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Simple and reliable protocol for identifying talented junior players in team sports using small-sided games

Robbie S. Wilson[1] | **Andrew H. Hunter**[1] | **Thiago V. Camata**[1] | **Charles S. P. Foster**[2] | **Gabriella R. Sparkes**[1] | **Felipe A. Moura**[3] | **Paulo R. P. Santiago**[4,5] | **Nicholas M. A. Smith**[1]

[1]School of Biological Sciences, The University of Queensland, St Lucia, Australia

[2]School of Medical Sciences, University of New South Wales, Sydney, NSW, Australia

[3]Sport Sciences Department, State University of Londrina, Londrina, Brazil

[4]School of Physical Education and Sports of Ribeirão Preto, University of São Paulo, Ribeirão Preto, Brazil

[5]Ribeirão Preto Medical School, University of São Paulo, Ribeirão Preto, Brazil

Correspondence

Robbie S. Wilson, School of Biological Sciences, The University of Queensland, St Lucia QLD 4072, Australia.
Email: r.wilson@uq.edu.au

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We designed and tested a protocol for measuring the performance of individuals in small-sided soccer games. We tested our protocol on three different groups of youth players from elite Brazilian football academies. Players in each group played a series of 3v3 games, in which individuals were randomly assigned into new teams and against new opponents for each game. We calculated each individual's average individual goals scored, goals scored by teammates, goals conceded, and net team goals per game. Our protocol was consistent across days and repeatable across groups, with intraclass correlation coefficients (ICCs) of 0.57–0.69 for average net goals per game across testing days. Players could achieve high success by scoring goals or ensuring their team concede few goals. We also calculated the first and second dimension of a principal component analysis based on each player's number of goals scored, goals scored by teammates, and number of goals conceded per game. Players that were overall high performers had higher PC_1 scores, while PC_2 scores represented the type of contribution made by a player to overall performance. Positive PC_2 values were indicative of high number of individual goals while negative values were associated with more goals from teammates and fewer conceded goals. Our design allows coaches and scouts to easily collect a robust metric of individual performance using randomly designed, small-sided games. We also provide simulations that allow one to apply our methodology for individual talent identification to other small-sided games in any team sport.

KEYWORDS

development, performance, skill, soccer, talent identification

1 | INTRODUCTION

Talent identification programs aim to select the individuals that are most likely to become successful professional adult players.[1-5] Individuals identified in these programs receive many benefits, including more focused and specialized coaching attention and the investment of resources, including money, equipment, and time.[6,7] In individual athletic sports, such as running, swimming, and cycling, it is relatively straightforward to create selection protocols to identify talent.[8-11] For instance, in an individual sport such as sprinting, coaches can use sprint speeds in training to directly predict success in competition. In team sports, however, the process is much less simple. Team sports are tactically complex, rely on the collective actions of individuals, and often include clear divisions of labor among the individuals within a team.[12-15]

In soccer, for example, each player on the team has a defined role—for example, attacker, midfielder, or defender—and the relative importance of activities undertaken during matches—for example, taking on defenders, crossing the ball, and shooting—varies according to this role.[16-18] This division of labor makes it unlikely that there will be a single formula for success in team sports and talent identification programs need tools that account for the diverse kinds of talent within a team.[14,19-22] In soccer, talented youth players are mostly identified by experienced scouts who observe and assess individuals during competitive matches or during training sessions.[23-25] Unfortunately, any process based on a single, qualitative opinion is inherently biased, and scouts, being human, are prone to repeated error and misjudgment—particularly if trying to isolate the performance of a single player from within that of the whole team.[3] As a result, there is widespread interest in the development of a more quantitative, scientific approach to talent identification.

A growing number of studies offer quantitative frameworks for talent identification in soccer,[3,4,26-28] yet uptake of these protocols among professional clubs and academies remains limited.[1,7] Most of these protocols compare the physical, technical, and/or psychological traits of selected players with those of non-selected players, and then base selection criteria on those traits where significant differences are detected between the groups.[3,4,29-32] This approach has several drawbacks. First, basing selection protocols on the differences between player levels (selected vs. non-selected; elite vs. non-elite) implicitly assumes that all the players within a playing level are of equal ability.[1,14,33,34] This is not the case. Second, basing selection protocols on isolated traits rather than combinations of traits (eg, height, speed, and dribbling) also assumes there is only one single formula or pathway to overall success.[14,33-36] Success in soccer is likely to be associated with a range of different combinations of traits; for example, some individuals may have combinations of traits better suited to defensive play, while others may have combinations of traits better suited to attacking play.

One way to circumvent these problems would be to quantify an individual's overall performance within the context of the team, in matches.[1,14,20] Such a protocol would enable the holistic evaluation of performance and emphasize talent as it is associated with match outcomes rather than particular physical or technical traits. However, it is notoriously difficult to assess individual performance in team sports,[1,2,14,20] because an individual's success depends not only on their own abilities, but the quality of their team and opponents. To do so, it is necessary to either: (i) directly measure the quality of all other participants in a match and statistically account for their effects on the focal individual or (ii) to design an assessment that sufficiently replicates and randomizes the number of games played by individuals to minimize any impacts of other player's quality on the focal individual's success.

