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Development of Motivation Model Towards Anthropometric, Soccer Skills, Maturity and Physical Fitness Using Machine Learning

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Abstract

Research in soccer has shown that players' technical, tactical, physical, and psychological abilities are required to meet the requirements of the competition. This study uses machine learning to develop a motivation model based on anthropometric, fitness, and soccer skills. Data were collected from 223 young Malaysian athletes consisting of Malaysia's Sport School soccer athletes who play in various positions (defender, midfielder and forward) aged 13 to 17 years old who participated in this study. Athletes are required to complete the study's instrument, which consists of the anthropometric component test, Task and Ego Orientation in Sport Questionnaire (TEOSQ), technical skill component and physical fitness test. Data analysis was carried out using hierarchical agglomerative cluster analysis (HACA) and discriminant analysis (DA). Hierarchical agglomerative cluster analysis is used to divide groups according to their homogenous psychological attributes of the athletes and discriminant analysis used for determining the differences in player performance. Three groups formed and successfully discriminated three groups on 13 independent variables with 79.82% (forward stepwise) total variance resulting with Machine Learning method (Artificial Neural Network) 67 athletes predicted with potential. A group tends to have the taller player because of the highest significance in height variables than others. From the result, all groups show their characteristics with unique attributes and need to intervene to characterize their training program based on the group's performance.

Keywords

Cluster analysis
Discriminant analysis
Motivation orientation

1. Introduction

Soccer is a highly complex sport influenced by physical, psychological, tactical and technical factors [1]. Research in soccer has demonstrated that players' technical, tactical, physical and psychological players to meet their needs during competition [2]. Therefore, careful observation of the athletic necessities to match play and components encouraging efficacious performance can guarantee that accuracy and rational assessments are taken for establishing the physiological, physical, tactical, technical and psychological components of preparing systematic talent recognition, identification and development training programs towards the development of the players. Normally, coaches and instructors feel difficult to choose an appropriate element of a soccer performance model that will fit a given set of multilateral factors [3].

The athletes should be motivated by two main sources, according to research. First, they may be motivated intrinsically (do sports activities for pleasure, fun or other self-determined reasons). Second, they may have been motivated by extrinsic factors (obtaining benefits, tangible and material such as money or trophies, or social rewards (prestige, public knowledge), or to avoid punishment). (Goal orientation is a determinant factor of an athlete's success in sport [4]. Psychological factors such as goal orientation, concentration and anxiety must be well controlled to produce the best performance in achieving this goal. When athletes' motor skills gaps are getting smaller today, greater mental resilience is required as competition becomes more intense. In sports, especially golf, success and failure are often associated with motivation, attention and arousal [5]. Thus, an athlete's mental preparation is essential before and after a competition [6].

Relevant parties do not seriously address these mental and psychological aspects because of inadequate service from sports psychology in many sports associations in Malaysia. There is not enough psychological training for all athletes to improve their mental strength. There is no scientific research analysis or a detailed report on that particular part, except only a general report in a local newspaper when they are defeated in a competition. This shows that research or documentation in sport psychology is still lacking in Malaysia [7]. This study investigates the dispositional of goal orientation on players' performance in different soccer positions.

2. Methodology

2.1. Players

223 soccer players were selected at the age of (17.40 ± 19.9 years old). The player came from different positions, such as defender, midfielder and forward. The player came from different states around Malaysia under Malaysia Sports School, where the generation of the new sport develops skills and discovers new talent. All the players and coaches who participated in the study obtained written consent.

2.2. Experimental Approach to the Problem

To answer the entire objective of this study, the researcher needs to do a fitness assessment of the performance variables following the standard protocols for the fitness evaluation.

2.3. Anthropometric Component

The Player had been tested for age, weight, sitting height, bicep, triceps subscapular, spiliac upper body circumference (MUAC), calf circumference (CC) and maturity.

2.4. Motivation Component

Using the Task and Ego Orientation Sport Questionnaire (TEOSQ), ego and task were collected. The questionnaire has been translated to Bahasa Malaysia using back translation to make sure the entire player is easy to understand. The questionnaire has been read and explained to the player; there is no fee to participate in the study.

2.5. Technical Skill Component

Player needs to perform various technical skill tests such as running with the ball, juggling (foot), juggling body, speed dribbling, long pass, short pass, shooting Top Right, shooting Top Left, shooting from the pass, and heading mid and side. All the players were given 3 trials, and the highest score was used for collecting data.

