1 (2026) 100024

Contents lists available at ScienceDirect

Football Studies

journal homepage: www.sciencedirect.com/journal/football-studies

# Quantifying individual and teammate effects on small-sided football performance through repeated-game observations

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ARTICLE INFO

*Keywords:*
Team Performance
Talent Identification
Small-sided games
Variance decomposition
Performance analysis

ABSTRACT

*Background:* Understanding what determines success in football, whether it stems from individual quality or teammate interactions, remains a significant challenge. Disentangling individual talent from teammate effects has proven particularly difficult in team sports.
*Aim:* Drawing inspiration from biology, we designed an experimental framework to separate the effects of individual players from those of their teammates.
*Methods:* Thirty-one NCAA Division III players (15 men, 16 women) competed in systematically reconfigured 3-versus-3 matches, allowing us to estimate variance components via mixed-effects models.
*Results:* Across both men's and women's datasets, teammate combinations explained more variance in team success (20–23 %) than individual players (11–12 %), though substantial residual variance (64–69 %) indicates performance depends on multiple factors beyond these measured effects. Individual rankings derived from these models correlated only weakly with scores from standardized, unopposed technical skill tests. In the men's dataset, teams composed of three distinct player archetypes outperformed less diverse teams; no such pattern emerged in the women's dataset.
*Conclusion:* These findings highlight the importance of team effects in small-sided football performance contexts, suggesting that scouting and analytics should better account for the emergent properties of team interactions when evaluating players.

"There are teammates who make you better. They're not necessarily the flashiest, the most famous, or the ones who score the most goals, but when you see them, you know you have a much better chance of playing well. That happened to me with Saviola. We understood each other, we saw the same play."
- Pablo Aimar

## Introduction

Understanding how individual and teammate factors contribute to performance in small-sided football can offer insight into the relative influence of personal skill and interpersonal coordination. This distinction remains difficult to establish in sports analysis.

In the context of football, assessing talent is especially difficult due to the sport's fluid, low-scoring, and interdependent nature [1]. Unlike sports where success can be more directly attributed to discrete actions, football outcomes often emerge from chains of events involving multiple players, making it statistically complex to isolate individual impact. This challenge is particularly important because performance depends not only on individual skill but also on how players interact with one another. For instance, two world-class strikers may underperform if they occupy the same spaces and limit each other's opportunities, illustrating how team dynamics can constrain, or enhance, individual contributions.

An ecological dynamics perspective reframes performance as an emergent property arising from interpersonal coordination rather than the aggregation of individual abilities [1,2]. Within this framework, players form functional synergies characterized by dimensional compression and reciprocal compensation, whereby teammates' degrees of freedom become coupled, enabling co-regulated action that transcends individual contributions [3]. Passos et al. [4] showed that collective team performance arises from the interpersonal interactions between players, with interaction quality differentiating successful from unsuccessful outcomes. In football, team tactics are governed by complex processes resulting from networks of interdependent parameters [5], suggesting that performance emerges from the coordination patterns between specific player combinations and not solely from isolated

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https://doi.org/10.1016/j.footst.2026.100024
Received 9 October 2025; Received in revised form 29 December 2025; Accepted 21 January 2026
Available online 22 January 2026

individual abilities. These developments call for analytical approaches capable of separating individual player effects from the emergent effects of specific teammate combinations, a decomposition that has received little empirical attention in the literature. While ecological dynamics theory proposes specific mechanisms underlying team performance, empirical approaches are needed that can first establish *whether* and *how much* teammate combinations matter before investigating the specific coordinative mechanisms through which these effects operate.

Understanding the true nature of player quality in football has clear practical consequences. In talent identification, for example, scouts, coaches, and analysts must predict future success based on limited, and often noisy, information [6]. Traditional scouting methods have long relied on either physical attributes or assessments of technical skill, either subjectively rated by scouts or by a battery of unopposed tests [7]. However, ecological dynamics theory predicts that a player's apparent quality may be significantly shaped by environmental context (e.g., teammates, tactical roles, opposition strength), though empirical quantification of these contextual effects remains limited. Recent advancements in data analytics and player tracking technologies offer more objective tools for evaluating performance, but these, too, struggle to separate the contributions of individuals from those of teammates [8]. A deeper understanding of how individual and contextual effects interact is therefore essential for more accurate assessments of talent.

