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Cross-sectional comparison of body composition and resting metabolic rate in Premier League academy soccer players: Implications for growth and maturation

Cross-sectional comparison of body composition and resting metabolic rate in Premier League academy soccer players: implications for growth and maturation

Original article

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ABSTRACT

For the first time we aimed to: (1) assess fat-free mass (FFM) and RMR in youth soccer players, (2) compare measured RMR to estimated RMR using previously published prediction equations, and (3) develop a novel population specific prediction equation. In a cross-sectional design, ninety-nine males from a Premier League academy underwent assessments of body composition (DXA) and RMR (indirect-calorimetry). Measured RMR was compared to estimated RMR values from five prediction equations. A novel RMR prediction equation was developed using stepwise multiple regression. FFM increased (P<0.05) between U12 (31.6±4.2 kg) and U16 (56.3±5.3 kg) after which no further increases occurred (P>0.05). RMR in the U12s (1655±195 kcal.day^{-1}), U13s (1720±205 kcal.day^{-1}) and U14s (1846±218 kcal.day^{-1}) was significantly lower than the U15s (1957±128 kcal.day^{-1}), U16s (2042±155 kcal.day^{-1}), U18s (1875±180 kcal.day^{-1}) and U23s (1941±197 kcal.day^{-1}) squads (P>0.05). FFM was the single best predictor of RMR (r^2=0.43; *P*<0.01) and was subsequently included in the novel prediction equation: RMR (kcal.day^{-1}) = 1315 + (11.1 x FFM in kg). Both FFM and RMR increase from 12-16 years old, thus highlighting the requirement to adjust daily energy intake to support growth and maturation. The novel prediction RMR equation developed may help to inform daily energy requirements.

Key words: RMR, DXA, fat-free mass, youth soccer

INTRODUCTION

The function of soccer academies is to produce players who can progress to and represent the club's first team (Wrigley *et al.*, 2014). As a player transitions through the academy pathway to the first team and adulthood, they undergo distinct phases of growth and maturation (Buchheit and Mendez-Villanueva, 2013; Towlson *et al.*, 2017). From a physical perspective, this elicits significant changes in fat-free mass (FFM), which has associated implications for the development of strength and soccer specific explosive movements (Wrigley *et al.*, 2014). Indeed, whilst we previously observed that U18, U21 and first team players from an English Premier League team possess similar amounts of absolute fat mass (~8 kg), there is an approximate difference of ~7 kg in FFM between U18 and first team players (Milsom *et al.*, 2015). In relation to physical development, these data therefore suggest that fat mass is less affected by age and that it may be more appropriate to monitor changes in FFM in youth soccer players.

Despite such comparisons of U18, U21 and first team players, no research has yet quantified changes in FFM as players progress through the academy pathway and through key phases of growth and physical development, i.e. pre, circa and post peak height velocity (PHV). An understanding of muscle growth and development (as quantified by dual-energy X-ray absorptiometry, DXA), is especially important as this will help practitioners tailor age-specific training and nutritional guidelines. Indeed, considering that FFM is the most metabolically active compartment (Müller *et al.*, 2013), progressive increases in FFM will also influence an individual's resting metabolic rate (RMR) and thus their energy requirements.

In this regard, an assessment of RMR (a major component of total energy expenditure; TEE) at least provides a platform to begin to develop age-specific energy requirements. Indeed, data from Indian youth soccer players demonstrates that RMR increases by ~400 $kcal.day^{-1}$ from the (chronological) ages of 10 to 13 (Cherian *et al.*, 2018). To the authors' knowledge, however, no research has yet quantified RMR in Premier League academy soccer players across the full age-range of a professional soccer academy, i.e. U12-U23. Whilst RMR can be assessed via indirect calorimetry, this method can be time consuming and requires specialist equipment, thus making it impractical in the applied environment. Consequently, an array of predictive equations have been developed to estimate RMR, though such equations may be limited as they are derived from non-athletic populations (Cunningham, 1980; Henry, 2005), and may not take into account FFM (Schofield, Thorpe and Sims, 2019). The latter is especially important considering FFM is the most metabolically active tissue (Müller *et al.*, 2013), and indeed it has recently been suggested that athlete specific equations should include FFM (within the equation) when estimating RMR (Schofield, Thorpe and Sims, 2019). Thus, there is a definitive need to develop population specific predictive equations according to changes in stature, body mass and FFM (Herrmann *et al.*, 2017) and moreover, across the age-range that is representative of soccer academies.

