed by the dribbler (True/False). Analysis was restricted to the same possession phases as above (Build Up, Create, Finish, Quick Break, Transition, and Chaotic). I conducted two tests to characterize off-ball movement during dribbles. First, I simply tested if the number of off-ball runs that occurred during a dribble affected probabilities of ball retention or ball progression regardless of the situation (phase of play, channel, etc.) or type of run. This was done using GLMM (binomial distribution with logit link). Second, I evaluated how collective off-ball team movement patterns, based on the number of each type of run that occurred during the dribble, affected retention and progression. To do this, I utilized k means clustering (maximum number of iterations=300), a machine-learning technique which groups data into clusters based on their characteristics (in this case the number and types of runs occurring during a dribble). I used cubic clustering comparison fit statistic (SAS Institute 1983) to determine the optimal cluster number of the dataset. This analysis identified 13 collective off-ball movement patterns. Of the 13, five movement patterns had less than 100 events, and were removed from analysis due to low sample sizes. This resulted in eight movement patterns that were included in the analysis. Separate Generalized Linear Mixed Models (binomial distribution with logit link) were developed to test for differences in the probability of ball retention and ball progression among the eight movement patterns. Highly unbalanced data and low sample sizes prevented more complex models which accounted for phase of play, channel, and other potential covariates as well as interactions. 95% Confidence Intervals (CI) were generated associated with probabilities of dribble success and key results were summarized in tables and figures.

RESULTS

Statistical analyses revealed that off-ball movement, evaluated both individually and collectively, significantly affected the probability of ball retention and progression during dribbling events.

Objective 1. For ball retention while dribbling, GLMM revealed Possession Phase, Run Type, and Run Channel all had significant effects on the probability of ball retention (Table 1). The likelihood of retention averaged 81.7% (CI: 81.0-82.5) across the six possession phases analyzed, but varied considerably across phases, ranging from 60.1% (CI: 55.3-64.6) during the Chaotic phase to 92.2% retention (CI: 90.0-94.0) during Quick Breaks. Run Type also had a significant effect on ball retention (Figure 1 and Table 1). In particular, the run type Pulling Half Space led to a significantly lower rate of ball retention, 66.7% (CI: 57.5-74.7), compared to other run types. Pairwise comparisons highlighted this result: for example, the odds of keeping the ball with Behind (84.7%), Cross Receiver (86.7%), and Overlap (85.4%) runs ranged from 2.17-2.77 times greater than the odds when a Pulling Half Space run is made (Table 2). Run Channel also affected the probability of ball retention (Table 1) and ranged from 76.8% (CI 74.9-78.5) in the near side wide channel to 87.8% (CI: 85.1-90.1) in the far-side half space; however, pairwise comparisons did not find significant differences between the channels.

Table 1. Results of Generalized Linear Mixed Models (GLMM) testing for factor differences in the probability of ball retention and ball progression during dribbling events.

	BALL RETAINED			BALL PROGRESSED		
Factor	**DF**	**Chi-Square**	**P**	**DF**	**Chi-Square**	**P**
Possession Phase	5	177.519	<0.0001	5	82.632	<0.0001
Run Type	9	33.218	0.0001	9	48.042	<0.0001
Run Channel	4	11.164	0.0248	4	1.2230	0.8743
Channel Difference	4	5.0173	0.2855	4	19.140	0.0007

