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Using Principal Component Analysis to Compare the Physical Qualities between Academy and International Youth Rugby League Players

Submission Type: Original Investigation

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Abstract

Purpose: To compare the physical qualities between academy and international youth rugby league (RL) players using Principal Component Analysis (PCA).

Methods: Six hundred and fifty-four males (age 16.7 ± 1.4 years; height 178.4 ± 13.3 cm; body mass 82.2 ± 14.5 kg) from 11 English RL academies participated in this study. Participants completed anthropometric, power (countermovement jump; CMJ), strength (isometric mid-thigh pull; IMTP), speed (10 and 40m speed) and aerobic endurance (prone YoYo IR1) assessments. PCA was conducted on all physical quality measures. A one-way analysis of variance (ANOVA) with effect sizes (ES) was performed on two principal components (PC) to identify differences between academy and international backs, forwards and pivots at under 16 and 18 age-groups.

Results: Physical quality measures were reduced to two PCs explaining 69.4% of variance. The first PC (35.3%) was influenced by maximum and 10m momentum, absolute IMTP, and body mass. 10m and 40m speed, body mass and fat, prone YoYo, IMTP relative, maximum speed and CMJ contributed to PC2 (34.1%). Significant differences ($p<0.05$, ES; -1.83) were identified between U18 academy and international backs within PC1.

Conclusion: Running momentum, absolute IMTP and body mass contributed to PC1, while numerous qualities influenced PC2. The physical qualities of academy and international youth RL players are similar, excluding U18 backs. PCA can reduce the dimensionality of a dataset and help identify overall differences between playing levels. Findings suggest RL practitioners should measure multiple physical qualities when assessing physical performance.

Key words: fitness testing; rugby league; talent identification; principal component analysis; physical qualities

Introduction

Governing bodies and sports clubs implement talent identification and development systems in their search for future stars [1]. These systems or "academies" aim to provide a positive learning environment to foster development, reduce the risk of injury, promote health and ultimately, produce players for the professional senior level [2, 3]. Given performance in sport is multifactorial [4], the routine assessment of general and specific physical qualities that are indicative of superior performance is important [5]. As such, measuring physical qualities is imperative for those within talent identification systems to evaluate and monitor athletes and programmes, inform training practices [6] and establish short- and long-term goals [7]. Furthermore, the physical qualities of athletes have been found to differentiate future success in adulthood [8], within team [9] and Olympic [10] sports.

Within research and practice, athletic performance capabilities are usually determined by measuring a multitude of physical qualities [7]. Understandably, the measurement of several physical qualities may pose a challenge for practitioners, considering the analysis and reporting of multivariate datasets [11]. Player development staff are required to collect, analyse, and report fitness testing data, and subsequently act upon the results within a timely manner to influence player development [5]. Furthermore, some variables may share similar information (i.e., collinearity) therefore making this process even more complex. Principal component analysis (PCA) is an analysis technique that removes data multicollinearity [12] and explains the variance within a dataset consisting of numerous variables into distinct principal components (PCs) [13]. By reducing the dimensionality of data, this enhances the visualisation of data in a 2-dimensional space, allowing for easier interpretation of multivariate data sets of participants, which is the case following the implementation of a fitness testing battery. Using a similar technique, Till and colleagues (2016) utilised singular value decomposition to group related fitness testing variables [1]. In doing so, future career attainment (i.e., playing professional rugby league [RL]) of under (U)13-15 players was predicted with reasonable accuracy using only two variables identified from the anthropometric and fitness measures.

Performance during RL match play can be characterised by the complex interaction of cognitive and physical qualities, combined with technical and tactical proficiencies [3]. Superior physical qualities are important for youth RL players [3], and have been well documented [6, 14-17]. Similar to other youth sports, players train and compete with a professional club, and a number of players are selected from their club to play international fixtures against other nations [18]. Whilst common for National Governing Bodies to select and run youth international teams, no RL research has determined the differences in physical qualities, between academy and international players using large multivariate datasets. Utilising large-scale investigations of multiple clubs has been advocated [3, 15, 19] to improve the generalisability of research findings and allow comparisons across playing levels (i.e., academy vs. international) within playing positions to occur.