With this in mind, the aims of this study were three-fold: (1) to assess changes in body composition (in particular FFM) and RMR in a cohort of youth soccer players from a Category One academy in the English Premier League; (2) to compare measured RMR with estimated RMR according to previously published prediction equations, and (3) to develop a novel prediction equation that is specific to Premier League academy soccer players.

MATERIALS AND METHODS

Overview of Study Design

In a cross-sectional design, participants were assessed for measures of body composition and RMR, under standardised conditions: ≥8 hours overnight fast and ≥12 hours after exercise (Bone and Burke, 2018), between 07:00–11:00. All testing procedures were conducted over a four-week period at the end of the 2017/18 season.

Participants

Ninety-nine (n=99; white = 82; black = 8; mixed race = 9) male soccer players from a Category One English Premier League soccer academy volunteered to participate the study, representing 87% of the club's academy players at the time of data collection. Players were categorised according to their respective age-group (U12, U13, U14, U15, U16, U18 and U23) based upon their age and/or the squad that they predominantly played for at the time of testing. Participant characteristics are presented in Table 1 and an overview of the typical in-season weekly training schedule is shown in Table 2. All experimental procedures and associated risks were explained to both the player and their parent/guardian, and written informed consent and assent were obtained respectively. Ethical approval was granted by the Wales Research Ethics Committee, UK (REC approval number: 17/WA/0228) and by the local University Ethics Committee.

<TABLE 1>

<TABLE 2>

Anthropometric Measures

Participants removed jewellery and wore only underwear for measures of stature, sitting height, body mass and whole-body DXA assessment. Participant's body mass (SECA, model-875, Hamburg, Germany), stature and sitting height (SECA, model-217, Hamburg, Germany) were measured to the nearest 0.1 kg, 0.1 cm and 0.1 cm respectively according to the International Society for the Advancement of Kinanthropometry (ISAK) guidelines (Marfell-Jones *et al.*, 2006) by an ISAK Level-1 practitioner. Two measurements were taken for each anthropometric measure, with a third taken if the first two measures differed by more than 2%. Where two measures were taken, the mean was recorded and if a third measure taken, the median was recorded.

Each participant underwent a whole-body fan-beam DXA scan (Hologic QDR Series, Discovery A, Bedford, MA, USA) where the effective radiation dose was 0.01 mSv per person. All scans were performed and analysed by the same trained operator in accordance with best practice procedures (Nana *et al.*, 2016). After conformation of regions of interest (left and right arms and legs and the trunk), each DXA scan was automatically analysed via the QDR software. Data included for analysis included whole-body and regional fat-free and fat mass and whole-body percent body fat. These measures were reported as a sub-total, i.e. whole-body minus the head. The test-retest reliability of the same DXA scanner used in the present study has been previously reported (Egan *et al.*, 2006). The coefficient of variation (CV) for whole-body FFM, fat mass and percent body fat were: 1.0%, 1.9% and 1.9% respectively.

Resting Metabolic Rate

Following all anthropometric measures, RMR was measured via open-circuit indirect calorimetry (GEM Nutrition Ltd, UK) using the recent protocol outlined by Bone and Burke (Bone and Burke, 2018). The calorimeter was calibrated against known gas concentrations: ‘zero’ (0.0% O_2 and 0.0% CO_2) and ‘span’ (20.0% O_2 and 1.0% CO_2) gases (BOC, Guildford, UK), prior to each measurement. Following calibration and before starting data collection, participants relaxed for ten minutes under a transparent ventilated hood in a supine position in a dark, quiet, thermoneutral room. Subsequently, data was collected over a 20-minute period (2 x 10-minute duplicates), in which data for the second 10 minutes was used to determine RMR. $\dot{V}O_2$ and $\dot{V}CO_2$ were measured continuously and mean one-minute values were provided throughout. $\dot{V}O_2$ and $\dot{V}CO_2$ were determined using the Haldane transformation (Haldane, 1918) and energy expenditure (kcal.day^{-1}) calculated using the Weir equation (Weir, 1949).

