Integrating biomechanical indicators in training load monitoring based on TRIMP model among elite basketball players

Indicadores biomecánicos y control de la carga de entrenamiento mediante TRIMP en baloncesto de élite

Authors

Mohammad Jaafar Majeed [1]
Rafid Habeb Qadori [2]
Safaa A. Ismaeel [2]

[1] Ministry of Education, Diyala Education Directorate, Diyala, (Iraq)
[2] Diyala University, (Iraq)

Corresponding author:
Safaa A. Ismaeel
sc_safaaismaeel@uodiyala.edu.iq

Received: 08-06-25
Accepted: 03-02-26

How to cite in APA

Majeed, M. J., Qadori, R. H., & Ismaeel, S. A. (2026). Integrating biomechanical indicators in training load monitoring based on TRIMP model among elite basketball players. *Retos, 78*, 14-22. https://doi.org/10.47197/retos.v78.116527

Abstract

Introduction: this study addressed the limitations of the traditional training impulse model in representing training load in elite basketball, a sport characterized by high mechanical stress and neuromuscular demands. the conventional model primarily reflected cardiovascular load and underestimated biomechanical contributions associated with explosive movements.
Objective: the objective of the study was to evaluate a hybrid training load model integrating biomechanical indicators with the traditional training impulse approach in elite basketball players.
Methodology: a quasi-experimental design was applied to a sample of 26 elite basketball players. training load data were collected using heart rate monitoring systems, force platforms, surface electromyographic recordings, and high-speed motion analysis. biomechanical indicators included ground reaction force, ground contact time, muscle electrical activity, and knee joint angle. statistical analyses involved paired sample tests, correlation analysis, and multiple regression procedures.
Results: the results demonstrated statistically significant differences between the traditional model and the hybrid biomechanical model in estimating training load. ground reaction force showed the strongest association with the hybrid model, followed by muscle electrical activity and ground contact time. regression analysis indicated that biomechanical indicators jointly explained a substantial proportion of training load variability, with knee joint angle identified as the most influential predictor.
Discussion: the findings were consistent with previous research emphasizing the importance of mechanical load and neuromuscular stress in high-impact sports. the hybrid model provided greater sensitivity in capturing external and internal load components compared with traditional cardiovascular-based approaches.
Conclusions: the integration of biomechanical indicators enhanced training load monitoring in elite basketball and supports a more comprehensive and individualized assessment approach.

Keywords

TRIMP; biomechanics; EMG; GRF; basketball; performance monitoring; hybrid model.

Resumen

Introducción: este estudio analizó las limitaciones del modelo tradicional de impulso de entrenamiento para representar la carga de entrenamiento en baloncesto de élite, deporte caracterizado por elevadas exigencias mecánicas y neuromusculares. dicho modelo reflejó principalmente la carga cardiovascular y subestimó los componentes biomecánicos asociados a movimientos explosivos.
Objetivo: el objetivo fue evaluar un modelo híbrido de carga de entrenamiento que integró indicadores biomecánicos con el enfoque tradicional de impulso de entrenamiento en jugadores de baloncesto de élite.
Metodología: se aplicó un diseño cuasi experimental en una muestra de 26 jugadores de baloncesto de élite. la carga de entrenamiento se registró mediante sistemas de frecuencia cardíaca, plataformas de fuerza, registros electromiográficos de superficie y análisis cinemático de alta velocidad. los indicadores biomecánicos incluyeron la fuerza de reacción del suelo, el tiempo de contacto, la actividad eléctrica muscular y el ángulo de la articulación de la rodilla. el análisis estadístico comprendió pruebas de comparación pareada, análisis de correlación y modelos de regresión múltiple.
Resultados: los resultados mostraron diferencias estadísticamente significativas entre el modelo tradicional y el modelo híbrido biomecánico en la estimación de la carga de entrenamiento. la fuerza de reacción del suelo presentó la asociación más elevada con el modelo híbrido, seguida de la actividad eléctrica muscular y el tiempo de contacto. el análisis de regresión indicó que los indicadores biomecánicos explicaron conjuntamente una proporción relevante de la variabilidad de la carga de entrenamiento, destacando el ángulo de la rodilla como el predictor más influyente.
Discusión: los hallazgos coincidieron con investigaciones previas que subrayaron la relevancia de la carga mecánica y el estrés neuromuscular en deportes de alto impacto. el modelo híbrido mostró mayor sensibilidad para integrar componentes de carga interna y externa.
Conclusions: la integración de indicadores biomecánicos mejora el control de la carga de entrenamiento y permite una evaluación más completa e individualizada en el baloncesto de élite.

