The journal represents original scientific researches of scientists from the East-European region.

The Journal welcomes articles on different aspects of physical education, sports and health of students which cover scientific researches in the related fields, such as biomechanics, kinesiology, medicine, psychology, sociology, technologies of sports equipment, research in training, selection, physical efficiency, as well as health preservation and other interdisciplinary perspectives.

In general, the editors express hope that the journal "Physical Education of Students" contributes to information exchange to combine efforts of the researchers from the East-European region to solve common problems in health promotion of students, development of physical culture and sports in higher educational institutions.

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CONTENTS

ORIGINAL ARTICLE

Changes in static balance ability in cadets during a six-month military training cycle

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Authors' Contribution: A – Study design; B – Data collection; C – Statistical analysis; D – Manuscript Preparation; E – Funds Collection

Abstract

Background and Study Aim Maintaining postural stability is a component of motor fitness and a prerequisite for the safe and effective performance of military tasks. Various forms of military training are used to develop physical preparedness and functional performance in cadets. However, their effectiveness in improving postural control and static balance ability during long-term standardized training remains a subject of practical interest. The aim of this study was to examine the effects of a six-month standardized military training programme on selected parameters of postural stability in cadets at a military academy.

Material and Methods The study included 38 cadets from the Military University of Technology (Poland). Postural stability was assessed twice at a six-month interval using the Romberg test performed on the FreeSTEP STANDARD stabilometric platform. Measurements included double-leg stance (eyes open/eyes closed) and single-leg stance on both limbs. Analyzed center of pressure (CoP) parameters comprised total path length (PL), confidence ellipse area (CEA), mean velocity (MV), and root mean square sway amplitudes in the mediolateral (X-RMS) and anteroposterior (Y-RMS) directions. Due to the non-normal data distribution, the Wilcoxon signed-rank test and effect size coefficient r were used.

Results No statistically significant changes were observed in any parameter during double-leg stance. Conversely, single-leg tests showed significant differences between eyes-open and eyes-closed conditions ($p < .005$), confirming the strong contribution of visual input to balance control. However, the six-month training period did not yield consistent improvements in single-leg stability. Partial enhancements were observed for the right leg, particularly under EC conditions. However, these changes were selective and not uniform across parameters or limbs.

Conclusions Standardized military training did not lead to systematic improvements in postural control among cadets. Single-leg stance tests demonstrated greater sensitivity to balance changes than double-leg stance. The findings suggest that enhancing postural stability in future soldiers may require the incorporation of targeted proprioceptive and sensorimotor exercises into the existing military training curriculum.

Keywords: stabilometric, Romberg's test, military training, cadets, land forces, body composition

Introduction

Efficient execution of military tasks requires a high level of physical preparedness and motor coordination. One of the components influencing movement efficiency and operational safety is the ability to maintain postural stability under various environmental and functional conditions. Balance control depends on the integration of visual, vestibular, and proprioceptive inputs, as well as on the effectiveness of neuromuscular regulation. In military training, cadets are exposed to repeated physical loads and demanding motor activities that may affect the mechanisms responsible for maintaining static balance and body control.

In this context, the ability to maintain balance is one of the elements of motor fitness that determines both the effectiveness of performing motor tasks and the safety of activities in various environmental conditions. Maintaining stability requires not only adequate physical condition but also coordinated interaction between the nervous and muscular systems [1, 2]. Maintaining balance is a complex process in which the nervous, muscular, and skeletal systems play important roles. Through the integration of sensory information and the execution of motor responses, these systems enable effective posture maintenance and counteract disturbances that may impair body stability [3].

In sensory processes, information from the visual, vestibular, and somatosensory systems provides the data necessary for the ongoing correction of

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body position. Proprioception enables precise monitoring of muscle length and tension, the range and direction of joint movements, and the action of external forces. Signals from muscle spindles, Golgi organs, and skin mechanoreceptors are integrated in the central nervous system and used to generate feedforward and feedback responses. These responses allow quick and adequate reactions to changing conditions [4]. Disorders in the functioning of any element of this system can lead to deterioration in postural stability and increase the risk of falls and injuries [5, 6]. Furthermore, fatigue negatively affects vestibular function, which is manifested by deterioration in balance test results as the exercise load increases [7, 8].

Soldiers and uniformed service officers perform tasks in variable and often difficult terrain under heavy physical strain, which requires maintaining a high level of balance [9]. An additional factor affecting stability is the need to carry weapons and personal equipment, which increases the physical load and raises the risk of loss of balance, falls, and injuries [10, 11, 12, 13]. Such injuries may temporarily prevent soldiers from performing their duties, which constitutes a significant organizational and tactical problem under training and operational conditions.

High balance efficiency is required not only of land force soldiers but also of military pilots, for whom postural stability, spatial orientation, and resistance to sensory disturbances are essential. Studies conducted using Special Aviation Gymnastic Instruments have confirmed that appropriately selected training can improve these abilities and increase the preparedness of military pilots to perform tasks in the air [14, 15, 16].

In Poland, Tomczak and colleagues [17] contributed to the assessment of soldiers' balance under conditions of physical exertion and sleep deprivation. Studies conducted during survival training (SERE) showed that even 24 hours of moderate and prolonged physical exertion combined with sleep deprivation led to deterioration in the ability to maintain balance [18]. It was also found that special forces operators performed better in stability tests than soldiers from other formations. In addition, military pilots with many years of experience tolerated balance disturbances better than cadets at flight schools. The negative effect of sleep deprivation on postural stability was also confirmed by Mantua et al. [19]. At the same time, studies showed that prolonged physical exertion reduced shooting accuracy, which emphasizes the role of postural control in the performance of basic combat tasks [20].

Among the studies conducted in the Polish armed forces using the Romberg test are those by Dziadek et al. [12], which assessed the impact of combat equipment on balance and the role of visual stimuli in the postural control of special forces operators.

Previous research on postural stability in military and paramilitary populations has predominantly been cross-sectional or has focused on short-term responses to exercise, sleep deprivation, or stressors. In these studies, the ability to maintain balance was most often assessed on a single occasion or at intervals of several hours or days, with emphasis placed on the immediate effects of fatigue rather than on long-term adaptive processes [17, 18, 19]. Similarly, studies involving special forces operators or military pilots were mainly based on intergroup comparisons according to experience or specialization, without systematic observation of changes over time [12, 15].

Analysis of previous studies has shown that postural stability in military personnel is influenced by physical exertion, sleep deprivation, combat equipment, and the specificity of operational tasks. Researchers emphasize that balance control is closely related to operational safety, movement efficiency, and the ability to perform motor tasks under demanding environmental conditions. At the same time, the dynamics of changes in postural stability during prolonged and standardized military training remain a relevant issue in the assessment of motor adaptation in cadets. This aspect continues to limit the evaluation of how routine military training influences long-term balance control and postural regulation.

Additionally, previous longitudinal observations in military populations have usually covered relatively short training periods and were primarily focused on early adaptive or transient responses to physical stress. Most studies also involved specialized military groups, whereas the period of military education represents a separate stage associated with the development of motor skills and functional adaptation in future soldiers. At the same time, longitudinal assessment of postural stability during a full military training cycle may provide additional information on balance adaptation under conditions of repetitive physical load, fatigue, and standardized training activities. The relationship between routine military training and changes in postural control therefore remains a relevant aspect in the evaluation of functional preparedness in cadets.

The aim of this study was to assess the impact of a six-month standardized military training programme on selected parameters of postural stability in cadets. It was hypothesized that prolonged military training, despite the absence of specialized balance exercises, would lead to adaptive changes in postural control. However, these changes were expected to be selective and dependent on sensory system load and physical fatigue.

Materials and Methods

Participants

The study involved 38 cadets from the Military University of Technology (WAT) studying computer science, mechatronics, and electronics. The mean height of the study group was 181.37 cm (SD = 11.34), whilst the mean body weight was 83.27 kg (SD = 6.24). The participants also included cadets actively training at the WAT sports club in football (n = 5), judo (n = 2), boxing (n = 2), and athletics (n = 2). In addition, 10 participants reported engaging in strength training for recreational purposes, whilst 4 actively participated in mountain tourism activities, including hiking and mountain running. The remaining cadets undertook only the compulsory military training programme and physical education classes.

Recruitment for the study was targeted and voluntary. Information about the study was provided to cadets during lectures at the Military University of Technology. Participants volunteered to take part of their own accord without any financial or organizational incentives. Before the study began, each cadet received detailed information about the purpose of the study, the measurement procedures, the nature of the Romberg test, and the operation of the stabilometric platform.

The inclusion criteria for the study were as follows: active cadet status at the Military University of Technology, participation in the compulsory military training programme and physical education classes, no medical contraindications to performing balance tests, and the provision of voluntary written consent to participate in the study.

The exclusion criteria for the study were as follows: injuries or musculoskeletal conditions sustained within the previous 6 months that could affect postural control (e.g. ankle sprains, knee injuries, or spinal injuries), diagnosed neurological or vestibular disorders, significant uncorrected visual impairments, or the use of medication affecting the nervous system or balance (e.g. sedatives or anti-epileptic drugs). Refusal to participate in the study or failure to complete the full measurement procedure also resulted in exclusion.

The study participants provided written consent to participate in the project in accordance with the principles of the Declaration of Helsinki. They were informed that they could withdraw from the study at any stage without giving a reason and without facing any academic or professional consequences. The research procedures were non-invasive and posed no risk to the participants' health.

Training programme

In accordance with the five-year study programme of the Military University of Technology [21], cadets undertake a total of 580 hours of physical education in the form of practical exercises. The aim of this training is to provide comprehensive physical and mental preparation for future soldiers, enabling them to operate effectively both in combat conditions and during peacetime service. This process involves the development of motor skills, the building of mental resilience, and the acquisition of skills required to perform military tasks.

During the study period, the cadets participated each semester in one 8-hour general military training session per week and two physical education sessions per week, each lasting 90 minutes. The exercise programme is presented in Table 1.

The study was conducted over two consecutive semesters, which made it possible to assess changes in balance ability over time within the context of a standardized military training programme.

Study design

The assessment of the balance abilities of fourth-year cadets at the Military University of Technology was based on the results of Romberg tests performed on the freeSTEP STANDARD stabilometric platform (FreeMED BASE, Poland). The tests were planned and conducted in accordance with applicable ethical standards. The study was approved by the Research Bioethics Commission of the University of Physical Education in Warsaw (No. SKE.0030.5.2026).

Table 1. The topics covered in physical education lessons and the number of hours allocated to them

No.	Course topics	Number of hours
1	Cross-country running and specialized obstacle course training	214
2	Gymnastics and strength training	124
3	Hand-to-hand combat	64
4	Swimming and water rescue	64
5	Volleyball	24
6	Basketball	24
7	Football	30
8	Theory of physical education, practical sessions in various sports and recreational activities, and tests	36

Before the study commenced, detailed documentation, including the study protocol, was prepared. Participants were informed about the purpose of the study, the methods used, and the possible risks associated with participation in the study.

Test of balance ability

All tests were performed barefoot, with participants standing directly on the stabilometric platform. During double-leg stance trials, the feet were positioned parallel at hip-width distance (approximately 10–12 cm between the medial borders of the feet), with the toes pointing forward at an angle not exceeding 10° of external rotation. Foot placement was visually checked and standardized using reference markings on the platform surface.

During single-leg stance trials, participants were asked to stand on the dominant leg, with the right and left legs tested separately. The non-supporting limb was flexed at the knee joint to approximately 90° and held off the ground without contacting the supporting leg. Arm position was identical to that used during the double-leg stance.

Test procedure

The stabilometric assessment was conducted according to a standardized Romberg test and included the following conditions:

- double-leg stance with eyes open (EO) – 30 s;
- double-leg stance with eyes closed (EC) – 30 s;
- single-leg stance on the right leg with eyes open (EO) – 10 s;
- single-leg stance on the right leg with eyes closed (EC) – 10 s;
- single-leg stance on the left leg with eyes open (EO) – 10 s;
- single-leg stance on the left leg with eyes closed (EC) – 10 s.

Each condition was performed once as a single valid trial, provided that the participant maintained balance for the entire recording duration without foot displacement, stepping, or contact of the non-supporting limb with the ground. If balance was lost during a trial, the attempt was repeated after a rest period.

A rest interval of at least 60 seconds was provided between consecutive trials to minimize fatigue effects.

For eyes-open conditions, participants were instructed to fix their gaze on a static visual target placed at eye level approximately 2 m in front of the platform. During eyes-closed conditions, participants closed their eyes immediately before the recording started.

Outcome measures

The following stabilometric parameters reflecting the magnitude and dynamics of CoP displacement were analyzed:

- total path length (PL) of the CoP (mm);
- confidence ellipse area (CEA) (mm^2), defined as the smallest ellipse covering 95% of CoP positions;
- mean velocity (MV) of CoP displacement ($mm·s^{-1}$);
- root mean square amplitude in the mediolateral direction (X-RMS) (mm);
- root mean square amplitude in the anteroposterior direction (Y-RMS) (mm).

All parameters were calculated automatically by the FreeSTEP software according to the manufacturer's algorithms and exported for further statistical analysis.

Statistical analysis

Statistical analyses were performed using appropriate non-parametric methods due to the characteristics of the data and the study design. The normality of the distribution of stabilometric parameters was assessed using the Shapiro–Wilk test (α = .05). The analysis revealed that most variables describing the range of center of pressure (CoP) displacement deviated significantly from a normal distribution. Therefore, non-parametric statistical procedures were applied.

Because the study involved repeated measurements within the same group of participants, including comparisons of values obtained before and after the training period as well as comparisons between test conditions such as eyes-open versus eyes-closed, differences between paired observations were analyzed using the Wilcoxon signed-rank test. This test is appropriate for dependent samples and does not require assumptions of normality or homogeneity of variance, making it suitable for the analysis of stabilometric data.

All statistical tests were two-tailed, and the level of statistical significance was set at $p < .05$.

Effect size estimation

To complement statistical significance testing and assess the practical relevance of the observed differences, the magnitude of effects was calculated using the effect size coefficient r, recommended for non-parametric paired comparisons based on the Wilcoxon signed-rank test. The magnitude of the effect was interpreted according to Cohen's criteria:

$r \approx .10$ – small effect;
$r \approx .30$ – medium effect;
$r \geqslant .50$ – large effect.

Reporting both p-values and effect size coefficients allows a more comprehensive interpretation of the results by providing information on both the statistical and practical significance of the observed changes in postural stability parameters.

All analyses were performed using STATISTICA software (TIBCO Software Inc., 2017), version 13.

Results

In the double-leg standing test, no statistically significant differences were observed between the first and second measurements for most of the analyzed stabilometric parameters under both eyes-open (EO) and eyes-closed (EC) conditions (Table 2).

The total length of the center of pressure trajectory (PL) increased in the second measurement under both visual conditions. However, these changes did not reach statistical significance (EO: p = .253; EC: p = .530) and were characterized by a small effect size (r = .11 for EO; r = .06 for EC). A similar pattern was observed for the confidence ellipse area (CEA). The increase in values in the second measurement was not statistically significant in either the EO (p = .310; r = .10) or EC (p = .952; r = .30) conditions.

For the mean velocity of the center of pressure (MV), a statistically significant increase was observed under EO conditions between the first and second measurements (p = .048), with a small effect size (r = .13). Under EC conditions, changes in MV were not statistically significant (p = .609; r = .05).

Analysis of the amplitude of lateral sway (X-RMS) revealed a significant increase in values between the first and second measurements under both EO (p = .014) and EC (p = .004) conditions. The effect size for this parameter was moderate (EO: r = .35; EC: r = .37), indicating deterioration in stability control in the frontal plane following the training period.

No statistically significant changes were observed in the amplitude of anteroposterior sway (Y-RMS) between measurements under either EO conditions (p = .054; r = .27) or EC conditions (p = .507; r = .09), despite an upward trend observed in the second measurement.

Analysis of the results of stabilometric tests during the single-leg standing test on the right leg revealed significant changes in postural control parameters between the first and second

Table 2. Results of stabilometric tests in a group of WAT cadets (n = 38) during double-leg stance under eyes-open (EO) and eyes-closed (EC) conditions.

Stabilometric variables	First measurement	Second measurement	Effect size (r)	p-value
PL (mm)				
EO	61.54 ± 112.79	106.24 ± 224.28	.11	.253
EC	58.96 ± 91.64	82.24 ± 123.93	.06	.530
Effect size (r)	.11	.02		
p-value	.107	.595		
CEA (mm^2)				
EO	144.42 ± 81.80	170.02 ± 70.12	.10	.310
EC	178.48 ± 96.17	200.95 ± 82.93	.30	.952
Effect size (r)	.05	.04		
p-value	.137	.067		
MV (mm/s)				
EO	5.04 ± 2.92	6.07 ± 2.55	.13	.226
EC	5.83 ± 3.25	6.77 ± 2.85	.05	.609
Effect size (r)	.13	.24		
p-value	.048*	.257		
X-RMS (mm)				
EO	.20 ± .11	.29 ± .12	.35	.014
EC	.42 ± .35	.56 ± .42	.37	.004**
Effect size (r)	.07	.11		
p-value	.076	.028*		
Y-RMS (mm)				
EO	.15 ± .10	.23 ± .10	.27	.054
EC	.31 ± .23	.41 ± .38	.09	.507
Effect size (r)	.29	.17		
p-value	.091	.160		

NOTE: EO – eyes open; EC – eyes closed; PL – total path length; CEA – confidence ellipse area; MV – mean velocity; X-RMS – root mean square amplitude in the mediolateral direction; Y-RMS – root mean square amplitude in the anteroposterior direction; * $p < .05$; ** $p < .005$.

measurements, particularly under conditions of visual exclusion (VE) (Table 3).

The total length of the center of pressure trajectory (PL) was significantly reduced in the second measurement under both EO (p = .007) and EC (p = .011) conditions. The effect size indicated a medium effect under EO conditions (r = .28) and a medium-to-large effect under EC conditions (r = .37), suggesting improvement in postural stability following the training period, which was more pronounced in the absence of visual information.

For the confidence ellipse area (CEA), a downward trend was observed under both visual conditions. However, the differences between measurements did not reach statistical significance (EO: p = .086; EC: p = .087), with a small-to-moderate effect size (r = .18–.25). At the same time, significant differences were found between EO and EC conditions in both the first (p = .042) and second measurements (p = .002).

The mean velocity of the center of pressure (MV) decreased significantly under EC conditions (p = .015), with a moderate effect size (r = .25), whereas under EO conditions these changes were not statistically significant (p = .387; r = .09). Differences between the visual conditions were significant both before and after training (p < .001).

Analysis of the amplitude of lateral sway (X-RMS) revealed no significant differences between measurements under EO conditions (p = .897; r = .014). However, under EC conditions, a statistically significant reduction in X-RMS values was observed (p < .001), with a small-to-moderate effect size (r = .058). Differences between EO and EC conditions were significant in both the first (p = .031) and second measurements (p = .006).

No significant changes were observed in the amplitude of anteroposterior sway (Y-RMS) between measurements under EO conditions (p = .508; r = .07). Under EC conditions, however, a significant

Table 3. Results of stabilometric tests in a group of WAT cadets (n = 38) during single-leg stance on the right leg under eyes-open (EO) and eyes-closed (EC) conditions.

Stabilometric variables	**First measurement**	**Second measurement**	**Effect size (r)**	**p-value**
PL (mm)				
EO	6248.656 ± 268.434	5813.61 ± 2349.48	.28	.007*
EC	26012.545 ± 37097.94	1515.90 ± 28313.04	.37	.011*
Effect size (r)	.23	.19		
p-value	.000**	.000**		
CEA (mm²)				
EO	575.53 ± 769.03	418.39 ± 526.09	.18	.086
EC	1124.54 ± 624.80	974.74 ± 571.30	.25	.087
Effect size (r)	.14	.15		
p-value	.042**	.002**		
MV (mm/s)				
EO	44.59 ± 69.38	32.21 ± 50.46	.09	.387
EC	100.94 ± 59.46	86.32 ± 56.33	.25	.015*
Effect size (r)	.34	.31		
p-value	.000**	.000**		
X-RMS (mm)				
EO	10.55 ± 12.53	8.12 ± 11.13	.014	.897
EC	13.23 ± 9.82	6.28 ± 2.35	.058	.000**
Effect size (r)	.15	.14		
p-value	.031*	.006*		
Y-RMS (mm)				
EO	5.14 ± 8.03	7.06 ± 9.57	.07	.508
EC	9.58 ± 7.22	4.52 ± 3.96	.29	.007*
Effect size (r)	.15	.14		
p-value	.035*	.004**		

NOTE: EO – eyes open; EC – eyes closed; PL – total path length; CEA – confidence ellipse area; MV – mean velocity; X-RMS – root mean square amplitude in the mediolateral direction; Y-RMS – root mean square amplitude in the anteroposterior direction; * p < .05; ** p < .005.

reduction in values was noted in the second measurement ($p = .007$), with a moderate effect size ($r = .29$). Differences between the visual conditions were significant in both measurements ($p < .01$).