When analysing the physical qualities of athletes, which involves large multivariate data sets, the use of PCA can overcome data multicollinearity while maintaining the majority of variance, therefore allowing differences between groups to be easily recognised [1]. Given the importance of assessing physical qualities for talent identification and development, and the limited research comparing international and academy standard players, this study aimed to use PCA to 1) compare the physical qualities between academy and international youth (U16 and U18) RL players within positions (i.e., backs, forwards and pivots), and 2) reduce the dimensionality of a multivariate national physical qualities testing battery.

Methods

Design

A national league-wide physical qualities testing battery was conducted by the lead researcher during a pre-season period (September – December 2019) at eleven professional club's training ground. The testing battery included anthropometric (height, body mass and body fat), muscular power (countermovement jump [CMJ]), and strength (isometric mid-thigh pull [IMTP]) measures completed inside each club's facility. Sprint (10, 20, 30 and 40 m) and aerobic endurance (prone Yo-Yo IR Level 1) measures were recorded outdoor on an artificial pitch. Prior to all testing sessions, participants provided information on their date of birth and playing position and completed a standardised warm-up. All testing was conducted between 17:00 and 19:00pm, with an average outdoor temperature of 9.7 ± 3.1°C. As a result, testing conditions were comparable during each session.

Subjects

Six-hundred and fifty-four males (age 16.4 ± 1.2 years) from eleven English RL academies participated in the study. Players were categorised by playing position (forwards n = 334, backs n = 213, pivots n = 107), age grade (U16 n = 284, U18 n = 370) and standard (academy [U16 n = 243, U18 n = 312], international [U16 n = 41, U18 n = 58]). Playing position was classified by a player's primary playing position. The U16 and U18 national performance squads (i.e., international) were initially nominated by professional academies, then selected by members of the England Performance Unit. Following three training camps, the squads were finalised and selected for competitive fixtures. The international players were not included with the academy data and were subsequently compared against their club counterparts. All experimental procedures were approved by the university's ethics committee (Declaration of Helsinki) with informed and parental consent obtained when a player was under 18 years at the time of data collection.

Anthropometry

Body mass and height were measured to the nearest 0.1 kg and 0.1 cm using a portable stadiometer (Seca 213, Hamburg, Germany) and analogue scales (Seca, Hamburg, Germany). Body fat was measured using a bio-impedance analyser (Tanita BF-350, Tokyo, Japan). This method is both valid and reliable in males with inter-day agreement (ICC = 0.978) [20].

Countermovement Jump

Two CMJs were performed on a calibrated portable force plate (Passport Force Platform, PASCO Scientific, California, USA), to provide measures of force-time characteristics [21]. Participants completed two trials with hands placed on the hips and were instructed to start in a standing position and drop to a self-selected depth before immediately jumping as high as possible [22]. Concurrent validity of this method with the same equipment has been reported [23]. The highest jump height (cm) was recorded and used for statistical analysis. Force plates have been shown to be reliable when quantifying CMJ height with an ICC and coefficient of variation (CV) of 0.85 and 3.8% respectively [19].

Isometric Mid-thigh Pull

Two maximal IMTPs were performed on a custom-built dynamometer (Takei Scientific Instruments, Niigata, Japan) sampling at 122Hz with a chain (51cm) and latissimus dorsi pulldown bar (120cm; Decathlon, Stevenage, United Kingdom). Participants followed the protocol outlined by Till and colleagues (2018) [24]. The highest absolute and relative scores (N) were used for analysis and peak force was calculated using a correction equation [24]. Relative peak force was calculated by dividing peak force by body mass. A strong significant relationship has been identified between the peak force derived from a dynamometer and a force platform ($r = 0.92$, $p<0.001$) [25] within RL players. In addition, the dynamometer has shown acceptable between day reliability (CV = 5.5% [4.5-6.9]) [26].

Speed and Momentum

Participants completed a 40 m speed test using photoelectric timing gates (Brower Timing Systems, Draper, UT, USA) placed at 10 m intervals, 150 cm apart and at a height of 90 cm. Participants stood with their front foot 50 cm from the first timing gate [27] in a two-point start and set off in their own time. All participants completed 2 maximal sprints with 3 minutes rest between repetitions. 10 m and maximum momentum were calculated by multiplying body mass by 10 m speed and maximum speed, respectively. Maximum speed was calculated by dividing the fastest 10 m split time by the distance between splits (10 m). All times were measured to the nearest 0.01 sec and the quickest time was used for statistical analysis. Previous research has reported Brower timing systems to be reliable when measuring 10, 20, 30 and 40 m sprints with mean typical errors expressed as CV of 2.5%, 2.2%, 2.2% and 1.8% respectively [26].