Resting metabolic rate was also estimated for each player using five different prediction equations (as outlined in Table 3). These equations were selected as they were developed using a similar sample size to the present study (n range: 51 - 223), and adhered to the two pre-determined criteria: 1) they were developed using participants of a similar age-range to those in the present study; and 2) they were developed using healthy, non-obese participants (athletic populations also included). The De Lorenzo (De Lorenzo *et al.*, 1999), Kim (Kim *et al.*, 2015) and Wong (Wong *et al.*, 2012) equations were developed using athletic populations, with the Kim (Kim *et al.*, 2015) equation using recreational soccer players.

<TABLE 3>

Calculation of Maturity Offset and Percent of Predicted Adult Stature

Somatic maturity (timing) was estimated for each participant by calculating maturity-offset (Mirwald *et al.*, 2002). This equation estimates the time in years from PHV and includes chronological age, stature, sitting height and body mass, and is accurate to ± 0.24 years (Mirwald *et al.*, 2002). A maturity-offset value was calculated for players in the U12-U18 squads as this is typically the timeframe in which PHV occurs in youth soccer players (Towlson *et al.*, 2017) and also the age-range in which the equation was developed (Mirwald *et al.*, 2002).

Predicted adult stature (PAS) was calculated using the Sherar equation (Sherar *et al.*, 2005) for U12-U18 squads. This equation includes chronological age, stature, sitting height, body mass, maturity offset and is accurate to ± 5.35 cm (Sherar *et al.*, 2005). Current percent of PAS (maturity status) was then calculated using the following equation: *(Current Stature ÷ Predicted Adult Stature) x 100*.

Statistical Analyses

Statistical comparisons between squads were performed using a one-way between-groups analysis of variance (ANOVA). Where significant main effects were present, Bonferroni post-hoc analysis was conducted to locate specific differences. Ninety-five % confidence intervals (95% CI) for the differences are also presented.

The relationship between body size variable(s) (stature and FFM) and RMR were initially checked for linearity (with a zero intercept), to identify if there was a linear, proportional relationship (significant correlation and slope $b = 1.0$) between body size variable and RMR (Tanner, 1949). Statistical and graphical (Figure 3) exploration identified that a linear, proportional relationship did not exist. Subsequently allometric scaling procedures were investigated to describe the relationship between body size variable and RMR. Firstly, a power function ratio (y/x^b) for each body size variable had to be determined, from log-linear regression analysis. The slope of the log-linear regression line for each body size variable (stature = 0.825; FFM = 0.285) generated the b exponent for which each body size variable was scaled to. This allometric approach produces a size independent RMR value by correlating the power function ratio with the body size variable. If the influence of body size has been removed, then this correlation should not differ from zero.

Pearson's correlation analysis was performed to determine the strength of association between measured RMR and predicted RMR (for each prediction equation). Least squares regression analysis was performed to determine the validity of the five prediction equations, where each prediction equation was regressed against the measured RMR value separately. If the intercept of the regression line was different from zero, it was deemed that fixed bias was present, and if the slope of the regression line was different from one, proportional bias was deemed present. Random error was quantified using standard error of the estimate (SEE) from the regression line. To evaluate the accuracy of each prediction equation, the mean 95% prediction interval (95% PI) was also calculated.

A novel population specific prediction equation was derived using stepwise multiple regression. Stature, % PAS, body mass and FFM were all entered as predictor variables. This analysis selects (one or more) significant predictor variables that produce the best model (i.e. equation), as described in detail by Field (2018). Data for the regression analysis conformed to the assumptions of non-zero variance, no multicollinearity, homoscedasticity, independent and normally distributed errors, independent data points and linearity (Field, 2018). Similar to the other prediction equations, this novel prediction equation was also analysed via least squares regression. All statistical analyses were completed using SPSS (version 24, SPSS, Chicago, IL) where $P<0.05$ is indicative of statistical significance. Data are presented as mean ± SD.

RESULTS

Participant characteristics including age, maturity offset, percent of PAS, stature and body mass are presented in Table 1.