In the single-leg standing test on the left lower limb, less pronounced changes were observed between measurements, whilst significant differences between EO and EC conditions were maintained (Table 4).

No significant changes were observed for the PL parameter between the first and second measurements under either EO conditions ($p = .249$; $r = .12$) or EC conditions ($p = .059$; $r = .20$), although an upward trend was observed under EC conditions. At the same time, differences between the visual conditions were significant both before and after training ($p < .001$), with a moderate effect size ($r \approx .22–.24$).

The confidence ellipse area (CEA) showed no significant changes between measurements under EO conditions ($p = .146$; $r = .21$) or EC conditions ($p = .886$; $r = .02$). However, differences between EO and EC conditions were significant in both measurements ($p \leqslant .017$), confirming a greater load on the postural control system under conditions of visual deprivation.

For mean sway velocity (MV), no significant changes were observed between measurements under either EO conditions ($p = .074$; $r = .19$) or EC conditions ($p = .995$; $r = .00$). At the same time, differences between EO and EC conditions were significant in both measurements ($p < .001$), with a medium-to-large effect size ($r = .37–.40$).

The X-RMS analysis revealed no significant differences between measurements under either visual condition (EO: $p = .437$; EC: $p = .987$), with very small effects ($r \leqslant .10$). Differences between EO and EC conditions were significant only in the second measurement ($p = .043$).

With regard to Y-RMS, a significant increase

Table 4. Results of stabilometric tests in a group of WAT cadets ($n = 38$) during single-leg stance on the left leg under eyes-open (EO) and eyes-closed (EC) conditions.

Stabilometric variables	First measurement	Second measurement	Effect size (r)	p-value
PL (mm)				
EO	322.93 ± 292.98	445.74 ± 622.85	.12	.249
EC	7867.78 ± 1470.36	9096.25 ± 2604.60	.20	.059
Effect size (r)	.24	.22		
p-value	.000**	.000**		
CEA (mm^2)				
EO	289.78 ± 86.02	312.99 ± 106.54	.21	.146
EC	965.93 ± 774.62	983.79 ± 715.87	.02	.886
Effect size (r)	.16	.19		
p-value	.017*	.000**		
MV (mm/s)				
EO	20.22 ± 6.04	21.81 ± 9.37	.19	.074
EC	90.00 ± 76.81	90.80 ± 71.75	.00	.995
Effect size (r)	.37	.40		
p-value	.000**	.000**		
X-RMS (mm)				
EO	5.54 ± 3.05	6.21 ± 2.68	.08	.437
EC	7.95 ± 8.99	9.92 ± 8.66	.01	.987
Effect size (r)	.03	.10		
p-value	.582	.043*		
Y-RMS (mm)				
EO	1.18 ± .68	5.94 ± 2.78	.43	.003**
EC	5.99 ± 5.87	7.34 ± 7.24	.04	.685
Effect size (r)	.19	.03		
p-value	.008*	.524		

NOTE: EO – eyes open; EC – eyes closed; PL – total path length; CEA – confidence ellipse area; MV – mean velocity; X-RMS – root mean square amplitude in the mediolateral direction; Y-RMS – root mean square amplitude in the anteroposterior direction; * $p < .05$; ** $p < .005$.

in the amplitude of sway was observed under EO conditions in the second measurement (p = .003), with a large effect size (r = .43). Under EC conditions, however, the changes were not statistically significant (p = .685; r = .04). Differences between the visual conditions were significant only in the first measurement (p = .008).

Discussion

The aim of this study was to assess the impact of six months' military training on the static balance of cadets. The obtained results indicate that no statistically significant changes were observed in any of the analyzed parameters during bipedal trials under either eyes-open (EO) or eyes-closed (EC) conditions. At the same time, the effect size values (r = .05–.37) confirm that the six-month training cycle did not significantly influence postural stability in this position. This finding is consistent with the literature, which states that bipedal tests are low-demand tasks and insufficiently sensitive to detect subtle adaptive changes in young, physically active individuals [4]. In populations such as military personnel, efficiently functioning proprioceptive, vestibular, and visual systems can effectively compensate for minor balance disturbances, making the bipedal stance an insufficient diagnostic challenge.

Different results were observed in single-leg trials, which are characterized by a higher level of difficulty and greater demand for precise sensory integration. For both the right and left limbs, statistically significant differences between EO and EC conditions were found (p < .001), with r values ranging from .14 to .34, indicating moderate to strong effect sizes. These findings confirm the dominant role of vision in maintaining stability under conditions of increased proprioceptive load. Similar observations regarding the role of sensory integration and visual control in maintaining postural stability were reported by Kamieniarz et al. [22]. These mechanisms correspond with postural control models described in the literature [3, 23]. Eliminating visual information substantially increases the demands placed on the somatosensory system. This becomes particularly evident in single-leg tasks.

The lack of differences between measurements taken before and after six months of training, both under EO and EC conditions, suggests that the standard military education programme does not significantly influence the development of postural control in tasks requiring high sensorimotor precision. These results are consistent with reports indicating that adaptations in single-leg balance control require specific training stimuli, such as exercises on unstable surfaces, precision tasks, and varied proprioceptive loads [5]. Traditional military training, however, focuses primarily on strength, endurance, and tactical skills, with limited emphasis on targeted balance training.

The single-leg tests conducted also confirm the role of sensory integration under conditions of limited visual input. Similar effects were reported by Tomczak [17] and Mantua et al. [19], who noted that postural control becomes particularly sensitive to sensory disturbances, fatigue, or sleep deprivation when the motor task is more demanding. The results of the present study confirm the typical pattern of dependence on visual information, which did not change as a result of training. This further supports the absence of adaptations within sensory balance control mechanisms.

A review of the literature indicates that soldiers' balance is largely determined by external load, both in terms of mass and equipment distribution. Studies by Schiffmann et al. [24] showed that additional equipment, even of low mass (e.g. 6 kg), leads to a linear increase in postural sway, including CoP path length and sway area. Similar results were reported for heavier loads ranging from 16 kg to 55 kg, which significantly increased the amplitude of movements in both the sagittal and frontal planes. Research by Loverro [10], Park [25], and Dziadek [12] additionally emphasizes that not only mass but also the distribution of the center of gravity affects postural stability. Shifting the center of mass forward or backward forces changes in postural control strategies and increases sway.

Muscle fatigue and prolonged exertion are also factors that impair postural stability. Fonseca et al. [26] demonstrated that heavy load (approx. 27 kg) significantly worsens stability, and Chander [27] noted that this effect becomes more pronounced under cumulative fatigue. Heller et al. [28] found that an 18-kg backpack significantly increases CoP sway parameters, confirming the direct influence of load on deterioration in postural control. Increased demands on the muscular system under heavy loads highlight the importance of maintaining a high level of physical fitness, as also emphasized by Nagai et al. [29].

The observed differences between EO and EC conditions confirm proper functioning of the balance system in the studied group. Both before and after training, stability clearly deteriorated when the eyes were closed, confirming typical sensory compensation mechanisms. The lack of changes in this pattern after six months of training indicates that the standard programme did not affect the reorganization or improvement of sensory integration.

Despite the absence of significant changes in the bipedal and single-leg results, the study confirmed the role of vision in maintaining stability, particularly under demanding single-leg conditions. The results also indicate that, to improve the postural stability of future soldiers, the training programme should be supplemented with targeted sensorimotor and proprioceptive exercises. Such exercises may enhance the effectiveness and safety of tactical tasks, particularly under equipment load and varied terrain conditions.

Limitations of the study and future research

The adopted approach did not involve modification of the measurement protocol or extension of the procedure to include additional and more demanding test conditions. Consequently, the obtained results reflect routine postural stability assessment, which may limit the detection of subtle neuromuscular and sensory adaptations, particularly in a population of young, physically fit, military-trained individuals. The absence of complex environmental and task-related stimuli may also have contributed to the low sensitivity of the double-leg tests and some single-leg trials to changes associated with the standard training programme.

In future studies, the methodology could be extended by introducing measurement conditions that better reflect the actual demands of military service.

The tests were conducted during autumn and spring. During this period, due to weather conditions, cadets did not participate in outdoor training at the physical fitness center on the 200-m obstacle course or the 500-m military pentathlon obstacle course. Exercises performed on these facilities may contribute to improved balance. The present study was conducted during a period when physical education classes mainly included gymnastics and strength training, hand-to-hand combat, swimming, and team games such as basketball and volleyball.

Conclusions

Single-leg tests are characterized by greater sensitivity to changes in postural control than double-leg standing tests. Improvement in stability following the training period was particularly pronounced for the right lower limb, especially under conditions without visual control, as confirmed by statistical significance and moderate-to-high correlation coefficients. For the left limb, the changes were more varied and less directly related to comparisons between measurements.

Longer-term studies or observations, for example over periods of 12–24 months, are needed to determine whether military training conducted at the Military University of Technology (WAT) under the standard curriculum contributes to improvement in balance.

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Conflicts of interest

The authors declare no conflicts of interest.

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Effects of specialized training on body composition, vertical jump and sprint performance in basketball players

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Authors' Contribution: A – Study design; B – Data collection; C – Statistical analysis; D – Manuscript Preparation; E – Funds Collection

Abstract

Background and Study Aim Basketball is a high-intensity, intermittent sport that requires well-developed strength, power, speed, and optimal body composition. The development of these physical components is associated with athletic performance, particularly in young adult players. Although combined training approaches incorporating strength, plyometric, and sprint exercises are widely used, their effectiveness in improving both morphological and performance-related variables remains a subject of practical interest. Therefore, this study aimed to examine the effects of an 8-week specialized training program on body composition, vertical jump performance, and sprint performance in basketball players aged 18–22 years.

Material and Methods A total of 20 volunteer basketball players aged 18–22 years participated in the study. All participants were actively competing at the university level. The training program was conducted three times per week for 8 weeks. It included structured strength, plyometric, and sprint-based exercises. Body composition was assessed using bioelectrical impedance analysis. Vertical jump performance was measured using the Countermovement Jump (CMJ) test. Sprint performance was evaluated using 20 m and 30 m sprint tests. Data were analyzed using paired-sample t-tests or Wilcoxon signed-rank tests, depending on data distribution. Effect sizes (Cohen's d) were calculated to assess the magnitude of changes.

Results The results indicated statistically significant improvements in all measured variables following the training program ($p < 0.001$). Body fat percentage decreased, while total and lower extremity muscle mass increased. Additionally, vertical jump performance (CMJ) improved significantly. Sprint times over both 20 m and 30 m distances decreased, indicating enhanced speed and explosive power. Effect size analysis demonstrated moderate to large improvements across variables.

Conclusions The 8-week specialized training program was associated with significant improvements in body composition, vertical jump performance, and sprint performance in basketball players. These findings suggest that integrated training approaches may contribute to performance-related adaptations. However, due to the absence of a control group, the results should be interpreted as within-group changes, and causal conclusions cannot be drawn. Future studies using controlled designs are recommended.

Keywords: basketball, plyometric training, body composition, vertical jump, sprint performance.

Introduction

Basketball performance is influenced by the interaction of multiple physical and physiological factors that contribute to the execution of sport-specific movements during training and competition. Players are required to repeatedly perform explosive actions such as sprinting, jumping, rapid changes of direction, and physical contact throughout the game. These demands place considerable stress on the neuromuscular system and are associated with the development of strength, power, speed, and body composition characteristics. Training strategies that combine different exercise modalities are commonly applied to support performance-related adaptations in basketball players.

Basketball is a high-intensity, intermittent team sport that requires the integration of multiple physical and physiological attributes, including strength, speed, agility, and explosive power. During gameplay, athletes frequently perform movements such as sprinting, jumping, rapid changes of direction, and acceleration, all of which are considered important determinants of performance [1]. Among these components, vertical jump and sprint ability play a fundamental role in game situations such as rebounding, shot blocking, fast-break execution, and defensive transitions.

Body composition is a factor associated with these performance outcomes. Parameters such as lean body mass, muscle mass, and body fat percentage directly affect force production and power output. Increased muscle mass, particularly in the lower extremities, has been associated with enhanced neuromuscular performance, whereas excessive body fat may negatively affect movement

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efficiency and speed [2]. In addition, recent findings have demonstrated relationships between body composition variables and physical performance indicators in basketball players, highlighting the role of morphological characteristics in athletic performance [3].

In recent years, combined training approaches incorporating strength, plyometric, and sprint-based exercises have been widely used to enhance basketball performance. Plyometric training has been shown to improve the efficiency of the stretch-shortening cycle, thereby increasing explosive power and contributing to improvements in both vertical jump and sprint performance [4, 5]. Similarly, strength and power training plays a role in enhancing neuromuscular function and athletic performance [6]. These adaptations are supported by evidence emphasizing the role of muscular strength and neuromuscular efficiency in sport performance [7].

Moreover, the stretch-shortening cycle has been identified as a mechanism underlying explosive movements, and its enhancement is associated with improvements in jump and sprint performance [8]. Previous studies have also demonstrated relationships between strength, sprint, and jump performance, suggesting that integrated training strategies may contribute to performance optimization in team sports [9, 10].

Analysis of research findings has shown that strength, plyometric, and sprint-oriented training approaches are associated with improvements in physical performance parameters in basketball players. Researchers emphasize that neuromuscular adaptations, explosive power, sprint ability, and body composition characteristics are interconnected components influencing sport-specific performance during competition and training. The combined effects of integrated training programs on both morphological and performance-related variables continue to attract scientific attention in basketball. In addition, the application of multidimensional training models in basketball involves methodological considerations related to the combined assessment of morphological and performance-related variables. Despite the growing body of research on strength, plyometric, and sprint-based training, most previous studies have focused on isolated performance variables or single training modalities. In many cases, body composition, vertical jump performance, and sprint performance have been investigated separately rather than within an integrated basketball-specific training framework. Furthermore, limited evidence is available regarding the concurrent effects of structured and multidimensional training programs on both morphological and performance-related adaptations within the same group of university-level basketball players, particularly when male and female athletes are evaluated together. Therefore, the assessment of these variables within a single training model may provide a broader evaluation of basketball-specific training adaptations and contribute to the development of integrated conditioning strategies. In this context, evaluating the influence of specialized training programs on body composition, vertical jump, and sprint performance remains relevant for examining performance-related adaptations in young adult basketball players.

Accordingly, the aim of this study was to examine the effects of an 8-week specialized training program on body composition, vertical jump performance, and sprint performance in basketball players.

It was hypothesized that the applied training program would lead to improvements in body composition (reduced body fat percentage and increased muscle mass), vertical jump performance, and sprint performance.

Materials and Methods

Participants

A total of 20 volunteer basketball players (11 males and 9 females) aged between 18 and 22 years participated in the study. All participants were actively competing at the university level. The inclusion criteria were as follows: (i) at least 2 years of licensed basketball experience, (ii) no musculoskeletal injury within the previous 6 months, and (iii) regular participation in training at least three times per week.

Participants had a mean basketball training experience of 4.3 ± 1.2 years and were assessed during the competitive season. In addition to the intervention program, all athletes regularly participated in routine basketball practices approximately 4–5 times per week. Players from different playing positions were included in the study to reflect the multidimensional physical demands of basketball.

All participants were informed about the procedures and provided written informed consent prior to participation. The study was conducted in accordance with the principles of the Declaration of Helsinki.

Research Design

This study employed a pretest-posttest single-group experimental design to examine the effects of an 8-week specialized training program on body composition, vertical jump performance, and sprint performance in basketball players. All measurements were conducted under standardized laboratory and field conditions before and after the intervention period.

Prior to baseline testing, all participants completed a familiarization session to reduce potential learning effects and ensure consistency in test execution. Before all performance assessments, participants completed a standardized 10-minute warm-up. The warm-up included light jogging, dynamic stretching, and movement-specific drills.

The specialized training program was implemented for 8 weeks with a frequency of three sessions per week. Each session lasted approximately 60–75 minutes and included strength, plyometric, sprint, and agility-oriented exercises. These exercises were designed to improve muscular strength, explosive power, and speed performance.

Strength exercises included squat, lunge, deadlift, and Bulgarian split squat movements. Plyometric exercises consisted of box jumps, squat jumps, lateral hops, drop jumps, and vertical jumps. Sprint and agility training included 20 m and 30 m sprint drills, T-tests, and ladder drills.

Strength exercises were performed at 60–80% of one-repetition maximum (1RM) to promote strength and hypertrophy adaptations. One-repetition maximum (1RM) values were estimated using submaximal testing procedures prior to the intervention period. Training loads were recalculated after the fourth week to ensure progressive overload and maintain the target intensity range throughout the intervention.

Plyometric exercises were performed at maximal effort with an emphasis on rapid force production and stretch-shortening cycle efficiency. Sprint and agility drills were performed at maximal or near-maximal intensity with standardized rest intervals between repetitions and sets.

Each training session included a 10–15 minute warm-up consisting of dynamic stretching and mobility exercises, followed by a 5–10 minute cool-down period including low-intensity activity and static stretching.

During weeks 1–4, athletes performed exercises at the lower end of the prescribed intensity range. During weeks 5–8, training volume and intensity were progressively increased by approximately 5–10% depending on individual performance and tolerance.

All sprint and plyometric exercises were performed on the same indoor basketball court surface under standardized environmental conditions. Participants wore the same type of basketball footwear throughout the intervention period.

All training sessions were supervised by certified strength and conditioning trainers to ensure participant safety, exercise standardization, and adherence to the protocol. Attendance was monitored throughout the intervention period, and all participants attended more than 90% of the scheduled training sessions.

The structure of the 8-week specialized training program is presented in Table 1. Table presents the structure of the 8-week specialized training program, including strength, plyometric, sprint, and agility-oriented exercises performed across three weekly training sessions.

Outcome Measurements

Body composition was assessed using a

Table 1. 8-Week Specialized Training Program for Basketball Players

Training Day	Training Focus	Exercise	Intensity	Sets × Repetitions / Distance	Rest, sec
Day 1	Strength + Plyometric	Squat	60–80% 1RM	3 × 8–10	90
		Lunge	60–70% 1RM	3 × 10	60
		Deadlift	60–80% 1RM	3 × 8	90
		Box Jump	Maximal effort	3 × 8	60
		Lateral Hop	Maximal effort	2 × 10	60
Day 2	Sprint + Agility	20 m Sprint	Maximal intensity	4 repetitions	90
		30 m Sprint	Maximal intensity	3 repetitions	120
		T-test	Maximal effort	3 repetitions	90
		Ladder Drill	High intensity	3 sets	60
Day 3	Strength + Plyometric	Squat Jump	Maximal effort	3 × 8	60
		Bulgarian Split Squat	60–70% 1RM	3 × 8	90
		Core Plank	Bodyweight	3 × 30 sec	45
		Drop Jump	Maximal effort	3 × 6	60
		Vertical Jump	Maximal effort	3 × 6	60

bioelectrical impedance analyzer (e.g., Tanita BC-418). Measurements included body weight, body fat percentage, total muscle mass, and segmental muscle distribution. All measurements were conducted in the morning under standardized conditions (fasted state and similar hydration levels).

Vertical jump performance was evaluated using the Countermovement Jump (CMJ) test. Participants performed three trials with one-minute rest intervals between attempts. The highest jump value was recorded for analysis.

Sprint performance was assessed using 20 m and 30 m sprint tests with a photoelectric timing system. Two trials were conducted for each sprint distance with adequate recovery periods between trials. The best performance value was used for statistical analysis.

All measurements were performed by the same assessors under identical testing conditions to improve measurement reliability and procedural consistency.

Statistical Analysis

All statistical analyses were performed using SPSS version 26.0 (IBM Corp., Armonk, NY, USA). Descriptive statistics are presented as mean ± standard deviation (Mean ± SD). Prior to analysis, data were screened for missing values and outliers. Normality was assessed using the Shapiro-Wilk test. Since all variables met the normality assumptions, pretest-posttest comparisons were analyzed using paired-sample t-tests. Effect sizes (Cohen's d) and 95% confidence intervals (CI) were calculated based on paired-sample comparisons to assess the magnitude and precision of the observed changes. The level of statistical significance was set at $p < .05$ for all analyses. Due to the single-group pretest-posttest design and relatively small sample size, the findings should be interpreted as exploratory within-group adaptations rather than definitive causal effects of the intervention program.