Prone Yo-Yo Intermittent Recovery Test Level 1

The prone Yo-Yo IR1 was completed according to protocols outlined previously [28]. The final level and distance achieved (m) was recorded following the second failed attempt to complete the shuttle in the allocated time, or volitional exhaustion. The reliability (CV = 9.9%) [16] and concurrent validity have previously been reported [28]. The distance achieved was used for statistical analysis.

Statistical Analysis

PCA was undertaken on physical qualities in line with previous methods [12, 29]. The number of PCs equals the number of inputted variables, and the first PC explained the most variance, and the last PC explained the least. This method reduces the dimensionality and complexity of the data, therefore enhancing the visualisation of data in a 2-dimensional space. The data were mean centred and standardised to unit variance, giving an $M \times N$ matrix (X). The covariance matrix of X was then computed by $X^T X$. The eigenvalues and eigenvectors were then determined from the covariance matrix through eigendecomposition. Lastly, the original data were subsequently projected onto the eigenspace of the covariance matrix which provided the PC scores [29]. The first and second PCs were extracted for further analysis as they explained the most variance in the dataset. Scatter plots for each positional group were created to visualise academy and international players and were colour coded.

The PC scores relate to an individual participant observation and are represented by the combined linear weighted contribution of the physical quality (i.e., the eigenvectors of each PC). To obtain the PC score, the matrix of eigenvectors and the matrix of the standardised physical quality measure are multiplied together. In doing so, this applies the coefficients of each eigenvector to the standardised data. For example, PC1 scores were calculated using the equation;

PC1 = *(0.25 x height) + (0.33 x body mass) + (0.16 x body fat) + (0.24 x CMJ) + (0.40 x IMTP) + (0.18 x IMTP relative) + (-0.22 x 10m) + (-0.24 x 40m) + (0.25 x maximum speed) + (0.41 x 10m momentum) + (0.43 x maximum momentum) + (0.07 x prone YoYo)* [11].

There were 522 complete data sets out of the total 654 (i.e., participants who completed all tests within the testing battery). Of the incomplete physical qualities data sets, 16% of the data were missing data, resulting in 3% missing from the total dataset. In order to retain as much data as possible, the missing data was imputed using a probabilistic PCA [30]. This approach was chosen following a pilot study where multiple methods of imputation were trialled using the missCompare R package [31]. The pilot study involved 1,414 complete observations from a similar testing battery where data points were randomly changed to missing before trialling the imputation methods. Probabilistic PCA deemed to be the most appropriate method based on imputation accuracy and computational efficiency.

Two one-way analysis of variance (ANOVA) were performed on both PCs to identify differences between playing standard (academy vs. international) within both age categories (i.e., U16s and U18s) and playing positions. Post-hoc testing involving pair-wise comparisons with Tukey Kramer correction was conducted with significance level set to $p = 0.05$. The magnitude of differences between academy and international players was calculated by effect sizes (ES). The magnitude of effects were classed as Cohen's *d*; trivial <0.2, small = 0.20-0.59, moderate = 0.60-1.19, large = 1.2-1.99, and very large >2.0 [32]. All data analyses were completed in R Studio (version 4.0.2), and the PCA was completed using the *prcomp* function from the *stats* package [33].

Results

Figure 1 (A) displays the scree plot of the PCA, depicting the explained variance of each PC. PC1 (35.3%) and PC2 (34.1%) accounted for 69.4% of the variance in the dataset. PC3 only added an additional 8.7% of the variance. The contribution of physical quality measures to PC1 and PC2 are shown in Figure 1 (B) and (C) respectively. Table 1 displays the component loadings of each measure to all PCs. Component loadings demonstrate the contribution of each physical quality measure to each of the PCs. Maximum momentum, 10m momentum, IMTP and body mass all strongly influenced PC1 (35.3% of the total variance). 40m speed, body mass, prone YoYo, IMTP relative, body fat, 10m speed, maximum speed and CMJ contributed to PC2 (34.1% of the variance). As such, PC1 typically represents body mass, strength and momentum qualities, and PC2 represents a variety of physical qualities.

