International Journal of Physical Education, Sports and Health 2019; 6(4): 38-44

P-ISSN: 2394-1685
E-ISSN: 2394-1693
Impact Factor (ISRA): 5.38
IJPESH 2019; 6(4): 38-44

www.kheljournal.com
Received: 26-05-2019
Accepted: 27-06-2019

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Prognostic validity of morphological, physiological and motor characteristics in classifying university athletes in different sports

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Abstract
Talent selection in university sport should be based on morphological, physiological and motor diagnostics for purposes of recommending or transferring athletes to specific sports for best performance. However, the predictive value of such testing is unclear. This study evaluated the validity of morphological, physiological, as well as specific motor performance prerequisites. The aim of this investigation was discriminating university athletes of different sports based on the morphological, physiological and motor characteristics. Two hundred and eighty-five university students belonging to twelve different sports and aged between 17 and 28 years (mean age 21.4 ± 2.1, CI 21.0-21.8 years) participated in this study. A cross-sectional analytical study design was used in the study. University athletes randomly selected volunteered as subjects. The physiological characteristics assessed included resting heart rate, the morphological characteristics assessed included; Body height, body weight and body fat percentage. Motor characteristics assessed included upper body and lower body muscular endurance. Neural Network (Multilayer Perceptron) was used to test whether it is possible to discriminate between athletes of the twelve sports and to assign each individual to his own sport on the basis of a unique profile of the morphological, motor, and physiological prerequisites. The data was also analyzed using Multivariate analysis of variance (Manova) to determine if the groups were significantly different on morphological, motor, and physiological characteristics. Statistical packages for social science version 25 was used in the analysis. The results showed that after a cross validated MLP (Multilayer perceptron) analysis using the leave "8.7%" out procedure, 34.6% of the 209 athletes were classified correctly and assigned as true positives to their own sport. The best classification result of 15.4% correct hits were obtained in handball and Tennis. No true positives were found in Chess and netball (0.0%). Manova analysis showed that, the individual test of differences in means was statistically different among the sports in all dependent variables except; Height (f (11,274) =1.087, p=.372), Pulse (f (11,274) =3.675, p=.070) and Percentage body fat (f (11, 274)=3.759, p=.065). The global test for equality of the mean vectors for the twelve sports groups was significant for groups (Pillai's T, $p<0.01$). This showed that the groups were statistically different in a linear combination of all dependent variables. In conclusion participation in specific sports should be associated with the selection of athletes with specific prerequisites.

Keywords: University athletes, morphological characteristics, physiological characteristics, motor characteristics, multivariate analysis of variance (Manova), neural networks

Introduction

There are many factors which contribute to the sports performance. Skill, psychological characteristics, powerful and capacious energy-production systems are all important factors in sports performance, but the main success factor in sports is body size, shape and morphology (Claessens *et al*., 1994) [8]. Understanding of the morphological, biomechanical and physiological demands of modern training methods is important especially for optimal and successful participation as well as selection, identification and comparison of talented athletes (Kruger, 2004) [4].

The requirement of a specific physique for good performance in particular sports had been supported by different studies (Carter & Heath, 1990) [6]. In a previous study investigating male and female athletes (Cavedon *et al*., 2015) [7], better performance in sport specific field

Tests was Associated with higher scores in physiological characteristics. Studies on the anthropometric characteristic of the human body indicate that athletes who play in a specific sport differ in somatic characteristics (Gaurav, Singh, & Singh, 2010) [13]. Anthropometric profile has been investigated in various sports, due to its relationship with physical and technical aspects (Grind staff, & Potach, 2006) [15]. The anthropometric profile of athletes changes according to their category, but some valences (e.g., speed, power and strength) correlate with the anthropometric evaluations which are fundamental for better performance during sports performance (Franchini *et al*., 2013).