Fat-Free Mass

There was a main effect of playing squad on FFM (P<0.01; Figure 1). FFM of the U12's (31.6±4.2 kg) was not different compared to the U13's (34.6±4.7 kg; P=1.00), though was lower than that of the U14's (43.2±8.9 kg; 95% CI = -19.23 to -4.00; P<0.01), U15's (49.3±6.5 kg; 95% CI = -25.48 to -9.94; P<0.01), U16's (56.3±5.3 kg 95% CI = -33.14 to -16.31; P<0.01), U18's (57.9±6.6 kg; 95% CI = -32.58 to -19.00; P<0.01) and U23's (62.6±5.9 kg; 95% CI = -38.45 to -24.15; P<0.01). FFM of the U13's was lower than that of the U14's (95% CI = -16.25 to -1.02; P=0.01), U15's (95% CI = -22.50 to -6.96; P<0.01), U16's (95% CI = -30.17 to -13.33; P<0.01), U18's (95% CI = -29.60 to -16.02; P<0.01) and U23's (95% CI = -35.47 to -21.17; P<0.01). There were no differences between the U14's and U15's (P=0.34), although the U14's had lower FFM than the U16's (95% CI = -21.53 to -4.69; P<0.01), U18's (95% CI = -20.96 to -7.38; P<0.01) and U23's (95% CI = -26.83 to -12.53; P<0.01). The U15's and U16's had similar FFM (P=0.25), however FFM of the U15's was lower than the U18's (95% CI = -15.05 to -1.11; P=0.01) and U23's (95% CI = -20.91 to -6.27; P<0.01). FFM of the U16's and U18's (P=1.00) and U16's and U23's (P=0.25) was similar, and there was no difference between the U18 and U23 players (P=0.15).

Fat Mass

There was a main effect of playing squad on fat mass (P=0.02; Figure 1), with the U13's (8.2±2.2 kg) displaying less fat mass than the U23's (11.1±3.4 kg; 95% CI = -5.83 to -0.07; P=0.04). There were no differences in fat mass between any other squads (P>0.05 for all pairwise comparisons).

Percent Body Fat

There was a main effect of playing squad on percent body fat (P<0.01; Figure 1). Percent body fat of the U12's (22.3 ± 5.7 %) was not different from the U13's (18.7 ± 4.3 %; P=0.23), however was higher than the U14's (16.8±4.3 %; 95% CI = 1.18 to 9.82; P<0.01), U15's (14.2 ± 2.2 %; 95% CI = 3.63 to 12.44; P<0.01), U16's (15.0 ± 2.4 %; 95% CI = 2.47 to 12.02; P<0.01), U18's (14.4 ± 2.1 %; 95% CI = 3.98 to 11.68; P<0.01) and U23's (14.3 ± 2.8 %; 95% CI = 3.90 to 12.02; P<0.01). The U13's percent body fat did not differ from the U14's (P=1.00) or the U16's (P=0.40), however was higher than the U15's (95% CI = 0.04 to 8.85; P=0.05), U18's (95% CI = 0.39 to 8.09; P=0.02) and U23's (95% CI = 0.31 to 8.42; P=0.02). There were no differences in percent body fat between the U14, U15, U16, U18 and U23 playing squads (P>0.05 for all pairwise comparisons).

<FIGURE 1>

Resting Metabolic Rate

There was a main effect of playing squad on RMR (P<0.01; Figure 2). RMR of the U12's (1655 ± 195 kcal.day^{-1}) was similar to that of the U13's (1720 ± 205 kcal.day^{-1}; P=1.00) and U14's (1846 ± 218 kcal.day^{-1}; P=0.23), however was lower than the U15's (1957±128 kcal.day^{-1}; 95% CI = -534.90 to -67.67; P<0.01), U16's (2042 ± 155 kcal.day^{-1}; 95% CI = -639.90 to -133.78; P<0.01), U18's (1875 ± 180 kcal.day^{-1}; 95% CI = -423.54 to -15.24; P=0.02) and U23's (1941±197 kcal.day^{-1}; 95% CI = -500.98 to -70.96; P<0.01). The U13's RMR was not different to the U14's (P=1.00), U18's (P=0.42) or U23's (P=0.04), however was lower than the U15's (95% CI = -470.21 to -2.97; P=0.04) and U16's (95% CI = -575.20 to -69.09; P<0.01). There were no differences in RMR between the U14, U15, U16, U18 and U23 playing squads (P>0.05 for all pairwise comparisons).