Table 2 displays the differences between academy and international players for both PCs. There was an overall significant difference between all academy and international players on PC1 [$(F_{2, 134}) = 3.22$, p = 0.043] and PC2 [$(F_{2, 134}) = 1.34$, p<0.001]. Pairwise comparison showed a significant difference (p = <0.001, large ES) between U18 academy and international backs on PC1. Although not significant, there were large differences identified between both U16 academy and international backs and forwards within PC1, and between U18 academy and international pivots. Within PC2, no significant differences were found with moderate differences between U16 academy and international forwards, and U18 academy and international backs and pivots. Table 3 presents the differences between positions at both playing levels. There were significant differences identified between U16 club forwards and pivots ($p=0.005$), U18 club backs and pivots ($p=0.04$), and U18 club forwards and pivots ($p<0.001$) within PC1 (table 3). On PC2, there were significant differences between U16 club backs and forwards ($p<0.001$), U16 club forwards and pivots ($p<0.001$), U18 club backs and forwards ($p<0.001$) and U18 club forwards and pivots ($p<0.001$). In addition, significant differences were found between U16 international backs and forwards ($p=0.016$), U16 international forwards and pivots ($p<0.001$), U18 international backs and forwards ($p<0.001$) and U18 international forwards and pivots ($p=0.012$).

Figure 2 plots PCs for each playing position at both age groups. Each individual player is colour coded according to playing level. This facilitates the visual interpretation of the differences between groups. For example, U18 international backs are mostly located toward the top right of the plot indicating high PC1 and PC2. This suggests that they display superior body mass, strength and speed qualities in comparison to academy backs. In contrast, the PC scores of U18 academy and international forwards and pivots are similar with a lack of distinct difference, indicating comparable physical qualities.

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Discussion

The primary aims of this study were firstly to evaluate the overall differences in physical qualities between academy and international youth RL players, and secondly, to reduce the dimensionality of a multivariate national physical qualities testing battery using PCA. Dimension reduction techniques capture the complexity of a dataset in fewer composite variables and allow data to be represented without the loss of information [1]. Maximum and 10m momentum, body mass and absolute IMTP had the highest component loadings on PC1. For PC2, 10m and 40m speed, body mass and fat, IMTP relative, maximum speed, prone YoYo and CMJ had the highest contributions and, therefore, captured unique additional variance. There was a significant difference identified between U18 academy and international backs within PC1. Overall, academy and international players compared at U16 and U18 age categories display similar physical qualities within two PCs, except U18 backs. Moreover, there were significant differences in physical qualities between positions within playing levels. The findings have identified that a multivariate physical quality data set is non-colinear and RL practitioners should implement testing batteries consisting of multiple measures to capture a meaningful proportion of the total information whilst using PCA may be useful for visual comparisons.

When comparing between playing levels, although overall differences were identified between academy and international levels for PC1 and PC2, pairwise comparisons only showed a significant difference between U18 academy and international backs on PC1. In addition, large but not significant differences were found between U16 academy and international backs and forwards, and U18 pivots within PC1. These findings suggest that international players are heavier, stronger with superior running momentum qualities. Moreover, significant differences identified on PC1 between U16 club forwards and pivots, U18 club backs and pivots and U18 club forwards and pivots highlight distinct positional variances within club players. Interestingly, insignificant positional differences were observed at the international level within PC1. These findings suggest that U16 and U18 international backs, forwards, and pivots display similar body mass, momentum, and strength qualities. Although no investigation has compared academy and international players, our results are in line with research that indicates strength and running momentum distinguish between playing levels in academy rugby union [34] and professional RL [35]. Moreover, strength and running momentum differentiate between those academy aged players attaining professional status [9].

Within PC2, no significant differences and only trivial to moderate effects were identified between playing levels. However, there were significant differences between backs and forwards, and forwards and pivots at both U16 and U18 club and international levels. These findings are comparable to previous research in academy RL whereby positional differences were found within playing levels [15]. The results further highlight the importance of anthropometric and physical qualities for increased playing standards, which should be planned within the development of youth RL players. On visual inspection of plots (figure 1), it seems that U18 positions cluster together (i.e., smaller ellipses shape). Therefore, it may be proposed that at U18s, positions are specialised with players having similar physical qualities. In contrast, U16 players display larger ellipses indicating increased variability in their physical profile and potentially less specialised toward position. Consequently, training should be tailored toward the physical qualities deemed important for positions [6].