Athletes from different types of sports on the other hand, can clearly be distinguished based on their physical profile even when discriminating between sports within the same category (Leone, Lariviere & Comtois, 2002; Pion *et al*., 2014) [10, 16, 25]. Studies have shown that participation in elite sport training was associated with the selection of athletes with specific prerequisites and also the development of the specific anthropometric, motor and physiological characteristics of a particular sport (Pion *et al*.,2015) [4, 22, 23]. In sports like table tennis, Maehner (2018) [20] found soccer players to be superior in sideward jumping and push-ups. In volleyball, talented players are characterized by a higher stature as well as by a better jumping ability (Rikberg & Raudsepp, 2011) [27]. In basketball, at players exhibit a lower level of static and dynamic balance compared to gymnasts and soccer players, respectively (Bressel *et al*., 2007) [3]. It is well-known that the heart rate at rest along with systolic and diastolic blood pressure are lower for endurance sports (Cornelissen *et al*., 2010) [9].

Talent selection should be focused on a multifaceted variety of general physical, physiological, psychomotor, and psychological performance diagnostics (Williams & Reilly, 2000) [26, 31]. According to Pion *et al*. (2015) [4, 22, 23], talent identification should be related to homogeneous samples and should aims at pinpointing the most promising athletes to engage in long-term, elite sport training Many sports are based on a complex, multi-dimensional performance profile (Buekers *et al*., 2015) [4]. Several talent identification programs in elite sport schools have implemented morphological, motor, and physiological diagnostics (Douglas, 2014; Kinugasa, 2014) [16]. Moreover, Olympic studies indicated that successful sports performance is often hindered by lack of appropriate physique (Tanner 1964, Carter, 1984) [5].

As all studies mentioned above were executed with Caucasian athletes from Europe, there is a lack of knowledge in regard to the makeup of Kenyan/African athletes hence creating a research gap for this study. To our knowledge this study is the first one comparing Kenyan elite athletes from different sports in regard to sports specific characteristics. From literature, a great variety of study design parameters have led to inconsistent research results, providing an inconsistent picture with regard to the discriminative validity of talent features addressing general and sport-specific performance prerequisites. There is therefore a need to enhance the current literature with scientific data on the anthropometric, motor, and physiological characteristics of Kenyan athletes in different sports. Taking into account the above issues and in view of the remaining uncertainty, this study had an aim of discriminating athletes of different sports based on the morphological, physiological and motor characteristics. We hypothesized that the anthropometric, motor, and physiological characteristics of athletes in different sports would be significantly different. With this in mind, the results of this study will provide evidence for the applicability of the different measures for talent identification in the different sports investigated.

Methods

The investigation took place among university athletes who were to participate in East Africa Inter-University games. A cross-sectional analytical study design was used in the study. First, some explanations about the study were given to the participants. Written consent was obtained from all subjects.

Subjects/groups

Two hundred and eighty-five university students aged between 17 and 28 years (mean age 21.4 ± 2.1, CI 21.0-21.8 years) participated in this study. The sample included subjects who participated in twelve sports; Athletics *n*=19), Hockey *n*=25), Tennis *n*=22), Handball *n*=22), Badminton *n*=12), Rugby *n*=27), Volleyball *n*=18), Soccer *n*=53), Netball *n*=17), Basketball *n*=31), Chess *n*=3), Karate *n*=37).

Measures

Physiological Characteristics

The physiological characteristics assessed included resting heart rate (bpm; Polar H10 Heart rate sensor, Polar Electro Inc., Finland) and Blood pressure (mmHg; HEM-1000, Blood Pressure Monitor, Omron Health Care Inc., Japan). Blood pressure of all subjects was measured in a sitting position on with the right forearm placed horizontally on the table by following the recommendations of the American Heart Association.