Here, we developed a simple, repeatable protocol based on option (ii), which identifies talented young soccer players based on their performance in small-sided games. We tested our framework on three different groups of youth players from elite Brazilian football academies. Players in each group each played in multiple 3 v 3 games, in which individuals were randomly assigned to new teams and opponents for each game so that no one played with the same pair of players or against the same team of opponents more than once. We assessed each individual's contributions to team success by recording a range of easy-to-measure metrics of attacking, defending, and net performance. We determined the reliability of these metrics of individual performance by calculating their repeatability across testing days in each of the group of players. Finally, to assess the applicability of our methodology to other small-sided games, we ran model simulations to show how playing different numbers of games might affect our ability to accurately predict success in games of different team sizes (3v3, 4v4, 5v5, 7v7, and 11v11).

2 | METHODS

2.1 | Subjects

We studied participants from three different groups of players taken from two different elite football academies in Brazil. The average age of the groups in this study was 12.1 years (standard deviation [SD] = 0.6; range 10.9–12.8 years) for Group A, 12.3 years (SD = 0.7; range 10.6–13.2 years) for Group B, and 14.8 years (SD = 0.2; range 14.3–15.1 years) for group C. All players were of high standard and competed in the local state competitions and some national club competitions. All guardians gave consent to be involved in the study, which was in accordance with ethical protocols for the University of Queensland, Australia, University of Londrina, and University of Sao Paulo, Brazil.

2.2 | Design

We ran a series of 3v3 matches for all three groups separately, such that individuals only competed within and against others within their group. For Group A, we conducted the series of games across three sessions with each separated by a day (N = 42 individuals; 33.8 ± 5.0 games per individual; range 20–44 games). For Groups B (N = 42 individuals; 26.4 ± 6.4 games per individual; range 9–34 games) and C (N = 26 individuals; 21.5 ± 4.8 games per individual; range 8–26 games), we assessed their series of games across two separate training sessions, with each session separated by a day. Before each session, players proceeded through their normal 15 min warm-up routine with their coach.

2.3 | 3v3 games

All games were held on a 35 m long by 25 m wide field with a 2 m wide by 1 m high goal at each end. These field dimensions are like those commonly used for youth soccer players aged 12 to 16 years.[37,38] A total of 240 games were played for Group A, 190 games for Group B, and 93 for Group C. For each group throughout the competition, we randomized the combinations of players for each game, so that teams were unlikely to be identical across different games. To achieve this, players were assigned teams by handing out tickets at random that corresponded to a field, team, and number. Those individuals that had not played in the previous round of games were the first to be given tickets. By mixing up the composition of each team, the performance of each individual could be averaged across games they played, such that an individual's average performance in the matches was unlikely to be dependent on any particular or combination of teammates. Each game lasted 4 min. All players received standardized instructions on the purpose of the game (ie, to contest each game as if it was a normal competitive match); however, players were unaware of the metrics of success being recorded. Coach encouragement or feedback was not permitted throughout the small-sided games.

Players were allowed to rest for 1–6 min between games, depending on whether they played in the game immediately following the last or whether they waited for the following game. There were four playing fields set up for Group A, five for Group B, and three for Group C. We used several playing fields so that multiple games were run simultaneously, such that most players at any one time were playing and the remaining players were ready for the following game. No player missed two games in a row. Because up to 20 games on each field were conducted in one training session, the natural effects of fatigue that occur during standard, longer matches were expected to affect the performance of individuals and their teams across the session. A team was chosen at random to start with the ball.

For each match, we quantified each individual player's total number of individual goals, total number of goals scored by their teammates, total number of goals scored by their team, total number of goals conceded by their team, and total net goals for the team (individual team's goals minus opposition team's total goals). Because all of these variables were easily observed, the inter-rater reliability was greater than 0.99. We used a different rater on each separate field.

We used principal component analysis (PCA) to characterize patterns of variation among correlated standardized measures, creating a multivariate measure of 3v3 match performance for each of the three groups of players. The PCA was conducted on each individual's average number of individual goals per game, average goals scored by teammates per game, and the average number of goals conceded by their team per game. The number of goals scored by the team and net goals for the team were excluded from the PCA because they are an exact summation of other included variables. For each group, all vectors loaded in the same direction for the first component of the PCA and explained 59.0 (Group A), 64.9 (Group B), and 58.4% (Group C) of the variation observed in the data (Table 1). Larger positive values for an individual indicated higher overall success across all traits measured in a game (for example, greater number of goals scored by focal individual, greater number of goals scored by their teammates, and fewer goals conceded against the focal individuals team), such that PC_1 can be thought of as a measure of overall success in the 3v3 matches. Note that conceded goals loads negatively onto PC_1, such that an individual with higher positive values of PC_1 will be more likely to concede fewer goals (better defensive performance). In other words, individuals with higher PC_1 have conceded fewer goals and equates with being a better defender. The second component of the PCA (PC_2) explained 26.9 (Group A), 23.2 (Group B), and 28.1% (Group C) of the variation observed in the data (Table 1). For each group, larger positive values indicated higher individual goals, while negative values indicated greater number of goals scored by teammates and fewer conceded goals per game. All principal component