2.6. Fitness Component

Fitness components include sit reach, sergeant jump, V sit up, speed 5-m, speed 10-m, speed 20 m and V02max. The player giving one minute to perform the test, and the highest score is used for data.

2.7. Data Analysis

By using the XLSTAT add-ons system, researchers used three methods of analysis. First is principal component analysis (PCA), then analysis continued with Discriminant Analysis (DA) and finally finished with artificial neural network (ANN).

A study stated that the principal component analysis is a commonly used analysis to reduce data from many variables to a smaller set of underlying factors that summarize the essential information contained in the variables [8]. The purpose is to obtain important information from the data schedule and state this information as a new set of orthogonal variables called principal components [9]. In this study, PCA was conducted on the 31 variables and summarised into 21 variables only.

Afterwards, hierarchical agglomerative cluster analysis (HACA) was assigned to separate any homogeneity that was the same as others by using task and ego orientation as variables. HACA is a robust method to identify and categorize components or subjects (observations/population) into clusters with more excellent homogeneity within the class and more significant heterogeneity among classes with regard to a predetermined selection criterion [10]. Moreover, Ward's technique utilizing Euclidean distances as a resemblance in HACA has shown to be very effective [11]. The findings were also shown by dendrogram divide by cluster and their homogeneity.

The discriminant analysis (DA) controls the variables that separate among two or more joined groups/clusters [11]. A descriptive discriminant analysis was conducted to identify which variables best discriminate the previously obtained clusters. Discriminant analysis is robust for these derived rate variables [12]. Three groups for relative performance patterns (three sampling groups represent low performance, medium performance, and high performance) were obtained and selected from HACA. Validation of discriminant models was conducted using the leave-one-out method of cross-validation [13]. The DA was put into the raw data using misclassified mode, predefined mode, corrected group (ANNs), backward stepwise and forward stepwise. Analysis using raw data of the performance of players with goal orientation results by HACA and next using predefined that computerized by excel XLSTAT to analyse predefined data. Using only significant parameters from PCA for performance and cluster from predefined group to run analysis data for the corrected group show significant higher for machine learning, analysis data for backward stepwise and forward stepwise.

Artificial Neural Networks (ANN) are usually considered as tools which can help to analyse cause-effect relationships in complex systems within a big-data framework. Neural network is a powerful computational data model that is able to catch and represent complex input/output relationships. The motivation for the development of neural network technology comes from the desire to develop an artificial system that could perform "intelligent" tasks similar to those performed by the human brain. With applying 100 hidden neurons in hidden layers, Rectified Linear Unit (ReLU) activation, and combined with Adam Optimization Algorithm Solver, this model was chosen to achieve this objective research.

3. Results

Table 1 exhibits the summary statistic of athletes. It shows the total number of 223 athletes in soccer. The athletes' minimum, maximum, mean and standard deviation scores are projected.

Table 1

Summary statistics of athletes

Variable	Observations	Minimum	Maximum	Mean	Std. deviation
Weight	223	26.90	90.50	56.51	9.47
Height	223	128.60	190.60	166.06	8.05
Sitting height	223	38.60	98.40	86.92	5.57
Biceps	223	2.80	12.30	4.10	1.14
Triceps	223	4.50	24.80	7.77	2.26
Sbs. capul	223	4.50	28.80	8.30	2.33
Sp. iliac	223	4.50	45.40	8.11	3.63
MUAC	223	2.30	34.60	24.73	2.89
CC	223	3.70	44.00	34.95	3.57
Maturity	223	1.00	5.00	3.85	0.79
S&R	223	0.00	27.00	13.25	5.18
SJ	223	2.69	198.00	64.30	14.85
V. Sit Up	223	2.00	7.00	5.90	0.96
505A	223	1.64	2.98	2.37	0.25
Speed 5 m	223	0.36	1.55	0.79	0.16
Speed 10 m	223	1.00	2.21	1.53	0.19

Variable	Observations	Minimum	Maximum	Mean	Std. deviation
Speed 20 m	223	1.50	4.08	2.85	0.29
FI	223	-1.55	6.43	0.48	0.84
VO2mx	223	29.93	63.73	47.38	7.68
Run w/ball	223	1.93	7.58	4.55	1.12
Juggling (foot)	223	5.00	52.00	38.83	11.23
Juggling body	223	3.00	9.00	7.39	1.97
Speed dribbling	223	16.91	29.30	20.95	2.33
Long passing	223	0.00	12.00	3.85	2.78
Short passing	223	1.00	15.00	10.00	3.53
Shooting top right (Dead Ball)	223	0.00	18.00	3.70	2.95
Shooting top left (Dead Ball)	223	0.00	13.00	3.57	2.91
Shooting from a pass (Foot)	223	0.00	26.00	8.18	5.57
Heading (mid_post)	223	0.00	18.00	9.02	4.52
Heading (side_post)	223	0.00	18.00	7.25	4.24

