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Are soccer players born later in the year more technically skilled than those born earlier in the year

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Abstract

In many youth sports, selection into elite training academies is dominated by athletes born earlier in the year. Previous research suggests this is partly due to these athletes being more physically developed than their younger peers. How athletes born later in the year survive in elite academies is less understood. Here, we tested the hypothesis that players born later in the year are more technically skilled than their peers born earlier in the same year. Using 150 youth players (10–19 years of age) from an elite Brazilian soccer academy, we measured each player's date of birth, height, and mass; sprinting ability; dribbling ability; and kicking accuracy and speed. We found most players in this academy were born in the first half of the year, and those born earlier in the year (relatively older) tended to be taller and heavier than those born later in the same year (relatively younger). In addition, relatively older players were faster when sprinting and dribbling the ball in a straight line. Conversely, relatively younger players were more accurate when passing the ball with their nondominant foot, providing some evidence these players were more technically skilled than their older peers of the same age. We suggest skill tests with youth players need to consider relative age and physical size in order to best assess a player's potential.

Keywords

Association football, birth date, relative age effect, team sport

Introduction

For many sports, youth participation is organised into annual age-groups defined by a cut-off date (e.g. commonly January 1 for soccer). Although this system aims to promote competitive fairness – a "level playing field" – this is not guaranteed. Those athletes born earlier in the selection year may be more experienced, and motivated,[1–3] providing a competitive advantage. Perhaps more obvious, the relatively older players have had longer to grow and physically develop and are likely larger than their younger peers.[4–7] This size advantage is beneficial in most sports, increasing physical performance,[8–10] and can be exacerbated during adolescents due to large variation in biological maturation among individuals of the same age.[2,11,12] Unsurprisingly, participation in youth sport at the elite level is dominated by athletes born earlier in the selection year, with this age bias (relative age effect) ubiquitous across many sports.[13–16]

The relative age effect in sports can have long-term consequences for talent identification and participation. For those born earlier in the selection year (relatively older) and preferentially selected into elite academies, these athletes gain access to higher levels of competition, training, and coaching compared to their non-selected peers.[17] This disparity in opportunity increases the chance relatively older athletes continue to be selected, with the bias towards relatively older athletes increasing as youth athletes age.[18,19] Conversely, talented (but likely smaller) athletes born late in the year (relatively younger) may be

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overlooked, potentially leading to negative experiences, self-perceptions of low competence, and ultimately drop-out from the sport.[17,20–22] This is unfortunate as the bias towards relatively older players dominating selection decreases in adult sport.[18] Thus, improving the identification and support of talented individuals born late in the year should be an important goal for any talent identification and development program in sport, not just for producing elite athletes, but for increased participation and equity.

A first step towards better identifying talented athletes born late in the year is determining if, and how, they differ to talented athletes born early in the year. One possibility is that they do not differ. The athletes born late in the year who get selected into elite academies may have similar physical statures to those born early in the year, creating a reasonably homogeneous group that persists through future years of selection. Evidence for this is contradictory.[5,6,23,24] Alternatively, if athletes born later in the year are, on average, less physically developed than their older peers, they may need to develop superior psychological, tactical, or technical skills to compete successfully against larger, faster, more powerful opponents.[25] This "under-dog hypothesis"[26] suggests being relatively younger during adolescents may be advantageous in the long-term when these athletes eventually catch-up physically by the time they are adults, but only if one is able to survive in the system. Evidence supporting this has been found in rugby union,[27] cricket,[28] ice hockey,[26,29] and soccer.[30,31] For example, compared to athletes born early in the year, those born late in the year have been shown more likely to achieve professional status,[30] and earn higher wages in professional soccer,[32] and ice hockey.[29] Despite this, previous research does not support the notion that relatively younger, or less physically developed athletes are more skilled than their older, larger peers of the same age.[24,33–35] However, these studies typically involved subjects within a limited age range, and/or some skill metrics may have favoured more physically developed individuals. For example, when testing young soccer players' dribbling speed, players dribbled the ball through a slalom course of five cones as quickly as possible, with a 10-m linear distance between consecutive cones.[33,35] However, it is possible that performance in such a test is equally reliant on both dribbling skill, and sprinting speed, with older, more physically developed players likely faster runners.[9,36,37] Thus, the hypothesis that youth athletes born late in the year may be more skilled than their relatively older peers warrants further investigation.

In this study, we tested if youth soccer players born later in the year were more technically skilled than their older peers within the same age cohort using analyses of 150 players between 10 and 19 years old from an elite Brazilian junior academy. First, we examined the extent of the relative age effect in this academy. Second, for each player, we measured their height and mass to confirm relatively younger players were smaller than their older peers of the same age. Third, we measured (ii) sprinting and dribbling speed through a series of straight and curved paths, (iii) dribbling ability with directed tasks using both feet, just the dominant foot, and just the nondominant foot, (iv) maximum kick speed with the dominant and nondominant foot, (v) passing accuracy with the dominant and nondominant foot, and (vi) pass and control ability using both feet. With this suite of tests, we could explore the differences between relatively older and relatively younger players within age cohorts across tasks which differed in the relative contributions of physical and technical ability. We predicted players born earlier in the year (relatively older) would be taller and heavier than those born later in the same year (relatively younger). Further, we predicted relatively older players would outperform relatively younger players on the tasks where physical stature may convey an advantage (sprinting, maximum kick speed).[9,37] Conversely, we predicted relatively younger players would outperform relatively older players on the tasks that focus on technical skill (directed dribbling, passing accuracy).