Morphological Characteristics

The morphological characteristics assessed included; Body height (BH) to the nearest 0.1 cm (Height Tester, Donghuateng Sports Apparatus Ltd, Beijing, China). Height (cm) was determined using a wall scale and a Broca plane with the head held in the Frankfort plane, Body weight (kg) was determined with a certified digital scale used for official weigh-ins for each competition. Body fat percentage was determined by body fat meter. The ideal weight and fat-lean ratio vary considerably for men and women and by age, but the minimum percent of body fat considered safe for good health is 5 percent for males. The average adult body fat is closer to 15 to 18% for men. Body weight to the nearest 0.1 kg (calibrated Seca Alpha 770) were measured according to standardized test prescriptions (Hawes and Martin, 2001)

Motor Characteristics

Motor characteristics assessed included upper body and lower body muscular endurance. Muscular endurance was assessed by mean of two imposed rhythm tests by metronome; push-ups (50 push-ups per minute till exhaustion) and sit-ups (sit-ups per minute till exhaustion) (Leone & Léger, 1985). Speed was meter by 40-meter dash in seconds.

Although most of the tests administered are very standardized and well-recognized assessments, test-retest reliability on the specific subject pool used in the present study could not be obtained. To counter this potential problem, all testers were thoroughly trained and familiarized with proper test administration prior to actual data collection.

Statistical analysis

Data analysis was done using the statistical program for social sciences (SPSS) version 25 (Inc., Chicago, IL, USA). In this study, the study variables were assessed by a two-tailed probability value of $p<0.05$ for significance. The discriminative validity of the three morphological, three motor, and two physiological measures was determined using a classification of athletes by means of a nonlinear neural network MLP (Multilayer Perceptron). Similarly, for the MLP analysis, three subsets were created for (i) training, (ii) testing of the predictive model, and (iii) the final classification of the left-out cases. Subsequently, the MLP was trained with 70% of all cases, whereas ten percent was used for testing the trained network. Finally, the classification was calculated for the hold-out of the remaining ten percent of cases. This specific type of leave-out strategy was repeated ten times so that each case should at least once belong to the left-out athletes that were finally classified. In accordance with the linear analysis described above, in a first attempt, the MLP was trained with all complete cases (n = 94). According to the learning character of neural networks methods, the MLP also makes minimal assumptions in regard to relations within the data. Thus, the MLP is able to determine linear as well as nonlinear relationships by its iterative learning mechanism. Along the learning process of neural networks, the prediction result may partly depend on the start vector that is set in a random mode; consequently, the results of the MLP may vary slightly from repetition to repetition (Pion *et al*., 2016) [22]. To quantify the validity of this talent identification strategy, the percentage of correct hits of the neural network classification was averaged over the ten trials and the mean value was used from there on. The classification quality of both methods was expressed by the proportion of correct hits, and was also classified as the percentage of athletes that were assigned as true positives to their own sport. An athlete was defined as false positive if he was classified as a participant of a specific sport for which he did not practice. The data was also analyzed using Multivariate analysis of variance (Manova) to determine if the groups were significantly different on quantitative variables. The assumption for Manova were confirmed before conducting the parametric test. The groups were mutually exclusive and no subject would belong to two groups at the same time, the predictor variables were independent of each other. The data were tested for assumptions of normality using the Shapiro Walk test, Skewness and Kurtosis were also checked. Homogeneity of variance was checked using the Levine test. Homogeneity of between groups variance-covariance matrix was checked using the Box M test. For significant differences Scheffe's post-hoc test will be used. It was considered because of the different group sizes.

Results

The results for overall descriptive statistics showed that the mean height and weight for all participants was 170.7± 13.3cm and 64.4±11.5kg respectively. Results for normality and across variables is shown in Table 1 below. From the findings, the data was violated a few instances of normality as shown from the skewness and kurtosis values (skew and kurtosis less than |-1.0| and |1.0|.

The descriptive statistics associated with all morphological, physiological and motor characteristics across the sports groups are reported in Table 4. It was seen that the netball group was associated with the numerically smallest mean of height (166.1±5.5), tennis group was associated with the numerically smallest mean of weight (57.6±7.9) and chess group was associated with the numerically smallest mean of abdominal endurance (30±10). The data satisfied the assumption for equality of covariance matrices with Box's M results showing it was above 0.01, hence leading to the rejecting of the null hypothesis that the observed covariance matrices of the dependent variables across groups were equal (Table 2). The data also met the assumption for homogeneity of variance between groups. The Levene's test was done based on means (Table 3).

