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A Biomathematical Clustering Framework for Classifying Neuromechanical Performance Profiles in Amateur Boxers

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ABSTRACT

Boxing effectiveness is strongly influenced by neuromuscular power generation and the efficient transmission of force through the lower extremities; however, traditional evaluation methods tend to assess these variables in isolation across athletes. A biomathematical clustering strategy provides a structured approach to extracting coherent performance patterns from complex, multidimensional biomechanical datasets. The present investigation proposes a biomathematical clustering model to categorise amateur boxers and quantify between-cluster variation, thereby facilitating tailored training interventions. A cohort of 30 amateur competitors underwent a series of standardised biomechanical tests, including Muscle Power (MP), reaction time (RT), rear-leg ground reaction force (GRF) relative to body mass, and maximal cross-punch (MCP) force output. Before analysis, all variables were rescaled through min–max normalisation. Unsupervised classification was executed via K-means clustering. The quality of clustering was assessed using indices of compactness and separation, specifically the Dunn Index and Davies–Bouldin Index. In contrast, the appropriate cluster count was determined using within-cluster sum of squares (WCSS) interpreted via the elbow method. Statistical procedures, including post hoc testing and effect size computation, were applied to evaluate intergroup differences. Additionally, principal component analysis (PCA) was utilised to project the data into a reduced-dimensional space for clearer visual interpretation of cluster distinctiveness. All computational procedures were implemented in Python. The analysis supported a three-cluster configuration. Cluster 3 (40%) exhibited superior performance characteristics, including elevated MP (7,700 ± 3,500 W), reduced RT (0.18 ± 0.03 s), and greater rear-leg GRF (1.55 ± 0.18 BW) relative to Cluster 2 ($p \leq 0.002$; d = 1.35–2.45). In contrast, Cluster 2 (46.7%) was characterised by diminished MP (4,000 ± 1,400 W) and prolonged RT (0.26 ± 0.07 s), whereas Cluster 1 (13.3%) showed moderate values across all measured variables. The biomathematical clustering framework successfully distinguishes discrete neuromechanical profiles among amateur boxers, thereby enabling cluster-specific training strategies and enhancing individual performance optimisation.

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1. Introduction

Boxing, categorised as a high-intensity combat sport, demands not only refined technical proficiency but also advanced physical and neuromuscular capacities. Success in the ring is contingent upon the athlete's ability to generate substantial force, exhibit rapid RT, and transmit force effectively through the lower extremities, while maintaining balance, coordination, and precision. The integration of these attributes is fundamental for producing rapid, forceful, and accurate punching actions.

Neuromechanical determinants, particularly MP, RT, and force transmission, play a pivotal role in shaping boxing performance. These components collectively influence movement efficiency, explosive capability, and punching effectiveness, thereby emphasising the necessity of evaluating them in an integrated manner rather than as isolated elements (Hausen et al., 2024). Traditionally, performance assessments in boxing have focused on discrete variables such as muscular strength, RT, or punch velocity. Although such measures provide useful insights, they fail to fully capture the

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complex interactions between neuromuscular and mechanical systems and may overlook critical performance-related patterns (Liu et al., 2025). Advancements in sports science have increasingly underscored the importance of analysing multidimensional performance datasets. By simultaneously examining multiple variables, researchers and practitioners can gain a more holistic understanding of athletes' capabilities, moving beyond the limitations of single-measure evaluations (Reis et al., 2024). Identifying patterns across diverse performance indicators enables the differentiation of athlete profiles, which can subsequently inform the design of individualised training programmes (Liu et al., 2022). Such profiling facilitates targeted interventions based on specific strengths and deficiencies, thereby enhancing both technical skill acquisition and physical conditioning (Jianjun et al., 2025).

The examination of neuromechanical characteristics using profiling approaches has deepened understanding of the interaction among power, speed, and force production in boxing. This perspective allows for clearer differentiation in athlete performance and supports the development of more precise coaching strategies (Kozin, Boychuk, et al., 2021). In this context, biomathematical clustering is an analytical technique that groups data based on shared characteristics, enabling the identification of patterns across multiple dimensions. Its application in boxing is particularly valuable, as it facilitates the classification of athletes according to combined neuromechanical attributes, including MP, RT, and force transmission (Van der Zwaard et al., 2019). Evaluating athlete performance across multiple dimensions provides the opportunity to detect meaningful patterns, compare distinct groups, and identify the variables that exert the greatest influence on performance outcomes. This approach enhances the understanding of how physical, mechanical, and neuromuscular factors interact to determine overall performance (Satılmış et al., 2023). Despite the rapid progression of sports analytics and performance monitoring, limited attention has been directed towards amateur boxing populations. Consequently, neuromechanical profiling remains underdeveloped at this level, highlighting the need for structured biomathematical clustering frameworks in amateur boxing research (Kozin, Falova, et al., 2021). Figure 1 illustrates the principal biomechanical and neuromechanical factors that underpin boxing performance.