Palabras clave

Biomecánica; carga de entrenamiento; impulso de entrenamiento; rendimiento deportivo.

Introduction

Over the past two decades, training load monitoring becomes a central pillar in high-performance sport due to its role in optimizing training adaptations, guiding periodization strategies, and reducing injury risk. Contemporary consensus emphasizes that effective monitoring requires an integrated interpretation of both the training stimulus imposed on the athlete and the psycho-physiological response elicited by that stimulus (Bourdon et al., 2017). In team sports, where training demands fluctuate substantially across microcycles and competitive phases, training load monitoring provides an applied framework that supports evidence-informed decision-making by coaches and performance staff (Foster et al., 2017).

Among internal load models, the training impulse approach remains one of the most widely used methods for quantifying cardiovascular strain by integrating session duration with relative heart rate response. This model offers a standardized estimation of physiological stress and is extensively applied across sports contexts to monitor endurance-related responses and overall session intensity (Bourdon et al., 2017). However, reliance on heart-rate–derived indicators presents recognized limitations in intermittent high-intensity sports, where rapid accelerations, brief recovery periods, and neuromuscular fatigue disrupt the expected relationship between external work and cardiovascular response, thereby masking meaningful variations in mechanical stress (Buchheit, 2014).

Basketball represents a particularly challenging context for training load monitoring based solely on internal cardiovascular models. The sport is characterized by repeated jumping, abrupt landings, high-frequency decelerations, and rapid changes of direction, actions that impose substantial mechanical and tissue-level loads that are not fully reflected by cardiovascular measures alone (Fox et al., 2017). Empirical evidence indicates that internal and external load measures do not consistently align during basketball training, suggesting that a single internal model may provide an incomplete representation of the total training burden experienced by players (Scanlan et al., 2014). Recent applied research in professional basketball further reinforces the need to interpret internal and external workload indicators jointly in order to accurately characterize weekly load fluctuations and competitive demands (Molina et al., 2024).

From a theoretical perspective, physiological and biomechanical load-adaptation pathways are increasingly considered partially distinct, with different response rates and implications for performance and injury risk (Vanrenterghem et al., 2017). Within this framework, a training load monitoring approach that integrates cardiovascular strain with biomechanical indicators offers a more comprehensive and individualized estimation of training stress in high-impact sports such as basketball. The inclusion of variables such as ground reaction force, electromyographic activity, and ground contact time provides valuable insight into neuromuscular and impact-related demands that may be underrepresented in heart-rate–based models (Scanlan et al., 2014; Gamonales et al., 2023).

Accordingly, the present study proposes a hybrid training load model that extends the traditional training impulse approach through the integration of key biomechanical indicators. The objectives of the research are to compare training load estimates derived from the traditional model and the proposed hybrid model in elite basketball players and to examine the relationships between the hybrid load index and selected biomechanical indicators. This approach aims to enhance the sensitivity of training load monitoring to basketball-specific mechanical and neuromuscular demands and to provide a more accurate and context-specific representation of training load variability.

Method

Research Design

The study followed an experimental-correlational approach with a quasi-experimental design to investigate the association between physiological and biomechanical variables and the traditional TRIMP model, with developing a hybrid integrative model (TRIMP-BIO). The methodology aimed at: Comparing the accuracy of the hybrid model (TRIMP-BIO) with the traditional TRIMP model and exploring the effect of biomechanical indicators on training load estimation and muscle fatigue quantification.