Results for the individual test of differences in means showed that there was statistically significant differences between the sports in all dependent variables except; Height (f (11,274) =1.087, p=.372), Pulse (f (11,274)=3.675, p=.070) and Percentage body fat (f (11, 274)=3.759, p=.065). Overall, the speed test had the highest Partial Eta squared (.216), which means that speed accounted for variance at 5% in the groups. Table 5 below shows the results in detail.

The researchers went ahead and conducted post- hoc analysis for the significant variables to find out exactly between which sports the differences were detected. Due to differences in group's sizes amongst the twelve sports groups, it was deemed necessary to interpret the Scheffe's test. Table 6 shows the results.

Due to uncertainty of meeting all assumptions for the Multivariate analysis of variance (Manova), the Wilks' Lambda in the multivariate test of differences in groups could not be interpreted. The researchers went ahead and interpreted the Pillai's Trace (Table 7). The global test for equality of the mean vectors for the twelve sports groups was significant for groups (Pillai's T, $p<0.01$). This showed that the groups were statistically significantly different in a linear combination of all dependent variables.

The application of the nonlinear MLP in a first attempt was based on the total sample of n = 286 athletes, and the ten trials led to an average classification rate of M = 42.7%, indicating that on average 122 original cases were collated correctly in regard to their respective sport. In a second attempt, a cross validated MLP analysis was applied, where in each of the ten repetitions 73.1n=209) % of the 286 athletes were used as training data set to calibrate the network, 18.2% n=52) of the cases were taken to test the network solution, and the remaining 8.7% n=25) of cases served as a hold-out data set for the cross-validated prediction of the sport group in which these athletes performed. On the basis of this leave 8.7% out procedure, 34.6% of the 209 athletes were classified correctly and assigned as true positives to their own sport (Table 8). The best classification result of 15.4% correct hits were obtained in handball and Tennis. No true positives were found in Chess and netball (0.0%).

Table 1: Overall descriptive statistics for the study variables

Variables	n	M	SD	CI 95%	Skewness	Kurtosis
Height	286	170.7	13.3	169.1-172.2	-6.136	.144
Weight	286	64.4	11.5	63.04-65.71	2.69	2.3
Pulse	286	86.03	17.4	83.9-88.7	-.144	.287
Abdominal endurance	286	46.6	11.93	45.2-48.0	.053	-.242
Upper body endurance	286	48.1	14.3	46.3-49.7	.247	.636
Body fat %	286	20.24	8.2	19.3-21.2	.673	-.101

Speed test	286	9.86	2.3	9.6-10.1	-.437	-.564
Note. M= mean; SD = standard deviation; CI = confidence interval						

Table 2: Box's Test of equality of Covariance matrices

	M	**F**	**Df1**	**Df2**	**Sig**
Box's M	832.966	2.567	280	29664.922	.021

Table 3: Levene's Test of Equality of Error Variances

Levene Statistic			**df1**	**df2**	**Sig.**
Height	Based on Mean	1.993	11	274	.029
Weight	Based on Mean	.333	11	274	.978
Pulse	Based on Mean	1.528	11	274	.121
Abdominal endurance	Based on Mean	1.729	11	274	.067
Upper body endurance	Based on Mean	2.839	11	274	.072
Body fat %	Based on Mean	2.626	11	274	.103
Speed test	Based on Mean	3.981	11	274	.200