From the PCA result, out of the thirty principal components (PCs) generated, only eight PCs with eigenvalues >1 were selected for the feed-forward ANN input selection parameter representing 71.68% of the total variance. Nevertheless, Table 2 highlighted the factor loading after the varimax rotation method in the PCA. Furthermore, the standardized VFs with absolute values equal to or greater than 0.70, as the selection edge is considered solid and stable, specify moderate to strong loadings on the extracted factors in the current study. However, it can be seen from Table 2 out of thirty parameters, only 21 parameters were identified as the most significant across all variables. Due to the transformations of a new data set, the output from this analysis was used as input for further analysis in HACA and DA.

Table 2

Factor loading of PCA analysis result

	D1	D2	D3	D4	D5	D6	D7	D8
Weight	0.75							
Height	0.80							
Sitting height	0.68							
Biceps		0.89						
Triceps		0.91						
Sbs. capul		0.87						
Sp. iliac		0.91						
MUAC								
CC								
Maturity	0.68							
S&R								
SJ	0.72							
V. Sit Up								0.89
505A						−0.80		
Speed 5 m				0.88				
Speed 10 m				0.87				
Speed 20 m				0.84				
FI								
VO2mx					0.71			
Run w/ball								
Juggling (foot)					0.68			
Juggling Body						0.67		
Speed Dribbling					−0.66			
Long Passing								
Short Passing					0.67			
Shooting TR (Dead Ball)			0.73					

	D1	D2	D3	D4	D5	D6	D7	D8
Shooting TL (Dead Ball)			0.75					
Shooting From a Pass (Foot)			0.63					
Heading (md_post)								
Heading (sd_post)							0.72	
Eigenvalue	6.12	4.57	2.42	1.95	1.38	1.30	1.14	1.02
Variability (%)	13.75	14.04	6.97	9.64	8.97	4.61	4.38	3.96
Cumulative %	13.75	27.79	34.76	44.40	53.38	57.99	62.36	66.32

Based on the technical skill-related components extracted by PCA, selection of the categorical dependent component was used in HACA, which led to the identification of HTHE (High Task, High Ego), LTME (Low Task, Moderate Ego) and MTLE (Moderate Task, Low Ego) groups. Figures 1 and 2 shows the result of the HACA.