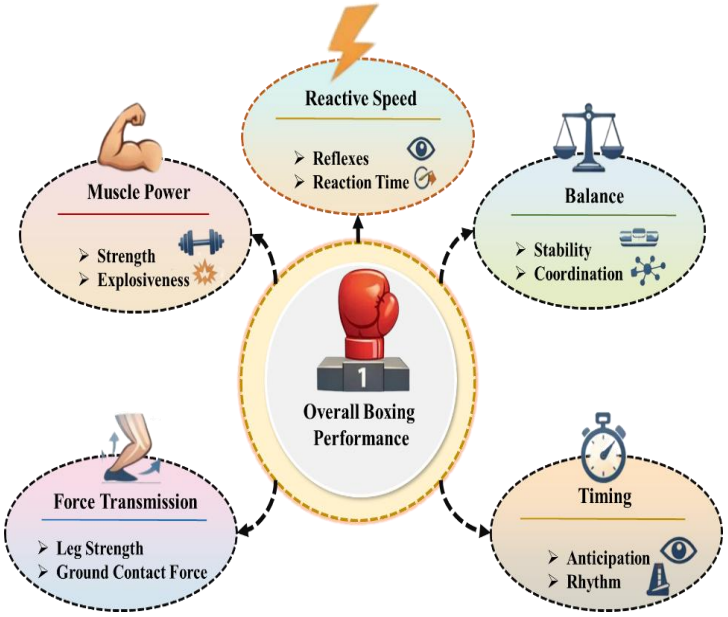


Figure 1: Key Factors Contributing to Overall Boxing Performance

1.1 Research Objective

The present study seeks to develop a biomathematical clustering framework to classify amateur boxers into distinct neuromechanical performance profiles by integrating multiple biomechanical variables. It further aims to determine the most appropriate cluster configuration using established validation metrics. In addition, the study evaluates inter-cluster variations to substantiate objective differentiation and to support the formulation of individualised training prescriptions.

1.2 Research Organization

Section 1 outlines the study's contextual foundation, including the research rationale, the identified gap, and the stated objectives. Section 2 examines key concepts related to athlete profiling and the biomechanical aspects of boxing performance. Section 3 details the methodological framework, encompassing data acquisition, normalisation procedures,

K-means clustering, cluster validation indices, PCA, and statistical analysis techniques. Section 4 reports the findings, with an emphasis on cluster outcomes and their respective characteristics. Section 5 interprets the results, addresses study limitations, draws conclusions, and highlights practical implications.

2. Literature Review

The study examines a range of determinants influencing punching performance in boxers, including fatigue, anthropometric characteristics, plyometric training, and neuromuscular conditioning. Table 1 summarises the principal findings of the reviewed studies, along with their methodological approaches and identified limitations.

Table 1: Summary of Key Studies on Punch Performance in Boxers

Reference	Data	Objective	Method	Key Findings	Limitations
Stewart et al. (2025)	10 male amateur boxers	Investigate the role of leg force in punching during fatigue	Dual force plates and boxing force sensor	Rate of Force Development (RFD) observed pre-fatigue; fatigue reduced punch effectiveness, especially for weaker punches	Not all punch types showed the same compensatory RFD response
Pinto et al. (2025)	69 boxers	Study the role of anthropometric measurements and muscle performance tests in punch impact	Anthropometric measurements and muscle performance tests	Body Height (BH) and Arm Span (AS) had the strongest predictive power on punch impact; Body Mass (BM) was less influential	Cross-sectional, absence of fatigue or dynamic performance examination
Venckunas et al. (2024)	12 elite male Olympian boxers	Examine anaerobic performance indices with HR and lactate	Maximal tests (punching bags, uphill treadmills, cycling/arm cranking)	Weak relationships between anaerobic performance variables; HRpeak correlated across tests, not lactate	Small sample size
Finlay et al. (2024)	10 high-level male amateur boxers	Examine acute neuromuscular performance and punch force	Isometric (ISO), elastic resistance (ER), and control conditioning exercises	ER and ISO exercises raised punch force, with ISO being the most effective; responses varied by individual	Lack of generalisation
Chottidao et al. (2022)	24 high school amateur boxers	Test the impact of lower extremity performance on punch performance	Plyometric and jump rope programs (30 min, 3 days/week)	Both programs enhanced RFD, punch RT, jab velocity, and rear-leg GRF	Adolescent sample, short intervention, no retention follow-up
Yi et al. (2022)	10 amateur boxers	Evaluate changes in Countermovement Jump (CMJ) and rear-hand punch performance post-exercise	Ballistic (squat jumps) and heavy-resistance exercises	Punching force and speed increased 9 minutes post-exercise, but CMJ did not vary significantly	Short-term follow-up, no long-term training effect
Söyler et al. (2025)	20 male professional boxers	Investigate the effect of punch velocity and fitness	Plyometric Stair Jump exercises (8 weeks)	Rear-Arm (RA) punch velocity correlated with submaximal bench press	Lack of left-arm predictive exercises, temporary intervention
Manoharan et al. (2025)	Wearable sensor data	Develop a multimodal system for punch classification	Wearable sensors and video measures with Query-by-Committee active learning	System classified punches with 91–95% accuracy with minimal labelled data	Dependent on sensor/video quality, may perform poorly in uncontrolled environments
Liu et al. (2025)	16 boxers (elite vs. junior)	Assess the performance of punches and lower-extremity performance	Vicon 3D motion capture	Greater punch velocity, force, impulse, and RFD in elite boxers, especially in the lead leg	Focus on only lead straight punches

Although prior research has generated valuable insights into punching biomechanics, the effects of fatigue, and training-related adaptations in boxing, much of this work has focused on isolated performance variables. Such approaches are often constrained by small sample sizes or short-term cross-sectional designs and rarely incorporate multidimensional unsupervised clustering techniques for integrated neuromechanical profiling.