TABLE 1 Principal components analysis (PCA) matrix based on a player's individual goals, number of goals scored by teammates, and number of conceded goals

	Group A		Group B		Group C	
Traits	**PC_1**	**PC_2**	**PC_1**	**PC_2**	**PC_1**	**PC_2**
Individual goals	0.85	0.50	0.21	0.83	0.45	0.78
Team—Individual goals	0.04	−0.43	0.38	−0.55	0.11	−0.52
Conceded goals	−0.53	0.75	−0.90	−0.04	−0.89	0.34
Total variance explained	59.0	26.9	64.9	23.2	58.4	28.1

The first and second component of the PCA and total variance explained is provided for Groups A, B, and C.

analyses were carried out using the "prcomp" function from the "stats" library in R.[39]

We used a randomized design to assess each individual's performance in the 3v3 games. Each team was randomly assembled for each game so that we minimized the probability that our metric of individual performance (net goals per game) was affected by differences among the individual's in the average quality of their teammates or opponents. To verify the effectiveness of our randomized design in minimizing the effects of the team on each individual's performance, we calculated the average quality of teammates, the average quality of opponents, and the average net quality of the teams, that each individual experienced throughout the entire 3v3 set of games. We showed each of these metrics for each group was close to a mean of zero and low SD (Table A1).

Each of these metrics was calculated for each individual for each group using the following:

$$\mu_{\mathrm{QT}_M} = \frac{\sum_{i=1}^{n} (\mu_{\mathrm{NG}_G} + \mathrm{TM}_1 + \mathrm{TM}_2)}{n} \tag{1}$$

$$\mu_{Q_{\mathrm{OP}}} = \frac{\sum_{i=1}^{n} (\mathrm{OP}_1 + \mathrm{OP}_2 + \mathrm{OP}_3)}{n} \tag{2}$$

$$\mu_{Q_{\mathrm{TP}}} = \mu_{\mathrm{QT}_M} - \mu_{Q_{\mathrm{OP}}} \tag{3}$$

where μ_{QT_M} refers to the average quality of teammates that an individual played with, μ_{NG_G} refers to the average net goals of the entire group, TM_1 refers to the quality of teammate 1, and TM_2 refers to the quality of teammate 2 for each game, $\mu_{Q_{\mathrm{OP}}}$ refers to the average quality of the opposition played against by an individual for each game, OP_1 refers to opposition player 1, OP_2 refers to opposition player 2, OP_3 refers to opposition player 3 in each game, and *n* refers to the number of games an individual plays.

2.4 | Simulations

We used simulations to estimate the number of games that are required for individuals to play in order to obtain a reliable estimate of their overall quality. Here, it is important to remember that an individual's score is their average net goals per game, which is a metric taken from the team results. Based on this, there are two main factors that will affect the number of games a player needs to play to get an accurate estimate of their quality: (i) the number of players on each team and (ii) the average number of goals scored across all games.

As the number of players increases on a team, the influence of any single player on the team's overall outcome will be proportionally diluted. That is, if each player on a team has similar abilities, then in 3v3 games, each player will have around 1/3rd of the influence on that team's performance. But, during a 7v7 game, any single player will have around 1/7th of the influence on their team. Thus, an individual's influence on a game becomes more diluted when the number of players on a team increases. This is referred to as the *dilution effect*, and means it will take proportionally longer to obtain a reliable and consistent measure of a player's average net goals per game with increasing number of players on each team.

We must also consider how the average number of goals scored in the matches will affect the number of games required to obtain a reliable measure of average net goals per game. Here, it is important to recall that our measurements of overall player quality are taken directly from an individual's average net team goals per game. The greater average number of goals scored per game will result in a greater SD in the group's player performance (average net team goals per game), while the mean average net goals per game remain as zero. This is important when simulating metrics of individual performances in two ways. First, matches with fewer goals are more likely to result in closer scores that show limited separation between the teams, thus making it even more difficult to extract an individual's signal from a team result. In contrast, larger scores with clear separation between teams will take fewer games to observe reliable, robust differences among individuals in average net team goals. Second, the scoring system in soccer games is in integers. When we use an individual's performance to simulate match outcomes, then we must take into consideration that any match result will be in whole numbers. For example, when simulating the result from two groups of 3 players, we may find that the collective score of individual qualities (sum of net team goals per game) is +2.38 for Team A and −0.10 for Team B, with the net result of +2.48 for Team A and −2.48 for Team B. Because all results of games are always in integers, the net score will be constrained to +2 for Team A (rounded number of nearest integer) and −2 for Team B. This will be particularly important when metrics of individual performance are small (mean 0, SD of 0.6) because constraining each result to integers will be mean that there will often be very little or no separation between teams.