GLMM results testing for main effects on ball progression while dribbling were similar (Tables 1-2, Figure 1). In this case, Possession Phase, Run Type, and Channel Difference all significantly affected progression probabilities. The likelihood of progressing the ball averaged 66.2% (CI: 65.3-67.1) across the possession phases analyzed. Effects of Possession Phase and Run Type on progression were generally similar to those on retention, albeit with overall lower success probabilities and a few notable differences: dribbles accompanied by runs Behind (71.2%, CI: 67.8-74.3) and Cross Receiver runs (71.8%, CI: 70.2-73.2) had a greater likelihood to progress the ball than dribbles accompanied by Pulling Half Space runs (51.4%, CI: 42.2-60.4), Pulling Wide runs (59.0%, CI: 51.4-66.2), and Underlaps (58.2%, CI: 51.7-64.1). Interestingly, certain run types exhibited ball progression probabilities that were noticeably lower than their probabilities for ball retention compared to other run types. For example, Underlaps and Overlaps, which both had above average probabilities (83.5% and 85.4% respectively) for retaining the ball, had below average probabilities for progressing the ball (58.0% and 61.6% respectively). Channel Difference also significantly affected ball progression. Pairwise comparisons showed that runs in the same channel or an adjacent channel to the dribble led to significantly lower odds of ball progression than runs two or three channels away (Table 2).

Figure 1. Off-ball probability of ball retention and progression (percent success ± 95% confidence intervals) during dribbling events by run type. Letters indicate significant differences from pairwise comparisons (Tukey Kramer).

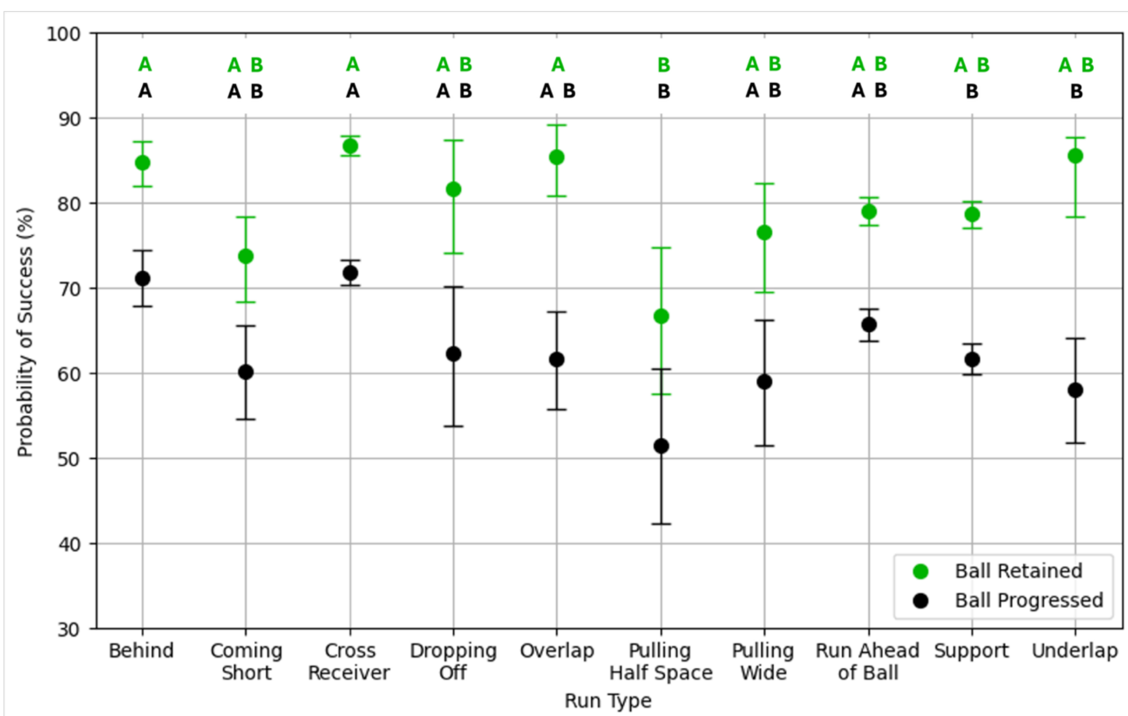

Table 2. Odds ratios of the probabilities of the ball being retained or progressed during a dribbling event identified as significantly different from one another in post-hoc pairwise comparisons (Tukey Kramer).