Methods

Subjects

We recorded the performance of 150 outfield soccer players from an elite junior academy in Brazil, whose senior professional team competes in the top national competition (Serie A). All players and guardians gave consent to be involved in the study, which was in accordance with ethical protocols for the University of Queensland, Australia (# - 2019001398), and University of Sao Paulo, Brazil (# - 3822.287/2020). On the first day of testing each player's age ($M = 14.79$, $SD = 2.45$, range = 10.34–19.83 years), height ($M = 166.55$, $SD = 13.80$, range = 135.5–195.6 cm), and mass ($M = 57.39$, $SD = 14.22$, range = 31.70–88.75 kg) were recorded.

Study design

We measured the sprinting, dribbling, and kicking performance of seven teams (U12, U13, U14, U15, U16, U17, and U20), with each team attending two 2-hour sessions with a day break between sessions. For each session, players were split into groups of three or four, then randomly assigned a starting station. Groups then progressed through each assessment station in the same sequence. On day one we measured sprinting and dribbling along straight and curved paths, and directed dribbling performance in the following sequence: dribble path 1, sprint path 1, dribble path 4, sprint path 4, dribble path 3, sprint path 3, dribble path 2, sprint path 2, left foot dribble 1, right foot dribble 1, right foot dribble 2, left foot dribble 2, both feet dribble 1, and both feet dribble 2. On day two we measured maximum kick speed, passing accuracy, and pass/control in the following sequence: passing accuracy (left and right foot), pass/control 1, pass/control 3, pass/control 5, kick speed (left and right foot), pass/control 2, pass/control 4, and pass/control 6 (more details below). Players were given a brief period to familiarise themselves with each task before completing multiple trials with rests between each trial. Prior to each session, all players completed their normal 15-min warm-up routine with coaches. No kick speed data were collected with the U13 team.

Sprinting and dribbling along with curved paths

The sprinting and dribbling performance of each player was measured using four 30 m long paths that differed in curvature, as in Refs.[38–40] (Supplementary Figure 1). On the ground, two lengths of 6 mm plastic chain (Kateli, Brazil) defined the outer boundaries of each path, creating a 1-m wide channel between them. Each path was comprised of straight sections interspersed with turns that were 45° (1/8 of a circle), 90° (1/4 of a circle), 135° (3/8 of a circle), or 180° (1/2 a circle). For each path, there was a designated entrance and exit, with all players completing each path in the same direction.

For both the sprinting and dribbling tasks along each path, players were instructed to start 0.5 m outside the entrance, then either sprint or dribble a size 5 soccer ball along the path as quickly as possible. When sprinting, players were instructed to keep their entire body within the boundaries of the chains. When dribbling, they were instructed the ball must remain within the boundaries of the chains, but their body could be inside or outside the chains. If players cut corners with their body (sprinting) or the ball (dribbling), the trial was repeated after a minimum rest of 30 s. To measure the time taken for players to navigate along each path two light gates (fusion sport, SMARTSPEED PT 2 Gate System), with the beam positioned at waist height, were placed at the entrance, and exit to each path. On each path, players completed three dribbling trials followed by two sprinting trials. For each trial, we calculated the average speed by dividing the distance travelled (30 m) by the time taken to complete. Then, for each path, the average of the three dribbling trials was the measure of dribbling, and the average of the two sprint trials was the measure of sprinting. Thus, each player had a measure of sprinting and dribbling along each of the four paths.

For both the sprinting and dribbling tasks, separate principal components analyses (PCA) were used to characterise variation among the correlated measures. Prior to analysis, the left skewed data for sprinting along Path 1 were corrected with a square transformation. Then, data for each path were standardised to a mean of zero and standard deviation of one before PCA. This rescaling or variables was used for all PCA below. The first principal component of sprinting (PC_{S1}) accounted for 75.6% of the variance, and the first principal component of dribbling (PC_{D1}) accounted for 79.7% of the variance (Supplementary Tables 1 and 2). For both sprinting and dribbling PCA, all vectors loaded in the same direction, with larger positive values indicating higher speeds. The sprinting and dribbling measures along Path 1 (straight) and Path 4 (most curvy) were also included as separate trait measures for analysis. Last, dribbling along Path 2 was also analysed separately, as it was similar to the dribbling task used in previous studies.[33,35]

Directed dribbling

Each player's ability to execute specific dribbling skills was assessed with six directed dribbling tasks – two tasks using the left foot only, two tasks using the right foot only, and two tasks that used both feet. Players reported which was their dominant and nondominant foot. For each task, 15 small cones were placed 0.8 m apart in a straight line (total linear distance = 12 m). Players were required to dribble through all 15 cones, executing a specific skill between each cone, with the instruction to complete the task as quickly as possible without making a mistake. In brief, when using only one foot, one of the tasks required players to alternately use the lateral and medial parts of the foot to dribble through the cones, while the other task required players to alternately use the lateral and underside parts of the foot. When using both feet, one task used the lateral and medial sides of both feet, and the other tasks used only the lateral side of each foot but also included a step-over (see Supplementary Material for a description of each skill). The total time to complete the task was measured with two light gates (fusion sport, SMARTSPEED PT 2 Gate System). The total number of errors was also recorded for each trial. An error was counted when a player touched the ball too many, or too few, times between two cones, or if they used the wrong foot, or part of the foot to execute the skill. Regardless of the magnitude of a mistake, only one error could be attributed between any two cones. During testing, we observed errors could help or hinder completing the task quickly. Thus, to penalise errors consistently, the total time to complete each trial was corrected with $adjusted\ time\ (s) = raw\ time + (0.1 * errors)$. The adjusted time was then used to calculate the average dribbling speed ($m.s^{-1} = 12\ /\ adjusted\ time$) for each trial. Depending on the time allowed for sessions, each player completed two or three trials on each dribbling task. For each dribbling task, the average speed across trials was calculated as the metric of performance.