<FIGURE 2>

Once the influence of body size variable on RMR was removed, there was no significant relationship between stature ($r^2<0.01$, p=0.78) and RMR or between FFM ($r^2<.01$, p=0.85) and RMR respectively (Figure 3).

<FIGURE 3>

<FIGURE 4>

Measured RMR vs. Predicted RMR

Predicted RMR using the Cunningham (1578 kcal.day^{-1}; 95% CI = 237 to 323; P<0.01), DeLorenzo (1769 kcal.day^{-1}; 95% CI = 49 to 130; P<0.01), Henry (1758 kcal.day^{-1}; 95% CI = 58 to 142; P<0.01), Kim (1466 kcal.day^{-1}; 95% CI = 359 to 427; P<0.01) and Wong (1693 kcal.day^{-1}; 95% CI = 131 to 200; P<0.01) equations all differed from measured RMR (see Figure 4). The random error (SEE) associated with each prediction equation was similar across all equations (163-165 kcal.day^{-1}), as was the 95% prediction interval for each prediction equation (327 - 330 kcal.day^{-1}; Table 4). The potential for any bias was assessed via visual inspection of the regression line (Figure 5). Apart from the novel prediction equation presented in the current study, all other prediction equations presented with both fixed and proportional bias, with the intercepts and slopes of all regression lines differing from zero and one respectively.

<TABLE 4>

<FIGURE 5>

Stepwise multiple regression revealed that stature (r^2=0.41), % PAS (r^2=0.34), body mass (r^2=0.42) and FFM (r^2=0.43) were all significant predictors of RMR (P<0.01). However, FFM was the single best predictor of RMR (accounting for 43% of the variation in RMR) and was the only predictor variable included in the novel prediction equation, with all other variables rejected as they did not significantly improve the fit of the model:

$$RMR\ (kcal.day^{-1}) = 1315 + (11.1 \times FFM\ in\ kg)$$

Given the potential difficulties of obtaining FFM (via DXA) and the simplicity of obtaining stature and body mass, we derived a second prediction equation (also using stepwise multiple regression) with only body mass and stature entered as predictor variables. In this second equation, body mass was the only predictor variable included, with stature being rejected:

$$RMR\ (kcal.day^{-1}) = 1254 + (9.5 \times body\ mass\ in\ kg)$$

DISCUSSION

Using a cross-sectional design, we report for the first time the changes in both FFM and RMR (as assessed by DXA and indirect calorimetry) between different age groups of Premier League academy soccer players. Importantly, we demonstrate that the largest changes in FFM and RMR typically occur between U12-U16, demonstrating this is a key period for growth and maturation. We also demonstrate that common prediction equations significantly underestimate RMR (in some cases as much as -844 kcal.day^{-1}) and that FFM is the single best predictor of RMR in this population. Subsequently, we present two novel prediction equations that are cost and time effective, accounts for FFM (and body mass) and that is specific to academy soccer players (U12-U23). From a practical perspective it is hoped that these data will help formulate age-specific estimates of RMR which may assist in calculations of energy prescription.

Similar to our previous observations on the transition from U18 to first team (Milsom *et al.*, 2015), we also observed little change in fat mass between the U12-U18 age groups. However, there was marked differences in FFM between the U12-U16 squads (Figure 1), with each year of development associated with a different magnitude in increase in FFM (U12-U13: ~3.0 kg; U13-U14: ~8.6 kg; U14-U15: ~6.1 kg; U15-U16: ~7.0 kg). The largest increase in FFM occurred during the transition from U13-U14, which also coincided with the largest increases in stature and body mass (Table 1). This is also the time-frame during which most players went through PHV (Table 1), the period of most rapid growth during the adolescent years (Malina *et al.*, 2015). Whilst mean differences in FFM between the U16, U18 and U23 squads may not be statistically different, it is important to consider individual differences. For example, examination of Figure 1 clearly demonstrates the within and between squad differences in such parameters of body composition. Considering the focus of an academy is to develop their player's characteristics towards those of the first team, our data clearly demonstrate the necessity to adopt an individualised approach to player development.