Results

According to the Shapiro-Wilk normality analysis, all variables met the normality assumptions. Therefore, pretest-posttest comparisons were analyzed using paired-sample t-tests.

Pretest and posttest comparisons of body composition variables are presented in Table 2. Body fat percentage decreased following the intervention period, whereas total muscle mass and lower extremity muscle mass increased. Large effect sizes were observed across all body composition variables (d = 0.86–0.92).

Pretest and posttest comparisons of vertical jump performance are presented in Table 3. CMJ performance increased following the 8-week intervention period. The observed effect size indicated a large magnitude of within-group change (d = 1.16).

Pretest and posttest comparisons of sprint performance are presented in Table 4. Sprint performance improved following the intervention period, as evidenced by reduced sprint times in both 20 m and 30 m tests. Large effect sizes were observed for both sprint variables (d = 1.00–1.10).

Overall, the 8-week specialized training program was associated with within-group improvements in body composition, vertical jump performance, and sprint performance. However, due to the absence of a control group, these findings should be interpreted cautiously and should not be considered definitive evidence of causal intervention effects.

Table 2. Pretest and Posttest Comparisons of Body Composition

Variable	Pretest (Mean ± SD)	Posttest (Mean ± SD)	t	p	Cohen's d	95% CI (Mean Difference)
Body Fat Percentage (%)	18.5 ± 2.3	16.9 ± 2.1	4.12	<0.004*	0.92 (large)	[-2.4, -0.8]
Total Muscle Mass (kg)	52.4 ± 5.6	54.1 ± 5.7	3.87	<0.007*	0.86 (large)	[0.6, 2.8]
Lower Extremity Muscle Mass (kg)	18.2 ± 2.0	19.3 ± 2.1	3.95	<0.006*	0.88 (large)	[0.5, 2.1]

*p < 0.05

Table 3. Pretest and Posttest Comparisons of Vertical Jump Performance

Test	Pretest (cm)	Posttest (cm)	t	p	Cohen's d	95% CI (Mean Difference)
CMJ	42.6 ± 4.1	46.3 ± 4.3	5.21	<0.001*	1.16 (large)	[1.5, 5.8]

*p < 0.05

Table 4. Pretest and Posttest Comparisons of Sprint Performance

Distance	Pretest (s)	Posttest (s)	t	p	Cohen's d	95% CI (Mean Difference)
20 m Sprint	3.21 ± 0.12	3.09 ± 0.10	4.48	<0.003*	1.00 (large)	[-0.18, -0.06]
30 m Sprint	4.75 ± 0.18	4.61 ± 0.16	4.92	<0.002*	1.10 (large)	[-0.22, -0.06]

*p < 0.05

Discussion

The present study examined the effects of an 8-week specialized training program on body composition, vertical jump performance, and sprint performance in basketball players. The findings demonstrated within-group improvements across all measured variables, generally supporting the study hypothesis. However, these findings should be interpreted cautiously, as the absence of a control group limits the ability to establish definitive causal relationships between the intervention and the observed adaptations.

The observed reductions in body fat percentage and increases in muscle mass are generally consistent with previous studies reporting favorable morphological adaptations following combined strength and high-intensity training interventions in athletes [11, 12]. Previous studies have suggested that such adaptations may be related to neuromuscular and metabolic responses associated with combined training interventions [13]. However, because external variables such as nutritional habits, sleep patterns, and additional physical activity were not controlled in the present study, the observed changes cannot be attributed exclusively to the intervention program. Differences between the present findings and previous studies may also be associated with variations in participant characteristics, seasonal phase, training duration, and exercise intensity.

The improvement observed in CMJ performance is consistent with previous studies indicating that strength and plyometric training approaches may contribute to enhanced explosive performance [14, 15]. Previous studies have further suggested that such improvements may be associated with adaptations related to the stretch-shortening cycle and neuromuscular function [16, 17]. However, since no physiological, biomechanical, or electromyographic measurements were performed in the present study, these potential mechanisms should be interpreted cautiously. Nevertheless, the effect size observed for CMJ performance suggests a substantial within-group adaptation following the intervention period.

Similarly, the reductions in sprint times observed in this study are generally consistent with previous research demonstrating that combined training programs may contribute to improvements in sprint and acceleration performance [18, 19]. Earlier studies have proposed that sprint performance may be influenced by factors such as maximal strength, rate of force development, and neuromuscular coordination [20]. In addition, integrated strength and speed-oriented training approaches have been suggested to support movement efficiency and sprint mechanics [21]. However, the current study design does not allow direct conclusions to be drawn regarding the specific physiological mechanisms underlying the observed sprint improvements.

Additionally, recent studies have provided further evidence supporting the role of combined and plyometric-oriented training strategies in improving sprint-related performance in basketball players. Barrera-Domínguez et al. [22] reported that individualized strength and plyometric training contributed to improvements in physical performance variables associated with acceleration and explosive actions in basketball athletes. Similarly, Huang et al. [23] demonstrated that plyometric training may improve speed, agility, and explosive strength performance in elite athletes, emphasizing the importance of neuromuscular adaptations for high-intensity sport activities. A recent meta-analysis by Zhou et al. [24] further confirmed that plyometric interventions may positively affect sprint capacity and overall athletic performance in youth basketball players. In addition, Cherni et al. [25] observed that combined plyometric and change-of-direction sprint training improved neuromuscular performance in elite female basketball players, suggesting that multidimensional training approaches may support speed-related adaptations in basketball-specific contexts. The findings of the present study are generally consistent with these recent observations, as significant reductions in both 20 m and 30 m sprint times were observed following the 8-week specialized training program. These similarities may indicate that integrated training approaches combining strength, plyometric, and sprint-oriented exercises can contribute to sprint-related performance adaptations in basketball players.

A contribution of the present study is the integrated evaluation of body composition, vertical jump performance, and sprint performance within a single basketball-specific training framework. While many previous studies have primarily focused on isolated performance variables or single training modalities, the present study attempted to provide a multidimensional assessment of both morphological and performance-related adaptations within the same athlete population [26]. This integrated perspective may be relevant for coaches and practitioners by supporting the development of more comprehensive basketball conditioning strategies.

Additionally, recent studies have increasingly emphasized the importance of multidimensional training and assessment approaches in basketball performance research. Previous investigations have demonstrated that integrated evaluations combining body composition, sprint ability, jump performance, and neuromuscular characteristics may provide a broader understanding of basketball-specific adaptations compared with isolated performance assessments [3, 22, 24, 27].

Recent evidence has also suggested that multidimensional training models may simultaneously influence several physical capacities, including explosive power, sprint performance, and movement efficiency in team-sport athletes [28]. In this context, the present findings further support the practical relevance of integrated basketball-specific conditioning approaches by demonstrating concurrent improvements in body composition, vertical jump performance, and sprint performance within the same athlete population.

Furthermore, previous studies have emphasized that combined training strategies may support concurrent improvements in multiple physical capacities without necessarily compromising performance adaptations [29, 30]. The present findings are generally consistent with this perspective and suggest that multidimensional training models may represent a practical approach for basketball conditioning programs. However, due to the single-group pretest-posttest design, the findings should be interpreted as exploratory within-group adaptations rather than definitive evidence of intervention effectiveness. Such training approaches may also contribute to the transferability of performance-related adaptations to basketball-specific tasks [31].

Additionally, recent evidence has further supported the effectiveness of multidimensional and combined training approaches for the simultaneous development of multiple physical capacities in basketball players. Previous studies and meta-analyses have demonstrated that integrated strength, plyometric, and sprint-oriented interventions may contribute to concurrent improvements in sprint ability, explosive power, neuromuscular performance, and overall athletic capacity without negatively affecting performance adaptations [22, 24, 25, 28]. Such findings reinforce the practical relevance of multidimensional conditioning models in basketball-specific settings and suggest that combined training strategies may facilitate the transfer of performance-related adaptations to sport-specific tasks. The present findings are generally consistent with this perspective, as improvements were simultaneously observed in body composition, vertical jump performance, and sprint performance following the 8-week training intervention.

From a practical perspective, the findings suggest that integrating strength, plyometric, and sprint-oriented exercises within the same weekly training structure may be beneficial for the simultaneous development of explosive power, sprint capacity, and body composition characteristics in basketball players. Coaches and practitioners may therefore consider implementing multidimensional training models rather than relying solely on isolated conditioning approaches.

Limitations of the Study and Future Research Directions

This study has several limitations. First, the absence of a control group substantially limits causal interpretation and reduces internal validity. Second, the relatively small sample size may limit the generalizability of the findings. Third, potential confounding variables such as nutritional habits, sleep quality, and additional physical activity were not controlled throughout the intervention period. In addition, the use of bioelectrical impedance analysis may have been influenced by hydration status, potentially affecting measurement accuracy. Another limitation is the combined analysis of male and female athletes without subgroup comparisons. Potential sex-specific adaptations may therefore have remained undetected.

Future studies should employ randomized controlled designs with larger sample sizes to confirm the present findings. In addition, future research should investigate sex-specific responses, position-specific adaptations, and the long-term effects of combined training interventions in basketball players. The inclusion of physiological and biomechanical measurements may further contribute to examining the mechanisms underlying training-related adaptations. Future research employing controlled experimental designs and larger sample sizes is recommended to further validate and extend these results.

Conclusions

The findings of this study demonstrate that an 8-week specialized training program was associated with improvements in body composition, vertical jump performance, and sprint performance in basketball players, supporting the initial hypothesis. These results highlight the role of integrated training approaches combining strength, plyometric, and sprint exercises in the development of physical performance components.

From a practical perspective, the implementation of such structured and multi-component training programs may provide benefits for coaches and practitioners aiming to optimize athletic performance in basketball. The simultaneous improvement of morphological and performance-related variables suggests that a holistic training strategy may represent an efficient approach in applied sports settings. However, the absence of a control group limits the ability to draw causal conclusions, and therefore the findings should be interpreted with caution.

Overall, the present study contributes to the growing body of research by providing an integrated perspective on training-induced adaptations and emphasizing the role of combined training strategies in the multidimensional development of basketball performance.

Conflict of Interest

The authors declare no conflict of interest.

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PHYSICAL
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REVIEW ARTICLE

Artificial intelligence–integrated wearable sensors for sports injury prediction and rehabilitation monitoring: a systematic review

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Authors' Contribution: A – Study design; B – Data collection; C – Statistical analysis; D – Manuscript Preparation; E – Funds Collection

Abstract

Background and Study Aim Wearable sensor technologies integrated with artificial intelligence (AI) and machine learning (ML) are increasingly used for continuous athletic monitoring. Despite their application, continuous monitoring of physically active populations in relation to injury susceptibility remains insufficiently implemented. This review synthesizes evidence on AI-integrated wearable systems for sports injury prediction and rehabilitation monitoring, emphasizing diagnostic performance and applicability to university physical education settings.

Material and Methods PubMed, Web of Science, Scopus, and ProQuest were systematically searched through December 2025 following PRISMA 2020 guidelines (PROSPERO: CRD42026130911). Studies involving athletes or physically active individuals using wearable sensors combined with AI/ML models (CNN, LSTM, RNN) for injury prediction or rehabilitation monitoring were eligible. Risk of bias was assessed using PROBAST.

Results From 1,004 identified records, 15 studies met the inclusion criteria. Six studies explicitly involved university-aged participants (18–29 years) or were conducted in university laboratory settings. IMUs were the predominant sensor modality. Deep learning models (CNN, LSTM) achieved classification accuracies of 86–95% and F1 scores exceeding 0.90. Workload-based models demonstrated a 15-fold increase in injury risk at acute-to-chronic workload ratios above 1.27. PROBAST assessment identified only two studies as having a low overall risk of bias. Four studies were at high risk, primarily due to small samples, absent external validation, and analytical limitations.

Conclusions AI-integrated wearable systems show considerable potential for injury monitoring in athletic and university physical education contexts. However, small samples, limited external validation, and heterogeneous injury definitions constrain the current evidence. Future research should prioritize multicenter prospective studies and explicitly target university student populations.

Keywords: wearable sensors, artificial intelligence, machine learning, injury prediction, rehabilitation monitoring, systematic review, university students, physical education

Introduction

The integration of digital technologies into health-related monitoring has expanded the use of advanced tools for assessing human movement and recovery processes. Wearable sensor systems combined with artificial intelligence enable continuous data collection and automated analysis in real-world conditions. At the same time, the identification of injury risk and the monitoring of rehabilitation remain complex due to the multifactorial nature of these processes and variability in individual responses. These factors complicate the consistent evaluation of injury-related outcomes and the effective tracking of recovery in physically active populations.

Wearable technologies have influenced sport and exercise science by enabling real-time tracking of movement-related indicators associated with injury risk and recovery during physical activity [1, 2]. Continued technological developments have expanded their use across amateur and high-performance sports settings, including university physical education programs [3]. These systems enable monitoring of functional movement patterns, workload indicators, and related parameters associated with physical activity [4]. Wearable sensors also provide field-based, non-invasive monitoring during practice and competitive scenarios, supporting their use by sports professionals and physical education practitioners [5].

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Students engaged in physical education programs, academic sport, and recreational physical activity represent a relevant population in the context of injury monitoring [6]. Compared to professional athletes, access to structured sports medicine support in educational settings may be variable, which increases the relevance of technology-assisted monitoring [7]. Physical education programs at bachelor's, master's, and doctoral levels incorporate monitoring practices as part of the educational process; however, the application of AI-integrated wearable systems within student and university sport contexts is not consistently implemented [8, 9]. Musculoskeletal injuries are among the most common health concerns in this population [10] and may affect both participation in physical activity and academic performance [11].

By generating biomechanical data, wearable technologies enable the identification of movement-related deviations and support the application of data-informed interventions [10]. Inertial measurement units (IMUs) have been validated for capturing joint movements and temporal characteristics during lower-body activities [12]. The identification of injuries remains complex in this context. Many injuries develop gradually due to cumulative mechanical load rather than acute events, with subtle changes in movement patterns often preceding clinical manifestation and remaining undetected by conventional assessments [13]. Wearable technologies allow continuous monitoring of movement and workload-related indicators, which supports earlier detection of potential injury-related changes in settings where access to structured supervision may be limited [14].

Artificial intelligence (AI), including machine learning (ML) and deep learning (DL) methods, is applied to process high-dimensional data generated by wearable technologies. Algorithms such as recurrent neural networks (RNNs) can analyze time-series data and identify patterns that are not readily detectable using traditional analytical approaches [15]. These models are used to estimate injury risk, monitor rehabilitation progress, and support the adjustment of management strategies [16]. The combination of wearable technologies and AI enables the integration of monitoring and analytical processes across injury prevention and rehabilitation monitoring, including applications in university physical education settings [17].

Despite implementation, the diagnostic and predictive effectiveness of AI-integrated wearable systems remains inconclusive. Existing reviews often concentrate on isolated applications, such as gait analysis, sensor engineering, or theoretical AI frameworks, without systematically evaluating injury risk detection or rehabilitation monitoring in applied physical activity contexts [15, 18, 19]. Recurring methodological limitations, including small sample sizes, heterogeneous sensor configurations, inconsistent injury definitions, and limited external validation, restrict generalizability and clinical translation [20, 21]. Individual studies report findings; however, a unified synthesis that evaluates methodological rigor, predictive accuracy, and implementation feasibility in relation to physically active populations is not consistently presented [13, 22, 23].

To date, no systematic review has synthesized the diagnostic performance and methodological robustness of AI-integrated wearable systems for injury prediction and rehabilitation monitoring in physically active populations, including university physical education contexts [24]. Clarifying this evidence base supports the development of early intervention strategies, return-to-activity decisions, and the integration of wearable technologies into university physical education programs [25].

Accordingly, the aim of this systematic review is to synthesize evidence on AI-integrated wearable technologies for sports injury prediction and rehabilitation monitoring, with emphasis on diagnostic performance and applicability to university physical education settings.

Methodology

The present systematic review was guided by the Preferred Reporting Items for Systematic Reviews (PRISMA) statement [26] and registered in the international database of systematic reviews in health and social care, PROSPERO (CRD420261309119). The study selection process is presented in Figure 1.

Information sources

A systematic literature search was conducted and updated through January 2026 in the electronic databases PubMed, Web of Science, SCOPUS, and ProQuest. The search used Boolean operators AND/OR in combination with the following keywords: "wearable technology", "sports medicine", "sports performance", "athlete", "injury prediction", "artificial intelligence", "rehabilitation", "sport", "university students", "physical education", "student athletes", and "academic sport".

Search Strategy

One author (RD) conducted the initial search and removed duplicates. Two authors (RS and TY) independently screened the titles, abstracts, and full texts of the retrieved studies. The search results were analyzed according to the eligibility criteria (Table 1). A fourth author (BJ) resolved disagreements between RS and TY.

Eligibility criteria were predefined using the PICOS framework to ensure transparent, systematic, and reproducible study selection (Tables 1 and 2). Studies were included if they involved athletic

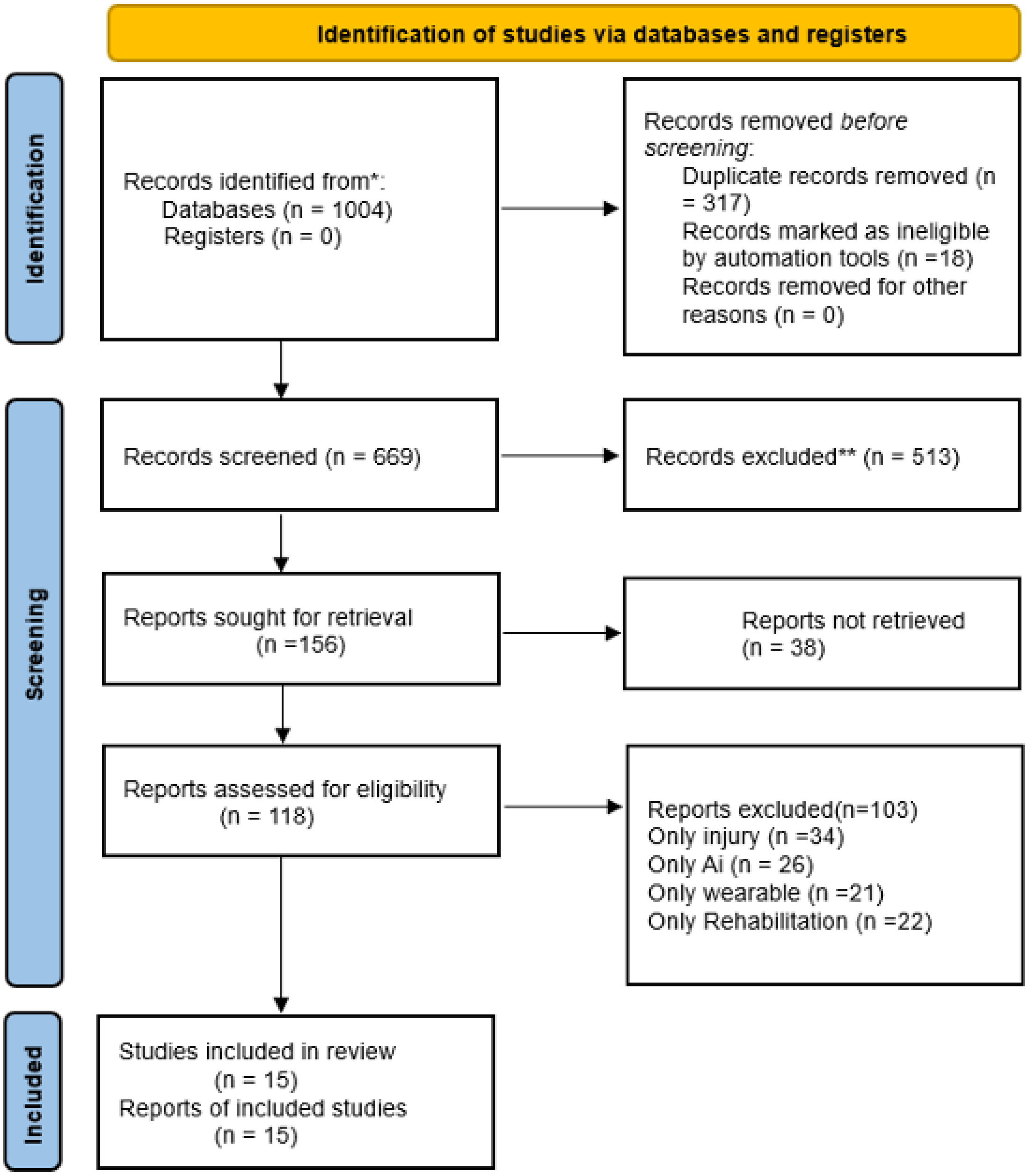

Figure 1. PRISMA flow diagram of the study selection

populations (amateur, professional, or elite) and used wearable technologies integrated with AI or ML models (e.g., IMUs, EMG, heart rate sensors) for injury risk prediction or rehabilitation monitoring. Studies involving university students, physically active students, or university-aged participants (18–29 years) engaged in academic sport or physical education programs were eligible for inclusion. Eligible studies were required to report extractable quantitative outcomes, such as diagnostic or predictive performance metrics (e.g., sensitivity, specificity, F1 score) or rehabilitation-related indicators (e.g., range of motion, compliance, recovery milestones).