BALL RETAINED DURING DRIBBLE					
Possession Phase	**Possession Phase**	**Odds Ratio**	**Odds Ratio SE**	**t-ratio**	**P**
Build Up	Quick Break	0.377	0.087	-4.21	0.0004
Build Up	Chaotic	2.598	0.530	4.68	<0.0001
Create	Finish	0.641	0.045	-6.25	<0.0001
Create	Quick Break	0.282	0.043	-8.13	<0.0001
Create	Transition	0.620	0.063	-4.67	<0.0001
Create	Chaotic	1.944	0.220	5.85	<0.0001
Finish	Quick Break	0.440	0.064	-5.58	<0.0001
Finish	Chaotic	3.032	0.322	10.45	<0.0001
Quick Break	Transition	2.196	0.360	4.80	<0.0001
Quick Break	Chaotic	6.877	1.195	11.09	<0.0001
Transition	Chaotic	3.130	0.404	8.84	<0.0001
Run Type	**Run Type**	**Odds Ratio**	**Odds Ratio SE**	**t-ratio**	**P**
Behind	Pulling Half Space	2.373	0.546	3.76	0.0066
Cross Receiver	Pulling Half Space	2.166	0.468	3.57	0.0130
Overlap	Pulling Half Space	2.773	0.756	3.74	0.0070
BALL PROGRESSED DURING DRIBBLE					
Possession Phase	**Possession Phase**	**Odds Ratio**	**Odds Ratio SE**	**t-ratio**	**P**
Build Up	Quick Break	0.568	0.100	-3.19	0.0177
Build Up	Chaotic	1.740	0.310	3.11	0.0231
Create	Quick Break	0.638	0.066	-4.32	0.0002
Create	Chaotic	1.951	0.212	6.14	<0.0001
Finish	Quick Break	0.670	0.062	-4.32	0.0002
Finish	Chaotic	2.051	0.208	7.08	<0.0001
Quick Break	Chaotic	3.058	0.402	8.50	<0.0001
Transition	Chaotic	2.442	0.286	7.61	<0.0001
Run Type	**Run Type**	**Odds Ratio**	**Odds Ratio SE**	**t-ratio**	**P**
Behind	Pulling Half Space	2.197	0.458	3.77	0.0063
Behind	Support	1.484	0.137	4.26	0.0009
Behind	Underlap	1.712	0.272	3.39	0.0248
Cross Receiver	Pulling Half Space	2.086	0.415	3.70	0.0083
Cross Receiver	Support	1.409	0.092	5.21	<0.0001
Cross Receiver	Underlap	1.626	0.234	3.37	0.0257
Channel Difference	**Channel Difference**	**Odds Ratio**	**Odds Ratio SE**	**t-ratio**	**P**
0	2	0.791	0.058	-3.17	0.0015
0	3	0.473	0.096	-3.67	0.0002
1	2	0.843	0.052	-2.71	0.0067
1	3	0.505	0.099	-3.45	0.0006
2	3	0.598	0.116	-2.63	0.0086

Objective 2. Analyses revealed that the number of runs occurring concurrently with a dribbling event had a significant effect on both ball retention (df=4; Chi-square=294.183; p<0.0001) and progression (df=4; Chi-square=347.396; p<0.0001). In both instances, the probability of success significantly increased with the number of concurrent runs (Figure 2). The likelihood of successfully retaining or progressing the ball with no off-ball movement was 66.0% (CI: 64.7-67.3) and 47.3% (CI: 45.9-48.7) respectively and increased to 90.7% (CI:86.4-93.7) and 76.5% (CI: 70.9-81.4) respectively with four concurrent off-ball runs. Odds ratios from pairwise comparison highlight the importance of off-ball runs to the probability of keeping and/or progressing the ball while dribbling (Table 3).

Figure 2. Relationship between the probability of ball retention and progression (percent success ± 95% confidence intervals) while dribbling with the number of concurrent off-ball runs. Statistical analysis excluded 5+ number of runs due to low sample sizes.