Principal components analysis (PCA) was used to characterise variation among the correlated measures of directed dribbling. Prior to analysis dribbling tasks with just the right foot and just the left foot were converted to dominant or nondominant for each player. The left skewed data for "dominant foot #2" were corrected with a square transformation. Including all directed dribbling tasks in the PCA the first principal component (PC_{DD1}) accounted for 69.48% of the variation (Supplementary Table 3). Including only one-footed tasks with the dominant foot, the first principal component (PC_{DDD1}) accounted for 86.01% of the variation (Supplementary Table 4), while the first principal component of the nondominant foot tasks (PC_{DDN1}) accounted for 87.28% of the variation (Supplementary Table 5). For each PCA of directed dribbling, all vectors loaded in the same direction with larger positive values indicating greater speeds.

Maximum kick speed

Using a size 5 soccer ball, players were instructed to kick the ball as fast as possible into a goal placed 4 m away from the ball's designated starting position (Supplementary Figure 2). Players were not given a target to aim at and executed three kicks each with both feet. To measure ball speed, we used two high speed cameras (Nikon Coolpix B500), both filming at 120 fps, and the DLTcal5 and DLTdv5 packages of MATLAB.[41] This protocol has been used previously[40,42] and exhibits high inter and intra-rater reliability[43] (see Supplementary Material for more details).

Passing accuracy

To measure passing accuracy players were required to pass (side of the foot) a size 5 ball and hit a wooden target (1.1 m × 0.5 m) from a distance of 15 metres. Two cones, 4 m apart, were placed 15 m from the target indicating where the ball should be kicked from. Two additional cones, also 4 m apart, were placed 10 m from the target (Supplementary Figure 3). To score one point, players were instructed the ball must hit the target and rebound back between the two cones 10 m from the target. This ensured players kicked the ball at a game relevant speed. If the ball hit the target but did not rebound between the 10 m cones that attempt received half a point. Zero points were allocated to passes that missed the target. On each foot, players executed three rounds of 10 passes, resting between each round (total of 30 passes with each foot). The metric of accuracy for each foot was calculated as a proportion: *accuracy* = total number of points/30.

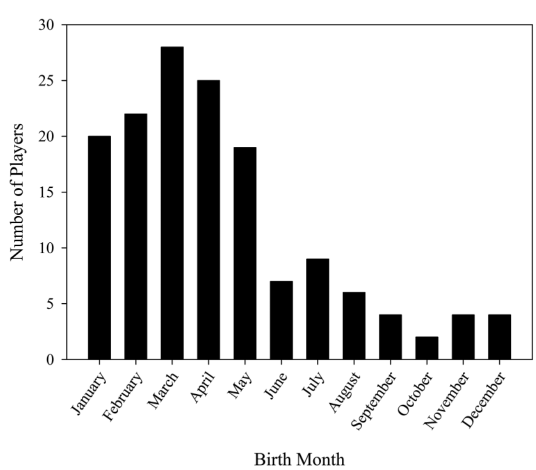

Figure 1. Frequency distribution of birth month for 150 athletes from an elite Brazilian Soccer Academy.

Pass/control

The passing and control ability of each player was assessed on six different tasks using specially designed wooden rebound boards (1.1 m × 0.5 m). Each task utilised a pair of rebound boards oriented 45°, 90°, or 135° from each other. Players were required to pass the ball alternately to each board and execute a specific control technique between each pass. A single trial was 45 s duration and players were instructed to complete as many passes as possible in that time while correctly executing the designated control technique. To commence each trial, players started with the ball equidistant between the two boards (Supplementary Figure 4). Four additional balls were placed behind them within close reach, but not impeding their actions. During the trial, if a player missed one of the boards with a pass, they quickly retrieved another ball and continued. The trial automatically ended if a player missed a board five times. The number of passes hitting either board was counted, along with mistakes. Any deviation from the designated pass and control technique for a task (see Supplementary Material) was considered an error. For example, taking an added touch, using the incorrect foot or part of the foot to control the ball, or passing with the incorrect foot. Regardless of the magnitude of the mistake, only one error was attributed between any two passes. To account for mistakes the passing metric for each trial was calculated as *passes* = total number of passes – (0.5 * number of errors). Players were given two trials on each of the six tasks, with the average of the two trials calculated as the score for that task.

Principal components analysis (PCA) was used to characterise variation among the measures of pass/control. Prior to analysis, the left skewed data for tasks one, two, and three were corrected with a square transformation. The first principal component (PC_{P1}) accounted for 58.15% of the variance (Supplementary Table 6). All vectors loaded in the same direction with greater positive values indicating more passes (better performance).

Statistical analysis

The statistical programR[44] was used for all analyses. A common approach in studies of the relative age effect is to group athletes into birth month quartiles.[7,24] For example, in Q1 are those athletes born in the first three months of the selection year, commonly January–March. As we had such a small sample size of athletes in Q4 ($N = 10$), it was more appropriate to categorise athletes by which half of the year they were born in (H1 = January–March, H2 = July–December). We first used a one-way Chi-square test to confirm if more players were born in the first half of the year than the second half of the year.

As most players were born in the first half of the year (Figure 1) subsequent analyses to identify relationships between relative age and our measured traits were run treating age as categorical (H1 v H2), and separate analyses treating age as a continuous variable. For the continuous measure of age, each player's date of birth (day and month) was converted to a decimal proportion of the calendar year, with 0 denoting the first day of January through to 1 denoting the 31st day of December of the same year. We also used two different methods of quantifying each measured trait, one using standardised raw scores, and the other using raw scores corrected for age and size[40] (see below) . Thus, these data were analysed four different ways: traits (standardised) ~ age (categorical) (ANOVAs); traits (standardised) ~ age (continuous) (linear regression models); traits (corrected) ~ age (categorical) (ANOVAs); and traits (corrected) ~ age (continuous) (linear regression models). We chose to present these different methods of analysing the same data as it highlights the difficulties researchers face in identifying trends in elite academies, where relative age effects exist (this is outlined further in the Discussion section).