Studies were excluded if they involved non-athletic populations, wearable devices without AI/ML integration, purely descriptive device development reports, non-peer-reviewed sources, or insufficient outcome data for extraction. Both prospective and retrospective original research designs were eligible, and no time restrictions were applied during study selection. Where included studies did not directly involve student populations, the transferability of findings to university physical education and student sport contexts was considered, provided that participant age profiles were consistent with university student demographics (18–29 years). This approach is consistent with methodological practice in sports and exercise science systematic reviews, where direct student-based evidence is limited.

Data Extraction

Data extraction was performed following a

Table 1. Inclusion criteria according to the PICOS conditions

Items	Details Inclusion Criteria
Population	Athletes and physically active individuals, including university students engaged in physical education programs, university sport, or academic training contexts. Where direct student-based evidence was unavailable, findings from university-aged athletic cohorts (18–29 years) were considered applicable to student populations.
Intervention	Use of smart wearable devices combined with AI or machine learning models (e.g., RNN, CNN, ARNN, RCNN) to detect injury risk or monitor rehabilitation progress.
Comparison	May include traditional assessment methods (e.g., manual screening, clinical evaluations), other wearable tools without AI, or no comparison.
Outcome	Diagnostic accuracy (sensitivity, specificity, precision, recall, F1 score) of injury risk prediction. Effectiveness in monitoring rehabilitation progress (e.g., joint range of motion, adherence, recovery milestones).
Study Design	Primary studies, including diagnostic accuracy studies, prediction model studies, and non-randomized interventions involving wearables and AI. Both retrospective and prospective designs were eligible.

Table 2. Inclusion and Exclusion Criteria

Category	Inclusion Criteria	Exclusion Criteria
Population	Studies involving athletes (amateur, professional, or elite) in any sport or training context; university students engaged in physical education, academic sport, or recreational physical activity; university-aged participants (18–29 years)	Studies involving non-athletic populations, general health monitoring, or non-sport use
Intervention	Use of wearable technologies (e.g., IMUs, EMG, heart rate sensors) combined with AI or ML models (e.g., CNN, RNN, RCNN) for injury risk detection or rehabilitation monitoring	Studies using wearables without AI/ML integration or purely manual assessment tools
Comparison	Studies comparing AI-driven wearables with traditional assessments, other devices, or baseline measures	No comparison and purely descriptive device design studies
Outcomes	Outcomes related to injury prediction (accuracy, sensitivity, specificity, F1 score) or rehabilitation monitoring (range of motion, compliance, progress tracking)	Studies not reporting relevant outcome metrics or with insufficient data for extraction
Study Design	Original research articles, including diagnostic accuracy studies, prospective or retrospective cohort studies, or model validation studies	Reviews, opinion pieces, case reports, editorials, or conference abstracts without full data
Language	Published in English	Non-English publications
Publication Type	Peer-reviewed journal articles	Non-peer-reviewed sources
Time Frame	No time restriction applied	Not applicable

standardized protocol based on the Cochrane Consumer and Communication Review Group's guidelines [27]. From each included study, relevant information was systematically retrieved, including the first author's name and year of publication, study design, type of athlete population (e.g., elite, recreational, sport-specific), and participant characteristics such as age, sex, and sample size. Where available, the academic or university affiliation of study settings was noted. Participant age profiles were assessed to identify studies involving university-aged populations. Further details collected included the type of wearable device and sensor technology used, the artificial intelligence or machine learning model applied (e.g., CNN, RNN, ARNN), and the purpose of the system, whether for injury risk detection or rehabilitation monitoring. Outcome measures such as diagnostic accuracy, precision, recall, F1 score, and recovery-related indicators were also extracted, along with contextual information about the study setting (e.g., laboratory or field-based). The data were independently extracted by RD and cross-verified by TY. Any discrepancies were resolved through consensus with RS and BJ. All data were compiled into a structured Excel spreadsheet for subsequent analysis.

Study Selection

The study selection process was carried out in multiple stages. Initially, duplicate records were removed using Zotero reference management software [28]. Following this, titles and abstracts were screened to identify studies that met the predefined inclusion criteria, which focused on the application of wearable technologies and artificial intelligence for injury risk detection or rehabilitation monitoring in athletic populations, including university students and physically active student populations. Full texts of the shortlisted studies were then independently reviewed by two authors, VNL and CVC, to confirm eligibility. Any discrepancies in study selection were resolved through discussion with a third reviewer, TY. Fifteen primary studies, including diagnostic accuracy studies, prediction model research, and observational designs, were included in this systematic review for final data extraction and analysis.

Quality Assessment / Risk of Bias Evaluation

Table 3 presents the risk-of-bias assessment using PROBAST. Only two studies were judged as low overall risk, while four demonstrated a high risk of bias, primarily due to analytical limitations. The Participants and Predictors domains were generally well addressed, as most studies recruited athletic populations and clearly defined wearable sensor metrics. However, concerns were identified in the Outcome domain, particularly regarding inconsistent injury definitions and the lack of blinded outcome assessment.

The Analysis domain represented the main source of bias. Several machine learning studies employed small sample sizes relative to the number of predictors. This increased the risk of overfitting. In many cases, cross-validation strategies were not clearly defined as subject-wise. This raised the possibility of data leakage between training and testing datasets. External validation was absent in the majority of studies. This limited generalizability. Additionally, few studies reported calibration metrics or assessed model robustness across independent cohorts.

Overall, while wearable-AI systems demonstrate predictive performance, methodological rigor, particularly in model validation and statistical handling, remains insufficient in many studies. Future research should prioritize larger multi-center datasets, transparent validation pipelines, and adherence to PROBAST and TRIPOD-AI reporting guidelines.

Risk-of-bias assessment was performed independently by two reviewers, RD and BJ, using the PROBAST tool across four domains (Participants, Predictors, Outcome, Analysis). Disagreements were resolved through consensus.

Results

From an initial pool of 1,004 references, 669 unique articles remained after removing 317 duplicates. Following screening, 15 full-text studies were included in the qualitative synthesis. These studies showcased the application of wearable sensors and AI tools to monitor athlete biomechanics, injury risk, and recovery in real time. Several included studies involved university-aged participants (mean age 18–29 years) or were conducted in university laboratory settings, providing findings with direct relevance to student populations and academic physical education contexts.

Several included studies are relevant to university student and physical education populations. Gil-Martín et al. [32] evaluated 407 participants with a mean age of 23.1 ± 6.6 years using an LSTM-based model to automate Y-Balance Test scoring. Khuyagbaatar et al. [34] compared 10 university-level wrestlers with 10 non-athlete student controls

Table 3. Risk of Bias Assessment Using PROBAST

Study (Author, Year)	Participants	Predictors	Outcome	Analysis	Overall Risk of Bias
Alzahrani and Ullah, 2024 [29]	Low	Low	Unclear	High	High
Chen et al., 2022 [30]	Low	Low	Low	Moderate	Moderate
Davis et al., 2024 [31]	Low	Low	Low	Low	Low
Gil-Martín et al., 2021 [32]	Low	Low	Low	Low	Low
Hunter et al., 2026 [33]	Low	Low	Low	Moderate	Moderate
Khuyagbaatar et al., 2025 [34]	Moderate	Low	Low	Moderate	Moderate
Kinjo et al., 2021 [35]	Low	Low	Low	Moderate	Moderate
Lapinski et al., 2019 [36]	Low	Low	Unclear	High	High
Mehta, 2019 [5]	Moderate	Low	Low	High	High
Ogasawara et al., 2021 [37]	Low	Moderate	Moderate	Moderate	Moderate
Pu and Liu, 2024 [1]	Moderate	Low	Low	High	High
Reiter et al., 2024 [38]	Low	Low	Low	Moderate	Moderate
Shahabpoor and Pavic, 2018 [39]	Low	Low	Low	Moderate	Moderate
Sufrinko et al., 2018 [40]	Moderate	Low	Low	Moderate	Moderate
Trbovich et al., 2021 [41]	Moderate	Low	Low	Moderate	Moderate

in a university gymnasium setting. Chen et al. [30] recruited young adults (approximately 20 years of age) in a university laboratory to assess plank technique classification using a 5-IMU machine learning system. Reiter et al. [38] recruited 11 active young adults (mean age ~26.5 years) in a university laboratory setting. Shahabpoor and Pavic [39] conducted a gait analysis study involving participants aged 21 ± 1 years. Sufrinko et al. [40] and Trbovich et al. [41] monitored adolescent athletes aged 12–19 years recovering from sport-related concussion.

Several studies utilized IMUs integrated with machine learning models to assess movement precision. One system classified plank exercises as either correct or containing one of six common faults, with 86% accuracy and over 90% sensitivity and specificity [30]. Another study used a Long Short-Term Memory (LSTM) model on IMU data from 407 subjects of university student age (mean 23.1 years) to automate Y-Balance Test scoring, reducing mean absolute percentage error (MAPE) to 7.9%, a 10% improvement over baseline models [32]. A smart mouthguard sensor was developed to detect excessive jaw clenching during sport-specific activities [35].

Physiological metrics were also captured in real time. Heart rate and acceleration data showed that athletes maintained approximately 80% of their maximum heart rate during restricted training sessions [37]. In a university gymnasium setting, Khuyagbaatar et al. [34] found that university-level wrestlers demonstrated better functional movement and core stability compared to non-athlete student controls. A multimodal wearable system combining IMUs, electromyography (EMG), and pressure sensors enhanced joint control, muscle activation, and heart rate regulation during physiotherapy interventions [29].

Kinetic data collection was also achieved using wearable technology outside laboratory settings. A single IMU placed on the cervical spine (C7) estimated vertical ground reaction forces during walking and running, with a normalized root-mean-square error (RMSE) of 4–8% [39]. This was demonstrated in a cohort of young adults aged 21 ± 1 years. Achilles tendon tensiometers recorded tendon loading of 8–10 times body weight during running [38]. Testing was conducted on young adults of university age (~26.5 years) in a university laboratory. Wearable magnetometer-IMU systems recorded angular velocities over 7,000°/s in throwing sports [36].

Biomechanical patterns recorded indoors versus outdoors varied significantly. Only 32.5% of outdoor running gait fell within lab-derived kinematic ranges [31]. In endurance contexts, “durability” was quantified by heart rate–speed decoupling. Less durable runners showed greater biomechanical deterioration during marathon efforts [33]. Elbow valgus torque tracking over a baseball season showed that an acute-to-chronic workload ratio (ACWR) above 1.27 increased injury risk by 15-fold [5]. Post-concussion recovery was monitored via wrist actigraphy in adolescent athletes aged 12–19 years [40]. Sleep efficiency, rather than total duration, predicted symptom severity the following day in adolescent athletes [41]. A hybrid CNN–LSTM model used in rehabilitation monitoring achieved F1 scores above 0.90 when identifying improper exercise execution [1].

Table 4 summarizes the methodological and contextual characteristics of the fifteen included studies. Most investigations employed observational or experimental cross-sectional designs, with only a limited number adopting prospective cohort methodologies. Sample sizes varied substantially, ranging from small laboratory cohorts ($n < 25$) to a single larger study including 407 participants. IMUs were the most frequently used sensor modality, followed by electromyography, heart-rate monitors, actigraphy, and specialized devices such as wearable mouthguards and shear-wave tensiometers. The majority of studies were conducted in controlled laboratory settings and involved single-session assessments, with limited longitudinal follow-up. Only a minority of studies evaluated injury outcomes prospectively. With respect to student population relevance, six of the fifteen included studies involved participants within the university student age range (18–29 years), and two studies were explicitly conducted in university gymnasium or laboratory settings [34, 39]. These studies provide the most directly transferable evidence for the application of AI-integrated wearables in university physical education and student sport contexts. Overall, the table highlights that while wearable-AI systems demonstrate technical feasibility and promising biomechanical monitoring capabilities, most evidence is derived from small, short-term, and predominantly laboratory-based investigations.

Table 5 presents the ML model characteristics, validation approaches, and analytical limitations across the included studies. Predictive performance varied depending on dataset size, model architecture, and validation strategy. DL approaches such as LSTM and CNN showed classification accuracy of approximately 86–95% and F1 scores exceeding 0.90 in controlled tasks. Most models used internal cross-validation without external validation cohorts. Sample sizes were often small ($n < 25$). A minority of studies included prospective injury outcomes or season-long monitoring designs. One study included 407 participants and applied subject-wise cross-validation [32].

Across the included studies, predictive performance varied depending on dataset size, validation strategy, and outcome definition. Deep

Table 4. Characteristics of the included studies

Study (Title / Authors / Year)	Study Design	Population	Device Used	Intervention	Comparator	Outcomes Measured	Follow-up	Country / Setting	Key Findings
Alzahrani and Ullah, 2024 [29]	Observational (cross-sectional, pre/post assessment)	50 athletes	Inertial sensors (MPU6050, MPU9250), EMG, MyoWare Muscle Sensor, FlexiForce sensor	Measured performance metrics with and without sensor	Baseline metrics without wearables vs. with wearable monitoring	Heart rate, joint angles, postural dynamics, muscle activation levels, ground reaction forces, stress/strain metrics, breathing patterns, fatigue levels	None (single-session)	Saudi Arabia / Field sports setting	Wearable technologies with analytics enhanced key performance metrics, enabling real-time, personalized interventions. Athletes showed measurable improvements, supporting their value in training optimization.
Chen et al., 2022 [30]	Experimental (cross-sectional, within-subject)	19 healthy volunteers (≈20 yrs, mixed gender)	Five IMUs (occiput, cervical, thoracic spine, sacrum, forearm)	Participants performed standard planks and 6 deviated plank postures (in random order)	Correct plank form vs. specific aberrant forms (within-subject)	Classification accuracy of plank technique (acceptable vs. aberrant), sensitivity/specificity for each deviation	None (single-session)	Taiwan / Lab setting	A 5-IMU machine-learning system achieved ~86% accuracy in detecting faulty plank techniques, offering real-time feedback to support coaching and injury prevention.
Davis et al., 2024 [31]	Experimental (within-subject crossover)	68 adult recreational runners (49 in cohort 1, 19 in cohort 2; all healthy females, age ~18–58)	Multiple wearable sensors (Garmin Forerunner 245 watch with GPS, Garmin HRM-Run/Tri chest strap, Stryd footpod)	Each runner completed an instrumented lab treadmill run and multiple outdoor runs with the same sensors	In-lab running vs. real-world free running (within the same subjects)	Gait metrics (speed, step length, vertical oscillation, stance time, leg stiffness) and statistical overlap between lab vs. outdoor gait distributions	Short-term (each subject's lab run plus 1–5 outdoor runs over days/weeks)	USA / University lab and outdoor courses	Lab-based gait patterns poorly reflected real-world gait (~32.5% overlap), while pooled multi-runner data showed better prediction (~90%), suggesting lab data alone are insufficient for real-world gait analysis.
Gil-Martín et al., 2021 [32]	Observational (retrospective model development)	407 athletes aged 23.1 ± 6.6 years; height 179.8 ± 42.1 cm; weight 89.3 ± 21.1 kg	Single wearable IMU (on foot or lower limb during Y-Balance Test)	Standardized Y-Balance Test (reach distance in 3 directions) for each participant	None (no control; all data used to train/validate model)	Normalized reach distance (YBT score) in each direction; model prediction error	None (one-time assessment per subject)	Spain & Ireland / Lab setting	A deep LSTM model accurately predicted Y-Balance Test scores from IMU data, outperforming previous methods and enabling objective balance monitoring.

Table 4. Continued

Study (Title / Authors / Year)	Study Design	Population	Device Used	Intervention	Comparator	Outcomes Measured	Follow-up	Country / Setting	Key Findings
Hunter et al., 2026 [33]	Observational cohort study	69 (64M & 5F); 44.4 ± 10.5 years, 1.78 ± 0.08 meters, and a mass of 73.3 ± 10.8 kg	Foot-worn accelerometer (for step metrics) and heart-rate monitor	Continuous biomechanical and HR monitoring throughout a marathon race (42.2 km)	Grouped by "durability" (low vs. high HR–speed decoupling during race) for comparison	Running dynamics (speed-adjusted step frequency, step length, duty factor, stiffness) across 5 km segments; HR–speed decoupling magnitude	Marathon duration (~3–5 hours per subject)	UK / Real marathon race	Durable runners showed more stable gait under fatigue, maintaining cadence and stride better than less durable peers. These patterns may reflect fatigue resistance, though it is unclear if they are trainable or innate.
Khuyagbaatar et al., 2025 [34]	Cross-sectional comparative study	20 young adults (10 elite wrestlers vs. 10 non-athlete controls)	Inertial sensors (IMUs) on key body segments during movement tests	All participants performed the Functional Movement Screen (FMS) battery with IMU recording	Group comparison: wrestlers vs. untrained controls	FMS scores on seven movements; detailed joint kinematics (angles, velocities) during each movement	None (one-time assessment)	Mongolia / University gym	Wrestlers showed better functional movement and core stability than non-athletes, with smoother motion patterns. IMU data highlighted sport-specific training benefits without increased injury-risk movements.
Kinjo et al., 2021 [35]	Device development and validation study	3 males (age 19–29)	Custom mouthguard with bilateral force sensors on molars, plus surface EMG for comparison	Lab tests: (1) static bite force calibration; (2) simulated clenching tasks (tapping, grinding); (3) high-intensity cycling test with mouthguard on	Comparison of mouthguard sensor outputs to reference EMG, video, and known weights	Bite force (N) measured by mouthguard; clench timing and duration; EMG signals for masseter muscle activity	None (acute tests)	Japan / University lab	The instrumented mouthguard accurately measured clenching force and timing during exercise, aligning with EMG patterns and proving durable and effective for monitoring clenching in sports.

Table 4. Continued

Study (Title / Authors / Year)	Study Design	Population	Device Used	Intervention	Comparator	Outcomes Measured	Follow-up	Country / Setting	Key Findings
Lapinski et al., 2019 [36]	Technical development and applied testing	8 baseball pitchers (2 collegiate, 6 professional)	Custom 9-axis IMU sensors (dual-range), wearable wireless sensor array on upper extremity segments	Two studies: (1) 2 collegiate pitchers threw with IMUs and optical motion capture (validation); (2) 6 professional pitchers threw with IMUs in a game-like outdoor setting	Lab optical motion capture and force calculations (for validation of IMU data)	Kinematics: angular velocities, accelerations, joint torques; novel metric "jerk" (rate of acceleration change); pitch velocity; joint stress estimates	None (single-session per study)	USA / Lab and on-field (bullpen)	The ultra-wide-range IMU system accurately captured high-speed pitching forces, outperforming optical systems in measuring peak torques and "jerk." It enables in-game monitoring of elite biomechanics and offers insights into injury risk.
Mehta, 2019 [5]	Prospective cohort (season-long monitoring)	18 male high-school baseball athletes aged 17.0 ± 0.7 years; height 185 ± 5.7 cm; mass 85.2 ± 7.6 kg	Motus THROW wearable sleeve sensor (IMU) on throwing arm, tracked elbow torque and throwing counts; mobile app for injury tracking	Tracked all throws for the entire 2017 season; computed acute-to-chronic valgus torque workload ratios (ACWR) weekly	Correlated high vs. low ACWR with injury incidence at the end of the season	Weekly acute-to-chronic elbow load ratio (ACWR); injuries (type and occurrence); performance (if noted)	6 months (pre-season and full season)	USA / School baseball team	High throwing workload spikes (ACWR >1.27) greatly increased injury risk. Pitchers were approximately 15 times more likely to be injured. Monitoring and maintaining ACWR ⩽1.3 is advised to prevent youth baseball arm injuries.
Ogasawara et al., 2021 [37]	Descriptive observational (case study of training camp protocols)	29 elite female handball players; 24 staff (Japan national team)	AI-based video system (for distancing) + Teijin "Smart Shirt" wearable ECG/ accelerometer for heart rate and activity	2-week centralized training camp under COVID-19 protocols (PCR testing, distancing feedback, HR monitoring)	Compared metrics to COVID-era guidelines (no control group per se)	On-court interpersonal distance (via AI); training intensity (HR, acceleration); COVID outcomes (positive cases); fitness test results	2 weeks (camp duration)	Japan / National Training Center "bubble" camp	Strict screening, daily testing, and real-time proximity/load monitoring enabled safe, high-intensity training with no COVID-19 cases. The JS-CPS system supported normal performance while ensuring safety.