We simulated soccer matches to investigate how many matches were required to reliably assess the quality of a player relative to others within an overall pool of players as a result of the (i) number of players on each team (dilution effect) and (ii) the standard deviation (SD) in net goals per game for the player group (goal effect). Using the *rnorm* R function, we generated a pool of 40 players of varying quality; each player's quality score was sampled from a normal distribution with a mean of 0 and SD of 0.6, 1.2, or 1.8, depending on the design outlined below. We iteratively designated each of the 40 players as the focal player, and then carried out simulations as follows:

(i) In addition to the focal player, other players were randomly sampled without replacement from the remaining pool of 39 players until the desired team sizes were filled. For example, in a 3v3 match, two and three other players were randomly sampled as teammates and opposition, respectively. This group of players represented one match.
(ii) The match outcome was determined by subtracting the mean opposition quality from the mean quality of the player's team (rounded to an integer). The resulting value was considered as a new estimate of the focal player's score for that match.
(iii) One hundred matches were completed, as per the first two steps, resulting in 100 measurements of the focal player's quality.

Using the results of all 100 matches, we then iteratively assigned each player a new quality score after playing 1:*n* amount of matches, for all values of *n* from 1:100. This allowed us to assess the R^2 value between all players' original actual quality scores and their estimated quality scores from the simulations after playing *n* games using the *lm* R function. This procedure was repeated in 10 replicate analyses. We then determined the mean R^2 value ($\pm$SD) across all 10 replicates for all number of matches from 1:100, and compared results for team sizes of 3v3, 4v4, 5v5, 7v7, and 11v11. This process was repeated using three different SDs of player qualities; 0.6, 1.2, and 1.8, which represented the low, medium, and high number of goals in matches, respectively.

2.5 | Statistical analysis

Estimates of repeatability for individual goals, team goals minus an individual's goals, goals conceded, team net goals, and the first two principal components across each day were calculated using ICCs. We fit a separate linear model for each team to determine the effect of the number of individual goals scored, team goals minus individual goals, and the number of conceded goals on team net goals. These models were carried out using the "lm" function from the "stats" library in R.[39] We also assessed the effect of the first two principal components (calculated above) and their interaction on an individual's net goals scored per game for Groups A, B, and C. These linear models were also carried out using the "lm" function from the "stats" library in R.[39]

3 | RESULTS

Repeatabilities were based on individual performances across match days, with individuals playing in 10–18 games in any one day. An individual's average net team goals were significantly repeatable across days for all groups tested (Table A2), with ICC of 0.66 for group A, 0.69 for group B, and 0.57 for group C. An individual's average number of goals scored per game was also significantly repeatable across days for all groups tested (Table A2), with ICC's of 0.49 for group B and 0.79 for groups A and C. An individual's average number of conceded team goals was only significantly repeatable across days for group B (Table A2). The first principal component based on individual goals, teammate's goals, and team-conceded goals was significantly repeatable across days for groups A and B, but not C (Table A2).

An individual's average number of goals scored per game was significantly positively associated with net team goals scored for Group A ($R^2 = 0.58$; $p < 0.0001$), Group B ($R^2 = 0.20$; $p = 0.001$), and Group C ($R^2 = 0.39$; $p < 0.0001$) (Figure 1). Similarly, the average number of goals scored by an individual's teammates was positively associated with net team goals scored per game for Group A ($R^2 = 0.19$; $p = 0.004$), Group B ($R^2 = 0.46$; $p < 0.0001$), and Group C ($R^2 = 0.15$; $p = 0.03$) (Figure 1). Finally, the average number of goals conceded per game by an individual was significantly negatively associated with net team goals scored per game for Group A ($R^2 = 0.63$; $p < 0.0001$), Group B ($R^2 = 0.79$; $p = 0.001$), and Group C ($R^2 = 0.74$; $p < 0.0001$) (Figure 1).

The first dimension from a PCA on all game traits—individual goals, teammate's goals, and goals conceded—was highly associated with an individual's net goals per game for groups A ($t = 24.20$; $p < 0.0001$), B ($t = 22.65$; $p < 0.0001$), and C ($t = 15.00$; $p < 0.0001$) (Table A3) (Figure 2). The second dimension from the PCA was significantly associated with an individual's net goals per game for both groups A ($t = -8.29$; $p < 0.0001$) and B ($t = 2.67$; $p = 0.0007$), but not Group C ($t = -0.80$; $p = 0.43$) (Table A3) (Figure 2). There were no significant interactions between PC_1 and PC_2 on an individual's net goals per game (Table A3).

To demonstrate the effect of the total number of games on the estimates of player quality in our simulated group of players, we show the relationship between a player's "true" quality and our "estimated" quality from the simulations. The relationship between "true" quality and "estimated" quality for 3v3 games increased from an R^2 of 0.28 after one simulated game, to an R^2 of 0.71 after 10 games, an R^2 of 0.91 after 50 games, and an R^2 of 0.95 after 100 games (Figure 3). For 7v7 games, the relationship between "true" quality and "estimated" quality increased from an R^2 of 0.03 after one simulated game, to an R^2 of 0.51 after 10 games, an R^2 of 0.70 after 50 games, and an R^2 of 0.87 after 100 games (Figure 3).