Here, we draw inspiration from biology, where researchers routinely disentangle the effects of genes and environment to explain variation in phenotypes. In this analogy, individual football players are akin to genotypes, teammates represent the environment, and match performance is the resulting phenotype. Just as biologists partition phenotypic variance into components attributable to genetics, environment, and their interaction [9], we aimed to separate the contribution of individual players from that of the surrounding team context. However, unlike controlled biological experiments where genotype-environment pairings can be systematically varied, football data are observational and constrained by limited substitutions and relatively stable lineups. To overcome this obstacle, we adopted an experimental approach. By repeatedly shuffling team configurations in small-sided games, we isolated the relative effects of individual players and their teammates on overall performance.

## Methods

### *Participants*

Football players from both NCAA Division III men's and women's teams participated in the study. A total of 31 student-athletes (15 men, 16 women), with a mean age of 20.6 (sd = 2.4) for the men and 20.4 (sd = 1.3) for the women, were recruited in spring 2024 (men) and spring 2025 (women). All participants had been recruited to compete at the collegiate level and possessed multi-year competitive playing experience. According to the participant classification framework proposed by McKay et al. [10], our players are best classified as Tier 3 ('highly trained/national level'). During the season, participants engage in structured team training for approximately 7–9 h per week and compete in 1–2 matches per week. Data collection for this study occurred during the off-season, when formal team training volume is substantially reduced. While off-season training status may have increased performance variability, all participants were equally affected, and the experimental design's focus on relative within-player effects across conditions mitigates concerns about absolute fitness levels. All participants provided informed consent prior to data collection. This study was approved by the Institutional Review Board at Kalamazoo College.

### *Small-sided games*

We conducted 3-versus-3 football matches to assess player performance in a controlled yet ecologically valid setting. Small-sided games have been extensively validated as tools for performance analysis and talent identification in soccer, demonstrating moderate-to-strong correlations with full-sided match performance [11] and coach assessments of player quality [12]. While SSGs introduce systematic differences from 11-versus-11 play, including higher ball contacts per player, altered space-to-player ratios, and modified tactical possibilities [13–15], they preserve critical elements of competitive football such as decision-making under pressure [16], spatial awareness and tactical coordination [14,17], and technical skill execution. Indeed, 3-versus-3 formats have been validated as reliable protocols for talent identification [18]. For our purposes, the trade-off between ecological realism and experimental control was acceptable: the reduced team size maximized our ability to systematically vary teammate combinations across matches.

Games were played on a 30 × 15 m (men) or 30 × 10 m (women) artificial turf field with small goals (1.5 ×2 m), with each match lasting 5 min followed by a 2-minute rest period. To maximize data collection across different teammate combinations, team compositions were varied between matches to ensure diverse player pairings. Teams were assigned with the goals of maximizing the number of different teammates each player partnered with, minimizing consecutive matches with identical teammate pairings, and providing each player exposure to different opponents. Team assignments were deliberately structured to achieve broad sampling of player-teammate-opponent combinations while avoiding systematic patterns that could bias results. Players were limited to playing no more than three consecutive games to preserve stamina and maintain performance consistency. At the conclusion of each match, we recorded the final score and individual goal scorers.

The men's dataset included a total of 39 matches played across 4 sessions, with each session lasting approximately 1 h. The mean number of matches per participant was 15.5 (sd = 2.8, range = 8–23 matches). A total of 256 goals were scored across all matches (mean = 6.56 goals per match). The women also played 39 matches in 4 sessions, with a mean number of matches per participant of 14.6 (sd = 6.7, range = 4–20 matches) and 4.1 mean goals per match. Across all matches, the systematic rotation of team compositions produced 85 unique two-player pairings in the men's dataset and 89 in the women's dataset, with pairs competing together an average of 2.8 times (sd = 1.6) and 2.6 times (sd = 1.4), respectively.

Our primary performance outcome was goal differential per match, calculated as the difference between goals scored and goals conceded by each team (e.g., in a 3–1 match, the winning team received +2 and the losing team −2). Goal differential was chosen as it represents a reliable measure of team success, with perfect inter-rater reliability. We also recorded individual goal scorers for each match to enable secondary analyses of offensive contributions. All matches were directly observed and scored in real time. The reliability of goal differential as a performance metric in small-sided games has been established in previous research [18].