Sample of the Study

The sample comprised of 26 elite basketball players (18–25 years), who enrolled in regular training programs, and they are healthy and free from chronic injuries. Participants were chosen via purposive sampling to affiliate with the study's technical and practical needs. Statistical analysis was run on the descriptive data to confirm homogeneity of some basic variables. The arithmetic mean, standard deviation, minimum, and maximum values were analyzed for each variable. Normality tests (Shapiro-Wilk/Kolmogorov-Smirnov) were calculated to prove the assumption of normal distribution, followed by a one-sample T-test to verify the absence of statistically significant deviations from theoretical population benchmarks. Results suggested that all variables followed a normal distribution ($p > 0.05$), with no significant differences perceived from expected values ($p > 0.05$), confirming sample homogeneity and its appropriateness for subsequent research procedures.

Table 1. Descriptive Statistics and Normality Test Results for the Study Sample (n = 26)

Variable	Mean	SD	Minimum	Maximum	Normality Test (p-value)	T-Test (p-value)
Age (years)	20.98	1.97	17.28	24.62	0.9662	0.414
Height (cm)	182.17	4.92	173.12	193.7	0.9284	0.1261
Weight (kg)	82.01	6.14	64.7	91.06	0.1221	0.5099
Years of Experience	5.25	1.31	2.22	8.11	0.7093	0.1856
Weekly Training Sessions	5.21	0.64	3.95	6.58	0.6965	0.4078

Research Variables

This study integrates biomechanical and physiological variables to assess training load in elite basketball players, using tools like EMG, force plates, TRIMP, and motion capture for precise, field-relevant analysis. Table (2) below outlines the specific variables used, along with their characteristics and measurement tools:

Table 2. Integrated Multidimensional Assessment Model for Training Load Variables in Basketbal

Variable Type	Variable Name	Measurement Unit	Measurement Method	Measurement Tool	Purpose of Measurement
Dependent	Hybrid Training Load (TRIMP-BIO)	Composite Unit (Point)	TRIMP + Biomechanical Indicators	HR Monitor + Biomechanical Lab	Represents internal physiological training load.
Dependent	Traditional Physiological Load (TRIMP)	Point	HR Zones × Duration	Polar/Garmin HR Monitor	Quantifies neuromuscular stress during dynamic tasks.
Dependent	Muscle Fatigue Index	Millivolts per Activation Time (mV/Activation Time)	EMG Analysis	Noraxon EMG System	Indicates external mechanical load (e.g., impact forces).
Independent	Ground Reaction Force	Newtons (N)	Force Analysis During Landing	Force Plate	Assesses neuromuscular fatigue via temporal movement patterns.
Independent	Ground Contact Time	Milliseconds (ms)	Video Recording + Analysis	High-Speed Camera + Kinovea Software	Measures movement efficiency and joint mechanics during jumps.
Independent	Knee Joint Angle During Landing	Degrees (°)	Video-Based Kinematic Analysis	Dartfish/Kinovea Motion Analysis Software	Evaluates muscle activation and fatigue in response to load.
Independent	Muscle Electrical Activity (Electromyography)	Millivolts (mV)	Surface EMG Measurement	Surface EMG Sensors	Input for TRIMP equation to quantify training duration.

Independent	Training Duration	Minutes (min)	Session Logging	Training Logbook	Subjective exertion rating integrated into TRIMP calculations.
Independent	Training Intensity (Rate of Perceived Exertion)	Borg Scale 0–10	Post-Session (30 min)	Borg CR-10 Scale	Represents internal physiological training load.

Tests for Research Variables

1. Conventional Training Load (TRIMP)

Tool Used: Heart rate monitor (Polar system)

Method of Application: The athlete wears a chest strap monitor throughout the training session to continuously record heart rate.