To allow raw performance scores on each trait to be analysed across all ages in the same model, raw scores were standardised. First, all players were grouped by the calendar year of their birth, consistent with Brazilian age categories. Then, within age groups, all measured traits, including height and mass, were standardised to a mean of zero and standard deviation of one. This preserves how players would be ranked on each trait within their age group, based simply on their observed performance. The standardised scores for each trait were checked for normality with the following traits corrected with transformations: height (log), mass (log), dribbling (PC_{D1}) (square), dribbling Path 2 (square), and sprinting Path 4 (log). Then, separately for each trait, the relationship between relative age and the standardised trait score was determined with both an ANOVA (age as categorical) and a linear regression model (age as continuous).

To correct measures of each trait for physical development, each player's age, height, and mass were first converted to an age and size index (ASI) (see below for more details). Then, separate linear regression models determined the effect of ASI on each measured trait, except for height and mass (Supplementary Table 7). Prior to analysis, the following non-Guassian trait measures were corrected with transformations; kick speed dominant foot (square), kick speed nondominant foot (square), passing/control (PC_{P1}) (square), and directed dribbling (PC_{DD1}) (square). For all players, residuals were calculated from each liner regression model, providing a measure of each performance trait, corrected for age and size. Then, separately for each trait, the relationship between relative age and the corrected trait score was determined with both an ANOVA (age as categorical) and a linear regression model (age as continuous).

Age and Size Index (ASI)

To characterise patterns of variance among the correlated measures of age, height, and mass, we used principal component analysis (PCA) to create an age and size index (ASI), as developed by Hunter and colleagues.[40] Decimal age was calculated as at the first day of testing, and these right skewed data were corrected with a log transformation prior to PCA. The first component (PC_{ASI1}) accounted for 90.1% of the variation (Supplementary Table 8). All vectors loaded in the same direction with larger positive values indicating greater ASI. Assessing biological maturity (e.g. percentage of adult height, skeletal age vs. chronological age, age at peak height velocity) is often invasive or require longitudinal data and often define an individual's maturity status relative to themselves, not against their peers. Conversely, with easily measured traits, the ASI allows comparison among athletes' *current* age and size, as it is differences in these that convey advantages to some athletes over others. As an athlete's, stature influences coaches' perceptions of their talent[45] and is more intuitively observable than maturity status, the ASI provides a practical method to alleviate age and size biases when assessing performance.

Results

As expected, most players in this soccer academy were born in the first half of the year ($\chi^2(1, N = 150) = 56.42, p \leq .001$) (Figure 1). A summary of players' height and mass is shown in Table 1. The following results are grouped by the four methods of analysis used, with only significant results presented, or results approaching significance. A summary of all analyses is provided in Table 2.

Standardised trait scores ~ decimal age (continuous)

When raw trait measures were standardised within calendar year of birth, players born earlier in the year were taller ($\beta = -0.16$, $p = .004$, $R^2 = 0.05$) and heavier ($\beta = -0.21$, $p =$

Table 1. Summary statistics for players' height (cm) and mass (kg), by age group (as at the end of the current year).

	Height (cm)						Mass (kg)					
	1st Half			2nd Half			1st Half			2nd Half		
Age	*N*	*M*	*SD*	*N*	*M*	*SD*	*N*	*M*	*SD*	*N*	*M*	*SD*
10	3	140.93	4.32	2	145.85	6.58	3	37.63	5.30	2	37.60	2.55
11	14	149.21	4.73	3	140.87	3.86	14	38.10	3.66	3	38.93	5.78
12	16	154.72	10.83	3	148.30	10.19	16	43.39	8.74	3	38.10	8.12
13	16	162.44	8.21	5	157.38	6.14	16	52.00	10.44	5	46.24	7.73
14	18	169.98	7.31	4	176.85	6.19	18	61.67	8.12	4	63.73	4.56
15	14	176.31	6.04	2	171.60	1.13	14	65.78	3.99	2	63.65	5.44
16	13	177.25	6.16	5	170.80	6.52	13	68.21	5.52	5	62.74	3.55
17	12	179.28	7.40	1	184.00	NA	12	70.16	5.74	1	79.80	NA
18	9	178.63	7.80	2	179.50	6.36	9	72.98	8.04	2	75.60	10.18
19	6	178.23	3.77	1	175.50	NA	6	71.90	6.97	1	66.45	NA

Data were further split into two groups, those born in the first half of the year and those born in the second half of the year. Presented for each category are the number of players (*N*), mean (*M*), and standard deviation (*SD*).

Table 2. Results of models of measured traits predicted by relative age, determined with four methods of analysis: standardised performance scores ~ birth date (decimal); standardised performance scores ~ birth date (1st half of year v 2nd half of year); corrected performance scores ~ birth date (decimal); corrected performance scores ~ birth date (1st half of year vs 2nd half of year).