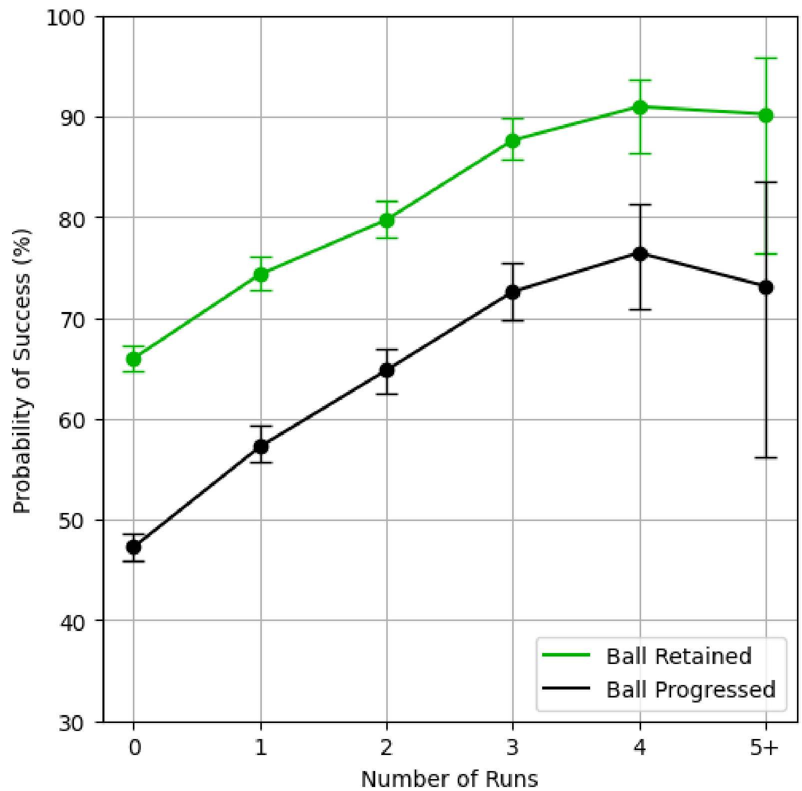

Table 3. Results of Generalized Linear Mixed Models (GLMM) testing for significance of the number of runs in the probability of ball retention and ball progression during dribbling events.

		Ball Retained			Ball Progressed		
Number of Runs	**Number of Runs**	**Odds Ratio**	**t Ratio**	**Prob>|t|**	**Odds Ratio**	**t Ratio**	**Prob>|t|**
1	0	1.504	-7.69	<.0001	1.514	-8.66	<.0001
2	0	2.045	-10.67	<.0001	2.051	-12.42	<.0001
3	0	3.768	-12.72	<.0001	2.982	-13.94	<.0001
4	0	5.016	-7.30	<.0001	3.634	-8.44	<.0001
2	1	1.36	-4.15	0.0003	1.354	-4.79	<.0001
3	1	2.505	-8.43	<.0001	1.969	-8.21	<.0001
4	1	3.335	-5.25	<.0001	2.399	-5.65	<.0001
3	2	1.842	-5.39	<.0001	1.454	-4.22	0.0002
4	2	2.452	-3.95	0.0007	1.771	-3.61	0.0028
4	3	1.331	-1.19	0.7578	1.218	-1.18	0.7608

The eight collective movement patterns identified by k means clustering varied considerably among one another in the type and number of runs (Table 4). I labelled clusters based on their dominant run types; for example, dribbling events in the cluster labeled "Crosses" averaged 1.07 Cross Receiver run, in addition to 0.68 Support runs, and 0.01 Dropping Off and Underlap runs (Table 4). GLMM models found significant differences in the likelihood of keeping (df=7; ChiSquare=248.859; p<0.0001) and progressing (df=7; ChiSquare=285.999; p<0.0001) the ball among the different collective movement patterns.