Measurement Mechanism:

TRIMP = Training Duration × Intensity Coefficient × $(HR_{exercise} - HR_{rest}) \div (HR_{max} - HR_{rest})$

This formula quantifies the internal training load by integrating session duration with relative heart rate effort, normalized against the athlete's heart rate reserve.

Interpretation Criteria: TRIMP values below 50 indicate a light training load, values between 50 and 100 indicate a moderate load, and values above 100 indicate a high training load.

2. Hybrid Training Load (TRIMP-BIO)

- Tool: Integration of TRIMP with biomechanical indicators (Ground Reaction Force [GRF], Electromyography [EMG], and Contact Time)
- Performance Method: A unified hybrid equation is created by combining the data collected during the training session.
- Measurement Mechanism:

TRIMP-BIO=TRIMP+w1(GRF)+w2(EMG)+w3(Contact Time) TRIMP-BIO=TRIMP+w1(GRF)+w2 (EMG)+w3(Contact Time)

The weighting coefficients (w1–w3) were derived empirically using correlation and regression analyses to reflect the relative contribution of each biomechanical indicator to the hybrid training load (TRIMP-BIO). Accordingly, the TRIMP-BIO model was treated as an exploratory hybrid model aimed at enhancing sensitivity to basketball-specific mechanical and neuromuscular demands rather than as a confirmatory predictive framework.

3. Ground Reaction Force (GRF)

- Tool: Force Plate (Huang, W.-Y., Huang, H., & Wu, C.-E. 2024)
- Performance Method: The athlete stands still on the force plate to record initial body weight, then performs a maximal vertical jump, ensuring both take-off and landing occur in the same position. Vertical force data is collected during both the push-off and landing phases, and the peak value is used as the strength indicator.
- Measurement Mechanism: GRF is measured in Newtons, with the peak value recorded.

Evaluation Index:

GRF Index=Peak GRF ÷ Body Weight

4. Ground Contact Time (Arboix-Alió, J., et. al 2024)

- Tool: High-speed camera + Kinovea software
- Performance Method: Jumps or running movements are recorded using a high-speed camera. The footage is then analyzed frame-by-frame to determine the duration of ground contact.

- Measurement Mechanism:

Contact Time=Number of Frames ÷ Frame Rate (frames per second)

Standards: The shorter the time, the superior the neuromuscular efficiency.

5. Knee Joint Angle

Tool: Motion Analysis Software (Kinovea)

6. Electromyography (EMG)

Tool: Surface EMG device (Noraxon)

Method of performance: The target muscles are chosen, which are the rectus femoris and the hamstring. Then, the skin is prepared by cleaning it with an alcoholic solution to remove oils and dead cells, and hair is removed if it is available to ensure good contact between the electrode and the skin. The NORAXON standards should be applied to accurately determine the position of the electrodes. Then, the electrodes suggested by the manufacturer are fixed on the indicated anatomical areas. The electrical signal is recorded during complete muscle rest (usually 3–5 seconds) to establish the baseline. The player is asked to perform a maximum voluntary isometric contraction (MVIC) against a fixed resistance for 5 seconds. The signal is recorded during this effort, with the attempt repeated 3 times with a rest interval (60–90 seconds). The dynamic signal is also recorded during athletic performance after measuring MVIC. EMG is recorded during the execution of the motor skill (such as jumping or landing).

7. RPE Scale

Tool: Borg CR-10 Scale

Method of performance: The player determines the level of effort 30 minutes after the training session. Measurement mechanism: RPE × training duration in minutes.

Standards: 0–2 Light, 3–5 Moderate, 6–8 High, 9–10 Maximum Effort.

Field procedures

The preparatory phase ensured a controlled environment through ethical approvals, informed consent, equipment calibration (Force Plate, EMG, HR monitors), and coordination with coaches. Baseline data (HRmax, MVIC, GRF) were collected. Players were trained on RPE usage. The five-day phase enhanced accuracy, participant readiness, and measurement reliability.

Results

Table 3 presents the descriptive statistics of the biomechanical and physiological training load variables, providing an overview of central tendency and variability across the study sample.