	Standardised ~ Decimal Birth	Standardised ~ Half of Year	Corrected ~ Decimal Birth	Corrected ~ Half of Year
Height	**$t=-2.95$, $p=.004^{**}$**	$F_{(1147)}=3.56$, $p=.06$		
Mass	**$t=-2.49$, $p=.014^{*}$**	$F_{(1147)}=1.39$, $p=.240$		
Kick Speed Dominant Foot	$t=-1.55$, $p=.123$	$F_{(1123)}=0.88$, $p=.349$	$t=0.21$, $p=.838$	$F_{(1122)}=0.25$, $p=0.617$
Kick Speed Nondominant Foot	$t=-1.35$, $p=.180$	$F_{(1122)}=0.12$, $p=.732$	$t=-0.34$, $p=.735$	$F_{(1121)}=0.44$, $p=.507$
Passing Accuracy Dominant Foot	$t=-1.56$, $p=.121$	$F_{(1142)}=1.32$, $p=.252$	$t=-1.07$, $p=.286$	$F_{(1141)}=0.49$, $p=.481$
Passing Accuracy Nondominant Foot	$t=0.373$, $p=.710$	**$F_{(1142)}=4.23$, $p=.041^{*}$**	$t=1.83$, $p=.067$	**$F_{(1141)}=8.61$, $p=.004^{**}$**
Sprinting (all paths)	$t=-1.89$, $p=.060$	$F_{(1142)}=0.22$, $p=.640$	$t=-1.28$, $p=.201$	$F_{(1141)}=0.03$, $p=.867$
Sprinting Path 1	**$t=-2.44$, $p=.016^{*}$**	$F_{(1141)}=3.49$, $p=.064$	$t=-0.86$, $p=.391$	$F_{(1140)}=0.39$, $p=.531$
Sprinting Path 4	$t=-0.082$, $p=.935$	$F_{(1119)}=0.46$, $p=.499$	$t=0.14$, $p=.888$	$F_{(1119)}=0.40$, $p=.527$
Dribbling (all paths)	$t=-0.84$, $p=.402$	$F_{(1148)}=0.02$, $p=.891$	$t=0.11$, $p=.909$	$F_{(1147)}=0.25$, $p=.620$
Dribbling Path 1	**$t=-2.41$, $p=.017^{*}$**	$F_{(1132)}=1.41$, $p=.237$	$t=-1.29$, $p=.199$	$F_{(1131)}=0.36$, $p=.551$
Dribbling Path 2	$t=-0.94$, $p=.348$	$F_{(1138)}=0.85$, $p=.358$	$t=-0.55$, $p=.580$	$F_{(1137)}=0.51$, $p=.476$
Dribbling Path 4	$t=-0.38$, $p=.706$	$F_{(1119)}=0.29$, $p=.594$	$t=1.03$, $p=.306$	$F_{(1118)}=1.73$, $p=.191$
Pass/Control	$t=-0.52$, $p=.604$	$F_{(1139)}=0.10$, $p=.753$	$t=0.84$, $p=.403$	$F_{(1138)}=0.32$, $p=.572$
Directed Dribbling (all)	$t=-0.383$, $p=.702$	$F_{(1141)}=0.07$, $p=.787$	$t=0.75$, $p=.453$	$F_{(1140)}=0.57$, $p=.453$
Directed Dribbling Dominant Foot	$t=-0.939$, $p=.349$	$F_{(1136)}=1.57$, $p=.213$	$t=-0.61$, $p=.542$	$F_{(1135)}=0.56$, $p=.456$
Directed Dribbling Nondominant Foot	$t=0.38$, $p=.705$	$F_{(1124)}=0.28$, $p=.601$	$t=0.70$, $p=.485$	$F_{(1123)}=1.35$, $p=.248$

Note. $^{*}p < 0.05$, $^{**}p < 0.01$.

.014, $R^2 = 0.03$) than those born later in the year (Figure 2). Those born earlier in the year were faster sprinters ($\beta = -0.87$, $p = .016$, $R^2 = 0.03$) and dribblers of the ball ($\beta = -0.90$, $p = .017$, $R^2 = 0.03$) along the straight path (Path 1). There was a trend approaching significance for relatively older players to be faster sprinters across all paths combined (PC_{S1}) ($\beta = -0.68$, $p = .060$, $R^2 = 0.02$).

Standardised trait scores ~ half of year born (categorical)

When raw trait measures were standardised within calendar year of birth, there was a trend approaching significance for players born in the first half of the year to be taller than those born in the second half of the year ($F_{(1147)} = 3.56$, $p = .060$) (Figure 2) When using the nondominant foot, players born in the second half of the year (relatively younger) performed better on the measure of passing accuracy ($F_{(1142)} = 4.23$, $p = .041$). There was a trend approaching significance for players born in the first half of the year to be faster sprinters along the straight path (Path 1) ($F_{(1141)} = 3.49$, $p = .064$).

Corrected trait scores ~ decimal age (continuous)

When trait measures were corrected for age and size (ASI), birth date as a continuous variable had no effect on any traits. However, there was a trend approaching significance for those born later in the year (relatively younger) to be more accurate passes of the ball with the nondominant foot ($\beta = 0.07$, $p = .07$, $R^2 = 0.02$).

Corrected trait scores ~ half of year born (categorical)

When trait measures were corrected for age and size (ASI), players born in the second half of the year were more accurate when passing the ball with their nondominant foot ($F_{(1141)} = 8.61$, $p = .004$).

Discussion

The aim of this study was to explore whether relatively younger soccer players were technically more skilled than their older peers. We found relatively older players were taller and heavier, giving them a physical advantage over relatively younger players of the same age. This physical advantage likely contributed to relatively older players being able to sprint and dribble the ball faster in a straight line. On only one of the measured traits, passing accuracy with the nondominant foot, did relatively younger players outperform older players, providing some evidence, albeit weak, that players born in the latter part of the year were more technically skilled than those born earlier in the year.

Most players in this elite soccer academy were born earlier in the year (Figure 1). Unsurprisingly, players born earlier in the year were more physically developed than those born later in the year (Figure 2). Consistent with previous findings,[15,20,46] these results suggest this soccer academy preferentially selected players within an age cohort that were older, taller, and heavier.