To address these shortcomings, the present study implements a biomathematical clustering framework that integrates RT, rear-leg GRF, MP, and MCP force. This multidimensional approach facilitates the objective classification of amateur boxers into distinct neuromechanical performance profiles, thereby supporting evidence-based and individualised training prescriptions.

3. Materials and Methods

This section outlines the procedures for data preparation, the standardised biomechanical testing protocols, and the criteria applied for participant selection. It further explains the process for identifying neuromechanical performance profiles using min–max normalisation and K-means clustering. Statistical analysis, together with PCA, is employed to assess inter-cluster differences and to visualise the degree of cluster separability. Figure 2 presents a stepwise representation of the biomathematical clustering process applied to amateur boxers.

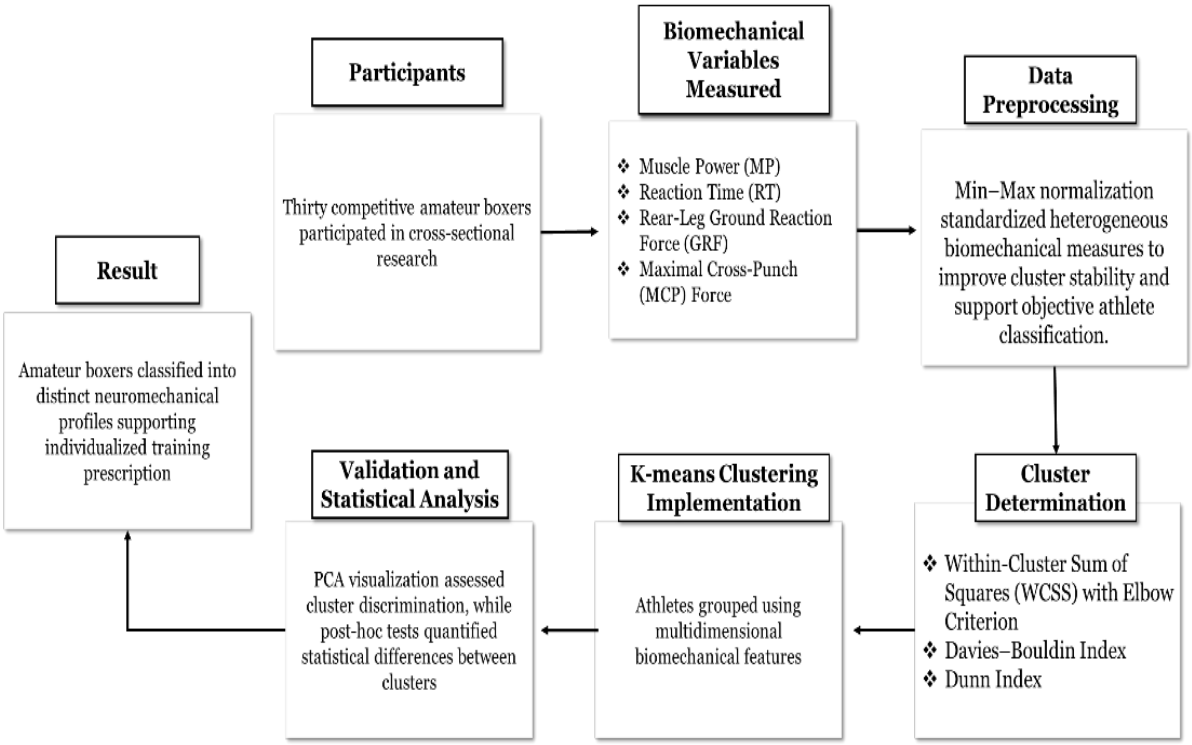


Figure 2: Methodological Framework for Neuro-Mechanical Performance Profiling

3.1 Participants

This cross-sectional investigation included 30 amateur boxers aged between 19 and 32 years, each with at least 2 years of competitive experience. Based on the outcomes derived from unsupervised machine learning procedures, participants were categorised into three groups: Cluster 1 (C1) (n = 4, 13.3%), Cluster 2 (C2) (n = 14, 46.7%), and Cluster 3 (C3) (n = 12, 40%). The allocation of athletes to these clusters reflects underlying variation in their biomechanical performance profiles, as identified through K-means clustering. All participants completed a series of biomechanical assessments designed to capture key neuromechanical performance indicators, including MP output, RT, rear-leg GRF, and MCP. These variables were selected for their critical relevance to evaluating boxing performance, particularly force production, movement speed, and the efficiency of force transfer.