In accordance with changes in stature, body mass and FFM, we also observed an increase in RMR between the U12-U14 age groups (U12: 1655 ± 195 $kcal.day^{-1}$; U13 1720 ± 205 $kcal.day^{-1}$; U14: 1846 ± 218 $kcal.day^{-1}$), thus highlighting the requirement to adjust total energy intake accordingly. Such data correspond with data from Indian soccer players where an increase in RMR of ~400 $kcal.day^{-1}$ from the ages of 10 to 13 (Cherian *et al.*, 2018) was also observed. It is noteworthy, however, that the RMR values in the present study are higher than those previously reported in youth soccer players. For example, the RMR values of the U13 players

(1720 ± 205 kcal.day^{-1}) were higher than those of Indian soccer payers of a similar age (1118 ± 265 kcal.day^{-1}), despite players in the present study being smaller in stature and having less body mass and FFM (Cherian *et al.*, 2018). Similarly, the U16 players studied here had higher RMR than age-matched Korean soccer players (2042 ± 155 vs. 1,648 ± 111 kcal.day^{-1}), though players in the present study were comparatively taller, heavier and had more FFM (Kim *et al.*, 2015). Such differences may be due to ethnicity (Henry, 2005) or methodological differences between studies, e.g. different rest periods prior to RMR measurements.

Once the influence of both stature and FFM were removed via allometric scaling (Figure 3), there was no significant relationship between either of these body size variables and RMR, i.e. when considering per cm of stature or per kg of FFM, RMR was the same across all age groups. These data contradict that of Harrell and colleagues (Harrell *et al.*, 2005), who suggested that relative RMR is greater in children and adolescents than adults. However, these researchers used standard ratio scaling which is deemed inappropriate (Weinsier, Schutz and Bracco, 1992) due to the contribution of body size variable (i.e. stature or FFM) to RMR not being constant.

The prediction equations evaluated in this study provide inaccurate estimations of RMR in Premier League academy soccer players (Figure 4). As an extreme example, estimated RMR using the Kim equation (Kim *et al.*, 2015) underestimated RMR by ~850 kcal.day^{-1} in one individual, despite this equation being developed in a population most similar to those in the present study (16-year-old recreational soccer players). Whilst such differences may be due to population specific factors (e.g. ethnicity, elite athletes vs. non-elite), methodological differences in assessment of predictor variables may also contribute. For example, although the Cunningham and the Kim equations both include FFM as a predictor variable, different methods were used to assess FFM. Indeed, FFM was estimated by Cunningham (Cunningham,

1980) using an equation that included body mass and age, whereas Kim and colleagues estimated FFM using bioelectrical impedance (Kim *et al.*, 2015). Thus, practitioners wishing to use prediction equations to estimate RMR should carefully consider not only the population in which the equation was developed, but also the precise methodologies used to determine the predictor variable(s). The use of inappropriate prediction equations could be potentially harmful to a player (or any athlete) if used to prescribe energy requirements, given the consequences of chronic low energy availability (Mountjoy *et al.*, 2018). In this regard, the development of the novel prediction equation(s) presented here holds ecological validity owing to the assessment of FFM (using DXA) as well as the assessment of RMR during a training phase that is representative of the typical training loads undertaken by academy soccer players. In situations where assessment of FFM is not possible, an alternative equation with only body mass required as a predictor variable has been generated.

The novel and population specific prediction equation presented here subsequently allows practitioners to estimate RMR in conditions where direct measurement is not possible. Further studies are now required in other cohorts of youth soccer players (perhaps in different ethnicities) to validate this equation. We also acknowledge that no information on training load or TEE is provided, both of which likely increase with age (Smith *et al.*, 2018). Additionally, the cross-sectional design does not allow us to assess longitudinal changes during key phases of growth and maturation. Future research should therefore adopt such designs to quantify changes in body composition and RMR of academy soccer players as they progress through the academy pathway, particularly around PHV.

In summary, we provide novel data describing changes in FFM and RMR of youth soccer players from a Category One English Premier League academy. We demonstrate that the largest changes in FFM and RMR typically occur between U12-U16, suggesting this is a key period for physical development during which energy requirements are increased. Our analysis also demonstrates that commonly used prediction equations significantly underestimate RMR and that FFM is the single best predictor of RMR in this population. As such, our novel prediction equation (that accounts for FFM) may be used when estimating RMR in academy soccer players.

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DECLARATION OF INTERESTS

The authors report no conflict of interest.

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