### *Mixed-effects model analysis*

We implemented a linear mixed-effects model to partition variance in team performance (goal differential) into components attributable to (1) individual player effects (the consistent contribution each player makes to their team's performance across all the different teammate and opponent contexts they experience), and (2) teammate combination effects (the emergent effect of specific player pairings that produces performance outcomes different from what would be predicted by summing the individual effects of those players). The model included random effects for individual players and for teammate combinations using the lme4 package in R [19]: Goal_diff ∼ (1|Player_ID) + (1|Teammates).

An important limitation of this model structure is that it does not include opponent effects as a separate variance component. While team assignments aimed to provide balanced opponent exposure, opponent quality necessarily varies across matches and is absorbed into the residual variance term. This means that (1) individual and teammate effects are estimated assuming random opponent assignment, (2) some residual variance reflects opponent effects, and (3) systematic imbalances in opponent strength could bias individual player estimates. Future studies with larger sample sizes could extend the model to include opponent effects as an additional random effect: Goal_diff $\sim$ (1|Player_ID) + (1|Teammates) + (1|Opponents), though this substantially increases data requirements.

The Player_ID term captures each individual's consistent effect on performance regardless of who they play with, while the Teammates term captures the unique synergistic (or antagonistic) effects of specific player combinations beyond what would be predicted from their individual effects alone. Note that our model partitions variance into individual and teammate main effects but does not include an individual $\times$ teammate interaction term. Such interactions (analogous to genotype-by-environment interactions in biology) would capture whether specific players' contributions systematically vary depending on which teammates they partner with. While such interactions likely exist, the current sample size and design prioritize estimating the relative magnitude of main effects. Variance components were extracted using the 'VarCorr' function. We also extracted individual player effects as best linear unbiased predictors (BLUPs) from the random effects structure, which represent each player's contribution to team performance after controlling for teammate composition. These individual effects were then used to rank players and examine correlations with both raw performance metrics (mean goal difference) and individual skill assessments. All analyses were conducted in R (version 4.4.1).

It should be noted that observations within the same match are not fully independent (goal differential values are perfectly correlated within teams and perfectly anti-correlated between opposing teams). This structure has several implications: the effective sample size for variance estimation is approximately half the number of observations, as each match generates two interdependent data points, standard errors of variance components may be underestimated if the model does not fully account for this dependency structure, and residual independence assumptions are technically violated. However, our mixed-effects approach remains appropriate for our primary analytic goal, to partition variance into individual and teammate components. The random effects for individual players and teammate combinations are estimated across multiple matches with systematically varied compositions, meaning each player and pair appears in different match contexts with different opponents. While the within-match dependency affects precision estimates, it does not systematically bias the relative magnitudes of individual versus teammate effects, which is the core question we address.

We attempted to estimate confidence intervals for variance components via bootstrap resampling at the match level (1000 iterations). However, these confidence intervals proved unstable, likely due to the combination of crossed random effects, finite sample size, and within-match dependency structure. Given this instability, we have chosen not to report confidence intervals and instead emphasize that the robustness of our findings is demonstrated by the consistent pattern across two independent datasets (men's and women's).

*Individual skill testing*

As a secondary analysis, we examined whether individual player effects derived from the mixed-effects model (which reflect in-game performance across varying team contexts) correlate with isolated technical proficiency assessed through standardized, unopposed skill tests. These technical assessments represent an independent measure of individual skill, distinct from the model-derived individual player effects described above.