Table 3. Descriptive Statistics of Biomechanical and Physiological Training Load Variables

Player	Traditional-TRIMP	TRIMP-BIO	GRF (N)	EMG (mV)	Contact Time (ms)	Knee Angle (°)
1	99.97	95.34	1998.5	0.826	236.0	48.7
2	93.62	112.13	2191.8	0.681	250.1	58.4
3	101.48	101.39	2254.6	0.805	287.2	51.6
4	110.23	104.79	2239.7	0.845	244.4	60.8
5	92.66	101.38	1974.1	0.923	246.4	52.5
6	92.66	128.38	2053.6	0.784	238.1	67.3
7	110.79	107.85	2149.7	0.763	192.0	53.3
8	102.67	96.37	2246.3	0.785	239.3	56.1
9	90.31	117.05	2028.1	0.884	241.5	62.9
10	100.43	94.57	2072.2	0.843	301.6	50.6
11	90.37	110.3	1934.0	0.783	235.2	59.4
12	90.34	86.44	1920.6	0.856	247.5	65.8
13	97.42	93.39	2221.9	0.827	239.1	48.4
14	75.87	110.17	2303.4	0.888	210.8	59.1
15	77.75	116.12	2089.2	0.771	268.6	59.6
16	89.38	109.89	2250.5	0.797	258.8	62.7
17	84.87	106.73	2154.2	0.793	259.8	50.6
18	98.14	104.69	2003.2	0.718	217.3	50.1
19	85.92	91.74	2154.2	0.841	275.1	61.1

20	80.88	100.08	2330.7	0.838	205.0	59.8
21	109.66	102.93	2094.6	0.82	254.7	59.5
22	92.74	119.63	2334.7	0.804	294.8	60.1
23	95.68	111.78	1707.0	0.721	215.2	53.9
24	80.75	88.61	2223.3	0.791	225.8	59.4
25	89.56	111.56	2113.1	0.796	242.5	59.8
26	96.11	103.76	2055.1	0.764	227.4	53.7

Table 4. Comparison of Training Load Estimates Derived from Traditional TRIMP and TRIMP-BIO Models

Variable	Mean	Standard deviation	Minimum value	Maximum value
Traditional TRIMP	93.47	9.39	75.87	110.79
TRIMP-BIO	104.89	10.03	86.44	128.38

Table (4) compares TRIMP and TRIMP-BIO training loads, showing a higher mean (104.89 vs. 93.47) and standard deviation in the hybrid model, indicating improved sensitivity to individual differences by integrating biomechanical data like EMG and GRF supporting findings by Impellizzeri et al. (2005) and Manzi et al. (2009) on the limitations of heart rate-based models in complex sports like basketball.

Paired Samples T-Test Results

Table (5) below displays the results of the paired samples T-test, conducted to compare the average training load as calculated by the traditional TRIMP model versus the hybrid TRIMP-BIO model. This test was aimed to confirm the study's first hypothesis:

Table 5. Paired-Samples t-Test Comparing Training Load Estimates between Traditional TRIMP and TRIMP-BIO Models

1st variable	2nd variable	Mean of 1st variable	Mean of 2nd variable	t-value	p-value
Traditional TRIMP	TRIMP-BIO	93.4715	104.8873	-4.0329	0.0005

The T-test showed TRIMP-BIO significantly outperforms traditional TRIMP in estimating load, confirming that integrating biomechanical and cardiac data offers a more accurate reflection of training demands and stress. Correlation Test Results Between TRIMP-BIO and Biomechanical Indicators

Table 6. Correlation Analysis between TRIMP-BIO and Selected Biomechanical Indicators

Variable	Correlation Coefficient (r)
GRF (N)	0.6153
EMG (mV)	0.4231
Contact Time(ms)	0.3618
Knee Angel (°)	0.2847

Table (6) shows significant correlations between TRIMP-BIO and biomechanical indicators. GRF had the strongest correlation (r = 0.6153), supporting Markovic & Mikulic (2010). EMG showed a moderate correlation (r = 0.4231), aligning with De Luca (1997). Knee angle and contact time had weaker correlations (r = 0.3618, r = 0.2847), indicating limited influence on load estimation.