For a multivariate physical qualities testing battery, within PC1, maximum and 10m momentum, absolute IMTP and body mass had the highest contributions. These findings are not surprising due to RL's collision demands and the importance of dominating opponents during contact [3]. Physiological factors (e.g., increased muscle cross-sectional area) may provide a potential explanation of these findings [36]. Greater muscle cross-sectional area, and subsequently, greater body mass may contribute to higher force production [37, 38] and running momentum. PC2 loadings were influenced by 10m and 40m speed, body mass and fat, IMTP relative, prone YoYo and CMJ. The results emphasise the relationship between both body mass, body fat and performance variables such as aerobic endurance [39] and sprinting[40]. Furthermore, the contribution of multiple variables to PC2, with similar loadings, (see figure 2C), highlights the importance of measuring and developing a range of physical qualities including strength, power, speed, endurance and body mass. Interestingly, height did not largely influence either PCs, while body mass explained variance on both. Furthermore, the high loadings of body mass to both PC1 and PC2 coupled with the differences observed between U18 backs further emphasises it as an important developmental factor for youth RL players as per previous investigations [9]. Additionally, as body mass influences both PCs, it is suggested that lean body mass is developed to negate the influence of excess body mass on running performance [17]. Correspondingly, these qualities require monitoring and evaluation throughout specific phases of the season. As such, PCA accounts for a large proportion of a data set allowing multiple qualities to be compared within an efficient manner. Therefore, those involved in team selection, decision making, and the development of youth RL players may use PCA to provide a concise overview and visualisation of general physical qualities.

The total variance explained by the first 2 PCs (69.4%) leaves 30.6% of variance unexplained between the remaining physical quality measures [41]. The findings capture a proportion of unique information within PC1 (i.e., running momentum, absolute strength, body mass), and these qualities are deemed important for performance in RL, and should be developed and evaluated regularly. Additionally, the contribution of eight physical qualities to PC2, alongside the lack of meaningful component loadings (>0.70) suggests that a multivariate testing battery does not provide similar information [41]. Moreover, low component loadings propose that singular variables do not heavily contribute (i.e., share similar information) to PCs. As such, our results advocate the use of assessing multiple physical qualities within a testing battery. Furthermore, the variability observed between PC scores alongside the minimal differences identified between playing levels highlight the influence of individual characteristics and potentially reinforces the importance of non-measured attributes. In addition, the findings support the notion that fitness testing and subsequent data is important, however, should be used in conjunction with rugby performance when decision making as per previous findings with practitioners [5]. As such, it may be posited that selection to higher playing standards (i.e., international) is attributed to a combination of superior physical, technical skill, tactical knowledge and/or psychological qualities.

A limitation of the current study is that testing was completed at a single time point during pre-season, and results may vary at different phases of the season. Therefore, future research should utilise PCA to reduce the dimensionality of data across multiple timepoints (i.e., longitudinally). Participants were limited to RL academies, as a result, the generalisability of the findings may be limited at lower playing levels. Lastly, sporting performance consists of a multitude of contextual variables. As such, the complex nature of sport cannot be solely attributed to physical qualities and data [1, 5], but inclusive of a technical, tactical and psychological factors.

Practical Applications

- By reducing the components of multivariate data sets, PCA provides a concise visualisation and interpretation of physical qualities and allows data to be presented simply to a range of stakeholders.
- Superior running momentum, absolute strength and body mass qualities are indicative of increased playing standards, and the improvement of these qualities are important for player development.
- Practitioners should aim to maximise the development of non-measured attributes including technical and tactical ability, sport-specific and psychological skills.

Conclusions

The findings suggest that multiple physical qualities are important for youth RL players, and therefore warrant development and regular assessment. By reducing the components of multivariate data sets, PCA can determine differences between playing levels and positions and proposes that a national multivariate physical qualities testing battery does not share similar information. Additionally, PCA provides a concise visualisation and interpretation of physical qualities and allows data to be presented simply to a range of stakeholders. As such, a testing battery consisting of multiple measures is required to provide the most information when assessing youth RL players' physical qualities. The findings substantiate that a variety of physical qualities including body mass, strength, power, running speed and momentum, and endurance are important for youth RL players. Therefore, strategies should be in place to maximise the development of such qualities in RL programmes and require regular monitoring and evaluation. In addition, practitioners should consider fitness testing data alongside rugby performance when making informed decisions.