We assessed individual skill using a standardized battery of tests adapted from Wilson et al. [20], which have been validated as reliable indicators of football skill proficiency, on 8 male and 9 female players (due to scheduling constraints, not all players could participate in the individual skill testing, which was done after all the 3-versus-3 games had taken place; players who did and did not complete technical testing did not differ in matches played [$p_{men}$=0.39, $p_{women}$=0.37] or individual player effect [$p_{men}$=0.20, $p_{women}$=0.19]). The testing battery comprised seven components: juggling (maximum touches using alternating feet within a 1.5 $\times$1.5 m square in 60 s), passing accuracy (8 passes with dominant foot targeting a zoned tarp from 20 m distance using inside-foot technique), shooting accuracy (8 shots targeting the same zoned tarp), lofted passing (8 aerial passes to a target from 35 m distance), dribbling (timed completion of a course involving straight-line dribbling, sharp directional changes, and technical maneuvering with 2-second penalties per cone contact), and 90° and 135° passing (timed completion of 10 cycles alternating passes between two rebound boards positioned 5 m away at 90° or 135° angles, with 5-second penalties for missed targets). All tests were video-recorded for accurate scoring, and raw scores were standardized (z-scores), with time-based measures inverted so that higher standardized scores consistently represented better performance across all tests. Principal component analysis was then used to derive a composite skill index using the first principal component, which served as each participant's overall isolated skill score for subsequent analyses.

*Team composition effect*

Lastly, to evaluate how team composition affects performance, we assigned players that participated in at least 10 matches an 'archetype' using standardized (z-scored) metrics for average goals, goal differential, teammate goals, and scoring consistency (operationalized as the negative coefficient of variation for goals scored, such that higher values indicate more consistent scoring). All z-scores were calculated separately within each sex to account for baseline performance differences between men's and women's datasets. Four distinct archetypes were created: 'goal scorer' (goals_z $>$ 0.5 and consistency_z $>$ 0; $n_{men} = 3$, $n_{women} = 3$), 'team catalyst' (teammate_z $>$ 0.5 and goals_z $<$ 0; $n_{men} = 2$, $n_{women} = 1$), 'defensive specialist' (diff_z $>$ 0 and goals_z $<$ 0; $n_{men} = 2$, $n_{women} = 0$), and 'role player' (all players not meeting the above criteria; $n_{men} = 4$, $n_{women} = 7$). We then compared how teams that had one, two, or three of the same type of player performed.

## Results

*Variance decomposition/mixed-effects model*

For the men's dataset, individual player effects accounted for 10.9 % of the total variance in goal differential, teammate combinations contributed 20.2 %, and residual variance was 68.9 % (Fig. 1). The women's dataset showed a similar pattern, with individual effects explaining 12.3 % of variance, teammate combinations 23.1 %, and residual effects 64.5 % (Fig. 1). The substantial residual variance (65–69 %) encompasses multiple sources of variation including match-to-match fluctuations in performance, opponent effects, environmental conditions, and other random variation inherent to low-scoring contests.

*Individual player effects*

Individual player effects ranged from $-1.7$ to $+0.9$ for men and $-1.29$ to $+1.34$ for women. These effects represent each player's contribution to goal difference after controlling for teammate combinations. The distribution of effects approximated normality in both datasets, with roughly equal numbers of players showing positive and negative contributions relative to the average. In the men's sample, individual player rankings demonstrated partial independence from goal-scoring totals: the highest scorer (32 goals) had an individual player effect of $-0.6$, suggesting his offensive production was