Table 4. Continued

Study (Title / Authors / Year)	Study Design	Population	Device Used	Intervention	Comparator	Outcomes Measured	Follow-up	Country / Setting	Key Findings
Pu and Liu, 2024 [1]	Algorithm development study (with pilot testing)	10 healthy athletes (for model evaluation; age not stated)	Wearable motion sensors collecting full-body biomechanics (exact devices not specified; likely IMUs on limbs/joints)	Participants performed 4 different rehab exercises (each 4 reps) to generate motion data for model training	n/a (algorithm performance compared to labeled "normal" vs. "abnormal" movement)	Model accuracy in detecting anomalous joint motions (injury risk) and classifying rehab exercise correctness (precision, recall, F1 score)	None (single-session data collection)	China / Lab setting	A two-part AI model using wearable data accurately detected injury-risk movements (~93.5% accuracy) and monitored rehab form (~95% accuracy), supporting athlete health management.
Reiter et al., 2024 [38]	Experimental lab study (validation of new device)	11 active young adults (6 M, 5 F; mean ~26.5 yrs)	Shear wave tensiometers strapped to both Achilles tendons; motion capture + force plates (for ground truth)	Participants walked and ran at 3 speeds on a force-instrumented treadmill; performed an isometric calf push for calibration	Tensiometer-derived Achilles force vs. inverse-dynamics ankle torque (gold standard) across speeds	Achilles tendon wave speed and force (via tensiometry); ankle plantarflexion torque (via force plate & kinematics); temporal gait parameters	None (single session)	USA / Univ. of Wisconsin lab	The study demonstrates that shear wave tensiometry is a valid method for assessing Achilles tendon loading during running, revealing significant increases in tendon wave speed, force, and ankle torque with higher locomotion speeds.
Shahabpoor and Pavic, 2018 [39]	Experimental methodological study	6 healthy males, age: 21 ± 1 years; weight 77 ± 16 kg; height 1.82 ± 0.08 m	Single lower-back IMU (accelerometer at the 7th cervical vertebra, C7); Tekscan in-shoe pressure insoles (for reference GRF)	Each subject walked overground (urban path with flat and sloped sections) wearing the IMU (and insoles for validation); also performed an instrumented lab walk for calibration	Comparison of IMU-estimated vertical GRF vs. actual measured GRF (from insoles or force plate)	Vertical ground reaction force (GRFv) time series for each gait cycle; estimation error (NRMSE)	None (single session)	UK (Sheffield & Bath) / Lab and outdoor campus	Using a Scaled Acceleration (SA) method, a single IMU at C7 estimated vertical GRFs with 4–8% error, improving accuracy by ~25% over previous methods. By dynamically scaling acceleration–force relations each step, it provided reliable GRF estimates in both lab and outdoor walking, enabling practical gait analysis outside the lab.

Table 4. Continued

Study (Title / Authors / Year)	Study Design	Population	Device Used	Intervention	Comparator	Outcomes Measured	Follow-up	Country / Setting	Key Findings
Sufrinko et al., 2018 [40]	Prospective observational (feasibility study)	20 concussed adolescent athletes (12–19 years, mixed sports)	ActiGraph GT3X+ tri-axial accelerometer (wrist-worn)	Wore accelerometer 24 hrs/ day for 1–2 weeks post-concussion; recorded sleep and activity continuously	None (correlational analysis over recovery)	Objective sleep metrics (total sleep time, sleep efficiency; "time in bed"); physical activity metrics (daily movement counts, intensity); clinical outcomes at follow-up (symptom scores, neurocognitive and vestibular tests)	~2 weeks post-injury (two clinic visits: 72 hrs and 6–18 days post-concussion)	USA / Sports concussion clinic	After concussion, athletes' activity increased and time in bed decreased during the first week. Higher early activity was linked to worse vestibular/ oculomotor outcomes, while poorer early sleep predicted slower reaction times later. These findings suggest that excessive activity and poor sleep soon after concussion may hinder recovery and show that wearables can effectively monitor recovery-related behaviors.
Trbovich et al., 2021 [41]	Prospective observational (EMA-based)	17 concussed adolescent athletes (12–19 years; ~47% female)	ActiGraph GT3X+ accelerometer (wrist) for sleep; Ecological Momentary Assessment (smartphone app) for symptoms	Wore actigraph continuously for up to 3–4 weeks post-injury; reported symptoms 3× daily via mobile app	No separate control (within-subject over time analysis)	Sleep quantity (total sleep time, TST) and quality (sleep efficiency, SE%) each night; next-day symptom severity (total and by symptom domain: cognitive-fatigue, migraine, mood) via EMA	~3 weeks post-concussion (or until return-to-play if sooner)	USA / Outpatient concussion care	The study found that sleep parameters, specifically sleep efficiency and total sleep time, are negatively associated with next-day symptoms in adolescents recovering from sport-related concussion, highlighting the importance of sleep intervention post-injury.

Table 5 Machine Learning Model Performance and Validation Characteristics

Study	**Sample Size**	**Sensor Type**	**ML Model**	**Validation Strategy**	**Key Performance Metrics**	**Major Analytical Limitation**
Pu and Liu, 2024 [1]	10 subjects	Wearable biomechanical sensors	ARNN, RCNN	Internal validation (unspecified split)	Accuracy 93–95%, F1 score 91–98%	Very small sample; no external validation
Chen et al., 2022 [30]	19 subjects	5 IMUs	Random Forest	Cross-validation	Accuracy >86%, Sensitivity >90%	Limited dataset size
Gil-Martín et al., 2021 [32]	407 subjects	IMU	LSTM-RNN	10-fold subject-wise CV	MAPE 7.3–7.9%	No external validation cohort
Mehta, 2019 [5]	18 athletes	Motus sleeve	Logistic regression	Observational cohort	OR = 15.2; RR = 14.9	Limited injury events; potential confounding
Khuyagbaatar et al., 2025 [34]	20 participants	IMU	Regression analysis	Group comparison	Significant ROM and CoM differences	Small sample; not a predictive model
Sufrinko et al., 2018 [40]	20 athletes	Actigraphy	Linear regression	Prospective analysis	Significant predictive sleep–symptom association	Limited cohort; no model validation
Trbovich et al., 2021 [41]	17 athletes	Actigraphy	Mixed-effects model	EMA-based longitudinal	Significant IRR associations	Small cohort
Shahabpoor and Pavic, 2018 [39]	Lab cohort	Single IMU	Scaled acceleration model	Validation vs. GRF	4–8% normalized RMSE	Not injury-specific
Reiter et al., 2024 [38]	Lab cohort	Shear wave tensiometry	Biomechanical modeling	Speed comparisons	Force 8–10 BW range	No injury outcome
Hunter et al., 2026 [33]	69 runners	Foot accelerometer + HR	Decoupling analysis	Segment comparison	Durability association	Observational; not predictive
Davis et al., 2024 [31]	49 + 19 runners	Wearable gait sensors	Overlap statistics	Field vs. lab comparison	32% subject-specific overlap	Not predictive; ecological focus
Kinjo et al., 2021 [35]	Controlled lab	Mouthguard sensor	Signal comparison	EMG comparison	Linear force detection up to 70 N	No injury prediction
Lapinski et al., 2019 [36]	Elite pitchers	Multi-IMU	Biomechanical modeling	Experimental validation	High-dynamic motion capture	No predictive ML model
Alzahrani and Ullah, 2024 [29]	Observational	IMU + EMG + pressure	ML adaptive analysis	Cross-sectional	Improved monitored metrics	No prospective injury validation
Ogasawara et al., 2021 [37]	National team	Multi-sensor system	CPS analytics	Real-world monitoring	Successful team monitoring	Not injury prediction

learning models such as LSTM and CNN showed classification accuracy of 86–95% and F1 scores exceeding 0.90 in controlled tasks [1, 30]. Many studies used internal cross-validation without external cohort testing. One study included 407 participants and applied subject-wise cross-validation [32]. Workload-based models reported associations between acute-to-chronic load ratio and injury risk (OR = 15.2) [5]. Most studies used small sample sizes (n < 25) and did not include independent test datasets or multi-season validation. A minority incorporated prospective injury outcomes.

Discussion

The aim of this systematic review was to synthesize evidence on AI-integrated wearable technologies for sports injury prediction and rehabilitation monitoring, with emphasis on diagnostic performance and applicability to university physical education settings. Across the 15 included studies, wearable technologies, particularly IMUs, electromyography (EMG) sensors, accelerometers, and tools such as wearable mouthguards and shear-wave tensiometers, demonstrated potential for continuous biomechanical and physiological monitoring in athletic settings. Several included studies involved university-aged participants or were conducted in university gymnasium and laboratory settings, providing evidence applicable to student populations engaged in physical education, academic sport, and university health monitoring programs. The key advancement lies not only in sensor deployment but also in the integration of ML and DL algorithms capable of transforming high-dimensional time-series data into clinically meaningful insights [1, 29]. IMUs remain the dominant sensing modality due to their portability, affordability, and capacity to capture high-frequency kinematic signals during field-based activities. These characteristics make IMUs suitable for university physical education environments, where cost-effectiveness and ease of use are prerequisites for practical implementation [3]. At the same time, sensor applications are expanding the scope of biomechanical assessment. Wearable mouthguards have been developed to quantify clenching force as a proxy for exertion [35]. Shear-wave tensiometers enable estimation of in vivo Achilles tendon loading during running [38]. These developments represent a shift from laboratory-based force-plate analyses toward real-time biomechanical monitoring in sporting environments. This transition is relevant for university physical education programs where access to laboratory-grade equipment is limited.

Predictive Modelling and Rehabilitation Monitoring

In predictive contexts, workload-derived indices such as the acute-to-chronic workload ratio (ACWR) were associated with injury risk in overhead sports. Elevated valgus workload ratios significantly increased elbow injury incidence in youth baseball athletes [5]. This workload monitoring approach is directly applicable to university sport programs, where student athletes often manage competing demands of academic study and athletic training. This increases susceptibility to overuse injuries from workload spikes [42, 43]. Additionally, ML architectures, including convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, demonstrated strong performance in movement classification and balance assessment tasks [30, 32]. The Y-Balance Test automated scoring system, validated on 407 participants of university student age (mean 23.1 years), is relevant for integration into university physical education screening protocols and pre-participation injury risk assessment for student athletes [32]. These models are suited to wearable-derived time-series data; however, predictive robustness remains dependent on dataset size, validation strategy, and population representativeness.

In rehabilitation contexts, accelerometer-derived sleep and activity metrics provided objective indicators of recovery following sport-related concussion [40, 41]. These findings have implications for university sport programs and student health services, where concussion management must account for both physical recovery and academic functioning. Return-to-participation decisions in university settings require consideration of cognitive load from academic demands alongside traditional return-to-play criteria, a dual burden not present in professional athletic contexts [44]. Compared with retrospective symptom reporting, wearable-based monitoring enables continuous tracking of recovery trajectories. Collectively, these findings suggest that AI-integrated wearables support both early injury risk identification and post-injury rehabilitation monitoring in university physical education and student health management contexts.

Methodological and Analytical Challenges

Despite promising predictive metrics, significant methodological limitations were identified. The most critical concern relates to analytical rigor. Many models were developed using small sample sizes. This increases susceptibility to overfitting and may inflate reported performance. Several studies relied exclusively on internal cross-validation without independent external validation cohorts. This limits generalizability. In some cases, unclear subject-wise data partitioning raised concerns regarding possible data leakage between training and testing sets.

Ecological validity remains another key challenge. Algorithms validated under controlled laboratory conditions may not maintain equivalent performance in real-world sporting contexts. For example, vertical ground reaction force estimation models validated in laboratory walking protocols may lose precision in dynamic outdoor settings [45]. Similarly, laboratory-derived gait patterns may not accurately represent real-world running biomechanics [31]. This gap between laboratory validation and real-world performance is particularly relevant for university physical education settings, where AI-integrated wearables would be deployed during dynamic, group-based classes rather than controlled individual assessments [31]. These findings emphasize the importance of external validation within authentic sporting environments.

Heterogeneity across athlete populations, including elite national teams, youth wrestlers, and baseball pitchers, further complicates generalization [34, 37]. The limited representation of student-specific populations across included studies also constrains direct applicability to university physical education contexts. This reinforces the need for future research explicitly targeting student cohorts. Technical limitations such as sensor dynamic range constraints and signal clipping during high-velocity pitching underscore the importance of hardware specifications in accurate biomechanical modelling [36].

Comparison with Previous Reviews

Several recent reviews have examined wearable technologies and AI within sports science; however, their scope and analytical depth differ from the present synthesis. Mason et al. systematically reviewed wearable devices for running gait analysis, primarily assessing measurement validity and biomechanical parameter accuracy. Their work provided insight into sensor reliability but did not specifically evaluate injury prediction models, rehabilitation monitoring applications, or diagnostic performance metrics of AI-integrated systems, or their applicability to student and university sport populations [19].

Musat et al. provided an overview of AI applications for injury risk prediction in sport, with emphasis on algorithmic frameworks and modelling approaches. Limited attention was given to wearable sensor integration, dataset validation strategies, and methodological rigor. No consideration was given to the applicability of AI-integrated systems within student or university sport contexts. The present review extends this perspective by examining how AI models are applied through wearable systems and by evaluating validation approaches and risk of bias using PROBAST [15].

Similarly, Rebelo and colleagues conducted a scoping review mapping wearable technology for injury prevention. Although informative in outlining technological applications, it did not synthesize diagnostic accuracy metrics, predictive robustness, or analytical limitations such as overfitting and absence of external validation. It also did not address the specific needs and constraints of student populations in academic sport and physical education settings. In contrast, the current review integrates quantitative performance indicators (e.g., accuracy, sensitivity, F1 score), validation characteristics, and structured methodological appraisal [24].

Collectively, whereas previous reviews addressed wearable validity, AI modelling, or injury-prevention frameworks separately, this study integrates these domains by evaluating AI-integrated wearable systems for injury prediction and rehabilitation monitoring in athletic populations, with attention to findings applicable to university students and academic physical education settings. By incorporating structured risk-of-bias assessment and validation analysis, this review extends previous descriptive approaches toward methodological evaluation and translational assessment.

The findings of this systematic review carry implications for student populations engaged in physical education programs, university sport, and recreational physical activity. University physical education programs present a context in which AI-integrated wearable technologies may serve dual purposes: enhancing educational learning outcomes and supporting student health.

Several findings from this review are transferable to student physical education settings. Chen et al., who validated a 5-IMU plank classification system on young adults of approximately 20 years of age, demonstrated how wearable-AI tools can provide real-time postural feedback during standardized exercises. This application is relevant to technique instruction and injury prevention within university physical education classes [30]. Gil-Martín et al. [32] validated an automated Y-Balance Test scoring system on 407 university-aged participants. This provides an approach to functional movement screening that may be integrated into pre-season student athlete assessments and physical education program evaluations. Mehta [5] showed that the ACWR-based workload monitoring approach is relevant for managing training loads among student athletes. These athletes face combined academic and training demands. This combination has been associated with increased injury susceptibility during high-stress academic periods, as reported by Lopes Dos Santos et al. [11].

From a rehabilitation perspective, wearable-based concussion monitoring, as demonstrated by Sufrinko et al. [40] and Trbovich et al. [41], is relevant in university sport programs, where return-to-participation decisions must account for both physical and cognitive recovery. Student athletes returning from concussion must navigate simultaneous academic obligations. Objective, continuous monitoring via wearables provides a tool for university sports medicine and student health services. Similarly, Pu and Liu [1] demonstrated that AI-driven rehabilitation monitoring systems achieving F1 scores above 0.90 reach accuracy levels that allow deployment in university physiotherapy services supporting student athlete recovery.

Khuyagbaatar et al. [34], who conducted IMU-based functional movement assessment in a university gymnasium setting, provide contextually direct evidence within this review. The study demonstrated that wearable systems can capture biomechanical differences between trained student athletes and non-athlete student controls. This finding supports the feasibility of deploying wearable-AI tools within university physical education infrastructure for performance monitoring and injury risk stratification.

However, several barriers to implementation in university settings must be acknowledged. Device cost and procurement constraints, data privacy considerations under institutional governance frameworks, variable technical literacy among physical education staff and students, and the absence of standardized protocols for wearable deployment in educational contexts represent implementation challenges. Furthermore, current evidence predominantly derives from laboratory or elite sport settings, with limited ecological validity for the group-based, multi-activity structure of university physical education programs, as highlighted by Davis et al. [31]. Future research should explicitly recruit university and student populations and generate evidence directly informing technology-assisted physical education practice at bachelor's, master's, and doctoral training levels.

Interpretability and Clinical Translation

Beyond predictive accuracy, clinical adoption of AI-integrated wearable systems depends on interpretability. Many DL architectures function as "black-box" models. This limits transparency regarding which biomechanical or physiological features drive injury risk predictions. For wearable-AI systems to serve as effective decision-support tools, models must provide explainable outputs that guide targeted interventions and training modifications.

Future developments should prioritize explainable AI methodologies and multimodal sensor fusion, integrating workload indices, heart rate dynamics, joint kinematics, and contextual performance variables [46]. Such integrative modelling may offer representations of athlete durability, fatigue accumulation, and injury susceptibility.

Limitations

Despite encouraging performance metrics, the current body of evidence remains methodologically constrained. Small sample sizes, limited external validation, heterogeneity in injury definitions, and insufficient prospective injury surveillance restrict the generalizability and clinical applicability of many reported models. Concerns regarding overfitting, data leakage, and lack of transparent reporting further indicate the need for more rigorous analytical standards. The limited representation of student populations across included studies constrains the extent to which findings can be applied to university physical education and student sport contexts without further targeted investigation.

Several methodological limitations were identified across the included studies. A recurrent concern was limited sample size and population representativeness, with many investigations employing small or narrowly defined cohorts. This constrains generalizability [30, 38]. Convenience sampling strategies and sport-specific or pediatric populations further restricted broader applicability [31, 40].

Design-related constraints were also evident. Many studies were short-term or preliminary in nature. This limits the ability to assess longitudinal injury outcomes or sustained rehabilitation trajectories [5, 35]. Laboratory-based protocols dominated the literature and often lacked ecological validity and real-world task variability [30, 31].

Instrumentation limitations were frequently reported. Sensor accuracy may be affected by soft-tissue artifacts during high-velocity movements [36]. Some systems required complex calibration procedures or substantial computational resources [1, 38]. Additionally, wearable validation was commonly confined to controlled environments. This limits translational robustness.

Analytical constraints further restricted interpretability. Several studies were exploratory in nature, lacked causal modelling frameworks, or did not account for interacting biomechanical and physiological variables. These limitations indicate the need for larger and more diverse cohorts, multi-season follow-up, real-world validation, and standardized methodological reporting in future wearable-AI research.

Additionally, publication bias and selective reporting may influence the apparent performance of AI models, as studies demonstrating non-significant or inferior predictive results are less likely to be published.

Future Directions

To enhance clinical translation and methodological robustness, future research should prioritize:

- Large-scale, multi-center prospective cohort studies
- External validation across independent athletic populations
- Standardized and consensus-based injury

definitions

- Transparent reporting aligned with TRIPOD-AI and PROBAST guidelines
- Multi-season longitudinal injury surveillance

Although methodological heterogeneity limits definitive conclusions, the collective evidence indicates changes in approaches to sports medicine. The integration of wearable hardware and interpretable AI may support a shift from reactive and subjective practices to data-driven athlete management strategies.

For AI-integrated wearables to achieve clinical translation, future research should prioritize multi-center prospective validation, standardized outcome definitions, explainable AI frameworks, and adherence to TRIPOD-AI reporting principles. Future studies should recruit university student populations, including physically active students, university sport participants, and physical education program enrollees at bachelor's, master's, and doctoral levels, to generate evidence informing technology-assisted physical education practice. External validation across diverse athletic populations, including student cohorts, is required to establish predictive reliability and decision-support utility.