Based on our simulations, we found the number of games required to estimate an individual's performance with an

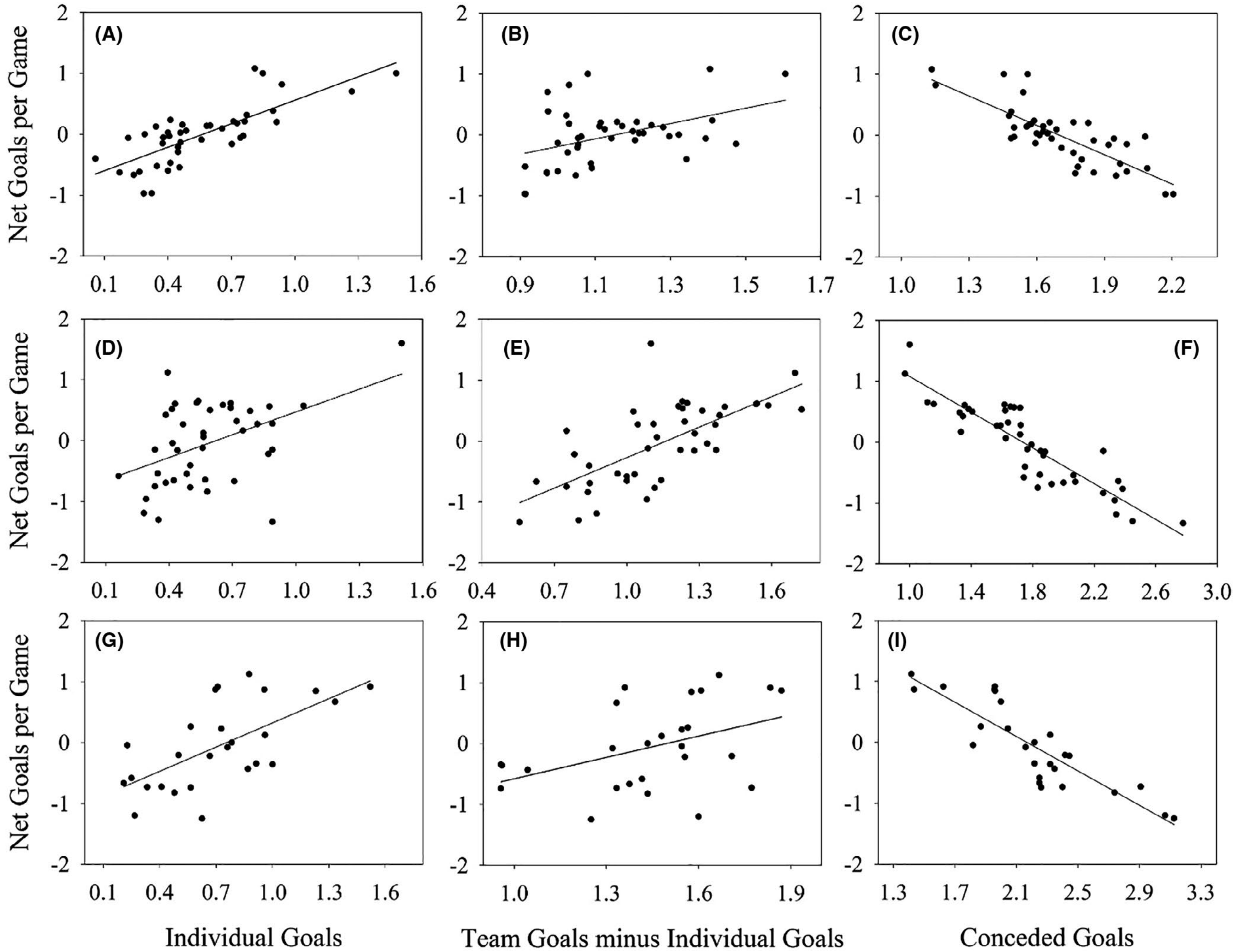

FIGURE 1 The relationship between an individual's average number of goals scored (A, D, G), the number of goals scored by a player's teammates (B, E, H), and the average number of conceded goals per game for their team (C, F, I), and the average number of net goals per game. The first row of panels represents the results for Group A (A, B, C), second row for Group B (D, E, F), and the bottom row for Group C (H, I, J). All correlations are significant

R^2 of at least 0.80 was approximately 28 games for the 3v3 matches, 28 for the 4v4 matches, 38 for the 5v5 matches, 65 games for the 7v7 matches, and greater than 100 games for the 11v11 games when we used a SD of an individual's average net team goals of 1.2.