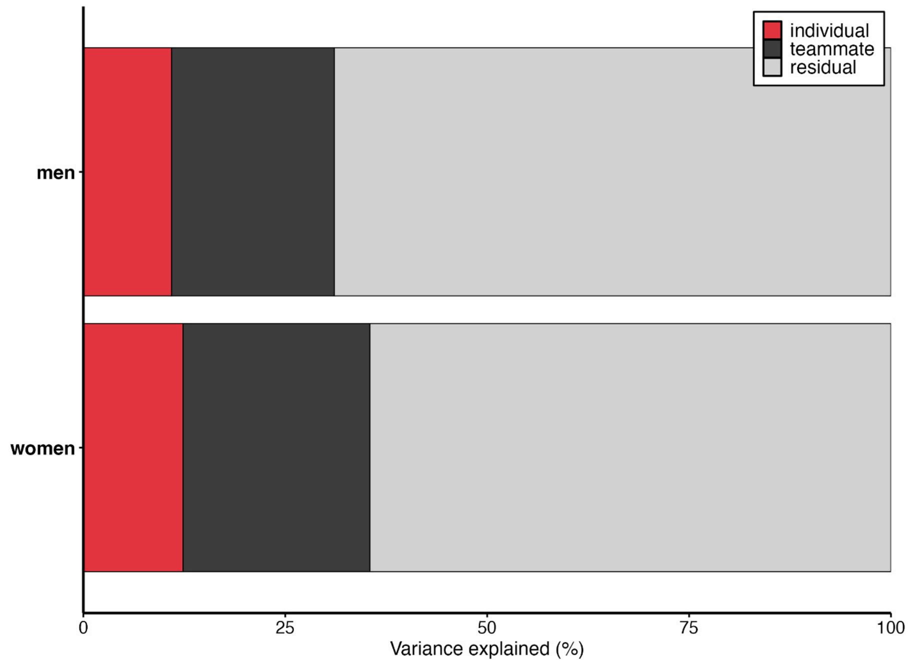


**Fig. 1.** Variance partitioning of football performance into individual and teammate components. Bars represent the percentage of variance in team goal differential explained by individual player effects (red), teammate combinations (black), and residual variance (gray) for women's (top) and men's (bottom) datasets. In both cases, teammate effects outweighed individual effects.

accompanied by negative defensive contributions or occurred disproportionately in matches his teams lost. In the women's dataset, the top goal scorer (38 goals) was also the second highest player by individual effects ranking (BLUP = +1.34), indicating more consistent alignment between offensive production and overall team contribution.

*Relationship with technical skills*

We examined whether individual player effects derived from competitive match performance correlated with a composite index of isolated technical skills (based on unopposed tests of juggling, passing accuracy, shooting, dribbling, and lofted passing). For the subset of 8 male players, the first principal component explained 41.7 % of the variance in isolated technical skills. The correlation between this 'skill index' and the individual player effects from competitive match performance was weak (r = 0.197; 95 % CI: [-0.560, 0.795]; p = 0.640; Fig. 2). For the 9 women, PC1 explained 49.2 % of variance and the correlation between the two variables, though not significant, was higher than for men (r = 0.567; 95 % CI: [-0.155, 0.894]; p = 0.111; Fig. 2).

*Team composition effect*

In the men's dataset, archetype diversity had a significant effect on goal differential ($F_{2,75} = 7.80$, $p < 0.001$, $\eta^2 = 0.17$), with teams containing three distinct player archetypes achieving the highest performance (mean goal differential = 1.24 ± 0.42 [SE]) compared to teams with two archetypes (-1.08 ± 0.45) or one archetype (-2.00 ± 2.04) (Fig. 3). Conversely, women's teams showed no significant relationship between archetype diversity and goal differential ($F_{2,75} = 1.07$,