Conclusions

The evidence indicates that AI-integrated wearable systems can support athlete health management through continuous biomechanical and physiological monitoring. High-dimensional sensor data, when analyzed using machine learning and deep learning architectures, can facilitate movement classification, workload quantification, and objective recovery tracking. These capabilities are relevant to student health monitoring and university physical education programs.

From an educational perspective, AI-integrated wearable technologies are relevant to university physical education programs and student athlete populations. The reviewed technologies provide means for injury risk screening, workload monitoring, rehabilitation tracking, and movement quality assessment within academic sport and physical education contexts. As wearable devices become more affordable and user-friendly, their integration into university physical education curricula and student health services may represent a next step. Successful implementation will require addressing barriers including device cost, data privacy governance, technical literacy among physical education staff and students, and the development of standardized deployment protocols suitable for educational environments.

In summary, wearable-AI systems indicate a shift from reactive injury management toward data-driven athlete care, including within university physical education programs and student sport environments. While technological feasibility has been demonstrated, methodological strengthening, translational validation, and targeted research in student populations are required before these systems can be implemented as routine tools in sports medicine practice and university physical education settings.

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Author Contributions

Rajdeep Das conceptualized the study, developed the review protocol, conducted the literature search, performed data extraction and analysis, and prepared the original draft of the manuscript. Renu Sharma contributed to study screening, methodological supervision, and critical revision of the manuscript. Tapes Yadav participated in article screening, data verification, and methodological review. Birendra Jhajharia assisted with the risk-of-bias assessment using the PROBAST framework and helped resolve methodological disagreements during the review process. Cătălin Vasile Ciocan contributed to study selection, interpretation of findings, and manuscript editing. Voinea Nicolae-Lucian assisted with full-text screening, methodological evaluation, and critical manuscript revision. All authors reviewed, edited, and approved the final version of the manuscript.

Conflict of interest

The authors declare no conflicts of interest.

AI Tools Usage

During the preparation of this manuscript, ChatGPT was used for language checking and assistance with phrasing to improve clarity. All content was reviewed and edited by the authors, who take responsibility for the final version of the manuscript and the accuracy of the presented information.

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ORIGINAL ARTICLE

Competitive anxiety in soccer: differences across playing roles and sport participation levels

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Abstract

Background and Study Aim Competitive anxiety is associated with psychological responses during sports performance in soccer. Players with different roles on the pitch may experience different psychological demands during competition. Despite the use of various approaches to psychological preparation in soccer, the relationship between competitive anxiety, playing roles, and sport participation level remains a subject of practical interest. This study aimed to examine competitive anxiety in relation to playing roles and the level of sports participation in soccer.

Material and Methods The study involved 78 male participants, including professional soccer players (N = 39) aged 17 to 21 from four clubs and amateur soccer players (N = 39) aged 17 to 22, who were physical education students recruited from Sport University. The roles of professional soccer players were categorized into two main groups: offensive (creative) and defensive (destructive), based on their primary functions on the pitch. To evaluate the competitive anxiety of all participants, the Sport Competition Anxiety Test (SCAT) was used.

Results Professional soccer players demonstrated significantly lower levels of competitive anxiety compared to students ($p = 0.028$). No significant differences in competitive anxiety were found between offensive and defensive players ($p > 0.05$). However, a moderate effect size ($d = 0.57$) suggested potential role-related variation.

Conclusions Competitive anxiety appears to be more strongly associated with sport participation level than with playing role. These findings support the idea of relative psychological similarity across playing roles. Coaches working with less experienced athletes should gradually increase competitive demands and use match-like training to support adaptive anxiety regulation.

Keywords: anxiety, personality traits, playing position, soccer, students.

Introduction

Soccer performance is influenced by the interaction of physical, technical, tactical, and psychological factors during competition. Among psychological factors, competitive anxiety is associated with emotional and behavioral responses that may affect decision-making, concentration, and execution of game actions under pressure. The manifestation of competitive anxiety in soccer can vary depending on the athlete's competitive experience and the specific demands associated with playing roles on the pitch. Differences in tactical responsibilities and match situations may contribute to variations in psychological responses among players during competition. At the same time, the interaction between competitive anxiety, playing roles, and sport participation level remains a relevant area for further investigation in soccer.

Elite-level soccer performance is influenced not only by physical and technical abilities but also by psychological factors, including competitive anxiety [1]. The relationship between athletes' personality traits and their playing roles is an important issue in high-performance sports. The roles of soccer players differ in the tasks performed during a game and in their playing positions on the field. These differences also extend to specific game rules applied to certain players, such as goalkeepers. Previous studies in team sports have shown that players in different positions differ in body composition [2], as well as in skills and abilities [3].

Such differences suggest that players in different positions may also differ in several personality characteristics. For instance, the hypothesis that central midfielders in a soccer team may be more extroverted than players in roles requiring more independent and autonomous actions, such as goalkeepers, is theoretically sound. One of the key functions of central midfielders is to coordinate and lead the team during gameplay [4]. Current literature indicates that the relationship between personality traits, including psychoticism,

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neuroticism, and anxiety, and athletes' playing positions remains an important issue in team sports.

Several studies in team sports have examined the relationship between playing roles and psychological characteristics of athletes. Research involving American football players showed that athletes in offensive positions demonstrated more effective anxiety management than players performing defensive roles [5]. In hockey, self-reported personality traits were not associated with playing position; however, forwards were perceived as more extroverted, less disciplined, and more open to new experiences than goalkeepers and defensemen [6]. Another study involving soccer players reported higher anxiety levels among attackers from mature teams and goalkeepers from youth teams compared to players in other roles. Differences in anxiety levels were also observed between First League players and players under 21 years of age [7]. These findings suggest that psychological characteristics in team sports may vary depending on tactical functions, competitive experience, and playing roles on the field. Additional evidence also indicates possible psychological differences between offensive and defensive players [9].

Analysis of research findings has shown that competitive anxiety in team sports may be associated with playing roles, tactical responsibilities, and the level of sport participation. Researchers emphasize that psychological responses during competition are influenced by both individual characteristics and the functional demands imposed on athletes during gameplay. At the same time, previous studies have typically examined competitive anxiety either in relation to sport participation level or to playing position separately, while findings regarding psychological differences between playing roles remain inconsistent. Existing studies have also mainly relied on traditional positional classifications, which may not fully reflect the functional roles of players in modern soccer. This situation continues to complicate the interpretation of the relationship between competitive anxiety, playing roles, and competitive experience within a unified analytical framework.

Based on previous findings and theoretical considerations regarding psychological demands in team sports, this study aimed to examine competitive anxiety in relation to playing roles and the level of sport participation in soccer. It was assumed that professional soccer players would demonstrate lower levels of competitive anxiety than physically active students. It was also hypothesized that competitive anxiety would differ between players performing offensive (creative) and defensive (destructive) roles.

Materials and Methods

Participants

This study involved 39 professional male soccer players from four soccer clubs. The ages of these participants ranged from 17 to 21 years, with a mean age of 18.27 (SD = 0.95). The control group consisted of 39 amateur sport students enrolled in undergraduate programs (years 1-4) at the Sports University. Their ages ranged from 17 to 22 years, with a mean age of 18.41 (SD = 1.10). The group of professional soccer players trained 9 hours per week, whereas the group of students trained 4.5 hours per week. Participants were recruited using a convenience sampling approach.

The inclusion criteria for both groups were as follows: a) age between 17 and 22 years; b) active engagement in regular physical or sport activity; and c) absence of self-reported neurological, psychiatric, or cardiovascular disorders. The exclusion criteria included incomplete questionnaire data and failure to meet the inclusion criteria. Recruitment was conducted through direct contact with soccer clubs for the professional group and through the Sports University for the student group.

All participants voluntarily agreed to participate in the study. Permission to conduct the study was obtained from the management of the soccer clubs and the university administration. Verbal informed consent was obtained from all participants before data collection. The study was conducted in accordance with the principles of the Declaration of Helsinki and was approved by the Local Ethics Committee of the Institute (Protocol No. 2).

Research Design

Measures

Competitive anxiety assessment

The level of competitive anxiety in both groups (experimental and control) was assessed using the Sport Competition Anxiety Test (SCAT) developed by Martens [10]. A translated and adapted version of the questionnaire was used for the assessment [11]. The questionnaire consists of 15 items, each with a corresponding response scored in points. It uses a three-point Likert scale with the following response options: A (rarely), B (sometimes), and C (often).

The total score ranges from 10 to 30 points, where 10 indicates very low competitive anxiety and 30 indicates very high competitive anxiety. Scores from 10 to 16 indicate a low level of anxiety, scores from 17 to 24 indicate an average level, and scores from 25 to 30 indicate a high level of anxiety. Ten items on the scale are used in the final scoring procedure, whereas the remaining five are buffer items and are not included in the calculation of the final score.

Personality assessment

At the second stage of the study, the personality traits of the professional soccer players were assessed using Eysenck's Personality Questionnaire (EPQ), which consists of 101 items [12]. This instrument was designed to assess several dimensions of personality structure, specifically Psychoticism, Extraversion, and Neuroticism [13]. The questionnaire was translated into Azerbaijani and adapted by the Department of Psychology at the State University. Although the internal consistency coefficients for several translated scales were relatively low, similar variability in reliability has been reported in previous studies using adapted sport-related personality measures in non-English-speaking samples. Therefore, the findings should be interpreted with caution and considered exploratory.

Descriptive statistics and Cronbach's alpha coefficients for personality traits among professional players and physical education students are presented in Table 1.

Table 1. Descriptive statistics and Cronbach's alpha coefficients for personality traits among professional players and physical education students.

Parameters	Soccer players			Students		
	Mean	SD	α	Mean	SD	α
Psychoticism	5.13	3.27	0.34	5.23	3.55	0.34
Extraversion	15.36	3.30	0.46	15.56	3.53	0.49
Neuroticism	12.26	4.99	0.86	12.36	4.66	0.73
SCAT	15.54	3.05	0.43	17.23	3.59	0.44

Note. SCAT = Sport Competition Anxiety Test.

Procedures and Data Collection

The present study employed a cross-sectional comparative design. Data collection was conducted in controlled settings, either within club facilities for professional players or in university classrooms for students. All participants completed the questionnaires under standardized conditions and received identical instructions. The assessment was administered in a non-competitive context to minimize situational influences on anxiety responses.

To assess competitive anxiety and personality traits, participants completed the Sport Competition Anxiety Test (SCAT) and the Eysenck Personality Questionnaire (EPQ). The questionnaires were administered in paper-based format after training sessions, and the completed forms were returned directly to the researcher. Participants first completed the EPQ, followed by the SCAT, to reduce the potential influence of sport-specific anxiety questions on general personality responses. Participants were given several days to complete the questionnaires in order to minimize time pressure and improve response accuracy.

Data collection and analysis were completed over a period of approximately six months. Before participant recruitment, the researcher communicated with coaches, club representatives, and university staff to facilitate access to both groups. Professional soccer players were recruited from four clubs based on their active participation in organized training and competition. The professional players participated in the study between the first and second phases of the competitive season. The control group consisted of physically active university students specializing in soccer at the Sports University.

The respondents completed the questionnaires independently and submitted them to the researcher for further analysis. The playing roles of the professional soccer players were identified using a designated section in the questionnaire form and were additionally verified through observational assessment. For the purposes of functional analysis, playing roles were categorized into two main types: creative and destructive.

The classification of players into functional roles was based on their primary playing position as reported by the participants and verified according to their typical tactical role within the team. Players were assigned to a role based on their dominant functional contribution during matches (offensive vs. defensive). Although the classification procedure relied on a single-rater assessment, predefined functional criteria were applied to reduce subjectivity. The absence of inter-rater reliability assessment is acknowledged as a limitation of the study.

The creative type included attacking midfielders, wingers, and forwards, whose primary function was to create and convert scoring opportunities. The destructive type included defenders and defensive midfielders, whose primary function was to disrupt the opponent's buildup and maintain defensive organization. Modern central midfielders may perform hybrid functions, which could contribute to psychological similarity across playing roles (Table 2). Although goalkeepers and other defensive-oriented players were classified as defensive due to their goal-protection responsibilities, modern tactical approaches may also involve them in offensive buildup and attacking situations, such as set pieces and long-range ball distribution.

The classification of playing roles into creative (offensive) and destructive (defensive) categories was applied as a functional approach based on the dominant task demands during gameplay. Creative roles included players primarily involved in the creation and conversion of scoring opportunities, whereas destructive roles included players whose primary functions were to disrupt opponent actions and maintain defensive stability. During the classification procedure, recommendations outlined in [5, 6] were taken into account.

At the same time, it was recognized that modern soccer includes hybrid and dynamic playing roles.

Therefore, the present classification was used to provide a controlled comparison of dominant functional demands and did not aim to fully represent the complexity of contemporary tactical systems. According to the final classification, 17 players were assigned to the creative group and 22 players to the destructive group (Table 3).

Midfielders with mixed or hybrid functions, such as box-to-box midfielders, were not included in the sample in order to maintain a clear functional distinction between players primarily focused on offensive buildup and those primarily focused on defensive disruption. Recommendations outlined in [15, 16] were also considered during the classification process. Hybrid midfielders were operationally defined as players regularly performing both offensive and defensive transitional functions. These players were excluded from the final role-based comparison because their tactical responsibilities did not allow clear assignment to either predominantly creative or predominantly destructive categories.

The identification process was based on players' self-reported primary playing position and the researcher's tactical evaluation of their dominant functional role within the team structure. Data collection and analysis were completed over a period of approximately six months.

Statistical Analysis

Initial data processing was performed using MS Excel. Statistical analysis was subsequently performed using IBM SPSS Statistics 23.0.

To test H-1 (differences between professional players and students), the Student's t-test and one-way ANOVA for effect size estimation were conducted, with group as the independent variable and competitive anxiety as the dependent variable. To test H-2 (differences between playing roles), the Student's t-test and one-way ANOVA for effect size estimation were conducted within the professional group, with playing role as the independent variable.

Assumptions of normality and homogeneity of variance were evaluated using the Shapiro–Wilk and Levene's tests, respectively. Parametric tests were

Table 2. Functional classification of soccer playing roles.

Field line	Traditional position	Primary functional orientation	Primary psychological demands
Goalkeeping	Goalkeeper	Destructive	High accountability for errors; ability to maintain concentration during prolonged periods of limited involvement
Defenders	Center-back / Full-back (wide)	Destructive	Sustained focus on interceptions and one-on-one defensive situations; responsibility for defensive organization [14]
Defensive midfield	Holding midfielder ("anchor")	Destructive	Continuous spatial awareness; disciplined positioning; frequent tactical disruptions
Central midfield	Central midfielder (box-to-box)	Mixed (creative + destructive)	High physical and cognitive workload; rapid transition between defensive and offensive actions
Attacking midfield	Attacking midfielder (playmaker)	Creative	Decision-making under pressure; creative problem-solving in limited space
Wings	Winger / Wide forward	Creative	High speed of execution; frequent one-on-one situations; responsibility for creating scoring opportunities
Attackers	Center-forward (striker)	Creative	Pressure associated with scoring opportunities; resilience following unsuccessful attempts

Table 3. Distribution of professional soccer players according to functional playing roles

Playing position	Field zone	Number of players	Primary functional orientation
Goalkeeper	Central	1	Destructive
Defender	Central	8	Destructive
Defender	Wide	7	Destructive
Defensive midfielder	Central	6	Destructive
Midfielder	Central	0	Mixed/Hybrid
Attacking midfielder	Central	11	Creative
Forward	Wide	2	Creative
Forward	Central	4	Creative

applied when the assumptions were met; otherwise, nonparametric alternatives were used. Effect sizes were reported using Cohen's d and eta-squared (η^2).

When the data met the assumptions of normal distribution, the Student's t-test was used to compare personality traits according to the Eysenck questionnaire. In other cases, the nonparametric Mann–Whitney U test was applied. In addition, the χ^2 test with Yates's correction for continuity was used to analyze differences between low and average anxiety levels among professional soccer players. The level of statistical significance was set at $p < 0.05$.

Results

Professional soccer players demonstrated significantly lower levels of competitive anxiety compared to physically active students. ANOVA revealed a significant effect of group, F(1, 76) = 5.04, p = 0.028, $\eta^2 = 0.062$, indicating a moderate effect size. The corresponding standardized mean difference was Cohen's d = 0.51 (Figure 1). The descriptive statistics and results of the group comparison are presented in Table 4.

Figure 1 presents the distribution of competitive anxiety scores among professional soccer players and physically active students, demonstrating generally higher anxiety scores in the student group.

Within the group of professional soccer players, competitive anxiety did not differ significantly between players performing creative (offensive) and destructive (defensive) roles. ANOVA did not reveal a statistically significant effect of playing role, F(1, 37) = 2.96, p = 0.09 (Table 5). However, the corresponding effect size indicated a moderate difference between groups (Cohen's d = 0.57). A post hoc power analysis ($\alpha = 0.05$, d = 0.57, n1 = 17, n2 = 22) indicated limited statistical power ($1 - \beta = 0.43$) for detecting moderate subgroup differences.

Descriptive analysis showed that professional soccer players predominantly demonstrated low to moderate levels of competitive anxiety, with no cases of high anxiety observed in the sample. In the group of physically active students, one participant demonstrated a high level of competitive anxiety (SCAT score = 25), whereas the remaining participants demonstrated low or moderate anxiety levels (Figure 1).

The χ^2 test with Yates's correction for continuity did not reveal statistically significant differences between low and moderate anxiety levels among professional soccer players ($p > 0.57$). The distribution of anxiety levels across playing roles is presented in Figure 2. The results indicated no statistically significant differences in the distribution of low and moderate anxiety levels between players performing creative and destructive roles.

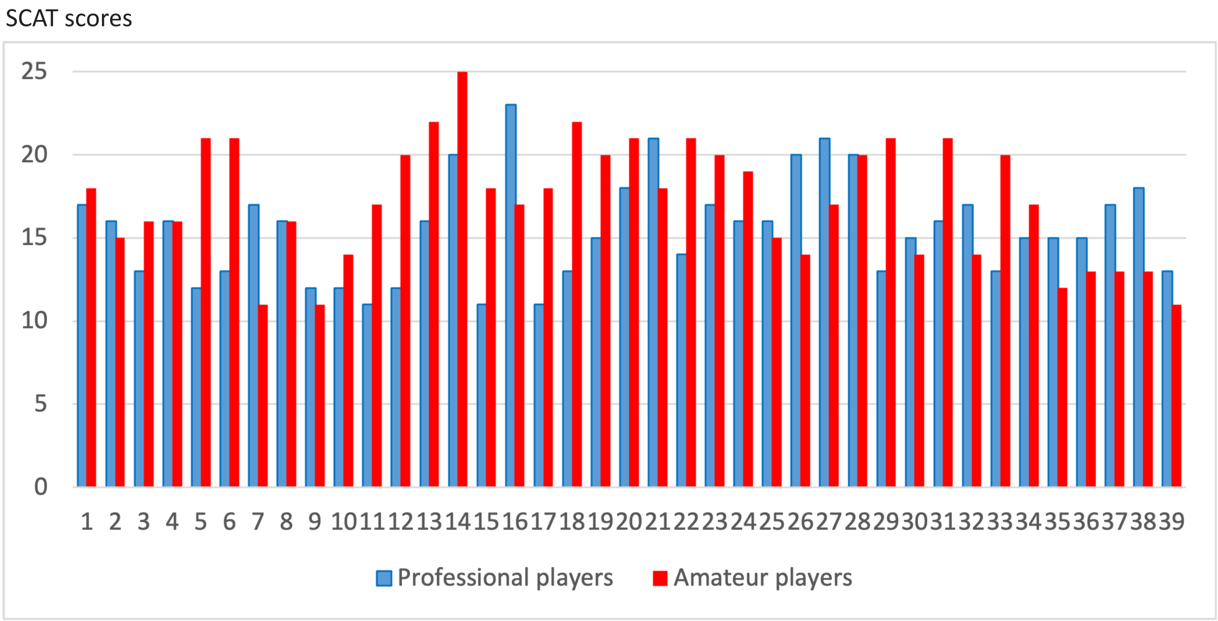

Figure 1. Distribution of competitive anxiety scores among professional soccer players and physically active students.

Table 4. Differences in competitive anxiety between professional soccer players and physical education students.