Discussion

The present study examined whether integrating biomechanical indicators into a traditional heart-rate–based training load model enhances the sensitivity of load quantification in elite basketball players. The main findings were that (i) the hybrid TRIMP-BIO model produced higher training-load estimates and greater dispersion than the traditional TRIMP approach (Table 4) and (ii) the difference between the two models was statistically significant (Table 5). Collectively, these outcomes support the premise that basketball training load is multidimensional and cannot be fully represented by cardiovascular strain alone. This interpretation aligns with contemporary consensus that training-load monitoring should integrate multiple sources of information rather than rely on a single internal load surrogate (Ismaeel, S. A., et. al 2025).

A key contribution of this work is that the hybridization approach is theoretically consistent with the load-adaptation framework that separates physiological and biomechanical pathways. Basketball sessions often contain short, high-force actions such as landings, cutting, and rapid decelerations, where mechanical tissue stress can be substantial despite transient or delayed heart-rate responses. Thus, a TRIMP-only index may underestimate meaningful between-player differences when the mechanical profile of training varies (e.g., different exposure to jump-landing volume, contact intensity, and neuromuscular demands) (Hamid, J. A. K., et, al. 2025). This mismatch between internal and external measures has been repeatedly reported in basketball contexts, reinforcing the argument that internal and external indicators may not be strongly aligned under intermittent, high-intensity conditions.

The correlational outcomes further clarify why TRIMP-BIO differed from TRIMP. Ground reaction force (GRF) showed the strongest association with TRIMP-BIO (Table 6), suggesting that impact magnitude during landing and direction-change actions is a major driver of the hybrid load signal. GRF is strongly linked to lower-limb loading and landing mechanics, which are known to influence tissue-level stress and injury-related biomechanical patterns in court sports. Therefore, including GRF likely increases the construct coverage of the training-load estimate in basketball by capturing high-impact exposures that are weakly represented by heart rate. In parallel, EMG-related contributions indicate that neuromuscular activation and fatigue-related modulation provide additional information beyond cardiovascular strain, which is consistent with the broader basketball monitoring literature emphasizing that mechanical and neuromuscular metrics provide a complementary layer of interpretation (Qadoori, R. H., et. al 2025).

Notably, the regression results (as summarized in this study) suggest that biomechanical indicators jointly explain meaningful variance in training load and that knee joint angle emerged as a prominent predictor. This is an important applied insight because knee kinematics during landings are not only performance-relevant but also mechanistically related to the distribution of joint loading. Monitoring knee-angle patterns alongside GRF and contact time may help practitioners distinguish between “similar” internal load sessions that nevertheless differ in mechanical risk profile. Such multidimensional interpretation is aligned with recent basketball-specific work calling for identifying reference variables that best represent each type of load and for establishing practical criteria to integrate internal and external monitoring systems (Safaa, A., & Hashim Fenjan, F. 2022).

From a practical standpoint, the findings support the use of TRIMP-BIO as a more sensitive load-monitoring tool for elite basketball compared with TRIMP alone. Coaches may benefit from using TRIMP-BIO to detect inter-individual differences in exposure to impact-dominant training content, inform recovery decisions, and refine microcycle planning. This applied direction is consistent with the growing interest in basketball load-monitoring methods that jointly use low-cost and field-feasible tools (e.g., HR-based indices with subjective and task-based indicators), as well as recent Retos contributions proposing daily internal load indices and systematic monitoring approaches in basketball. In addition, prior Retos research has emphasized that internal and external load characteristics can vary by game format and competitive context, which further strengthens the rationale for adopting integrative models when interpreting basketball training demands (Hashim, H., et. al 2025).