3.2 Biomechanical Assessments

Biomechanical measurements were obtained following the completion of standardised training programmes. Participants were instructed to refrain from strenuous physical activity for at least 24 hours before testing to minimise residual fatigue and ensure an accurate baseline performance. Four post-intervention variables, selected for their biomechanical relevance to boxing, were included in the K-means clustering analysis:

- MP (Watts): Peak jump power assessed via the CMJ, reflecting the explosive capacity of the lower limbs, which is essential for generating force during punching actions.
- RT (Seconds): The interval between a visual stimulus and the initiation of movement, representing sensorimotor processing speed required for rapid and effective boxing responses.
- Rear-Leg GRF: The maximal ground reaction force generated by the rear leg, indicative of force transmission during a maximal cross-punch and contributing to overall punching power.

- MCP Force (Newtons): The peak force produced during a maximal cross-punch, representing the ultimate delivery of power to the target, and serving as a critical performance metric in boxing.

3.3 Min-Max Normalization for Standardizing Biomechanical Data and Enhancing Clustering Accuracy

Min–max normalisation was applied to the raw biomechanical variables, including MP, RT, rear-leg GRF, and MCP, to enable valid performance profiling of amateur boxers. Variations in measurement units, testing conditions, and individual differences can produce disparate magnitudes across variables, such as MP in watts and RT in seconds. Using non-scaled data can disproportionately influence cluster formation and obscure critical inter-variable relationships when processed directly. Min–max normalisation rescales each variable to a defined range of 0 to 1, preserving the temporal dynamics and relative variability of the biomechanical responses while ensuring consistency across all measurements. This uniform feature scaling is essential for stabilising the K-means clustering process and allows for meaningful differentiation between athlete profiles. Additionally, it guarantees that all variables contribute equally to the Euclidean distance metric used in clustering, preventing any single feature from dominating the analysis. Each feature in the set of biomechanical attributes is normalised according to equation (1):

$$u' = \frac{u - \min(B)}{\max(B) - \min(B)} \times (\text{new_max}_B - \text{new_min}_B) + \text{new_min}_B \quad (1)$$

Where u' denotes the normalized feature value, u represents the original biomechanical data point, and $\max(B)$, $\min(B)$ corresponds to the maximum and minimum values of feature B, respectively. The parameters new_max_B and new_min_B define the target normalization range, which is set to [0, 1]. Min–max normalisation enables more precise delineation of distinct performance clusters by enhancing the stability of the clustering analysis, preserving consistent inter-feature relationships, and increasing the sensitivity of the K-means model to subtle variations in boxer performance through the uniform scaling of heterogeneous biomechanical features.

3.4 Determining the Optimal Number of Clusters

Multiple cluster validity metrics, including the Elbow Criterion, Davies–Bouldin Index, and Dunn Index, were employed to determine the optimal number of clusters (L) for the K-means algorithm. These methods evaluate clustering quality by considering both cluster compactness and inter-cluster separation.

3.4.1 WCSS with Elbow Criterion

The Elbow Criterion utilises the WCSS to determine the optimal number of clusters. Its objective is to identify the point beyond which increasing the number of clusters yields only a minimal reduction in intra-cluster variance. The WCSS for each cluster count L is computed using equation (2):

$$WCSS = \sum_{l=1}^{L} \sum_{w_{jl} \in D_l} (w_{jl} - N_l)^2 \quad (2)$$

D_l refers to set point data in cluster l, N_l is the centroid, and w_{jl} is the $j^{\text{-th}}$ data point. The Elbow point is determined at the stage where further increases in the number of clusters result in only minimal reductions in WCSS.

3.4.2 Davies-Bouldin Index

This metric assesses both the separation and compactness of clusters by quantifying the ratio of between-cluster distance to within-cluster dispersion. Lower index values indicate more distinct and well-separated clusters, which is crucial for differentiating discrete neuromechanical profiles. It is expressed as equation (3):

$$DB = \frac{1}{L} \sum_{l=1}^{L} \max_{l' \neq l} \left(\frac{\sigma_l + \sigma_{l'}}{d(N_l, N_{l'})} \right) \quad (3)$$

Where σ_l represents the dispersion of cluster l, and $d(N_l, N_{l'})$ denotes the distance among the centroids of clusters l and l'.

3.4.3 Dunn Index

This index evaluates cluster separation by calculating the ratio between the largest intra-cluster diameter and the minimum inter-cluster distance. Higher values indicate more distinct and compact clusters, reflecting better-defined cluster boundaries. It is computed using equation (4):

$$DI = \frac{min_{l \neq l'}(d(N_l, N_{l'}))}{max_l(diameter\ (D_l))} \quad (4)$$

Here, $diameter\ (D_l)$ is the extreme distance within cluster l. Larger values of the Dunn Index indicate better separation between clusters, supporting the goal of accurately identifying distinct performance profiles.