The number of games required to estimate an individual's relative performance with an R^2 of at least 0.80 was sensitive to the SD of net team goals per game (Figure 4). However, this sensitivity to SD was greater for those games with more players. For example, for the 3v3 games, the SD of net team goals per game did not influence the number games needed to be played to obtain an R^2 of at least 0.80 (Figure 4). In contrast, for the 7v7 games, a SD of 0.6 meant that around 100 games per individual were required in order to obtain an R^2 of at least 0.80, but this decreased to around 60 games when there was a SD of 1.2 (Figure 4).

4 | DISCUSSION

Our protocol for estimating an individual's performance in small-sided games was consistent across days and repeatable across groups of players. A player's average net team goals per game had ICCs that ranged from 0.57 to 0.69 across the three player groups when tested across different days. Our easy-to-measure metrics not only provided robust estimates of an individual's overall performance in small-sided games but also the type of contribution an individual makes to the team. Average individual goals scored per game, goals scored by teammates, and the average number of goals conceded per game were all correlated with a player's average net team goals, but not necessarily correlated with each other or exhibit the same magnitude in PCA loadings across the different player groups (Table 1). This shows that there are

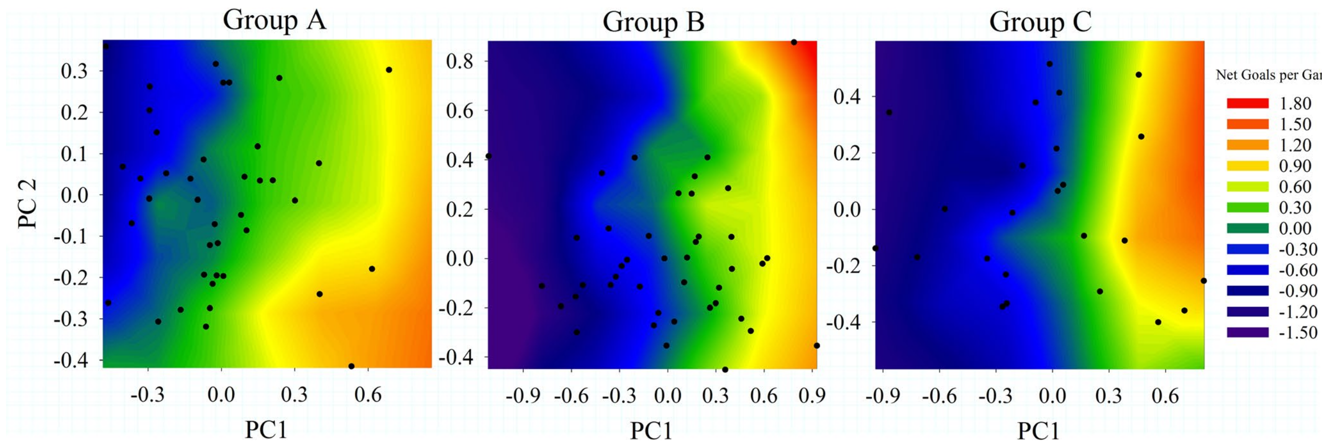

FIGURE 2 The relationship between an individual player's average performance (PC_1), the type of contribution they make to their team's performance (PC_2), and the average number of net goals scored per game (color heat-map). PC_1 and PC_2 are derived from the first two dimensions of a principal component analysis on a player's goals scored per game, goals scored by teammates, and goals conceded per game. Positive PC_2's indicate a high number of goals scored by an individual (good attackers) and negative PC_2's are those individuals that concede few goals per game (good defenders).