Fig. 1

Result of HACA analysis

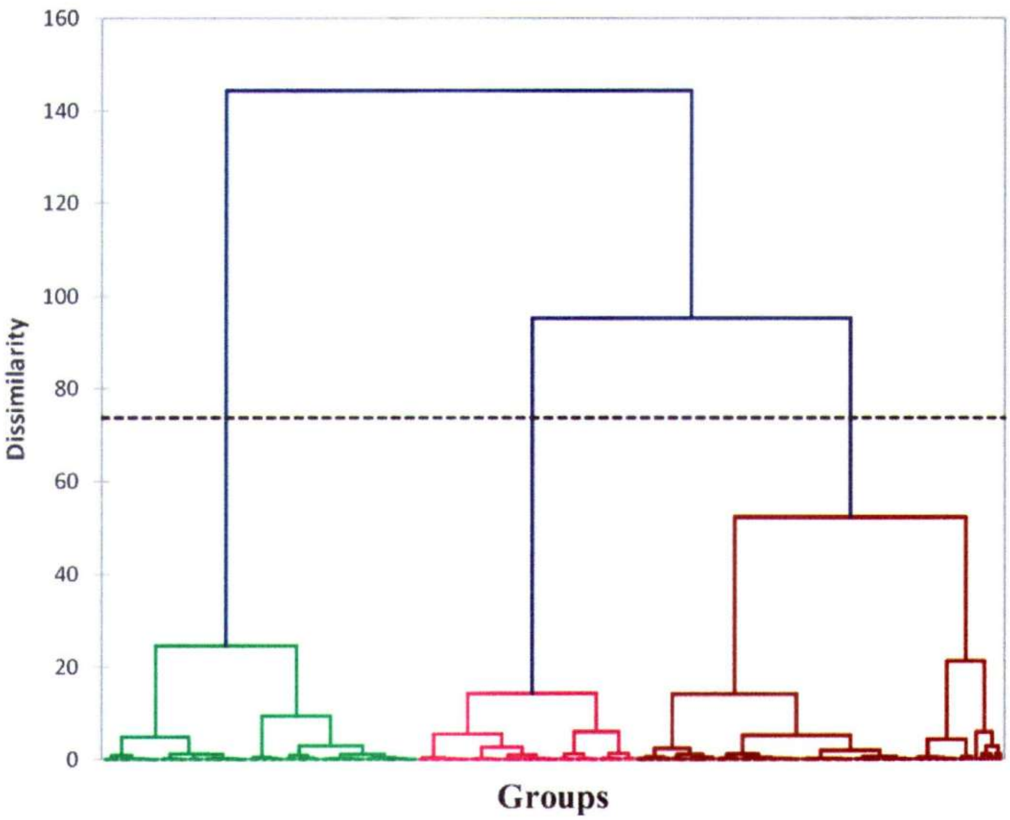
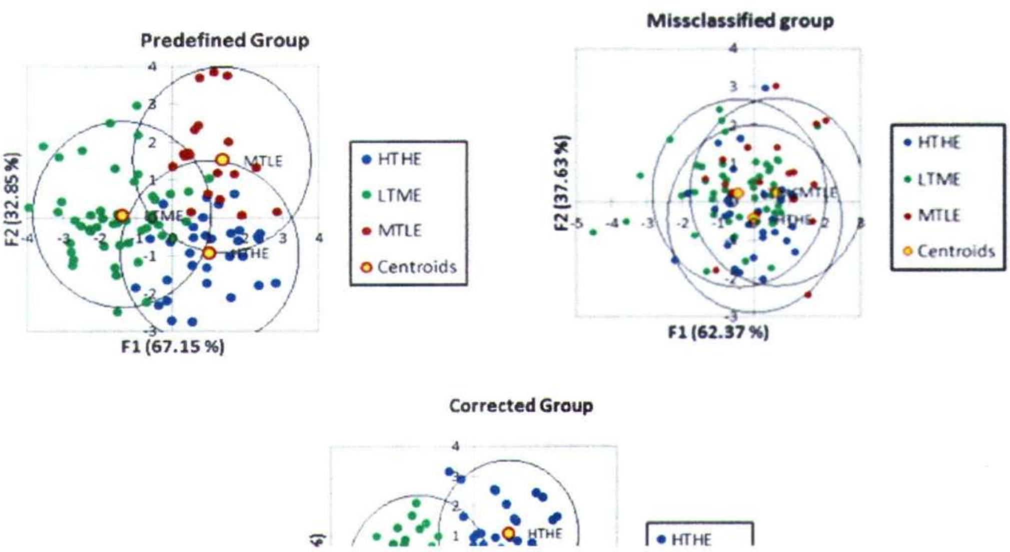


Fig. 2

Observations chart by HACA analysis results



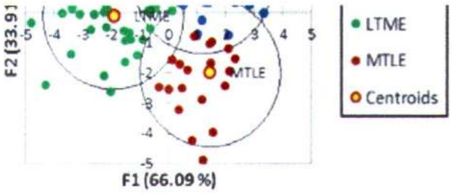


Table 3 shows the discriminant analysis conducted for further analysis. DA is applied using cluster analysis defined by HACA in order tool for goal orientation of the player. HACA was performed using task and ego orientation to define different clusters for goal orientation. Misclassified mode, predefined mode, Corrected mode, and backward stepwise and forward stepwise mode methods were selected to perform the DA. The precision results showed that misclassified mode, with a total of 40.36%. While the predefined mode with a total of 82.96%, the Corrected group reported a total of 93.72% for backward stepwise (11 independent variables) and forward stepwise (11 independent variables), both with a total of 92.83% AQ1 (Table 4).