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Table 1. Differences in PC scores between club and international backs, forwards and pivots

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12
Normalised eigenvalues	4.23	4.09	1.04	0.86	0.61	0.44	0.41	0.17	0.08	0.01	0.00	0.00
% of variance explained	35.3	34.1	8.7	7.2	5.2	3.7	3.5	1.5	0.7	0.1	0.00	0.00
Cumulative variance %	35.3	69.4	78.1	85.3	90.5	94.2	97.7	99.2	99.9	100.0	100.0	100.0
Height	0.25	-0.20	0.09	0.75	0.02	-0.10	0.06	-0.54	0.03	0.01	0.00	-0.00
Body mass	0.33	-0.34	0.17	-0.01	0.10	0.01	0.05	0.26	-0.03	-0.38	0.35	-0.63
Body fat	0.16	-0.33	-0.12	-0.60	0.11	0.07	-0.07	-0.67	0.05	0.01	-0.00	0.00
CMJ height	0.24	0.29	0.02	0.09	0.22	0.88	-0.06	-0.03	0.02	0.00	-0.00	-0.01
IMTP	0.40	0.01	0.48	-0.12	-0.21	-0.06	-0.03	0.06	-0.02	-0.28	-0.66	0.02
IMTP relative	0.17	0.32	0.55	-0.15	-0.34	-0.08	-0.09	-0.13	0.00	0.24	0.55	-0.02
10m speed	-0.22	-0.31	0.35	0.06	-0.31	0.04	-0.59	0.06	-0.40	-0.10	0.10	0.24
40m speed	-0.24	-0.36	0.35	0.01	0.08	0.13	0.00	0.13	0.77	0.19	-0.04	-0.03
Max speed	0.25	0.31	-0.29	0.04	0.08	-0.25	-0.65	0.00	0.45	-0.19	0.03	0.02
10m momentum	0.41	-0.23	-0.08	-0.03	0.00	0.00	0.24	0.25	0.10	-0.15	0.28	0.72
Max momentum	0.43	-0.18	-0.12	-0.00	0.11	-0.08	-0.16	0.25	-0.14	0.77	-0.15	-0.10
Prone YoYo	0.07	0.32	0.24	-0.09	0.79	-0.30	0.30	-0.03	0.03	0.00	0.00	-0.00

Abbreviations; CMJ, countermovement jump; IMTP, isometric mid-thigh pull; PC, principal component; PCA, PC analysis. The component loadings (i.e., positive and negative) represent the direction of loading of each variable in the PC.