Participants	N	Mean	SD	SE	95% CI		t	p
					Lower Bound	Upper Bound		
Soccer players	39	15.54	3.05	0.49	-3.19	-0.19	-2.24	0.028
Students	39	17.23	3.59	0.57	-3.19	-0.19		

Table 5. Differences in competitive anxiety between creative and destructive playing roles among professional soccer players.

Playing role	N	Mean	SD	SE	95% CI		t	p
					Lower Bound	Upper Bound		
Creative	17	16.47	3.20	0.78	-0.29	3.60	1.72	0.094
Destructive	22	14.82	2.79	0.59	-0.34	3.65		

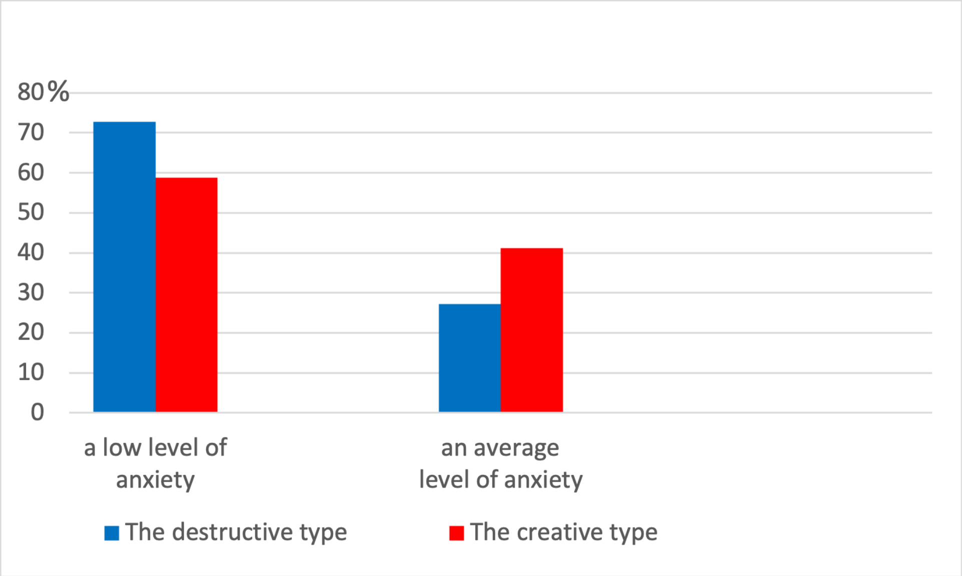

Figure 2. Distribution of competitive anxiety levels across playing roles among professional soccer players.

Further analysis of personality traits based on Eysenck's Personality Questionnaire (EPQ) revealed no statistically significant differences between players performing creative and destructive roles across all measured dimensions (all $p > 0.05$), including Psychoticism, Extraversion, and Neuroticism. The descriptive statistics for personality traits according to playing role are presented in Table 6.

Table 6. Differences in personality traits between creative and destructive playing roles among professional soccer players

Scale	Creative		Destructive	
	Mean	SD	Mean	SD
Psychoticism	5.88	3.26	4.55	3.23
Extraversion	15.18	2.90	15.50	3.64
Neuroticism	13.88	5.59	11.00	4.19

Discussion

The present study examined competitive anxiety in relation to the level of sport participation and functional playing roles in soccer. The results demonstrated that professional soccer players exhibited significantly lower levels of competitive anxiety compared to physically active students. This finding supports the assumption that regular participation in organized competitive sport may contribute to the development of more adaptive emotional regulation and anxiety management mechanisms. Continuous exposure to training routines, competitive situations, and performance-related demands may facilitate greater psychological stability in athletes. These findings are consistent with previous studies reporting lower anxiety levels among individuals regularly engaged in sport participation [17, 18].

In contrast, no statistically significant differences were found between players performing creative and destructive roles. These findings suggest that competitive anxiety may not be strongly differentiated according to functional playing role in soccer. From a theoretical perspective, this may reflect the high level of functional integration characteristic of team sports, where psychological demands are distributed across players rather than being limited to specific positions. Modern soccer requires athletes in different roles to perform under similar cognitive and emotional demands, including rapid decision-making, sustained attention, and adaptation to dynamic game situations.

At the same time, the absence of statistically significant differences should be interpreted with caution. Although the role-related effect was not statistically significant, the observed effect size was moderate ($\eta^2 = 0.074$; Cohen's $d = 0.57$) [19]. This finding suggests that potential role-related differences cannot be completely excluded and may not have been detected due to the limited statistical power of the study and the broad functional classification applied. It is also possible that subtle variations in competitive anxiety exist across playing roles but require more differentiated positional categories for detection.

The present findings are also consistent with previous studies reporting limited differences in personality traits across playing positions in team sports. Overall, the results support the perspective that psychological characteristics in team sports may be influenced more by shared performance demands than by positional specialization.

Furthermore, the personality trait findings observed in the present study are generally consistent with results reported in other team sports. Cameron and colleagues reported that neuroticism scores in hockey players did not differ substantially between goalkeepers, defenders, and attacking players [6]. Although those authors identified differences in stereotypical personality profiles across playing roles, no significant differences were found in self-reported personality traits. Similarly, a study involving female basketball players did not reveal differences in anxiety or neuroticism across playing positions [20]. These findings are consistent with the present results and support the assumption that anxiety may be associated with relatively stable temperamental characteristics linked to neuroticism [21].

The absence of differences in personality traits between creative and destructive playing roles provides additional support for the findings related to competitive anxiety (Table 6). In addition, the EPQ results were generally similar between professional soccer players and physical education students across the measured personality dimensions (Table 1).

The absence of differences in both competitive anxiety and personality traits across playing roles suggests that functional roles in soccer may not be strongly differentiated at the level of stable psychological characteristics. This finding supports the interpretation that shared performance demands in team sports may have a greater influence on psychological profiles than positional specialization.

At the same time, some previous studies have reported role-related differences in anxiety among soccer players [7]. However, that study focused on anxiety as a situational or pathological condition rather than as a relatively stable personality-related characteristic. In contrast, a study involving African soccer players aged 14–18 years reported no differences in anxiety levels or worry management between goalkeepers, defenders, midfielders, and forwards [22].

Additional evidence from a large-scale study involving more than 2,000 participants from 16 team sports showed differences between offensive and defensive players only in the trait of extraversion. The subgroup analysis conducted specifically on soccer players did not reveal statistically significant differences in neuroticism or extraversion [4]. Similarly, research involving American football players demonstrated differences between offensive and defensive players only in the ability to control anxiety [5].

In interpreting the present findings within established theoretical frameworks, it is relevant to consider the developmental hypothesis and the selection (or gravitational) hypothesis commonly discussed in sports psychology [18, 23]. The developmental hypothesis proposes that long-term engagement in a specific sport or playing role may influence psychological characteristics, whereas the selection hypothesis suggests that individuals with certain predispositions are more likely to select or be assigned to particular roles. In the present study, no significant differences in competitive anxiety were observed between players performing different playing roles. This finding does not support the assumption that role-specific demands in soccer are associated with clearly differentiated levels of competitive anxiety.

From a theoretical perspective, the present findings may be considered within both developmental and selection frameworks; however, the cross-sectional design of the study does not allow direct differentiation between these mechanisms. Although the absence of role-related differences may be consistent with the selection hypothesis, such an interpretation remains tentative. Longitudinal studies are required to determine whether competitive anxiety develops through sport participation or reflects relatively stable pre-existing individual characteristics.

From an ecological and functional perspective, modern soccer may impose similar cognitive and emotional demands on players regardless of tactical role. These demands include time pressure, decision-making under uncertainty, and continuous interaction with teammates and opponents. As a result, positional differences may become less pronounced at the psychological level, particularly with respect to competitive anxiety. A similar interpretation was proposed by Terwiel and Kritzler [4], who suggested that commonly assumed psychological differences between playing roles may reflect stereotypes rather than empirically established patterns. Nevertheless, this interpretation should be treated with caution because the present data do not permit direct testing of these theoretical mechanisms.

In summary, previous studies have examined anxiety and personality traits across different playing positions in team sports; however, the present study applied a functional approach based on offensive (creative) and defensive (destructive) playing roles rather than relying exclusively on traditional positional categories. In addition, the study examined both role-related differences and differences associated with sport participation level within a single analytical design. The study also focused specifically on competitive trait anxiety in young soccer players. This approach made it possible to examine whether psychological characteristics in soccer are more closely associated with functional tactical demands or with the overall level of sport participation.

Practical implications for coaches

The present findings suggest that competitive anxiety in soccer may be more strongly associated with the level of sport participation than with specific playing roles. From a practical perspective, these findings indicate that coaches may prioritize the development of general psychological skills related to anxiety regulation across all players rather than limiting psychological interventions to particular playing positions. Psychological preparation strategies, including stress management, attentional control, and pre-performance routines, may therefore be implemented at the team level.

At the same time, the observed moderate effect size suggests that subtle role-related differences may still exist. Consequently, coaches should remain attentive to individual differences and situational demands when applying psychological strategies in practice. In addition, the lower levels of competitive anxiety observed among professional players may reflect the influence of regular exposure to competitive environments. Coaches working with less experienced athletes may therefore consider the gradual increase of competitive demands and the inclusion of match-like training conditions to facilitate adaptive anxiety regulation. Overall, the findings support the use of both team-based psychological preparation and flexible individual adjustments according to athletes' responses and performance contexts [24].

Limitations

Several limitations of the present study should be acknowledged. The relatively small sample size, particularly in subgroup comparisons between creative and destructive playing roles, may have limited the statistical power to detect moderate effects. Given the observed moderate effect size, larger samples may provide greater sensitivity for identifying potential role-related differences in competitive anxiety. In addition, the use of self-report questionnaires may have increased the risk of response bias.

The classification of playing roles was based on a simplified functional dichotomy and may not fully reflect the complexity of tactical functions in modern soccer. In addition, the study did not include an assessment of inter-rater reliability, which may limit the precision of role assignment. Future studies should consider the use of multi-rater classification procedures and more differentiated role categories.

Several translated scales also demonstrated relatively low internal consistency coefficients, particularly the Psychoticism scale and SCAT [25]. Therefore, findings involving these measures should be interpreted with caution. Future research should include larger samples, multidimensional role classifications, and performance-related variables to further examine the relationship between psychological characteristics and functional playing roles in soccer.

Future directions

The present findings indicate several directions for future research. Future studies may examine whether similar patterns of competitive anxiety are observed across different sports, including both team and individual disciplines. It may also be useful to investigate whether differences in functional roles or performance styles within a specific sport are associated with variations in competitive anxiety. Such approaches may contribute to a broader understanding of the relationship between task demands and psychological characteristics in sport.

Longitudinal research designs may help clarify whether competitive anxiety is influenced by long-term sport participation or reflects relatively stable individual predispositions. In addition, future studies should examine competitive anxiety in more ecologically valid settings, including real-time competitive situations, in order to better capture the interaction between psychological states and performance demands.

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Conclusions

Professional soccer players demonstrated lower levels of competitive anxiety than physically active students of a similar age. At the same time, no statistically significant differences in competitive anxiety were observed between players performing creative (offensive) and destructive (defensive) roles. These findings suggest that competitive anxiety in soccer may be more strongly associated with the level of sport participation than with functional playing role.

The results also indicate that players with different tactical responsibilities may experience similar levels of competitive anxiety despite differences in their on-field functions. However, the observed moderate effect size suggests that subtle role-related variations may still exist. Therefore, psychological preparation strategies may be applied broadly across players while remaining flexible to individual responses and situational demands.

Overall, the present study provides additional evidence regarding competitive anxiety in soccer within a functional framework based on creative and destructive playing roles.

Conflict of Interest

The author declares no conflict of interest.

AI Tools Usage

The authors acknowledge the use of AI tools, including ChatGPT and Google Gemini, for language refinement and general editorial feedback. All scientific content, interpretations, and conclusions remain the responsibility of the authors.

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ORIGINAL ARTICLE

Comparative analysis of somatotype indicators and performance rates in cadets engaged in kettlebell lifting

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Authors' Contribution: A – Study design; B – Data collection; C – Statistical analysis; D – Manuscript Preparation; E – Funds Collection

Abstract

Background and Study Aim The bioimpedance method is used to evaluate body composition due to its objectivity, non-invasiveness, and ease of use at various levels. Its application helps establish the relationship between body composition and physical performance, predict competitive success, and assess training efficiency. This method is widely used in strength sports. The aim of this study was to compare the somatotype indicators of cadets engaged in kettlebell lifting with their actual competitive performance.

Material and Methods Sixty-two kettlebell lifting athletes, all cadets at military academies, were divided into two groups. Group 1 included 42 athletes aged 20.67 ± 0.39 years, with competitive levels ranging from beginner to first-class athlete. Group 2 consisted of 20 athletes, with a mean age of 22.20 ± 0.54 years. Their competitive level ranged from national- to international-level competitors (Candidate for Master of Sports, Master of Sports, and International-Class Master of Sports). The age difference between the groups was statistically significant ($p < 0.05$). Body height and body mass, body fat percentage (%), muscle mass percentage (%), visceral fat level (%), and basal metabolic rate (kcal) were measured. Total muscle mass (kg), fat mass (kg), body mass index (BMI), fat-free mass index (FFMI), skeletal muscle mass index (SMI), and performance index were calculated. To characterize the data, the median and the 1st (25th) and 3rd (75th) quartiles were determined. The significance of differences between groups was assessed using Rosenbaum's nonparametric criterion (Q) and the information measure of correlation (I) between the analyzed characteristics.

Results Most somatotype indicators showed similar values in both groups. Most participants had a body fat percentage above the average range and a muscle mass percentage within the average range. Most participants also had a BMI above the average range, an FFMI below the average range, and a high SMI. A significant increase in the performance index was observed in Group 2 ($Q = 13$, $p < 0.05$). A significant predominance of individuals with below-average FFMI was found in Group 1 ($2I = 67.54$, $p < 0.01$). Quartile ranges were established for the evaluated indices in kettlebell athletes. A performance index value of 155–209 was observed within the interquartile range for Group 1, whereas for Group 2 this range was 238–358. The interquartile range for FFMI was 16–18 kg/m^2 in Group 1 and 16–17 kg/m^2 in Group 2. The interquartile range for SMI was 8.1–9.2 kg/m^2 in Group 1 and 8.2–9.0 kg/m^2 in Group 2.

Conclusions Competitive performance differed significantly between the groups, whereas most somatotype indicators showed similar values. Quartile ranges were established for the performance index, FFMI, and SMI in kettlebell athletes. The bioimpedance-derived indices used in this study can be applied to characterize the somatotype features of kettlebell athletes and to compare athletes with different levels of competitive performance.

Keywords: kettlebell sport, somatotype, bioimpedance method, indices, performance.

Introduction

Athletic performance is influenced by a combination of morphological, functional, technical, and psychological factors. The contribution of these factors varies depending on the characteristics and competitive requirements of a particular sport. In strength-endurance sports, body composition is associated with the ability to perform prolonged physical work and maintain performance under training and competitive loads. Therefore, the assessment of somatotype characteristics represents one of the approaches used to characterize athletes and compare competitors with different levels of sports qualification.

In this context, non-invasive methods for assessing physiological parameters are widely used in sports

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science [1, 2]. One such method is bioimpedance analysis (BIA). BIA facilitates the assessment of body composition and is characterized by objectivity, non-invasiveness, and ease of use [2, 3, 4, 5].

Another study [6] reported the applicability of bioimpedance analysis in population-based research. Differences in somatotype characteristics associated with participation in sports were identified. Reduced body fat levels were observed in one in five child athletes. The authors proposed the use of this indicator for monitoring and preventing health disorders.

BIA evaluates the main components of body composition, including muscle and fat tissue. Changes in these components reflect training-related adaptations in athletes. Associations have been reported between body fat content, skeletal muscle mass, physical exercise volume, physical activity, and athletic performance [1, 7].

A review by Castizo-Olier et al. [8] examined the applicability of bioimpedance analysis for assessing body composition, hydration status, and other physiologically and clinically relevant characteristics. The authors highlighted the need to establish standardized testing procedures and to investigate the relationships between physiological variables and bioelectrical signals in sports and exercise settings.

Body composition indicators are also important for assessing nutritional status. They allow for an evaluation of the characteristics of the “athlete-nutrition” system. This improves the analysis of athletes’ functional status and performance [9].

The use of BIA enables the identification and comparison of athletes’ profiles across different sports based on the level of development of their physical qualities (strength, endurance). In the study by Rueda-Cordoba et al. [10], body composition in athletes was examined according to the volume and nature of training loads. Higher values of body mass, muscle mass, and bone mass were observed in athletes who performed strength and interval training. A lower body fat percentage was observed in endurance athletes than in those who performed interval training.

Another study conducted a comparative analysis of the physical development and somatotype characteristics of girls and young women who participated in dance and gymnastics [11]. Differences in the harmony of physical development, as well as in muscle and fat tissue composition, reflect the specific impact of each sport on the athletes’ bodies. The use of BIA expands the data obtained from the analysis of anthropometric parameters and indices.

BIA is an important and convenient tool for establishing body composition standards for athletes in various sports [4, 12, 13]. The development of such standards and assessment scales enables the optimization of athlete selection and the prediction of success. In a study by Toselli et al. [13], the morphological characteristics of young elite basketball players were assessed to establish reference values for somatotype. The study utilized the results of somatotype analysis and bioelectrical impedance vector analysis (BIVA). The findings provide a comprehensive approach to athlete selection and performance prediction.

A similar design was used in the study by Wagner et al. [12]. The authors examined athletes from various sports. The study included students who participated in baseball, rock climbing, cycling, figure skating, gymnastics, ice hockey, lacrosse, pickleball, powerlifting, racquetball, rodeo, rugby, soccer, swimming, frisbee, and volleyball. The results enabled the calculation of percentile ranks for body fat percentage and fat-free mass index (FFMI).

The influence of body composition on strength and power indicators in young alpine skiers was studied by Bertozzi et al. [14]. It was confirmed that body composition, particularly body mass and the muscular component, is a significant predictor of strength and power indicators in athletes participating in this sport.

Similar results were obtained by Dopsaj and Siljeg [15]. The authors assessed the relationship between body composition and performance in sprint swimmers. They concluded that the impact of changes in body composition on athletic performance, and the relationship between the two, should be considered within an individualized methodological approach in elite sports.

The use of BIA complements the analysis of anthropometric indicators and helps establish the specific characteristics of a sport [5, 16, 17]. In the study by Busta et al. [16], BIA was used to compare morphological indicators among female canoe slalom athletes. The importance of muscle strength and power in this sport was confirmed. Predictors of success include well-developed musculature, relatively low body mass due to limited hypertrophy of the lower limbs, and low body fat.

The monitoring and assessment of functional parameters in athletes participating in strength sports are described in the study by Khomenko et al. [18]. Their implementation provides information about adaptive potential. This serves as a basis for adjusting training programs. The study of somatotype plays a role in monitoring. Changes in the fat component of the somatotype help establish body composition indicators.

Analysis of the research findings has shown that bioimpedance analysis is used to assess body composition, characterize athletes’ somatotype features, and examine their relationship with physical performance. Researchers emphasize the applicability of this method for monitoring athletes’ condition, establishing reference values, and comparing representatives of different sports and qualification levels. The available literature confirms the use of BIA in sports, including strength sports. However, in kettlebell lifting, no indicators are available for the rapid assessment of athletes' morphological characteristics and their relationship with competitive performance. The absence of specific somatotype standards for kettlebell lifting athletes limits the analysis and interpretation of these characteristics within this sport.

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Materials and Methods

Participants

Sixty-two kettlebell athletes, all cadets of military academies, were divided into two groups:

- Group 1 – 42 athletes, mean age 20.67 ± 0.39 years, with competitive levels ranging from beginner to first class;
- Group 2 – 20 athletes, mean age 22.20 ± 0.54 years, with competitive levels ranging from Candidate for Master of Sports to International-Class Master of Sports (according to the Ukrainian sports classification system).

The age difference between the groups was significant ($p < 0.05$). All participants provided informed consent to participate in the study in accordance with international bioethical requirements. The study design was approved by the Bioethics Committee of the Kharkiv State Academy of Physical Culture (Protocol No. 5, October 30, 2025).

Study Design

The study design involved the determination of body height and somatotype indices. Body height was measured using an electronic height measurement device (China). The OMRON BF511 body composition monitor (Japan) was used to determine somatotype indices. Body mass, fat percentage (%), muscle percentage (%), visceral fat level (%), and basal metabolic rate (kcal) were measured. To assess fat and muscle percentages, the standards recommended by Omron Healthcare [19] were applied.