Despite these contributions, several limitations should be acknowledged. First, the TRIMP-BIO structure used an additive hybrid formulation and the weighting coefficients were derived empirically; therefore, generalization of the specific weights may require replication across teams, seasons, and training phases. Second, although the sample size reflects an elite cohort, future work should validate the model in larger samples and examine whether TRIMP-BIO improves prediction of performance changes, fatigue markers, or injury outcomes compared with TRIMP alone. Finally, expanding the hybrid framework to include additional external-load metrics (e.g., accelerometry-based load, jump count, deceleration density) may further improve sensitivity while preserving practical feasibility. Recent syntheses and empirical studies in basketball highlight the need to establish common criteria and reference variables for internal and external load monitoring, which provides a clear roadmap for subsequent validation studies.

Conclusions

The present study demonstrates that integrating biomechanical indicators into a traditional heart-rate–based training load model enhances the sensitivity and interpretability of training load monitoring in elite basketball players. The hybrid TRIMP-BIO model produced significantly higher and more dispersed training load estimates than the conventional TRIMP approach, indicating an improved ability to capture inter-individual differences in exposure to training stress.

The findings confirm that basketball training load is multidimensional and cannot be fully represented by cardiovascular strain alone. Biomechanical variables, particularly ground reaction force, contributed substantially to the hybrid load index, highlighting the importance of impact-related mechanical stress during jumping, landing, and direction-change actions. Electromyographic activity and ground contact time further enriched the load profile by reflecting neuromuscular demands that are weakly coupled to heart-rate dynamics.

From an applied perspective, the results support the use of TRIMP-BIO as a more comprehensive and sport-specific monitoring tool compared with traditional TRIMP. By integrating internal physiological responses with external mechanical and neuromuscular indicators, the hybrid model provides a more accurate representation of basketball-specific training demands. This approach may assist coaches and practitioners in optimizing training prescription, managing recovery, and identifying potentially harmful loading patterns that are not evident through cardiovascular measures alone.

Overall, the study reinforces the value of multidimensional training load monitoring and suggests that biomechanically informed extensions of existing models can improve decision-making in high-impact team sports such as basketball.

Acknowledgements

The authors would like to express their sincere appreciation to all the basketball players who voluntarily participated in this study and demonstrated full commitment throughout the data collection process. Special thanks are extended to the coaching and technical staff for their cooperation and assistance in facilitating the training sessions and measurement procedures. The authors also acknowledge the support provided by the College of Physical Education and Sports Sciences at the University of Diyala for granting access to laboratory facilities and measurement equipment. No external funding was received for the conduct of this research.

Financing

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. All procedures and data collection were conducted without external financial support.

References

Arboix-Alió, J., Puigdellívol, J., Reina, M., & Vázquez-Guerrero, J. (2024). Ground reaction forces, asymmetries, and performance of change-of-direction tests in elite female basketball players. Journal of Sports Sciences, 42(4), 353–362. https://doi.org/10.1080/02640414.2023.2293668

Bourdon, P. C., Cardinale, M., Murray, A., Gastin, P., Kellmann, M., Varley, M. C., & Cable, N. T. (2017). Monitoring athlete training loads: Consensus statement. *International Journal of Sports Physiology and Performance, 12*(Suppl 2), S2-161–S2-170. https://doi.org/10.1123/IJSPP.2017-0208

Buchheit, M. (2014). Monitoring training status with HR measures: Do all roads lead to Rome? *Frontiers in Physiology, 5*, 73. https://doi.org/10.3389/fphys.2014.00073

Capdevila, L., et al. (2024). Non-invasive HRV protocol and new index to assess internal load in basketball. *Retos, 54*. https://doi.org/10.47197/retos.v54.102596

De Luca, C. J. (1997). The use of surface electromyography in biomechanics. *Journal of Applied Biomechanics, 13*(2), 135–163.

Foster, C., Rodriguez-Marroyo, J. A., & de Koning, J. J. (2017). Monitoring training loads: The past, the present, and the future. *International Journal of Sports Physiology and Performance, 12*(Suppl 2), S2-2–S2-8.