The probability of ball retention varied significantly among collective movement patterns, ranging from 66.0% (CI: 64.6-67.3) among dribbles with no off-ball runs to 85.2% (CI: 80.4-89.0) among dribbles in the Overlaps movement pattern group (Figure 3). Probability of ball progression ranged from 47.3% (CI: 45.9-48.7) among dribbles with no off-ball runs to 67.0% (CI:64.3-69.7) among dribbles in the Stretch movement group (Figure 3). Pairwise comparisons revealed complex relationships between ball retention and possession among collective movement patterns.

Table 4. Team collective movement pattern groups identified by k means clustering of concurrent runs (number and type of runs) during dribble events (N=10,613). Numbers are the mean number of runs of each run type per collective movement pattern.

		Collective Movement Pattern Description (from k means clustering)							
		No Runs (n=4880)	**Coming Short** (n=222)	**Pulling Wide** (n=148)	**Ahead of Ball** (n=1038)	**Crosses** (n=2721)	**Stretch** (n=1144)	**Underlaps** (n=203)	**Overlaps** (n=257)
Run Type	**Behind**	0	0.06	0.05	0	0	0.59	0	0.11
	Coming Short	0	1.05	0.14	0	0	0	0	0
	Cross Receiver	0	0.11	0.04	0	1.07	0.24	0.37	0.39
	Dropping Off	0	0	0	0	0.01	0	0	0
	Overlap	0	0.01	0	0	0	0	0.02	1.01
	Pulling Wide	0	0	1	0	0	0	0	0
	Run Ahead of Ball	0	0.18	0.28	1.31	0	0.84	0.08	0.31
	Support	0	0.08	0.07	0	0.68	0.66	0	0.28
	Underlap	0	0	0.01	0	0.01	0	1	0

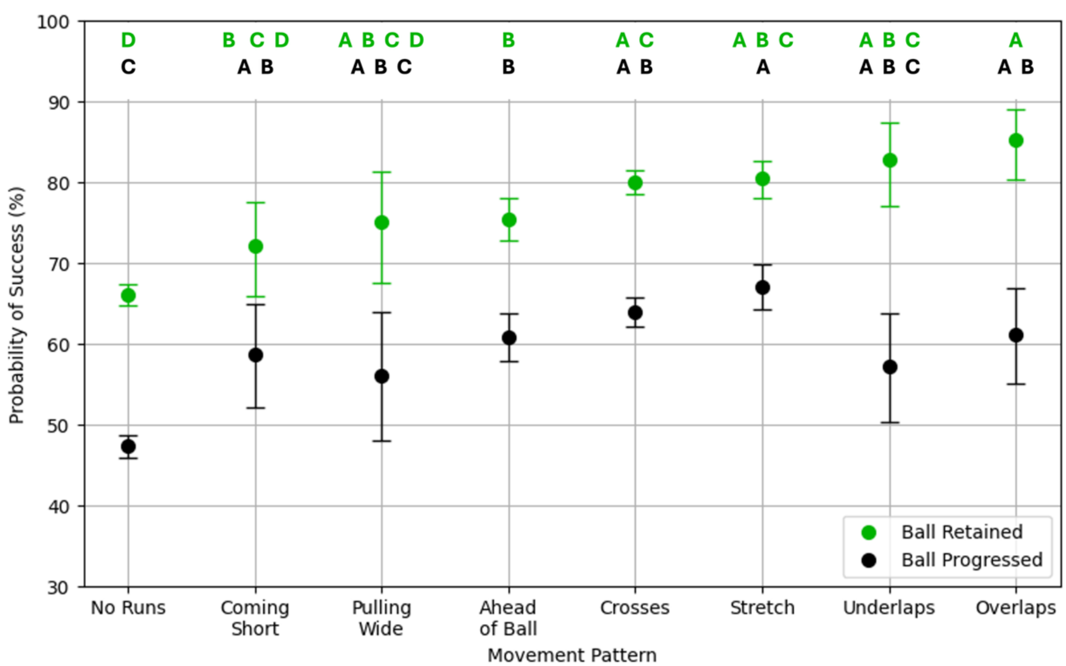

Figure 3. Differences in probabilities of ball retention and progression (percent success ± 95% confidence intervals) among collective movement pattern groups identified by k means clustering. Letters indicate significant differences from pairwise comparisons (Tukey Kramer).