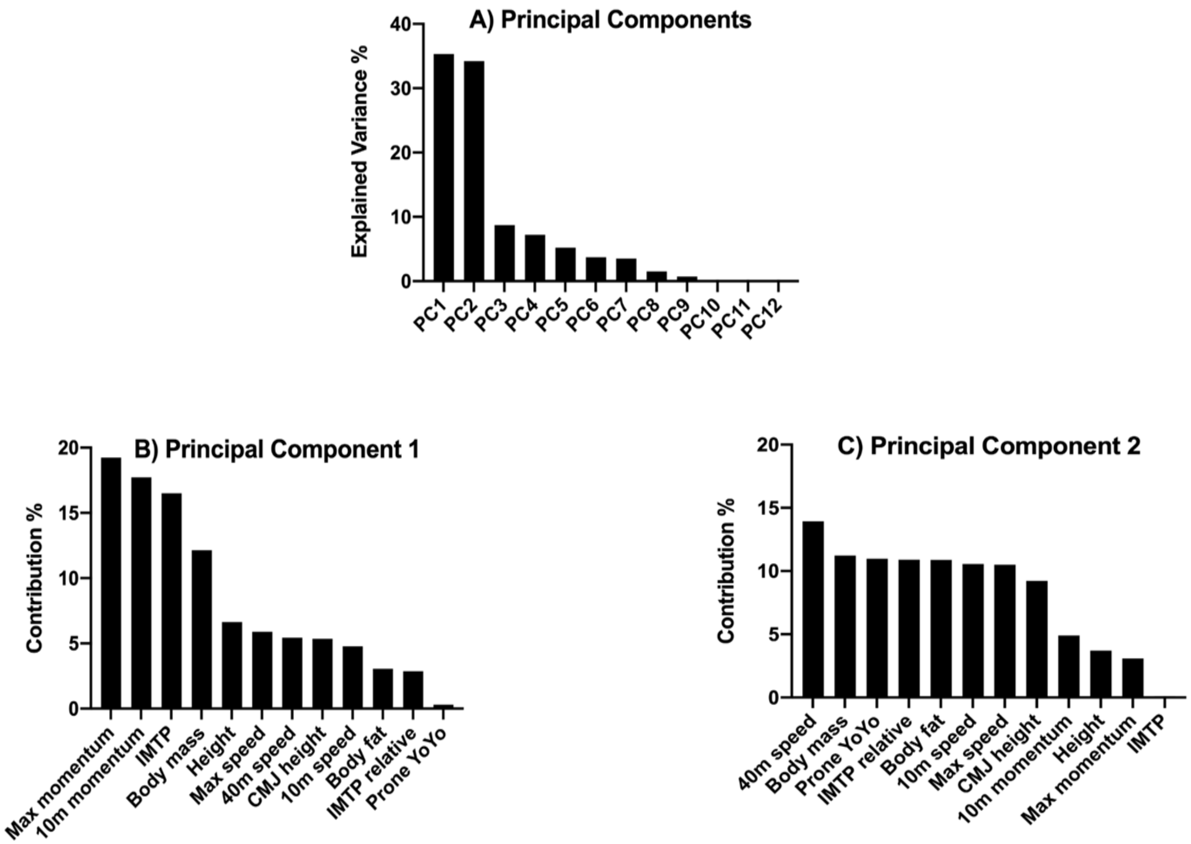

Figure 1. (A) Scree plot for the PCA and the associated fractional variance attributed to each PC; (B) Contribution of variables to PC1; (C) Contribution of variables to PC2

Table 2. Differences in PC scores between club and international backs, forwards, and pivots.

	PC1			**PC2**		
	Club	**International**	***p* value (ES)**	**Club**	**International**	***p* value (ES)**
U16						
Backs (n = 85)	-0.81 ± 1.54	0.26 ± 1.08	0.238 (-0.81 large)	0.65 ± 1.33	1.18 ± 1.75	0.918 (-0.34 small)
Forwards (n = 153)	-0.55 ± 1.05	0.44 ± 1.27	0.188 (-0.84 large)	-1.94 ± 1.55	-0.88 ± 1.64	0.217 (-0.66 moderate)
Pivots (n = 46)	-1.79 ± 1.99	-1.18 ± 1.43	0.863 (-0.35 small)	1.27 ± 1.60	1.36 ± 1.42	1.00 (-0.06 trivial)
U18						
Backs (n = 128)	0.99 ± 1.24	3.04 ± 0.96	p<**0.001* (-1.83 large)**	1.50 ± 1.00	2.37 ± 1.47	0.274 (-0.69 moderate)
Forwards (n = 181)	1.66 ±1.36	2.09 ± 0.87	0.956 (-0.37 small)	-1.31 ± 1.63	-1.51 ± 1.58	0.999 (0.12 trivial)
Pivots (n = 61)	0.00 ± 1.60	1.40 ± 0.17	0.356 (-1.22 large)	0.76 ± 1.21	1.31 ± 0.38	0.973 (-0.62 moderate)

Abbreviations; ES, effect size; PC, principal component. Values are presented mean ± SD and p-value (ES; inference).

**Significant difference ($p < 0.05$) highlighted in bold.*

Table 3. Positional differences between club and international players

	PC1		PC2	
	Club	**International**	**Club**	**International**
U16				
Backs vs forwards	0.93 (-0.22 small)	0.99 (-0.17 trivial)	**p<0.001* (1.78 large)**	**0.016 (1.21 large)**
Backs vs pivots	0.13 (0.55 moderate)	0.15 (1.14 large)	0.74 (-0.41 small)	1.00 (-0.09 trivial)
Forwards vs pivots	**0.005 (0.80 large)**	0.054 (1.22 large)	**p<0.001* (-2.01 large)**	**p<0.001* (-1.44 large)**
U18				
Backs vs forwards	0.12 (-0.53 moderate)	0.61 (0.98 large)	**p<0.001* (2.01 large)**	**p<0.001* (2.54 large)**
Backs vs pivots	**0.04 (0.68 moderate)**	0.24 (2.36 large)	0.26 (0.66 moderate)	0.72 (0.99 large)
Forwards vs pivots	**p<0.001* (1.13 large)**	0.94 (1.14 large)	**p<0.001* (-1.42 large)**	**0.012 (-2.45 large)**

Abbreviations; ES, effect size; PC, principal component. Data are presented as p-value (ES; inference).