Table 4: Group descriptive statistics for the study variables

	Athletics ***n=19***	**Badminton** ***n=12***	**Rugby** ***n=27***	**Volleyball** ***n=18***	**Soccer** ***n=53***	**Netball** ***n=17***	**Basketball** ***n=31***	**Chess** ***n=3***	**Karate** ***n=37***	**Hockey** ***n=25***	**Tennis** ***n=22***	**Handball** ***n=22***
Height	169.9±10.2	170.4±8.7	175.3±7.2	175.8±7.9	170.1±9.3	166.1±5.5	169±31.3	175±9.5	171.1±7.6	167.4±12.9	168.6±7.9	173.5±7.9
Weight	59.8±9.2	59.2±10.3	73.3±9.2	65.5±9	65.7±16.7	59.3±8.2	67.2±9.8	64.1±11.7	61.7±8.8	62.9±7.6	57.6±7.9	69±9.1
Pulse	79.9±17.0	91.8±12.3	77.8±14.1	95.4±16.4	84.9±18.4	91.8±16	78.5±17	95±18.2	81.4±13.9	93.2±20.3	89.2±18.2	94.7±13.9
Abdominal endurance	41.9±10	38.8±12	51.8±11.4	53.3±11.5	42±8.8	37.1±10.2	47.9±12.2	30±10	54.1±10.4	47.2±10.3	46.2±8.3	49.2±15.4
Upper body endurance	56.3±18.2	56.1±20.8	57.9±15	50.4±8.1	38.7±10.6	39±6.2	50.1±14.1	31.7±19	47.8±10.2	52.6±16.6	46±10.1	49±11.4
Body fat %	18.5±7.4	18±8.4	18±4.6	21.1±7.2	21.6±7.3	23.1±5.9	23.2±8	20.2±1.5	16.6±7.1	21.5±9.5	15±9.5	25.4±10.5
Speed test	10±1	9±2	11±1	11±2	10±2	7±1	10±2	6±3	11±2	9±2	9±2	9±3

Table 5: Tests of Between-Subjects Effects

Source	**Dependent Variable**	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**	**Partial Eta Squared**
Sports	Height	2110.450	11	191.859	1.087	.372	.042
	Weight	5482.424	11	498.402	4.245	.000	.146
	Pulse	11131.314	11	1011.938	3.675	.070	.129
	Abdominal endurance	8456.541	11	768.776	6.559	.000	.208
	Upper body endurance	12346.765	11	1122.433	6.690	.000	.212
	Body fat %	2507.638	11	227.967	3.759	.065	.131
	Speed test	320.937	11	29.176	6.851	.000	.216

Table 6: Scheffe's Multiple Comparisons

Dependent Variable	**(I) Sport**	**(J) Sport**	**Mean Difference (I-J)**	**Std. Error**	**Sig.**	**95% Confidence Interval**	
						Lower Bound	**Upper Bound**
Weight	Rugby	tennis	15.691*	3.1120	.010	1.753	29.630
Abdominal endurance	Netball	volleybal	-16.160	3.6614	.049	-32.559	.239
		karate	-16.963*	3.1721	.004	-31.171	-2.756
	Karate	soccer	12.119*	2.3193	.006	1.731	22.507
Upper body endurance	Athletics	soccer	17.565*	3.4634	.009	2.053	33.077
	Rugby	soccer	19.154*	3.0625	.000	5.437	32.871
		netball	18.852*	4.0103	.028	.890	36.814
	Soccer	athletics	-17.565*	3.4634	.009	-33.077	-2.053
		rugby	-19.154*	3.0625	.000	-32.871	-5.437
		hockey	-13.902	3.1426	.047	-27.977	.174
Speed test	Rugby	netball	4.13*	.639	.000	1.27	6.99
	Volleybal	netball	3.68*	.698	.005	.55	6.81
	Soccer	netball	3.05*	.575	.004	.47	5.63
	Netball	karate	-3.41*	.605	.001	-6.12	-.70

Table 7: Multivariate Tests

Effect		**Value**	**F**	**Hypothesis df**	**Error df**	**Sig.**	**Partial Eta Squared**
Intercept	Pillai's Trace	.995	7749.285b	7.000	268.000	.000	.995
	Wilks' Lambda	.005	7749.285b	7.000	268.000	.000	.995
Sports	Pillai's Trace	1.000	4.151	77.000	1918.000	.000	.143
	Wilks' Lambda	.321	4.376	77.000	1613.412	.000	.150

Table 8: Original and cross-validated classification of n = 209 single cases of university athletes from eleven different sports on the basis of seven performance characteristics.