3.5 K-Means Clustering

K-means clustering was applied to integrated measures of MP, RT, rear-leg GRF, and MCP to classify amateur boxers into distinct neuromechanical performance profiles, thereby supporting individualised training programmes. By clustering multidimensional biomechanical data, latent patterns and interrelationships among performance variables were revealed, enhancing the objectivity and interpretability of athlete profiling. This approach enabled the identification of boxer groups exhibiting similar neuromechanical characteristics, providing a foundation for evidence-based training prescriptions and performance optimisation.

Optimal clustering solutions were achieved using the K-means partitional algorithm, which minimises the sum of squared errors to determine cluster arrangements with the lowest cumulative within-cluster variance. Let the biomechanical dataset consist of M samples, each measured across m performance variables, thereby forming an m-dimensional feature space.

Step 1: Dataset Representation

Each boxer is represented by a feature vector as defined in equation (5):

$$w_j = (w_{j1}, w_{j1}, w_{j2}, \ldots, w_{jn}) \quad (5)$$

Where w_j denotes the feature vector of the j^{th} boxer, w_{jn} is the value of the n^{th} biomechanical variable for boxer j, n is the number of performance variables, and $j = 1,2,\ldots,N$.

Step 2: Determination of Cluster Number

The Elbow Criterion, Dunn Index, and Davies–Bouldin Index were employed to determine the optimal number of clusters, L, to ensure an appropriate balance between cluster compactness and separation.

Step 3: Initialization of Centroids

Initial cluster centroids $M_l(l = 1,2,\ldots,L)$ were randomly chosen from the dataset. Let D_l be the set of samples, and let m_l be the number of samples in cluster l, defined in equation (6):

$$\sum_{l=1}^{L} m_l = M \quad (6)$$

Where m_l denotes the numerical number of boxers, M represents the whole number of boxers in the dataset.

Step 4: Computation of Cluster Centroids

The centroid of cluster D_l was calculated as the mean of all feature vectors within the cluster, as expressed in equation (7):

$$N_l = \frac{1}{m_l} \sum_{j=1}^{m_l} w_{jl} \quad (7)$$

Where N_l denotes the centroid vector of cluster l, w_{jl} represents the feature vector of the j boxer, and m_l is the number of samples.

Step 5: Within Cluster Variation

The within-cluster variation for a given cluster was computed using equation (8). Where, f_l^2 is the within-cluster variance, w_{ji} denotes the boxer's observation vector, and N_l is the centroid. This measure represents the dispersion of samples around the cluster centroid.

$$f_l^2 = \sum_{j=1}^{m_l} (w_{ji} - N_l)^2 \quad (8)$$

Step 6: Total Within-Cluster Sum of Squares

The total clustering error across all clusters is defined by equation (9), where F^2 represents the total WCSS. The K-means algorithm seeks to minimise this value to achieve compact and internally homogeneous clusters.

$$F^2 = \sum_{l=1}^{L} f_l^2 \quad (9)$$

Step 7: Distance Measurement

The Euclidean distance between each boxer and cluster centroid was calculated by equation (10). Where $C(N_l - w_j)$ represents the distance between boxer j and centroid l, N_{lk} signifies the value of the k^{th} variable in centroid l, w_{jk} refers

to the k^{th} variable representing values under cluster, and m is the number of variables. Each boxer was assigned to the cluster whose centroid was closest.

$$C(N_l - w_j) = \sqrt{\sum_{k=1}^{m}(N_{lk} - w_{jk})^2} \quad (10)$$

Step 8: Iterative Optimization

Steps 3–7 were repeated iteratively until the clustering process converged, as indicated by no further changes in cluster membership or centroid positions. At this point, the algorithm had achieved a stable, locally optimal partitioning of the biomechanical data. Through continuous minimisation of within-cluster variance, the model generated compact and well-separated clusters, enhancing the clarity and reliability of athlete classification and supporting more precise, evidence-based training prescriptions.

3.6 PCA for Visualization of Cluster Separability

Following K-means clustering, PCA was applied to visualise the separability of clusters in a lower-dimensional space. PCA effectively reduces the dimensionality of the high-dimensional biomechanical dataset (MP, RT, rear-leg GRF, and MCP) while retaining the majority of its variance. This dimensionality reduction facilitates clearer visualisation of how effectively the K-means algorithm has distinguished clusters, thereby making the distribution and relationships among the various neuromechanical performance profiles more interpretable. To implement this, the correlation structure of the normalised biomechanical data (D) was computed using equation (11).

$$L_D = \frac{1}{p-1}(D - \overline{D})(D - \overline{D})^T \quad (11)$$

Where, D represents the original high-dimensional biomechanical data, $\overline{D}$ is the mean-adjusted feature matrix derived from the biomechanical measurements of all participants. p denotes the total number of participants. $(D - \overline{D})^T$ used in calculating the covariance matrix for identifying patterns and clustering boxers based on their performance characteristics. The eigenvalues and corresponding eigenvectors of the covariance matrix L_D were calculated to obtain the principal components. The two principal components accounting for the greatest proportion of variance were selected to reduce the data to two dimensions for visualisation. A scatter plot of these components (PC1 versus PC2) was generated, with each point representing a boxer and coloured according to the cluster assigned by the K-means analysis. This approach enabled visual assessment of cluster distinctiveness, confirming that boxers with similar neuromechanical performance characteristics were consistently grouped by the clustering algorithm.