Table 3

Confusion matrix for the cross-validation results of DA

Sampling groups	% Correct	Group assigned by DA		
		HTHE	LTME	MTLE
Misclassified mode				
HTHE	38.46	30	33	15
LTME	49.45	33	45	13
MTLE	27.78	17	22	15
Total	40.36	80	100	43
Predefined mode				
HTHE	87.50	70	5	5
LTME	82.00	11	82	7
MTLE	76.74	8	2	33
Total	82.96	89	89	45
Corrected group				
HTHE	95.51	85	1	3
LTME	93.26	4	83	2
MTLE	91.11	3	1	41
Total	93.72	92	85	46
Backward stepwise (11 independent variables)				
HTHE	94.38	84	1	4
LTME	92.13	5	82	2
MTLE	91.11	3	1	41
Total	92.83	92	84	47
Forward stepwise (11 independent variables)				
HTHE	94.38	84	1	4
LTME	92.13	5	82	2
MTLE	91.11	3	1	41
Total	92.83	92	84	47

Table 4

Evaluation result of Machine Learning

Method	AUC	CA	F1	Precision	Recall
Neural network	0.974	0.876	0.876	0.876	0.876
Naive Bayes	0.8	0.639	0.642	0.656	0.639
Logistic regression	0.933	0.812	0.811	0.811	0.812

Using Orange software to analyze data for machine learning shows that Artificial Neutral Network have higher results from analysis data compared to other machine learning.

Artificial neural network show the significant parameters shown in Table [5]. Showing that a p-value of < 0.05 significant are from height, sitting height, maturity, V-sit up, 505, juggling body, speed dribbling, shooting TR and TL, shooting from passing, heading, task and ego orientation.

Table 5

Artificial neutral network with P-value under 0.05

Variables	P-value
Height	0.001
Sitting height	0.000
Maturity	0.002
V sit up	0.000
505	0.000
Juggling body	0.000
Speed dribbling	0.000
Shooting TR	0.000
Shooting TL	0.000
Shooting from passing (foot)	0.000
Heading	0.000
Task	0.004
Ego	0.000

4. Discussion

This present study identifies the factor contributing to player performance in different clusters using Artificial Neutral Network (ANN) technique. Based on the technical skill-related components extracted by PCA, selection of the categorical dependent component were used in HACA, which led to the identification of HTHE (High Task, Low Ego), LTME (Low Task, Moderate Ego) and MTLE (Moderate Task, Low Ego) groups.

Psychological factors such as goal orientation, concentration and anxiety must be well controlled to produce the best performance. When the competition becomes more intense, greater mental resilience is required because motor skills gaps among athletes today are getting smaller. Success and failure in sports, mainly golf is often associated with motivation, attention and arousal [14]. Thus, mental preparation for athletes before and during the competition is essential [5]. Williams et al. (1995) [15] indicated that the performance-related feedback of an individual's sports ability could have implications for an athlete's motivational orientation regarding the task and ego involvement.

Findings showed significant effects for goal orientation that involved task and ego among different goal profiles in the two fundamentals area in goal orientation: task and ego. The task is to achieve mastery over the task through applying relevant skills and ego, which is the motivation to pursue and realize that the ego-oriented goal is fuelled by competition. This study considered that cluster 1 (low task and medium ego-LT/ME) had more excellent goal orientation in both task and ego and athletes in cluster 2 (high task and high ego-HT/HE) and compared to cluster 3 (moderate task and low ego-MT/LE). Results also suggest that it is possible that athletes in cluster 2 would probably benefit during adversities in competition due to reasonable control over themselves, leading to more excellent goal performance. Furthermore, athletes in cluster 2 (high task and high ego) tend to invest more in task and ego orientations; the players focus more on task orientation whereby portrayed as an intrinsically motivated state that leads to persistence when failing, perseverance when faced with difficulties and a fulfilling sense of achievement if the task was mastered, improvement was experienced, and ability was successfully expressed thus the player gaining more on motivation which is aimed at being the best rather than doing one's best (ego). The driving force is to demonstrate a superior and higher ability compared to others rather than one's ability, irrespective of how it compares to others [16, 17]. Positive competition can be generated because of the benefits of having better control over the negative energy, which is unproductive. These findings support the suggestions by [18, 19, 20, 21, 22] that moderate to high task and ego orientation patterns can complement a competitive situation.

5. Conclusion

This study research investigates whether goal orientation impacts player performance and has been clarified using machine learning of artificial neural network as a result of confirmation. 32 parameters have been tested for 223 athletes using PCA and have been minimised to only 21 parameters from performance parameters. Using HACA, 3 clusters, HTHE, LTME, and MTLE, have been identified that different the athletes by task and ego parameters. Next, using DA to combine cluster and performance parameters that contribute to athlete's results achievements by using DA research get to narrow down the performance that contributes the biggest to the study and combine the goal orientation from athletes. Lastly, using machine learning to identify the parameter that contributes the most to athletes shows that from 32 to only 13 parameters, including task and ego orientation. Show that only 13 parameters contribute to athletes' performance with goal orientation of athletes.