		Athletics	Badminton	Rugby	Volleyball	Soccer	Netball	Basketball	Chess	Karate	Hockey	Tennis	Handball	Percent Correct
Training	Athletics	7	0	0	0	1	0	1	0	1	0	1	3	50.0%
	Badminton	2	0	2	0	2	0	1	0	0	0	0	2	0.0%
	Rugby	1	0	6	5	2	0	3	0	1	0	0	4	27.3%
	Volleyball	0	0	0	8	3	0	0	0	0	0	0	3	57.1%
	Soccer	1	0	0	3	19	0	3	0	1	0	2	6	54.3%
	Netball	1	0	0	0	4	0	0	0	0	0	5	0	0.0%
	Basketball	2	0	1	2	6	0	8	0	0	0	0	4	34.8%
	Chess	0	0	0	0	0	0	0	0	0	0	2	1	0.0%
	Karate	1	0	0	13	4	0	1	0	6	0	4	3	18.8%
	Hockey	1	0	1	1	3	0	3	0	1	0	3	4	0.0%
	Tennis	3	0	0	4	1	0	0	0	2	0	5	0	33.3%
	Handball	0	0	0	7	2	0	3	0	0	0	0	3	20.0%
	Overall percent	9.1%	0.0%	4.8%	20.6%	22.5%	0.0%	11.0%	0.0%	5.7%	0.0%	10.5%	15.8%	29.7%
Testing	Athletics	0	0	0	0	1	0	1	0	0	0	0	0	0.0%
	Badminton	1	0	0	0	1	0	0	0	0	0	0	0	0.0%
	Rugby	0	0	1	1	1	0	0	0	0	0	0	1	25.0%
	Volleybal	0	0	0	2	2	0	0	0	0	0	0	0	50.0%
	Soccer	0	0	0	2	8	0	0	0	0	0	1	2	61.5%
	Netball	0	0	0	0	1	0	0	0	0	0	3	0	0.0%
	Basketball	0	0	0	3	0	0	0	0	1	0	0	1	0.0%
	Chess	0	0	0	0	0	0	0	0	0	0	0	0	0.0%
	Karate	0	0	0	0	1	0	1	0	1	0	1	0	25.0%
	Hockey	0	0	0	2	0	0	0	0	0	0	0	1	0.0%
	Tennis	0	0	0	0	1	0	0	0	1	0	3	0	60.0%
	Handball	1	0	0	0	0	0	2	0	0	0	0	3	50.0%
	Overall percent	3.8%	0.0%	1.9%	19.2%	30.8%	0.0%	7.7%	0.0%	5.8%	0.0%	15.4%	15.4%	34.6%

Discussion

The aim of this investigation was to compare morphological, physiological and motor characteristics among university students participating in different sports in Kenya. The discriminative validity of three morphological, three motor, and two physiological measures was determined across twelve sports. The sample included subjects who participated in twelve sports; Athletics *n*=19), Hockey *n*=25), Tennis *n*=22), Handball *n*=22), Badminton *n*=12), Rugby *n*=27), Volleyball *n*=18), Soccer *n*=53), Netball *n*=17), Basketball *n*=31), Chess *n*=3), Karate *n*=37). This study moved away from discriminant analysis technique and used a nonlinear statistical method to identify the most relevant talent characteristics of each of the twelve sports and reversely confirm the results. From the findings 34.6% of the 209 athletes were classified correctly and assigned as true positives to their own sport. Although the proportions vary, these findings are consistent with finding of a study by Zhao *et al*., (2019) [32] where discriminative validity of generic test battery's allowed the original correct assignment of 98.9% of cases into their correct sports by means of the discriminant analysis. In the same study, the use of multilayer perceptron, Allowed 71.0% of classified correctly into their original sport (Zhao *et al*., 2019) [32]. This shows that multilayer perceptron results were 28% lower compared to discriminant analysis results. Possible reason for the huge inconsistency is unknown. In support of the study findings was findings by Leone *et al*. (2002) [18-19] where 88% of athletes from four different sports (skating, swimming, tennis, and volleyball) were correctly classified by means of a discriminant analysis, Opstoel *et al*. (2015) [22] reported a correct classification of 85.2% of high active U12 athletes into their own sport (ball sports, dance, gymnastics, martial arts, racquet sports, and swimming). Hohmann *et al*. (2015) also reported a correct assignment of 76.8%, using alternatively the neural network method multilayer perceptron (MLP) the authors reported a lower classification rate of 69.6%. These findings also show that MLP as a classification technique yielded lower classification percentages compared to discriminant analysis.