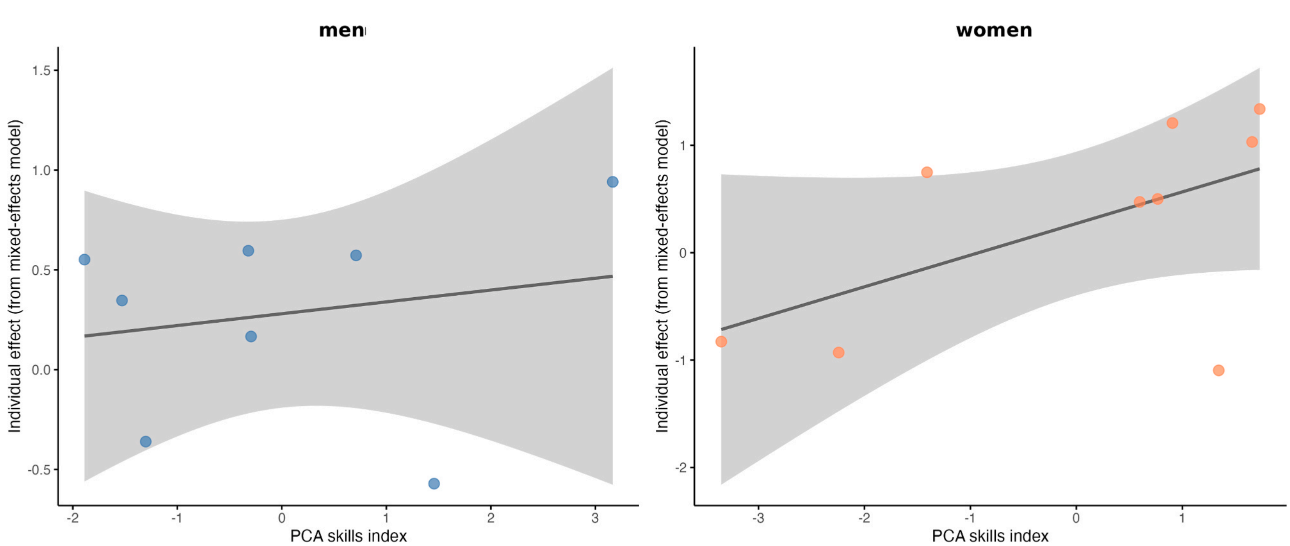


**Fig. 2.** Relationship between individual player effects (from mixed-effects variance decomposition of 3-versus-3 matches) and technical skill proficiency (unopposed skill tests). Correlations were weak for men (left; r = 0.197, p = 0.640) and moderate for women (right; r = 0.567, p = 0.111).

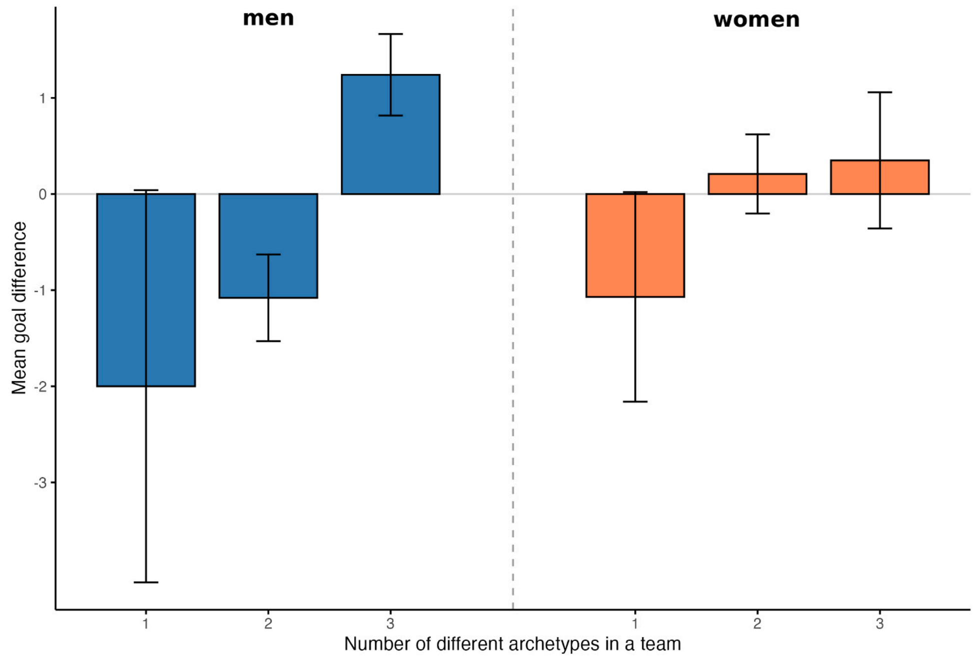


**Fig. 3.** Effect of archetype diversity on team performance. Mean goal differential (±SE) for teams composed of one, two, or three distinct player archetypes. Men's teams with three archetypes outperformed those with less diversity (left; $p < 0.001$), while no significant differences were observed for women's teams (right; $p = 0.35$).

$p = 0.35$, $\eta^2 = 0.03$), with performance remaining relatively stable across all diversity levels (3 archetypes: 0.35 ± 0.71; 2 archetypes: 0.21 ± 0.41; 1 archetype: −1.07 ± 1.09) (Fig. 3). However, this null finding should be interpreted cautiously: the women's dataset had fewer distinct archetypes overall (no defensive specialists, only one team catalyst), resulting in only 3 teams with three different archetypes.