3.7 Pairwise Post-hoc Comparisons

To identify significant differences between clusters, post hoc analyses were conducted on the biomechanical variables (MP, RT, rear-leg GRF, and MCP). Pairwise comparisons were performed to determine which clusters differed for each variable. The Honestly Significant Difference (HSD) was calculated for each comparison to assess statistically significant differences between cluster means, with the critical difference computed using equation (12).

$$HSD_{jk} = q_{\alpha,l.eg}\sqrt{\frac{MSE}{2}\left(\frac{1}{p_j} + \frac{1}{p_k}\right)} \quad (12)$$

HSD_{jk} refers to the Significant Difference between the means of clusters j and k, $q_{\alpha,l.eg}$ is the critical value from the studentized range distribution at the significance level α, with l clusters and eg degrees of freedom, MSE is the mean square error pooled across the clusters, and p_j and p_k are the sample sizes of clusters. A mean difference exceeding the HSD signifies a statistically significant distinction between clusters for the corresponding biomechanical variable, indicating which clusters exhibit the greatest performance responsiveness.

4. Results

This section identifies three distinct neuromechanical performance clusters, supported by validation metrics. Although punching force did not differ significantly across clusters, substantial variation was observed in MP, RT, and rear-leg GRF. All PCA, clustering, and validation analyses were conducted using Python.

4.1 Cluster Validation and Quality Metrics

The optimal number of clusters was determined using the Elbow Criterion and corroborated by validation metrics (Davies–Bouldin Index = 1.048; Dunn Index = 0.727). Table 2 summarises the distribution of participants across the three

clusters, with C1 representing the smallest group and C2 the largest. Although C1 included only four athletes, the distinct biomechanical characteristics of these individuals justify their classification as a separate cluster.

Table 2: Distribution of Participants Across Clusters

Cluster	Number of Participants (n)	Percentage (%)
C1	4	13.3%
C2	14	46.7%
C3	12	40.0%

PCA indicated that the first two principal components accounted for 74.5 percent of the total variance (PC1: 45.2 percent, PC2: 29.3 percent), representing a substantial reduction in dimensionality while preserving cluster discrimination. Figure 3 presents the PCA results for the three performance clusters (C1: Intermediate, C2: Moderate Power, C3: Speed-Power) based on the biomechanical variables.

The first two components capture 74.5 per cent of the variance, and the clusters are clearly separated, demonstrating distinct neuromechanical performance profiles. Stars indicate cluster centroids, and ellipses depict the distribution of each cluster.

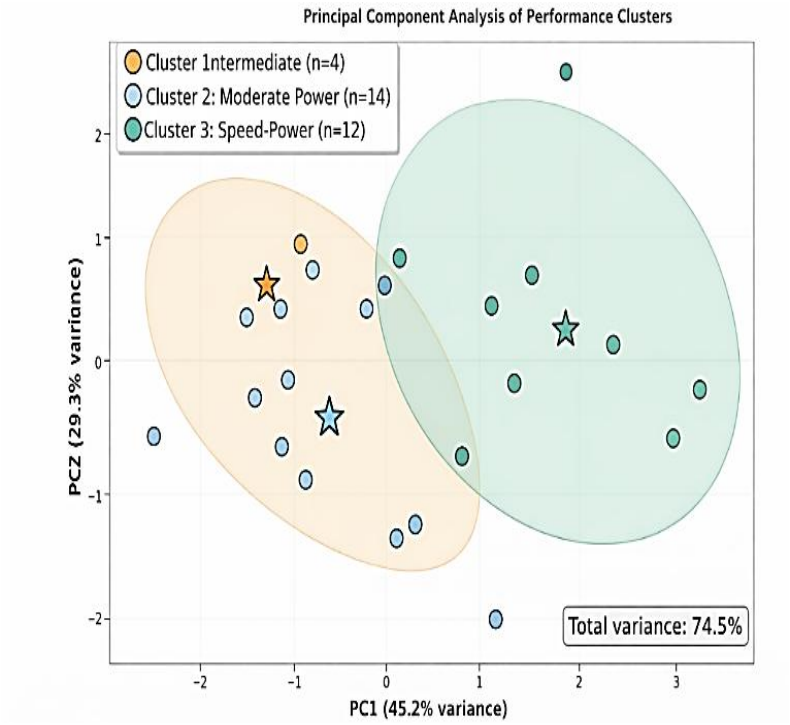


Figure 3: PCA of Performance Clusters in Amateur Boxers

4.2 Post-Hoc Pairwise Comparisons and Effect Sizes

Post-hoc pairwise comparisons were conducted for variables showing significant differences, as summarised in Table 3, which reports p-values and Cohen's d values to quantify the magnitude of differences between clusters. The effect size indicates the practical significance of these differences, with large or very large values reflecting meaningful distinctions between clusters.