Supporting previous research, players born earlier in the year (relatively older) were faster sprinters than those born later in the year (relatively younger), likely due to their larger stature.[9,36,37] Although most evident when running in a straight line, this relationship disappeared when players ran through the curviest path, suggesting greater physical development did not confer an advantage when greater agility was required. Similarly, relatively older players were faster dribblers of the ball, but only along the straight path. Previous research[33] found older players within an age cohort were faster dribblers on a task with a similar layout to path 2 used in this study, where no effect was found. However, Figueirdeo and colleagues used 10 m straight sections interspersed with turns, while our straight sections were much shorter (3–4 m). Intuitively, the longer straight sections benefit faster sprinters (relatively older) as they have more opportunity to reach higher running/dribbling speeds unattainable by their slower running peers. We suggest the relationships between relative age and dribbling speed identified previously,[33] and here when dribbling in a straight line, were confounded by sprint speed. Although dribbling quickly with the ball in a straight line is a desirable ability in soccer, and worth evaluating (eg. for wide playing positions), coaches, and researchers should consider our findings when designing tasks to measure dribbling ability. For example, fast, in close dribbling may help retain possession and create scoring chances in confined areas in the attacking 18-yard box, a desirable ability for strikers. If wanting to remove the effect of sprint ability to assess such skill, we suggest dribbling tasks do not include dribbling the ball in a straight line more than 3 or 4 m.

Relatively younger players were more accurate when passing the ball with the nondominant foot. Passing accurately is a technical skill, with increased proficiency associated with motor control, not muscular power.[40] Thus, more physically developed players are unlikely to gain an advantage for passing accurately. Our finding that relatively younger players were more accurate is evidence these players were more technically skilled than their relatively older peers. It is unclear why younger players were more accurate on the nondominant foot, but not the dominant foot. Possibly, they used their nondominant foot more than their older peers during training and games, increasing proficiency. If so, we would expect to see a similar effect on the directed dribbling tasks with the nondominant foot, which was not the case. However, it is unsurprising we found a relationship between relative age and passing accuracy on one foot and not the other as Hunter and colleagues[40] reported a weak

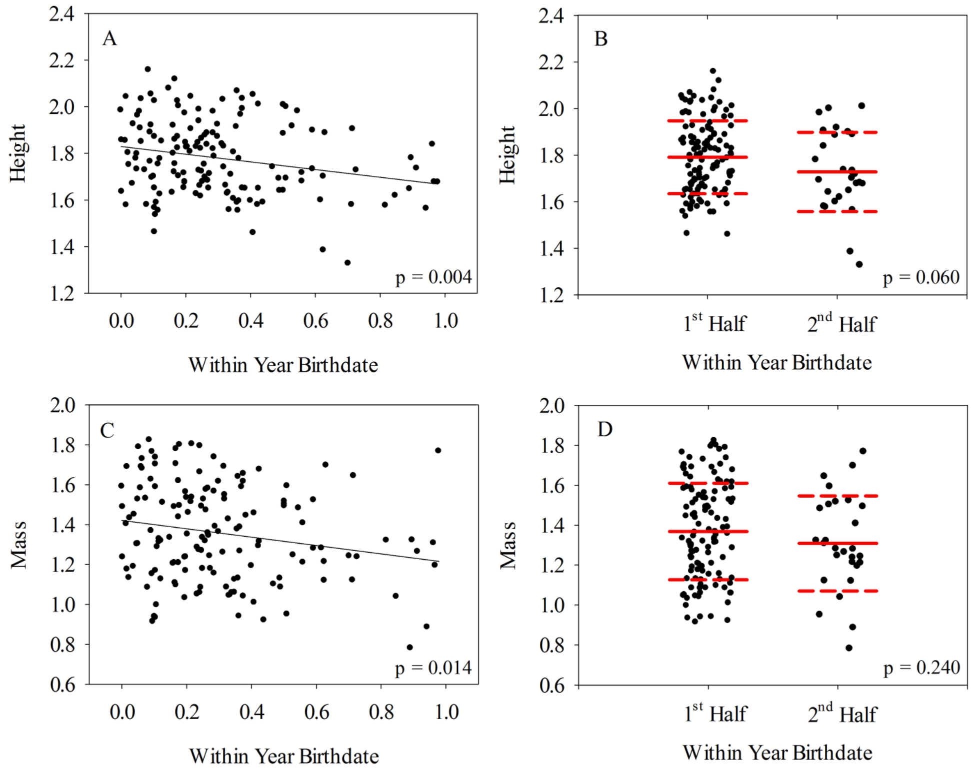

Figure 2. Relationships between date of birth and height (panels A and B), and date of birth and mass (panels C and D). Data for height and mass were first standardised (mean = 0, *SD* = 1) within birth year, then log transformed. For panels A and C, date of birth is treated as a proportion of the calendar year. For panels B and D, date of birth is treated as categorical, grouped by which half of the year players were born in. Solid red lines indicate mean. Dotted red lines indicate ± standard deviation.

association between dominant foot accuracy and nondominant foot accuracy.

For youth soccer players, relative age and physical size can influence performance in games and in assessments of skill or physical conditioning – making it difficult to fairly rank players and predict future potential. This is the basis of the relative age effect in youth sport. To determine the effect of relative age on various performance traits, we first analysed raw performance scores standardised within players' birth year. This method ranks players' observed ability within their age cohort, while also preserving how much better or worse an individual's performance was compared to their peers. We also corrected performance scores based on each player's age, height, and mass (age and size index (ASI)). For each trait, this method attributes a score (residual) to each player relative to an expected benchmark for someone of similar development. Players with a positive residual are performing better than expected for their ASI, while players with a negative residual are performing worse than expected. With that in mind, relatively older players outperformed relatively younger players only when standardised raw scores were analysed. When scores were corrected for ASI, all such effects disappeared. This suggests that were those relatively younger players given time to "catch-up" physically, they would likely perform equally well on those performance traits (sprinting and dribbling in a straight line). Conversely, on the trait that relatively younger players outperformed older players, non-dominant foot passing accuracy, this effect was evident for both standardised scores and ASI corrected scores. This suggests that when the younger players "catch-up" physically to their older peers, their better passing accuracy should persist. This strengthens the evidence that these relatively younger players, on this performance trait, were more technically skilled than their older peers.