## Discussion

Our experimental design allowed us to partition the effects of individual skill and team context on performance in small-sided football matches. We found that while individual players contributed meaningfully to a team's goal differential (11–12 %), their impact was consistently outweighed by the effect of teammate composition (20–23 %). This pattern, which held across both men's and women's datasets, underscores how much team performance depends on who you play with. The finding that teammate combinations explained approximately twice the variance in performance compared to individual players suggests that player pairings matter substantially for performance outcomes. However, our model structure, which partitions variance into individual and teammate main effects without interaction terms, cannot distinguish between two interpretations of this result. The teammate variance could reflect purely additive effects (where the combined impact of players X and Y equals the sum of their individual effects, and this sum varies across different pairings), or it could reflect true emergent synergies (where players X and Y together produce effects greater or less than the sum of their parts through interpersonal coordination). While ecological dynamics theory posits that the latter mechanism (interpersonal synergies, shared affordances, and coordinated action [21–23]) underlies team performance, our statistical approach quantifies the magnitude of teammate pairing effects without identifying whether they arise through additive combination or emergent coordination. This limitation notwithstanding, the substantial contribution of teammate combinations (regardless of mechanism) challenges approaches that focus exclusively on individual capabilities and underscores the importance of considering who plays with whom.

It is important to note that these effects, while consistent across datasets, collectively account for only about one-third of total performance variance. The substantial residual variance (64–69 %) indicates that performance in small-sided games depends on multiple factors beyond individual and teammate effects measured here, including opponent quality, match-specific dynamics, and the inherent variability of low-scoring contests. Our conclusions therefore focus on the relative contributions of these measured components rather than their absolute predictive power.

The ~20 % of variance explained by teammate combinations reflects the systematic effect of specific player groupings beyond what individual player effects alone predict, emphasizing that team success depends on the unique complementarities among players rather than their isolated abilities alone, whether these complementarities are additive or emergent. It should be noted that our variance decomposition approach provides a statistical approximation of these interaction effects rather than a direct measure of behavioral coordination dynamics. This emergence reflects the formation of team synergies, functional units in which relatively independent degrees of freedom become coupled to behave as one [23,24]. Interestingly, individual performance rankings based on the mixed-effects model showed only weak correlations with isolated technical skill tests, suggesting that in-game effectiveness is not easily predicted by unopposed drills. Additionally, team performance was maximized when players of distinct archetypes were combined, at least in the men's dataset, highlighting the importance of complementary roles in driving team success. Together, these results reinforce the view that football performance is shaped not only by individual skill but also by the emergent dynamics of team interaction.

Our results align with recent work by Bransen and Van Haaren [25], who developed metrics showing that player 'chemistry' (defined as the residual performance of player pairs after accounting for individual effects) contributes meaningfully to team performance. While their approach explicitly models interaction effects (whether specific players perform differently together than expected from their individual abilities alone) and ours partitions main effects, both studies highlight that player pairing dynamics matter beyond individual capabilities. Further, Vilar et al [26]. demonstrated that local player numerical dominance and coordination dynamics in sub-areas of play are fundamental to team success in football, emphasizing that performance emerges from spatially-localized interactions.

Similar patterns emerge in other performance domains. Analysis of Formula One racing [27] revealed that constructor effects account for approximately 88 % of performance variance while driver effects account for only 12 %. In Australian Rules Football, the distribution of individual contributions within teams significantly affects match outcomes, with more evenly distributed goal-scoring patterns associated with greater success [28]. These findings suggest that team effectiveness emerges not just from individual capabilities but from how those capabilities are distributed and coordinated within the group. Similarly, research in organizational psychology has shown that team effectiveness depends not only on the competencies of individual members but also on their ability to coordinate, communicate, and adapt to dynamic situations [29–31]. And even in studies of animal behavior, scientists have found that the success of group-living species often hinges on coordination and distributed cognition rather than on the capabilities of any one individual [32]. Thus, while scouting and analytics have historically focused on identifying elite individual talent, a growing body of research now advocates for models that capture synergies, complementarities, and interdependencies [33,34].

Our findings raise important questions about how talent is identified and evaluated in football. Traditional scouting paradigms often emphasize isolated skill assessments or highlight standout performances in specific contexts, but such approaches may overlook players whose value emerges primarily through team interactions [7,35]. The weak correlation between isolated technical skills and player effects in more realistic contexts suggests that proficiency in drills may not reliably predict a player's influence on team success. This is consistent with recent work arguing for a shift toward ecological, context-rich assessments of skill and adaptability [36].