Table 3 (a): Post-Hoc Pairwise Comparisons and Effect Sizes

Variable	Comparison	P-Value	Cohen's d	Effect Size
MP	C3 vs. C2	0.001	1.45	Very Large Effect
	C3 vs. C1	0.035	1.02	Large Effect
	C2 vs. C1	0.423	0.45	Medium Effect (NS)
RT	C3 vs. C2	0.002	1.35	Very Large Effect
	C3 vs. C1	0.120	0.80	Large Effect

Table 3 (b): Post-Hoc Pairwise Comparisons and Effect Sizes

Variable	Comparison	P-Value	Cohen's d	Effect Size
Rear Leg GRF	C2 vs. C1	0.263	0.67	Medium Effect (NS)
	C3 vs. C2	<0.001	2.45	Extremely Large Effect
	C3 vs. C1	0.004	2.18	Extremely Large Effect
MCP	C2 vs. C1	0.725	0.20	Negligible Effect (NS)
	C3 vs. C2	0.046	0.92	Large Effect
	C3 vs. C1	0.060	0.89	Large Effect
	C2 vs. C1	0.314	0.38	Small Effect (NS)

Figure 4 illustrates the Cohen's d effect sizes for pairwise comparisons of performance clusters (C3 vs. C2, C3 vs. C1, and C2 vs. C1) across the biomechanical variables. The effect sizes indicate the magnitude of neuromechanical differences between clusters, with larger values reflecting greater disparities. These results highlight the relative strengths and weaknesses of each cluster, providing a robust basis for designing individualised training programmes tailored to specific performance profiles.

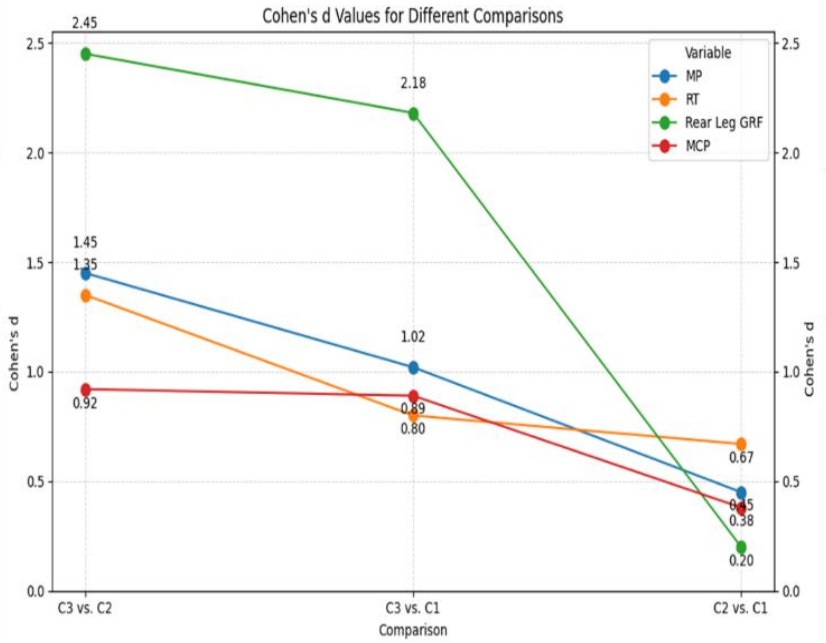


Figure 4: Cohen's d Values for Biomechanical Variable Comparisons

4.3 Percentage Difference Analysis

The extent of biomechanical variation was assessed using the percentage differences between cluster means. Table 4 presents the percentage differences for all key variables across clusters, enabling identification of the most pronounced performance disparities and quantification of the degree of biomechanical distinction between clusters.

Table 4: Percentage Difference Analysis

Variable	Comparison	Percentage Difference
MP	C3 vs. C2	+95.4%
	C3 vs. C1	+70.8%
	C1 vs. C2	+14.5%
RT	C3 vs. C2	-30.2%
	C3 vs. C1	-18.4%
	C1 vs. C2	-17.1%
Rear Leg GRF	C3 vs. C2	+28.7%
	C3 vs. C1	+32.8%
	C2 vs. C1	+3.3%
MCP	C3 vs. C2	+2.1%
	C3 vs. C1	+2.4%
	C2 vs. C1	-0.7%

Figure 5 illustrates the percentage changes in biomechanical variables between performance clusters. The plot highlights the extent of differences in neuromechanical characteristics, with the most pronounced variation observed in MP

between C3 and C1. These disparities support the classification of amateur boxers into distinct performance profiles and inform the design of targeted, individualised training programmes.