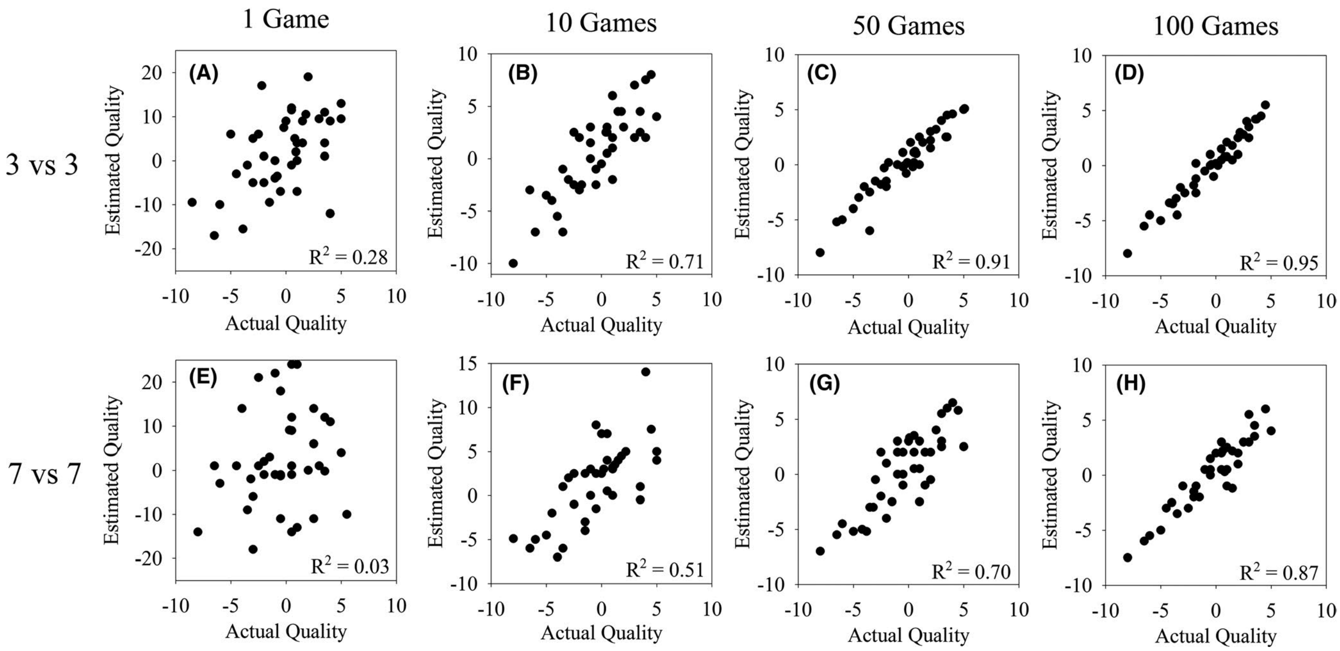

FIGURE 3 The relationship between a player's "actual" quality (net goals per game) and their "estimated" quality based on the simulations conducted for the 3v3 games after 1 (A), 10 (B), 50 (C), and 100 (D) matches, and for the 7v7 games after 1 (E), 10 (F), 50 (G), and 100 (H) matches. The R^2 for each regression is provided

multiple ways that a player can attain high overall game effectiveness (average net team goals per game) in the 3v3 games. For example, players can achieve high match effectiveness by scoring a high number of individual goals or ensuring their team concedes few goals. This allows one to identify high-performing individuals that are specialized for different team roles.

Several previous studies suggest small-sided games can be an effective means for objective assessment of individual player performance. Bennett et al.[20] showed higher level players had a greater number of attempted and completed passes, number of touches, and total skill involvements than lower-level players in 4v4 small-sided games. In addition, Fenner et al.[2] found players with higher ratings from expert coaches had higher average performances in 4v4 small-side games (set points awarded for win, draw, and loss), thus showing agreement between player's game performances and coach assessments. Our study provides several improvements in design for using small-sided games for talent identification. First, our design does not assume that there is only one

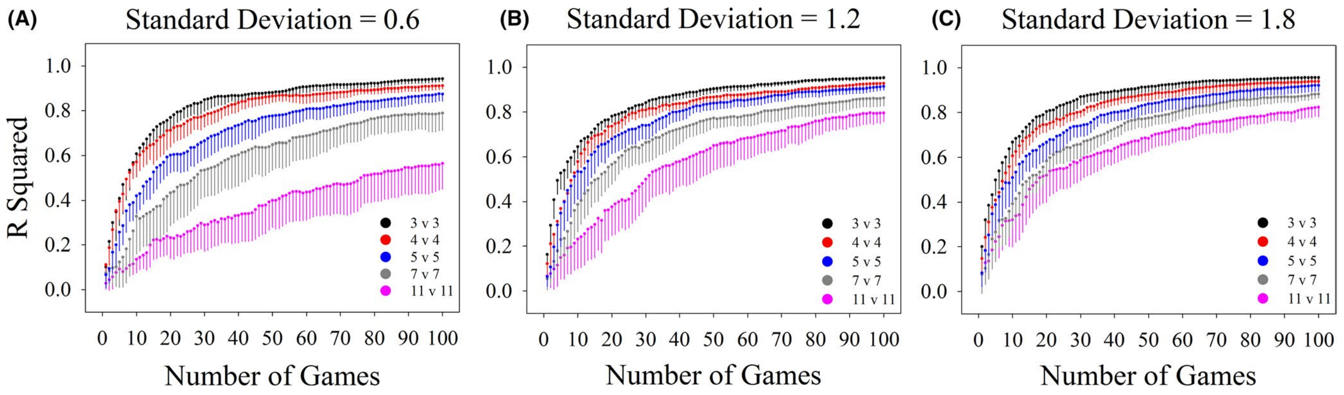

FIGURE 4 The relationship between the number of simulated games and the R^2 between "actual" and "estimated" quality for the group of players when the standard deviation of quality is 0.6 (A), 1.2 (B), and 1.8 (C). Each colored line represents a small-sided game with different number of players. Each datum point is a mean ± standard deviation ($N = 10$)

single formula for success but allows for multiple ways for individuals to attain high performance. Individuals divide their labor in the pursuit of better team performance, and our method of assessment allows players to use their unique set of traits to optimize their contributions. Second, we obtain metrics of individual performance that are relative to all other individuals in a testing group, rather than comparing the differences between player levels (selected vs. non-selected; elite vs. non-elite). This allows one to provide an objective and relative rank between players within a player group. Third, we use relative metrics of team performances during the 3v3 games, where individuals accrue points according to the relative performances of two competing teams, allowing for more fine-scaled measurements of relative performances. Rather than using a standardized points system where individual's get points for winning, drawing, or losing,[20] the points are awarded according to the net goal difference. Thus, a far superior team with three good players will be awarded points according to the goal difference in the game (eg, 6 pts for 6-0), recognizing that team dominance and ability will be reflected in the relative scores. Finally, the collection of just three more variables from each game (individual goals, goals by teammates, and conceded goals) allows one to describe both an individual's overall average match effectiveness, and the type of contributions the player makes to the team.