Lastly, we analysed these data using relative age as continuous and categorical variables. Because we found an effect of age on some performance traits using one version of age, but not the other (e.g. height, mass, passing accuracy, sprinting), this reduces confidence in our findings. It also highlights the difficulty in researching age effects in elite academies. The structure and culture of selection/deselection in academies provide an attractive study environment. However, with so few players selected into academies born late in the year, confidently identifying trends is inherently difficult. We have shown here that different results can be found depending on how such data are analysed. Even collecting longitudinal data in such academies does not alleviate this bias towards greater numbers of players born early in the year. Recent reviews of talent identification research in soccer suggest that most studies have limited range in who they sample, with performance on any measured trait likely to be relatively homogenous compared to the general population of athletes.[47,48] Here, we tried to identify differences between players born early in the year and players born later in the year who had already been selected into the academy. To better understand the pathway for relatively younger athletes, a better approach may be to identify how the relatively younger players who *were* selected differ from the relatively younger players who *were not* selected. Such an approach would help reveal the traits that allow these players to overcome the bias towards selecting relatively older athletes into elite academies.

Conclusions

In our study, we found limited evidence that relatively younger soccer players were more technically skilled than their older peers of the same age. Relatively younger players performed better only on a test assessing passing the ball with their nondominant foot. Although two-footed players are highly sought after at the professional level,[49] it is unclear how this skill contributes to selection at the youth level, or if the effect found here would be observable during a selection process without rigorous testing. Regardless, increased proficiency on such a technical skill likely helps relatively younger, smaller players compete against larger, faster opponents. We also found relatively older players gain an advantage when sprinting and dribbling the ball, particularly in a straight line. However, by controlling for age and size, we showed the relatively younger players would likely perform equally well when given time to develop physically. From this, we suggest for coaches wishing to assess skill and physical performance within an age cohort in youth athletes, using a similar approach could alleviate the bias of the relative age effect, providing a more accurate estimate of an athlete's potential. Such an approach could be used when selecting players to enter an elite academy, not just with those players already selected. This would likely help identify a greater number of relatively young players with future potential.

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Supplemental material

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References

1. Ward P, Hodges NJ, Williams AM, et al. Deliberate practice and expert performance: Defining the path to excellence. In: *Skill acquisition in sport: Research, theory and practice*. London: Routledge, 2004, pp.231–258.
2. Musch J and Grondin S. Unequal competition as an impediment to personal development: a review of the relative age effect in sport. *Dev Rev* 2001; 21: 147–167.
3. Shearer E. The effect of date of birth on teachers' assessments of children. *Educ Res* 1967; 10: 51–56.
4. Brauer B. Anthropometrische Untersuchungen an gesunden Kindern und Jugendlichen im Alter von 13 bis 18 Jahren.[Anthropometric measurements on 13 to 18 years old healthy children and adolescents]. *Ä Rztliche Jugendkd* 1982; 73: 174–181.
5. Carling C, Le Gall F, Reilly T, et al. Do anthropometric and fitness characteristics vary according to birth date distribution in elite youth academy soccer players? *Scand J Med Sci Sports* 2009; 19: 3–9.
6. Hirose N. Relationships among birth-month distribution, skeletal age and anthropometric characteristics in adolescent elite soccer players. *J Sports Sci* 2009; 27: 1159–1166.
7. Gil SM, Badiola A, Bidaurrazaga-Letona I, et al. Relationship between the relative age effect and anthropometry, maturity and performance in young soccer players. *J Sports Sci* 2014; 32: 479–486.
8. Espenschade AS. Restudy of relationships between physical performances of school children and age, height, and weight. *Res Q* 1963; 34: 114–153.
9. Gastin PB and Bennett G. Late maturers at a performance disadvantage to their more mature peers in junior Australian football. *J Sports Sci* 2014; 32: 563–571.
10. Philippaerts RM, Vaeyens R, Janssens M, et al. The relationship between peak height velocity and physical performance in youth soccer players. *J Sports Sci* 2006; 24: 221–230.
11. Cameron N and Bogin B. *Human growth and development edited by Noël Cameron and Barry Bogin*. 2nd ed. Amsterdam, London; Waltham, MA, Amsterdam; Boston: Elsevier/Academic Press, Academic Press, 2012.
12. Jackowski SA, Erlandson MC, Mirwald RL, et al. Effect of maturational timing on bone mineral content accrual from