Summarize it, showing that results from HTHE and 13 parameters need to sharpen so that athletes can perform much better and even more incredible, resulting in an athlete with better achievement not just in psychology but also in their performance. It can help the player to have a better future in order to become a professional player in future.

References

1. Reilly T, Williams AM, Nevill A, Franks A (2000) A multidisciplinary approach to talent identification in soccer. J Sports Sci 18(9):695–702

2. Abdi H, Williams LJ (2010) Principal component analysis. Wiley Interdiscipl Rev Comp Stat 2(4):433–459

3. Gastin PB, Meyer D, Huntsman E, Cook J (2015) Increase in injury risk with low body mass and aerobic-running fitness in elite Australian football. Int J Sports Physiol Perform 10(4):458–463

4. Barbanti V (2013) The multicomponent anthropometric model for assessing body composition in a male pediatric population: a simultaneous prediction of fat mass, bone mineral content, and lean soft tissue. J Obes

5. Majzub R, Muhammad TA (2011) Goal orientation and achievement of junior in golfers Malaysia. Procedia Soc Behav Sci 15:1644–1649

6. Zifonun G, Hoffmann L, Strecker B, Ballweg J (1997) Grammatik der deutschen Sprache. Walter de Gruyter

7. Majzub RM, Bataineh MZ, Ishak NM, Rahman S (2011) The relationship between locus of control and academic achievement and gender in a selected higher education institution in Jordan. In: Proceedings of the 8th WSEAS international conference on education and educational technology (Corfu Island: WSEAS Press). pp 215–220

8. Thorpe MG, Milte CM, Crawford D, McNaughton SA, Lawrence M, Ball K, Worsley A, Nanayakkara J, Margerison C, Hart MJ, Torres S (2017) Predictors of change in dietary patterns determined by principal component analysis in Australians >55 years. J Nutrit Intermedi Metab 8:73

9. Abdi H, Williams LJ (2010) Principal component analysis. Wiley Interdiscipl Rev Comput Stat 2(4):433–459

10. van de Wetering M, Francies HE, Francis JM, Bounova G, Iorio F, Pronk A, van Houdt W, van Gorp J, Taylor-Weiner A, Kester L, McLaren-Douglas A (2015) Prospective derivation of a living organoid biobank of colorectal cancer patients. Cell 161(4):933–945

11. Abdullah MR, Maliki M, Husin AB, Musa RM, Kosni NA, Juahir H, Haque M (2016) Multi-hierarchical pattern recognition of athlete's relative performance as a criterion for predicting potential athletes. J Young Pharm 8(4)

12. Parker TS, Chua L (2012) Practical numerical algorithms for chaotic systems. Springer Science & Business Media

13. Chua TS, Tang J, Hong R, Li H, Luo Z, Zheng Y (2009) NUS-WIDE: a real-world web image database from National University of Singapore. In: Proceedings of the ACM international conference on image and video. ACM, p 48

14. Wann DL (1997) Sport psychology. Pearson College Division

15. Williams L, Gill DL (1995) The role of perceived competence in the motivation of physical activity. J Sport Exerc Psychol 17(4):363–378

16. Breiger J, Cumming SP, Smith RE, Smoll F (2015) Winning, motivational climate, and young athletes' competitive experiences: some notable sex differences. Int J Sports Sci Coach 10(2–3):395–411

17. Steinberg G, Grieve F, Glass B (2001) Achievement goals across the lifespan. J Sport Behav 24(3):298–306

18. Hodge K, Petlichkoff L (2000) Goal profiles in sport motivation: a cluster analysis. J Sport Exerc Psychol 22(3):256–272

19. Kassim M, Rustam S (2021) Measuring physical fitness for military cadets' officers. https://doi.org/10.1007/978-981-15-5856-6_55

20. Kassim M, Othman N, Ujang E (2020) The level of physical fitness among first year female students in national defence university of malaysia. J Phys Confe Ser 1529(2). https://doi.org/10.1088/1742-6596/1529/2/022072

21. Kassim M, Ujang E, Othman N (2020) The association between physical activity and basic fitness tests in female junior reserve offic er training unit (ROTU), national defence university malaysia (NDUM). J Phys Conf Ser 1529(2). https://doi.org/10.1088/1742-6596/1529/2/022073

22. Atan SA, Kassim M (2020) Development of a soccer-specific running protocol for young soccer players. https://doi.org/10.1007/978-981-15-3270-2_11

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