Our simulations provided a structure for applying our methodology to most other small-sided games, including those of other team sports where individuals compete collectively in open play. When applying our methodology to other small-sided games with different team sizes, it is important to consider two factors. First, as the number of players on a team increases then the relative contributions an individual player can make to their team will be diluted. Based on our simulations, we found this dilution effect to mean the number of games required to estimate relative individual performance will increase from around 20 games for the 3v3 matches to around 60 games for 7v7 matches. Second, the average number of goals per game will also affect the number of games required to obtain a robust measure of individual performance. We explored this by varying the SD in individual performance used in the simulations. Across the three player groups in which we collected empirical data, the approximate mean individual player performances were 0 with a SD of 0.6. Variation in the number of goals per game did not greatly affect the number of games required to estimate individual player performance for both the 3v3 and 4v4 matches. However, estimating individual performances was highly sensitive to the number of goals scored per game for all games involving more than 4 players per team. When there was a low number of goals per game (SD = 0.6), it was not possible to provide a relative estimate of individual performance within 100 games for the 7v7 matches—making this an unworkable methodology. However, when there are a higher number of goals per game (SD = 1.8), individual performance could be estimated in 7v7 games within 60 matches. Thus, any strategies that will increase the number of goals per game, such as manipulating the duration of each game, the size of the field, and goals, will allow more rapid estimates of individual performance. Regardless, our simulations reveal practical ways to help improve design protocols for assessing the quality of individual players from small-sided games. However, there is still much room for improvement in protocol design and the simulations can help this process. Future work could explore how the number of individuals in a playing group, the number of players on each side, and the average number of goals in each game, all interact to influence the assessment of reliable metrics of individual quality.

It is not clear how our metric of individual performances from the 3v3 games translate into performance in other small-sided games or 11v11 matches. The ultimate aim of talent identification programs is to identify players that will be successful in 11v11 matches in adult competitions. Clearly, much remains to be done to show whether our methodology has any predictive value across youth development to adult competitions. However, any performance metric derived from competitive games in which individuals must perform a high number of technical skills under the constraints of gameplay should be considered a likely candidate for high predictive power. Empirically interrogating this idea should be of high importance going forward, and one could start with longitudinal studies to establish if the successful players at one age continue to be successful throughout their youth career.

One weakness of using small-sided games for talent identification is that the metrics of individual performance are not comparable across different groups of players. A player's ultimate performance will be dependent on those that they are competing against. An outstanding player may have a high relative performance score when competing against average players but lower when competing against other high-level players. By discovering which isolated athletic, technical, or psychological traits underlie high performance in small-sided competitions, one can thus provide metrics of performance that are independent of other players, and comparable to groups for other teams, competitions, or countries.[40,41] Because our design of small-sided games provides a single metric of overall performance, it is possible to design experiments that identify the traits most predictive of overall performance. It is imperative that such experiments explores inter-individual variation in possible underlying traits and small-sided games. Such analyses are commonly used in evolutionary biology, and recent application in soccer has demonstrated their utility for identifying the traits associated with success in attacking and defending performance.[14,34-36] For example, dribbling speed is considered critical to the outcome of soccer matches, and recent studies showed that a multidimensional metric of dribbling speed, as measured along several curved paths, is a strong predictor of individual attacking performance when the objective was to take on and beat a single defender,[35] goal-scoring ability when taking on a single defender a goalkeeper,[42] and defensive performance.[34] In addition, in an analysis of multiple skill, athletic, and balance traits in semi-professional soccer players, Wilson et al.[14] found that skill—rather than athletic ability—was the best predictor of success in 11-a-side matches.

5 | PERSPECTIVE

Our study design can allow coaches and talent scouts to easily collect a robust metric of individual performance when using randomly designed, small-sided games. The identity of the participants, the number of goals scored by each player, and the final score in the game are the only data that need to be collected from each game. Based on these data, it is possible for coaches to quantify an individual's overall performance and their type of contribution (Figure 2). Our protocol is consistent across days and repeatable across groups of players. In addition, we provide simulations that provide a structure for applying our methodology to other small-sided games in soccer and other team sports for individual talent identification.

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CONFLICT OF INTEREST

No conflict of interest.

DATA AVAILABILITY STATEMENT

Data available upon request.

ORCID

Robbie S. Wilson https://orcid.org/0000-0002-0116-5427
Andrew H. Hunter https://orcid.org/0000-0002-9378-593X
Thiago V. Camata https://orcid.org/0000-0001-9249-8851
Felipe A. Moura https://orcid.org/0000-0002-0108-7246

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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