**Significant difference (p < 0.05) highlighted in bold.*

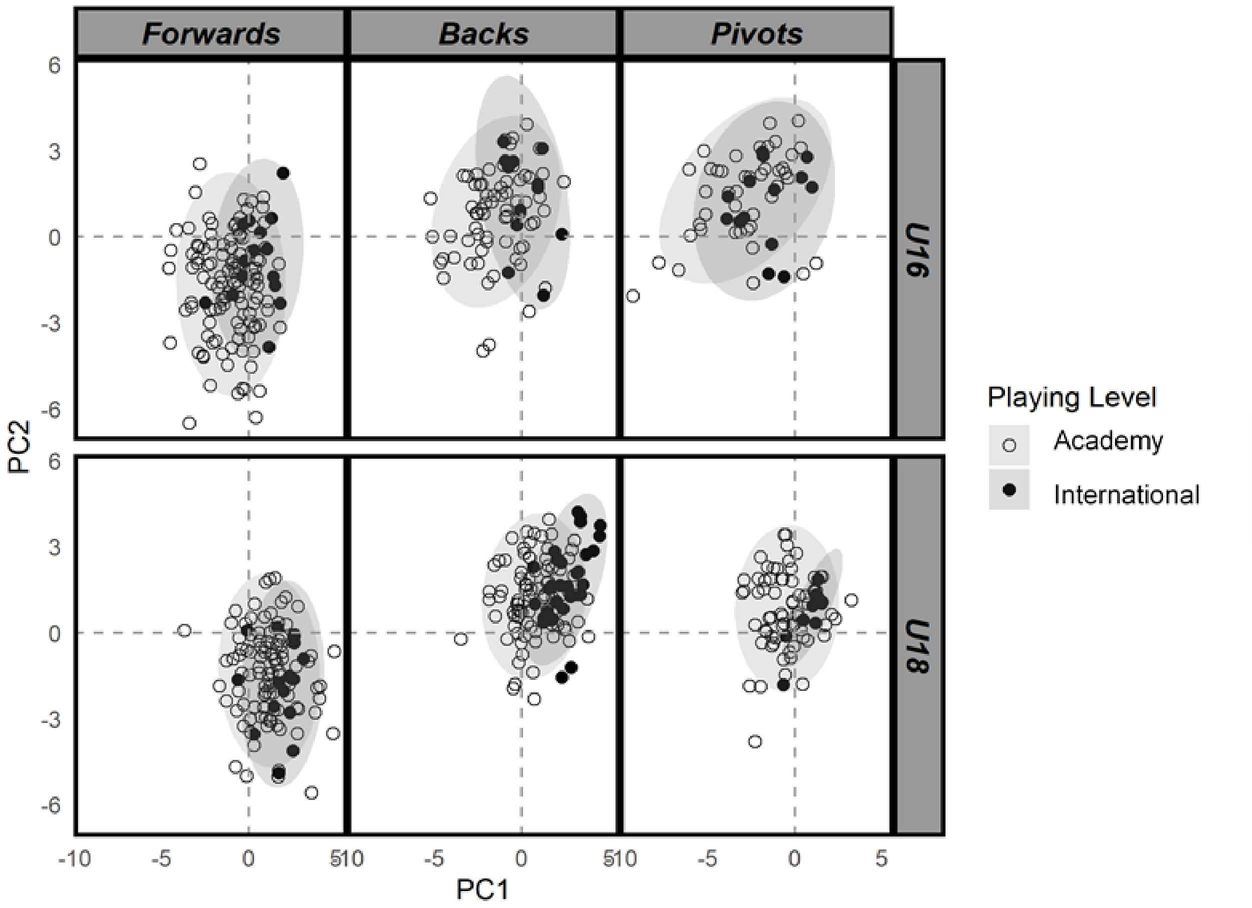

Figure 2. Scatterplot of the 1st (x-axis) and 2nd (y-axis) PC "scores" for each positional group at U16 and U18. Academy players are indicated by open circles, and international players, by filled circles. Ellipses are included to distinguish playing level. PC indicates principal component