DISCUSSION

Results from this research highlight that dribbling success is not simply dependent upon the skill of the dribbler but rather is influenced by the off-ball movements of teammates. The value of off-ball movement in improving dribbling outcomes varied depending on a number of factors, including possession phase, the number and types of runs, run channel, and more. Effects were seen in analyses of both individual runs and collective team movement patterns.

The finding that dribbling success is influenced by situation (possession phase) and off-ball movements (e.g. run types and channels) is intriguing and provides potential opportunities to develop situation-specific off-ball run triggers during dribbling actions that will improve dribbling outcomes. Once triggers are identified, they can be incorporated by coaching staff into player development and tactical models. To fully develop this, a more complex model, which includes additional main effects (e.g. dribble channel) and well as interactions among effects (e.g. possession phase x run type) would need to be developed and analyzed with more robust machine learning-based predictive models (e.g. Random Forest). This would require a larger dataset than what was available for my analyses.

One striking finding from my analyses was the strong, positive relationship between the number of off-ball runs and dribbling success. Just one off-ball run increased the dribble success probability of ball retention and progression by nearly 10% compared to no off-ball runs; dribbling events with four concurrent runs increased the dribbling success by approximately 25%. As noted above, this finding allows for the development of clear guidelines that can be incorporated into training sessions. This analysis did not consider other important factors such as those pertaining to the situation (e.g. possession phase, location on the field) and their interactions due to insufficient sample sizes in some instances. More complex models need to be developed to more fully test and validate these findings in order to develop clear coaching points and metrics that can be incorporated into soccer analytics datasets (e.g. Skillcorner).

Evaluating collective off-ball movement patterns provided additional insight to how movement can impact dribbling outcomes. Outcomes whether in terms of retention or progression were affect by team movement. These findings, again, highlight the degree to which the lack of movement (no off-ball runs) negatively impacts dribbling outcomes (it was the only movement pattern with a ball progression probability < 50%). While differences were found among the movement patterns, interpretation of pairwise comparisons were difficult due to large confidence intervals (a product of low sample sizes for some patterns as well as variation in the data). This analysis did not account for possession phases, location, and other key factors (or their interactions) which if included, may clarify relationships. As noted above, a larger dataset and more sophisticated machine learning analyses would provide a more complete understanding. Despite the limitation of my analysis, results provide strong evidence highlighting the importance of collective team movement in affecting dribbling outcomes.

CONCLUSION

In summary, results from this research highlight three keys, interrelated points:

- Dribbling success is affected by team movement and therefore dribbling outcomes are not solely the product of the dribbler's skill; thus, players without the ball are active participants during a teammate's dribble.
- Off-ball movement patterns and their impact on dribbling success can be described and characterized; therefore, situation-specific movements can be taught and quantified.

- Additional analyses are needed to fully characterize relationships between dribbling and off-ball movement in order to develop key principles and triggers as well as to quantify metrics that can be incorporated into analytics packages.

Findings from this study directly contradict the notion that dribbling cannot be understood by teammates and that dribbling creates confusion and should therefore be limited as suggested by Jon Dahl Tomasson (quote on page 1). Actions for players to take when a teammate is dribbling can be described and taught, allowing players to "communicate through dribbling" similarly to how Tomasson describes how players communicate through passing. Future research should build upon these findings to further advance our understanding of the language of dribbling.

Literature Cited

Hamilton, J., & Rafelt, M. (Hosts). (2025, February 17). Equilibrium (No. 2) [Audio podcast episode]. In *The Third Circle*. https://shows.acast.com/the-3rd-circle/episodes/67b33fedbce64a060191be64.

SAS Institute Inc. (1983). SAS Technical Report A-108: Cubic Clustering Criterion. Cary, NC: SAS Institute Inc. https://support.sas.com/kb/22/addl/fusion_22540_1_a108_5903.pdf.