Implementing this shift toward ecological, context-rich assessment requires specific changes to how academies evaluate players. Rather than relying solely on individual skill tests or observing players in fixed lineups, academy coaches and scouts should systematically vary teammate configurations during small-sided game assessments. This approach allows evaluators to distinguish between players who consistently elevate team performance across diverse partnership contexts and those whose contributions are more dependent on specific teammates. Academies could implement longitudinal tracking systems that record player performance across multiple small-sided 3-game configurations, using variance decomposition methods similar to those employed here to quantify both individual effects and teammate chemistry. Such data would help identify not only technically skilled individuals but also players who possess the harder-to-measure quality of making their teammates better.

Several limitations should be acknowledged. First, while small-sided games provide ecological validity and control over teammate configurations, they could differ from full-sided matches in spatial dynamics and tactical structure [15,37,38]. The results may therefore not fully generalize to 11-v-11 competitions, where positional roles and formations introduce additional layers of interdependence. Future studies with larger team sizes or incorporating dynamic interaction metrics (e.g., pass networks, movement entropy) could provide a more comprehensive understanding of emergent team behavior. Second, our relatively small sample ($N = 31$) of NCAA Division III players limits the generalizability of our findings. Replicating this variance decomposition approach across larger samples spanning multiple competitive levels (from youth to elite professional) would help determine whether the relative contributions of individual versus teammate effects vary with player caliber. Third, the technical skill assessments were conducted on a subset of participants (8 men, 9 women) due to scheduling constraints, resulting in severely underpowered analyses (post-hoc power: 8 % for men, 38 % for women). The weak correlations observed for men ($r = 0.197$) could reflect either a genuinely weak relationship or simply insufficient power to detect a moderate effect. Definitive conclusions about the relationship between isolated technical skills and in-game effectiveness will require adequately powered studies. Fourth, we cannot rule out the possibility that learning or familiarity effects influenced performance across the four testing sessions, particularly as players adapted to the 3-versus-3 format or became more familiar with certain opponents. While our experimental design systematically varied team compositions to minimize systematic biases from such effects, future studies could explicitly model session-level or temporal trends to assess whether performance dynamics changed over time. Moreover, our model did not explicitly partition opponent effects, which were instead absorbed into residual variance. While this simplification was necessary given sample size constraints, it means opponent quality variation contributed to the large residual variance we observed. A more comprehensive decomposition would separate opponent effects from other residual sources and include individual × teammate interaction terms to capture how specific players' contributions vary depending on their partner combinations.

To summarize, our experimental approach revealed that football success emerges from the interplay of individual talents and teammate interactions, with combination effects consistently outweighing individual contributions. While individual players undoubtedly matter, the finding that teammate combinations consistently account for roughly twice the performance variance of individual effects, a pattern replicated across both men's and women's datasets, suggests that team-level interactions play a substantial role in determining outcomes in small-sided games. These findings challenge traditional approaches to talent evaluation that focus primarily on isolated individual abilities. As football analytics continues to evolve, models that explicitly capture the emergent properties of team interaction (rather than merely aggregating individual contributions) will likely prove valuable for understanding and predicting success, particularly when applied to similar competitive contexts. Ultimately, our findings provide empirical support for what many coaches have long intuited: in football, as in many collaborative endeavors, the whole can be greater than the sum of its parts.

## CRediT authorship contribution statement

**Santiago Salinas:** Writing – original draft, Supervision, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Miyani Sonera:** Writing – review & editing, Investigation, Data curation. **Shun Yonehara:** Writing – review & editing, Methodology, Investigation, Data curation.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgements

We are grateful to the student-athletes who participated in the study, as well as to Coaches Lumumba Shabazz, JD Nord, and Jill Leibforth for their generous support and collaboration. We thank Steve Munch, Alexander Oonk, and four anonymous reviewers for comments that greatly improved the manuscript. This work was supported by research fellowships to SY and MS from the Biology Department at Kalamazoo College. Lastly, SS would like to dedicate this work to Marcelo Bielsa, a fellow leproso, whose unwavering clarity, conviction, and thoughtful integrity continue to serve as an inspiration.

## Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.footst.2026.100024.

## Data availability

Data files are available on FigShare

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