The study was conducted in the morning on an empty stomach. The participants refrained from consuming liquids for at least 2 hours before testing. The interval between the study and physical exercise was at least 24 hours. The indoor microclimate conditions in the room where the study was conducted complied with hygiene standards.

The athletes' performance was assessed based on competition protocols. The study included the protocols of the All-Ukrainian kettlebell lifting competition in memory of Prof. Yu. O. Reznikov (Lviv, November 21–22, 2025) and the kettlebell lifting championship of the Dynamo Physical Culture and Sports Society of Ukraine among national teams of higher education institutions (Lviv, April 7–9, 2026).

These competitions are classified as national-level events and are designed to classify kettlebell lifting athletes by skill level, form regional teams, and create a reserve pool for the national team in this sport.

Procedure

Based on specific somatotype indicators, muscle mass (kg) and fat mass (kg) were calculated as the product of the percentage of muscle (or fat) tissue and body mass, divided by 100. The results obtained were used to calculate several indices.

Body Mass Index (BMI) was calculated as the ratio of body mass (kg) to body height squared (m^2). For men, the average value is considered to be within the range of 20–25 kg/m^2.

The Fat-Free Mass Index (FFMI) was calculated using the formula:

$$FFMI = (BW - BF) / (HT^2) \quad (1),$$

where BW is body mass (kg), BF is body fat (kg), and HT is height (m).

The index value is assessed according to the following scale:

- 16–17 – below average;
- 18–19 – average;
- 20–21 – above average;
- 22 and above – high.

The Skeletal Muscle Index (SMI) was calculated as the ratio of skeletal muscle mass (kg) to body surface area (m^2). An index value of less than 7.0 kg/m^2 is considered low in men, whereas a value greater than 7.0 kg/m^2 is considered high.

Performance was assessed as the total weight of kettlebells lifted during competition. This metric was evaluated in the biathlon event (two-arm jerk and snatch, each performed for 10 min) and in the P12 event (12-minute kettlebell snatch). The kettlebell weights were 24 kg and 32 kg in the biathlon event and 24 kg in the P12 event. In the snatch event, athletes were allowed to switch hands only once. In the P12 event, athletes were allowed to switch hands without restriction.

The performance index was calculated as the ratio of the total weight lifted by the athlete during competition (kg) to the athlete's muscle mass (kg).

Statistical Analysis

Statistical analysis of the obtained data was performed using Microsoft Excel 2019 (version 2506). To characterize the data, the median (Me) and the 1st (25%) and 3rd (75%) quartiles were determined. The significance of differences between groups was assessed using Rosenbaum's non-parametric criterion (Q). Differences were considered significant at $p < 0.05$.

To characterize the distribution of indicators, relative values and their errors were calculated. The significance of differences was assessed using Kullback's information measure of correlation (I). The significance of the 2I value was assessed using the χ^2 distribution table. Differences were considered significant at $p < 0.05$.

Results

The results are presented in Tables 1 and 2. The results presented in Table 1 show no significant differences between the groups ($p > 0.05$). The median body fat percentage in both groups was above average. Participants in Group 1 were distributed as follows according to this indicator: below average – 0%, average – (4.76 ± 3.29)%, and above average – (95.25 ± 3.29)%. In Group 2, the proportions of such participants were 0%, (10.00 ± 6.71)%, and (90.00 ± 6.71)%, respectively. The 2I value was 0.58. The differences were not statistically significant ($p > 0.05$).

The median muscle mass percentage was within the average range. Participants in Group 1 were distributed as follows according to this indicator: below average – (45.24 ± 7.68)%, average – (45.24 ± 7.68)%, and above average – (9.52 ± 4.53)%. In Group 2, the proportions of such participants were (35.00 ± 10.67)%, (45.00 ± 11.12)%, and (20.00 ± 8.94)%, respectively. The 2I value was 1.43. The differences were not statistically significant ($p > 0.05$).

The median visceral fat level in both groups was within the above-average range. The distribution of athletes in Group 1 was as follows: average values of this indicator were observed in (16.67 ± 5.75)% of participants, and above-average values in (83.33 ± 5.75)%. In Group 2, the proportions of such participants were (30.00 ± 10.25)% and (70.00 ± 10.25)%, respectively. The 2I value was 1.40. The differences were not statistically significant ($p > 0.05$).

Table 1. Somatotype Indicators of Kettlebell Athletes

Indicators	Group 1 (n = 42)			Group 2 (n = 20)		
	25%	Me	75%	25%	Me	75%
Body height, cm	175.00	180.75	183.50	175.00	178.00	182.00
Body mass, kg	73.93	82.20	92.38	69.65	74.90	90.80
Body fat percentage, %	29.98	33.15	37.68	25.88	29.95	35.85
Muscle mass percentage, %	31.53	34.35	36.15	31.33	35.00	38.53
Visceral fat level, %	11.00	13.00	16.00	8.00	11.50	14.50
Basal metabolic rate, kcal	1737.25	1846.50	1982.75	1678.50	1747.00	1956.00
Fat mass, kg	22.80	27.51	33.26	18.40	23.14	31.73
Muscle mass, kg	26.79	27.73	29.20	26.64	27.38	28.34
Body mass index, kg/m^2	23.49	24.97	28.70	21.17	23.92	27.56
Fat-free mass index, kg/m^2	15.97	16.89	17.95	16.20	16.72	17.71
Skeletal muscle mass index, kg/m^2	8.13	8.65	9.25	8.27	8.61	8.96

Note: 25% is the first quartile, Me is the median, and 75% is the third quartile.

Table 2. Performance Indices of Kettlebell Athletes

Indicators	Group 1			Group 2		
	25%	Me	75%	25%	Me	75%
General performance index, a.u.	154.73	190.87*	208.50	238.91	284.86	358.85
P12 performance index, a.u.	53.17	62.02*	69.54	85.14	91.68	97.55
Biathlon performance index, a.u.	157.46	194.87*	215.34	256.41	307.99	364.00

Note: 25% = first quartile, Me = median, 75% = third quartile; * differences are statistically significant ($p < 0.05$).

Basal metabolic rates in both groups did not differ significantly and were generally within the normal range for young men.

An individual analysis of the distribution of the calculated indices also reflected the similarity of the participants' results. The BMI in Group 1 was distributed as follows: below average – (9.52 ± 4.53)%, average – (45.24 ± 7.68)%, and above average – (45.24 ± 7.68)%. In Group 2, the proportions of such athletes were (10.00 ± 6.71)%, (45.00 ± 11.12)%, and (45.00 ± 11.12)%, respectively. The 2I value was 0. The differences were not statistically significant ($p > 0.05$).

Athletes in Group 1 were distributed according to FFMI values as follows: below average – (73.81 ± 6.78)%, average – (21.43 ± 6.33)%, above average – (4.76 ± 3.29)%, and high – 0%. In Group 2, the proportions of such athletes were (85.00 ± 7.98)%, (10.00 ± 6.71)%, 0%, and (5.00 ± 4.87)%, respectively. The 2I value was 67.54. The differences were significant ($p < 0.01$).

Based on SMI values, all participants belonged to the high skeletal muscle mass group ($SMI > 7.0$ kg/m^2). Quartile standards were established for the evaluation of indices used in kettlebell athletes. Given the specific nature of kettlebell lifting, FFMI and SMI can be used to assess athletes' condition. The average range for the first index was 16–18 kg/m^2 in Group 1 and 16–17 kg/m^2 in Group 2. For the second index, the corresponding ranges were 8.1–9.2 kg/m^2 and 8.2–9.0 kg/m^2, respectively. Values below or above these ranges indicate whether athletes are below or above average.

Table 2 presents the performance indices of kettlebell athletes. This indicator was calculated for all participants and separately according to competition type: P12 (12-minute kettlebell snatch) and biathlon.

A statistically significant higher general performance index was observed in Group 2 ($Q = 13$, $p < 0.05$). Similar differences were found for P12 ($Q = 10$, $p < 0.05$) and the biathlon event ($Q = 10$, $p < 0.05$).

The quartile norms of this index can also be used to assess the performance of kettlebell athletes. For athletes in Group 1, the interquartile range of the biathlon performance index was 157–215. For athletes in Group 2, this range was 256–364. In the P12 event, the interquartile range was 53–70 for Group 1 and 85–98 for Group 2. Values below these ranges are classified as below average, whereas values above these ranges are classified as above average.

Discussion

The aim of this study was to compare the somatotype indicators of cadets engaged in kettlebell lifting with their competitive performance. The results showed no significant differences between the groups in the majority of somatotype indicators. At the same time, athletes in Group 2 demonstrated significantly higher values of the general performance index, as well as the performance indices in the P12 and biathlon events. Significant differences between the groups were also identified for the distribution of athletes according to FFMI values. Quartile ranges were established for the performance index, FFMI, and SMI, enabling the characterization of the distribution of these indicators in kettlebell athletes with different levels of sports qualification.

The use of BIA opens up new opportunities for studying athletes' body composition and improving athletic performance. This method is particularly important in strength sports, including kettlebell lifting. Information on body composition allows for the assessment of athletes' strength, power, and performance in this sport.

Similar results were reported in a study by Silleras et al. [5], which assessed body composition and functional status in rugby athletes. Strength and muscle mass are important in this sport. The study of morphology and body composition is important for optimizing the athletic performance of rugby athletes.

The use of BIA in strength sports is driven by several advantages. The results obtained allow its recommendation as a tool for monitoring the condition of strength athletes. This method assesses body composition, muscle condition, and internal physiological states without invasive procedures. The results of this study are consistent with the findings of other studies [2, 4, 7].

The study design is based on examining body composition characteristics in strength athletes of varying ages and skill levels. This approach is common in sports science. It allows for the identification of qualities that have enabled athletes to reach the elite level. In a study by Rovnaya et al. [20], a comparison of the condition of armwrestling athletes of varying skill levels using indices identified predictors of success. In another study [21], a comparison of the morphofunctional indicators of elite female synchronized swimmers and a control group served as the basis for developing a selection methodology for this sport.

Performance was used as the second criterion for comparing participants. The quantitative nature of this criterion is a necessary and sufficient condition for the analysis. The validity of this approach is supported by studies examining the relationship between morphological indicators and athletic success.

For example, in a study by Busta et al. [15], the relationships between body composition characteristics and the performance of elite male butterfly sprinters were examined. A direct significant correlation was found between somatotype components and swimming performance.

An important finding of the study is the similarity of most of the results obtained. This can be explained by the specific selection of participants. All of them were cadets at military academies. One of the distinctive features of their training was a relatively high volume of physical conditioning. This training is aimed at developing qualities such as strength and strength endurance. The national system of military training includes a large number of such exercises, including kettlebell lifting. The absence of significant differences among the studied indicators may reflect similarities in the participants' levels of physical fitness.

Similarities in age may also have influenced the similarity of morphological indicators. Virtually all participants were within the age range of 18–27 years. The identified age differences may reflect variations in training experience and athletic proficiency among the participants.

Analysis of somatotype indicators reveals certain trends. First of all, the median muscle mass percentage was higher than the median fat mass percentage in all participants. However, athletes in Group 1 showed virtually no difference between the median fat and muscle mass percentages (the difference was 1.2%).

Participants in Group 2 showed more pronounced differences, with a median difference of 5.05% between fat and muscle mass percentages. In our view, this illustrates a higher level of training among elite athletes.

BIA results show that the participants were predominantly individuals with an average muscle mass percentage and an above-average fat mass percentage. This trend can be explained by the specific nature of kettlebell lifting. The training loads in this sport are prolonged and predominantly aerobic. This necessitates the presence of fat tissue as an energy substrate for oxidation. Additionally, kettlebell lifting does not require a large amount of muscle mass. The main requirements are functionality and the ability to perform prolonged aerobic work. The results suggest that, for elite-level kettlebell athletes, functional indicators may be stronger predictors of success than morphological indicators.

The observed level of visceral fat can be explained by the age-related characteristics of most participants. Visceral fat accumulation occurs in most adults. This was confirmed by the results. However, among older participants, the median value of this indicator was lower than that observed in younger athletes. There was also a tendency toward a higher proportion of participants with an average level of visceral fat in Group 2. In our opinion, this may be due to the high volume of aerobic training performed by top-level athletes.

These exercises help reduce body fat, including visceral fat. Another factor that, in our view, contributed to the similarity of somatotype indicators is the standards used. The standards employed were developed by Omron Healthcare based on the results of scientific studies published in the early 2000s [19]. These standards have been in use for more than 20 years and, naturally, require updating. Furthermore, they were designed for the general population. Athletes belong to a specific age- and occupation-based group and require specialized standards. The importance of developing such standards, taking into account the specific impact of sport on athletes' condition, is highlighted in several publications [4, 8, 12, 13]. In this context, developing body composition standards specifically for kettlebell athletes is a pressing scientific and practical task.

To improve the quality of the analysis, the index method was used. This method is widely used in sports science. This is due to the simplicity, clarity, and informativeness of indices, which allow the assessment of relationships between indicators. Thus, in a study by Podrigalo et al. [17], the physical characteristics of elite combat sports athletes were analyzed using specialized indices. The validity of their use for monitoring athletes' functional condition was demonstrated. The high informativeness of the indices, which illustrated the ratios of limb segments, was also noted.

In another study [20], the index method was used to identify predictors of success among armwrestling athletes. Sport-specific indices were established. These indices allow the characterization of the qualities required for elite-level performance.

In this study, the body mass index (BMI), fat-free mass index (FFMI), skeletal muscle index (SMI), and performance index were used. The latter indicator was proposed by the authors and allowed the linking of competition results to the athletes' muscle mass.

BMI is most commonly used in medical practice, physical education, and sports [9]. This indicator is important in sports for assessing an athlete's body composition. BMI serves as an indicator of an athlete's health and performance. However, this index is highly nonspecific and poorly suited to specific sports-related tasks. This significantly limits its application in sports. The results, in particular the relatively large number of participants with above-average BMI values, confirm this conclusion.

The Fat-Free Mass Index (FFMI) and the Skeletal Muscle Index (SMI) were used in this study to address this limitation. They are more specific for assessing the condition of kettlebell athletes than BMI. Their use improves the analysis of kettlebell athletes' condition. They are calculated similarly to BMI but provide a more accurate assessment of physical fitness and help distinguish between muscle and fat mass [3, 12].

FFMI is a metric that assesses lean body mass relative to body height. The participants' FFMI values indicate that they were below average. In our view, this reflects the specific impact of the sport on the athletes' bodies. As previously noted, prolonged aerobic exercise requires a certain amount of adipose tissue. The results suggest that this index is more objective for strength sports than the absolute and relative somatotype indices and BMI. Differences in this index between the groups allow us to propose it as a criterion for differentiating strength athletes by skill level. This is supported by existing literature. The FFMI is recognized as a sport-specific index in strength sports. It has been established that athletes in such sports as powerlifting and rugby have greater body mass and higher FFMI values [12].

Another study [3] analyzed the characteristics of somatotype and speed qualities in athletes. An increase in body fat content was found to correlate with decreases in linear speed and coordination. Given that these qualities are not as important in strength sports, a sufficient level of body fat in athletes is logical.

The SMI values for all participants indicated high muscle mass. This allows us to consider this index specific to strength sports and recommend its use for monitoring the condition of kettlebell athletes. The results confirm existing literature data.

In a study by Dopsaj et al. [15], the SMI was used to confirm the relationship between somatotype components and the performance of elite sprint swimmers. The use of SMI significantly improved the quality of the analysis.

The performance index illustrates the relationship between competition results and kettlebell lifters' somatotypes, linking competition results to muscle mass. Kettlebell athletes compete in multiple kettlebell lifts. The winner is determined by the highest number of lifts. In the event of a tie, the athlete with the lower body mass wins. Thus, the proposed index is calculated based on the characteristics of competitive activity in kettlebell lifting. Moreover, the calculation procedure allows for a more accurate assessment of the relationship between performance and morphological characteristics, since it uses muscle mass rather than body mass.

This approach is common in strength sports. In another study [23], predictors of success were identified for the evaluation of competitive performance in powerlifting. The authors studied the effect of competition frequency on the strength (relative and absolute) of powerlifting athletes. Strength indicators were assessed based on points scored in competitions. It was confirmed that greater success was associated with the number of competitions in which the athletes participated.

The validity of this approach is supported by the literature. The study by Palazzo et al. [24] evaluated the relationships between energy expenditure and body composition in athletes from various sports. The authors used an index of energy expenditure per unit of lean body mass, similar to the one tested in this study.

In this study, three competition formats were evaluated: the biathlon event with 24 kg kettlebells, the biathlon event with 32 kg kettlebells, and the P12 event, which involved a 24 kg kettlebell snatch for 12 min. The exercises differed in duration (10 min and 12 min), kettlebell weight (24 kg and 32 kg), and number of kettlebells (one and two). This necessitated a standardized approach for comparison. Total weight lifted was selected as this criterion. The athletes' morphological condition in the proposed index is represented by muscle mass (kg). The ratio of these two indicators reflects the efficiency of muscle activity in kettlebell athletes. It is logical that high-level kettlebell athletes have significantly higher values of this index. The results in Table 2 confirm the objectivity and clarity of this index regardless of the exercises performed.

The results obtained are also important for predicting the performance of kettlebell athletes. Sufficient levels of muscle tissue ensure high performance capacity.

The validated performance index demonstrates the optimization of the functional condition of elite athletes. This is supported by existing literature. In a study by Durkalec-Michalski et al. [22], the relationship between body composition indicators and physical performance in martial arts athletes was examined. It was found that the levels of somatotype components correlated with aerobic capacity and might influence the level of biochemical adaptation in athletes.

The proposed norms allow for the assessment of athletes' performance levels by quartiles. The interval between the 1st and 3rd quartiles is considered the average range and is taken as the norm. Accordingly, values below the 1st quartile correspond to values below the norm, and values above the 3rd quartile correspond to values above the norm. This approach allows for the standardization of the assessment of both morphological indicators and performance. It aligns with accepted standards in sports science and with the results of previously cited studies [4, 12, 13].

The results obtained are consistent with previously published data on the differentiation of body composition in athletes specializing in different sports [25]. Differences in somatic composition and in the internal proportions of body structure components have been demonstrated among athletes with different training specializations. The findings support the usefulness of index-based approaches for characterizing sport-specific morphological features and identifying differences associated with training specialization. These observations support the application of body composition indices for the assessment and comparison of athletes in kettlebell lifting.

The proposed standards are specific to kettlebell lifting. However, their practical application is limited by the age- and social-specific characteristics of the participants. They can be used as indicative standards for monitoring athletes' condition, evaluating training effectiveness, and differentiating skill levels.

The set of indices used and the standards developed can be applied in practice to the training of kettlebell athletes. Their practicality and clarity make them suitable for use in the selection process, for adjusting training loads, and for predicting success and skill development. Changes in the indices and transitions between quartiles serve as objective criteria for analysis and evaluation.

Limitations and Future Directions

The study was limited to kettlebell athletes who were cadets at military academies. Therefore, the results should be interpreted with regard to the age and social characteristics of the participants. Future research should focus on developing percentile tables for body composition indicators in kettlebell athletes. Such tables may be used for monitoring athletes' condition, forecasting performance, and evaluating training effectiveness.

Conclusions

A comparative analysis was conducted of the somatotype indicators of kettlebell athletes and their performance in competitions. A performance index was validated that reflects athletes' competition results and muscle mass levels. Athletes with high levels of athletic skill had significantly higher values of this index. The participants showed similar somatotype indicators. This may be related to several factors. The participants were of similar age, and all were cadets at military academies. Their training included a large volume of strength exercises, including kettlebell lifting. The objectivity and informativeness of the indices used were confirmed in comparison with absolute and relative somatotype indicators. The use of quartiles allowed the establishment of average ranges for assessing the condition of kettlebell athletes. High SMI values reflect the strength-oriented nature of kettlebell lifting, whereas body fat levels reflect the characteristics of the training loads in this sport. The results obtained support the recommendation of the bioimpedance method and the set of indices used as a tool for monitoring the condition of kettlebell athletes.

Conflict of Interest

Author Wladyslaw Jagiello is a member of the editorial board of the journal. To ensure an objective and unbiased review process, the manuscript was handled by an independent member of the editorial board, and the peer review was conducted by external reviewers with no affiliation to the author. The author did not participate in the peer-review process or in any editorial decision-making related to this manuscript. The remaining authors declare that they have no conflicts of interest.

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