In the current study, volleyball players were the tallest (175.8±7.9), they were taller than basketball players by a margin of 6.8 centimeters. Ziv & Lidor (2009) [33] reported that basic anthropometric features (body height and particular body segment lengths) have been proven relevant for youth expert athletes in basketball. In addition, other studies found that height is the key ingredient to make it to the top in volleyball (Duncan, Woodfield & Al-Nakeeb, 2006) [11]. In the present study it was also noted that basketball players were the second heaviest in body weight (67.2±9.8) after rugby (73.3±9.2). In specific sports like rugby, the size, shape and proportions of athletes are important considerations in player's performance and usually the better the performance the more critical the relationship will be (Bell & Rhodes, 1975; Toriola *et al*., 1987) [29]. Apostolidis *et al*., (2004) [1] noted that an optimal body mass has been shown to be related to success in running basketball. In consistent with Apostolidis' study, Nikolaidis *et al*. (2015) [21] found that an excess body mass had a negative effect on sprinting ability in basketball players. In the present study soccer players had a relatively low upper body endurance. Studies have shown that soccer players should demonstrate high levels of both upper and lower body strength for sport-specific actions including throwing-in and kicking the ball (Reilly, Bangsbo & Franks, 2000) [26-31].

Conclusions

The study concludes that the morphological, physiological and motor characteristics of sports students was significantly different in some sports as shown in the Scheffe's post hoc analysis table. This means that morphological, physiological and motor characteristics were key in selecting athletes in these specific sports. This study is not without limitations. The first limitation is the relatively small sample size, especially in chess (n = 3). This study did not asses many indicators of the morphological, motor and physiological characteristics, hence the interpretation of the results may not be a clear reflection. Our interpretation of the findings is bound by the fact that it was only focused on university athletes. This study recommends, for wider generalization of results, the replica of the study may be extended to other regions. Players could have been playing at different competitive levels with possible differences in the development of their motor and physiological characteristics. In this work, however, there are also a number of strengths to be highlighted. First, the data provided in this study help to fill some important gaps in the literature providing better understanding of the physical characteristics that discriminate athletes into different sports. Second, our finding may have an important impact on the classification system.

Acknowledgments
We would like to express our gratitude to athletes for their co-operation. And not to forget the extraordinary efforts of the field staff.

Ethical disclosures
Protection of human and animal subjects.
The authors declare that the procedures followed were in accordance with the regulations of the relevant research ethics committee and with those of the Code of Ethics of the Declaration of Helsinki.

Confidentiality of data.
The authors declare that they have followed the protocols of the university on the publication of the data.

Right to privacy and informed consent.
The authors have obtained the written informed consent of the patients or subjects mentioned in the article. The corresponding author is in possession of this document.

Competing interest
The authors declare that they have no competing interests.

Authors& contributions
Micky Olutende Oloo and Dr. Maximilla Wanzala conceived the paper, designed and performed the study. Anthony Muchiri contributed the data collection, integrity, and analysis. Prof Edwin Wamukoya conceived the paper and was the paper’s peer reviewer. All authors read and approved the final manuscript.

Funding
No financial support was provided.

Disclaimer
The findings and conclusions presented in this manuscript are those of the authors and do not necessarily reflect the official position of Masinde Muliro University of Science and Technology

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