childhood to adulthood: evidence from 15years of longitudinal data. *Bone* 2011; 48: 1178–1185.
13. Thompson AH, Barnsley RH and Stebelsky G. "Born to play ball" the relative age effect and major league baseball. *Sociol Sport J* 1991; 8: 146–151.
14. Boucher JL and Mutimer BTP. The relative age phenomenon in sport: a replication and extension with ice-hockey players. *Res Q Exerc Sport* 1994; 65: 377–381.
15. Helsen WF, Winckel J and Williams AM. The relative age effect in youth soccer across Europe. *J Sports Sci* 2005; 23: 629–636.
16. Edgar S and O'Donoghue P. Season of birth distribution of elite tennis players. *J Sports Sci* 2005; 23: 1013–1020.
17. Helsen WF, Starkes JL and Van Winckel J. The influence of relative age on success and dropout in male soccer players. *Am J Hum Biol* 1998; 10: 791–798.
18. Cobley S, Baker J, Wattie N, et al. Annual age-grouping and athlete development. *Sports Med* 2009; 39: 235–256.
19. Tribolet R, Watsford ML, Coutts AJ, et al. From entry to elite: the relative age effect in the Australian football talent pathway. *J Sci Med Sport* 2019; 22: 741–745.
20. Malina RM, Reyes MP, Eisenmann JC, et al. Height, mass and skeletal maturity of elite Portuguese soccer players aged 11–16 years. *J Sports Sci* 2000; 18: 685–693.
21. Smith RE. Toward a cognitive-affective model of athletic burnout. *J Sport Exerc Psychol* 1986; 8: 36–50.
22. Gould D and Petlichkoff L. Participation motivation and attrition in young athletes. In: FL Smoll, RA Magill and MJ Ash (eds) *Children in sport*. Champaign, IL: Human Kinetics, 1988, pp.161–178.
23. Sherar LB, Baxter-Jones AD, Faulkner RA, et al. Do physical maturity and birth date predict talent in male youth ice hockey players? *J Sports Sci* 2007; 25: 879–886.
24. Schorer J, Baker J, Büsch D, et al. Relative age, talent identification and youth skill development: do relatively younger athletes have superior technical skills? *Talent Dev Excell* 2009; 1: 45–56.
25. Schorer J, Cobley S, Büsch D, et al. Influences of competition level, gender, player nationality, career stage and playing position on relative age effects. *Scand J Med Sci Sports* 2009; 19: 720–730.
26. Gibbs BG, Jarvis JA and Dufur MJ. The rise of the underdog? The relative age effect reversal among Canadian-born NHL hockey players: a reply to Nolan and Howell. *Int Rev Sociol Sport* 2012; 47: 644–649.
27. McCarthy N and Collins D. Initial identification & selection bias versus the eventual confirmation of talent: evidence for the benefits of a rocky road? *J Sports Sci* 2014; 32: 1604–1610.
28. McCarthy N, Collins D and Court D. Start hard, finish better: further evidence for the reversal of the RAE advantage. *J Sports Sci* 2016; 34: 1461–1465.
29. Fumarco L, Gibbs BG, Jarvis JA, et al. The relative age effect reversal among the National Hockey League elite. *PLoS One* 2017; 12: e0182827.
30. Kelly AL, Wilson MR, Gough LA, et al. A longitudinal investigation into the relative age effect in an English professional football club: exploring the 'underdog hypothesis'. *Sci Med Footb* 2020; 4: 111–118.
31. Cumming SP, Searle C, Hemsley JK, et al. Biological maturation, relative age and self-regulation in male professional academy soccer players: a test of the underdog hypothesis. *Psychol Sport Exerc* 2018; 39: 147–153.
32. Ashworth J and Heyndels B. Selection bias and peer effects in team sports: the effect of age grouping on earnings of German soccer players. *J Sports Econ* 2007; 8: 355–377.
33. Figueiredo AJ, Coelho e Silva MJ and Malina RM. Predictors of functional capacity and skill in youth soccer players. *Scand J Med Sci Sports* 2011; 21: 446–454.
34. Figueiredo AJ, Gonçalves CE, Coelho E, et al. Youth soccer players, 11–14 years: maturity, size, function, skill and goal orientation. *Ann Hum Biol* 2009; 36: 60–73.
35. Malina RM, Cumming SP, Kontos AP, et al. Maturity-associated variation in sport-specific skills of youth soccer players aged 13–15 years. *J Sports Sci* 2005; 23: 515–522.
36. Malina RM. *Growth, maturation, and physical activity*. 2nd ed. Champaign, IL: Human Kinetics, 2004.
37. Wong P-L, Chamari K, Dellal A, et al. Relationship between anthropometric and physiological characteristics in youth soccer players. *J Strength Cond Res* 2009; 23: 1204–1210.
38. Wilson RS, Smith NM, Santiago PRP, et al. Predicting the defensive performance of individual players in one vs. one soccer games. *PLoS One* 2018; 13: e0209822.
39. Wilson RS, Smith NMA, Ramos SdP, et al. Dribbling speed along curved paths predicts attacking performance in match-realistic one vs. One soccer games. *J Sports Sci* 2019; 37: 1072–1079.
40. Hunter AH, Smith NM, Camata T, et al. Age-and size-corrected kicking speed and accuracy in elite junior soccer players. *Sci Med Footb* 2022; 6: 29–39.
41. Hedrick TL. Software techniques for two- and three-dimensional kinematic measurements of biological and biomimetic systems. *Bioinspir Biomim* 2008; 3: 1–6.
42. Hunter AH, Angilletta MJJr, Pavlic T, et al. Modeling the two-dimensional accuracy of soccer kicks. *J Biomech* 2018; 72: 159–166.
43. Hunter AH, Angilletta MJ and Wilson RS. Behaviors of shooter and goalkeeper interact to determine the outcome of soccer penalties. *Scand J Med Sci Sports* 2018; 28: 2751–2759.
44. R Core Team. *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing, https://www.R-project.org/ (2016).
45. Furley P and Memmert D. Coaches' implicit associations between size and giftedness: implications for the relative age effect. *J Sports Sci* 2016; 34: 459–466.
46. Massa M, Costa EC, Moreira A, et al. The relative age effect in soccer: a case study of the São Paulo Football Club. *Rev Bras Cineantropometria Amp Desempenho Hum* 2014; 16: 399–405.
47. Williams AM, Ford PR and Drust B. Talent identification and development in soccer since the millennium. *J Sports Sci* 2020; 38: 1–12.
48. Bergkamp TL, Niessen ASM, den Hartigh RJ, et al. Methodological issues in soccer talent identification research. *Sports Med* 2019; 49: 1–19.
49. Bryson A, Frick B and Simmons R. The returns to scarce talent: footedness and player remuneration in European soccer. *J Sports Econ* 2013; 14: 606–628.