Fox, J. L., Scanlan, A. T., & Stanton, R. (2017). A review of player monitoring approaches in basketball: Current trends and future directions. *Journal of Strength and Conditioning Research, 31*(7), 2021–2029. https://doi.org/10.1519/JSC.0000000000001964

Gamonales, J. M., et al. (2023). Analysis of the external and internal load in professional basketball players during the pre-season. *Sports, 11*(10), 195. https://doi.org/10.3390/sports11100195

Hamid, J. A. K., Salama, O. A. I., Sadiq, A. J., Zohear, A., Jasim, T. A., & Ismaeel, S. A. (2025). Three-dimensional quantitative analysis of kinematic variables in discus throwing performance. *Journal of Sport Biomechanics, 10*(4), 310–322. https://doi.org/10.21859/JSportBiomech.10.4.407.1

Hashim, H., Mohammed, S. A., Ali, B. M., Ismaeel, S. A., & Nasir, M. (2025). Biceps and triceps muscle activation under progressive loads: Functional symmetry of the upper limbs. *Journal of Sport Biomechanics, 11*(1), 64–78. https://doi.org/10.61186/JSportBiomech.11.1.64

Huang, W.-Y., Huang, H., & Wu, C.-E. (2024). Differences in the lateral and vertical jump performances of elite male basketball players—An axial stabilization training program. Applied Sciences, 14(11), Article 4832. https://doi.org/10.3390/app14114832

Impellizzeri, F. M., Rampinini, E., & Marcora, S. M. (2005). Physiological assessment of aerobic training in soccer. *Journal of Sports Sciences, 23*(6), 583–592. https://doi.org/10.1080/02640410400021278

Ismaeel, S. A., et al. (2025). Transformations in muscular mechanical properties and the impact of dynamic balance on free kick accuracy in elite football players. *Retos, 64*, 899–904.

Li, G., et al. (2024). The impact of internal and external loads on player performance: Evidence and implications for load monitoring. *Biology of Sport*.

López-Sierra, P., et al. (2025). A comprehensive analysis of internal and external load monitoring systems in basketball. *Scientific Reports, 15*, 25768. https://doi.org/10.1038/s41598-025-25768-w

Manzi, V., et al. (2009). Relation between individualized training impulses and performance. *Medicine & Science in Sports & Exercise, 41*(11), 2090–2096.

Markovic, G., & Mikulic, P. (2010). Neuro-musculoskeletal adaptations to plyometric training. *Sports Medicine, 40*(10), 859–895.

Molina, R., et al. (2024). Analysis of weekly internal and external load fluctuations in professional basketball. *Kinesiology, 56*(2). https://doi.org/10.26582/k.56.2.8

Reina, M., et al. (2020). Comparación de la carga interna y externa en competición oficial de 3 vs. 3 y 5 vs. 5 en baloncesto femenino. *Retos*.

Safaa, A., & Hashim Fenjan, F. (2022). Biomechanical analysis and EMG activity during the snatch lift. *International Journal of Psychosocial Rehabilitation*.

Scanlan, A. T., Tucker, P. S., Wen, N., & Dalbo, V. J. (2014). Relationships between internal and external training load models during basketball training. *Journal of Strength and Conditioning Research, 28*(9), 2397–2405. https://doi.org/10.1519/JSC.0000000000000458

Vanrenterghem, J., Nedergaard, N. J., Robinson, M. A., & Drust, B. (2017). Training load monitoring in team sports. *Sports Medicine, 47*(11), 2135–2142. https://doi.org/10.1007/s40279-017-0714-2

Authors' and translators' details:

Mohammad Jaafar Majeed	mohammadmajeed1990@gmail.com	Author
Rafid Habeb Qadori	rafid.habib@uodiyala.edu.iq	Author
Safaa A. Ismaeel	sc_safaaismaeel@uodiyala.edu.iq	Author