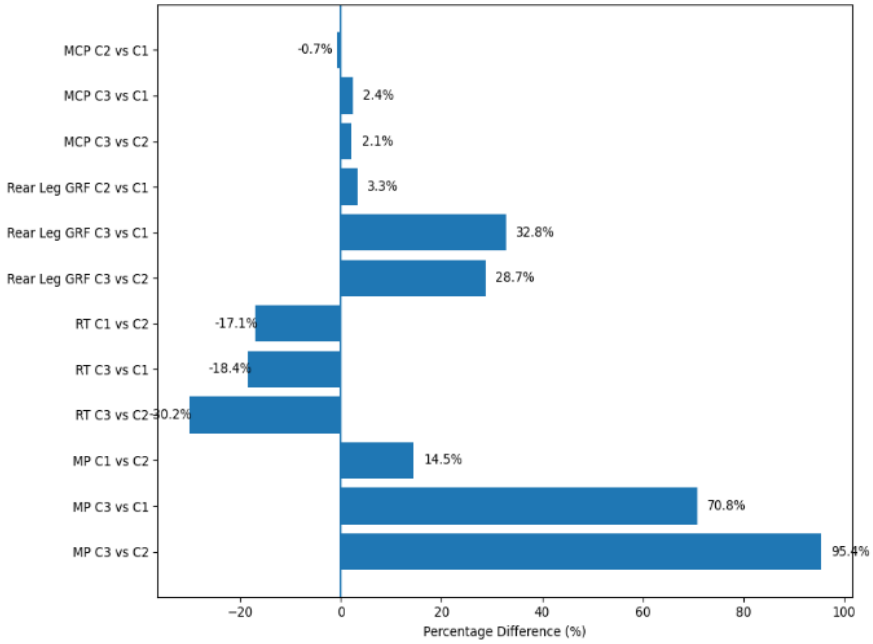


Figure 5: Percentage Differences in Biomechanical Variables Across Clusters

4.4 Cluster Characterization

The primary biomechanical variables defining the three clusters (C1, C2, and C3) are RT, MP, rear-leg GRF, and MCP. Table 5 provides a detailed description of each cluster, presenting the means and standard deviations of these variables. This information highlights the distinctive characteristics of each cluster and is essential for understanding the unique performance profiles of amateur boxers, thereby guiding the development of targeted training strategies.

Table 5: Cluster Characterization Based on Key Variables

Cluster	Profile Description	MP (W)	RT (s)	Rear Leg GRF (BW)	MCP (N)
C3	Speed-Power Profile	7,700±3,500	0.18±0.03	1.55±0.18	9.50±1.20
C2	Moderate Power Profile	4,000±1,400	0.26±0.07	1.18±0.14	9.60±1.15
C1	Intermediate Profile	4,450±1,550	0.23±0.05	1.13±0.11	9.90±0.80

5. Discussion

The present study proposes a biomathematical framework for classifying amateur boxers into distinct neuromechanical performance profiles. While prior sports performance profiling research has provided valuable insights, it has often been constrained by small sample sizes, cross-sectional designs, and the absence of long-term follow-ups. For instance, Stewart et al. (2025) and Pinto et al. (2025) highlighted limitations arising from small sample sizes, restricting the generalisability of findings. Similarly, Venckunas et al. (2024) and Finlay et al. (2024) noted the lack of long-term intervention evaluations, preventing conclusions regarding the enduring effects of training. Additionally, the cross-sectional nature of several studies limits their ability to establish causal relationships among performance variables and outcomes, as reported by Chottidao et al. (2022) and Yi et al. (2022). In contrast, the proposed framework overcomes these limitations by applying K-means clustering and PCA, offering a more data-driven and objective categorisation of athletes. This methodology not only addresses issues of sample size and design but also enables a deeper understanding of the diverse neuromechanical phenotypes in amateur boxers, facilitating the development of more individualised training programmes.

The approach provides a factual, objective means of assessing athletes' strengths and weaknesses through biomathematical clustering. Consequently, it can lead to more precise training interventions and improve performance analysis in sports science. An additional advantage is its potential to guide future research by extending similar methods to other sports. Moreover, this framework could be integrated into educational curricula, enabling students to learn advanced techniques for athlete profiling and performance optimisation. The study holds significant practical implications

for sports science and coaching. It allows the design of highly specific, custom training programmes aligned with the neuromechanical profiles of amateur boxers. Coaches can develop interventions tailored to each athlete's individual strengths and weaknesses, maximising training outcomes and performance improvements. This approach applies to other sports requiring coordinated physical and neuromechanical attributes, thereby providing a basis for more targeted and personalised athlete development.

Despite these advances, several limitations remain. Future research should aim to increase the sample size to include a more diverse population of boxers with varying levels of experience and training. Longitudinal studies are necessary to examine the effects of different training programmes on the identified performance profiles and to explore causal relationships among neuromechanical variables and boxing performance. Additionally, the use of advanced sensor technologies could enable more precise, real-time biomechanical measurements, enhancing the accuracy of clustering outcomes and the overall validity of the proposed framework.

6. Conclusion

Amateur boxers were classified according to their neuromechanical performance profiles, providing a framework to optimise training and performance outcomes. The results revealed significant differences between clusters across key biomechanical variables, including MP, RT, rear-leg GRF, and MCP force. Cluster C3 exhibited the highest MP (7,700 ± 3,500 W) and the shortest RT (0.18 ± 0.03 s), whereas C1 showed the lowest MP (4,450 ± 1,550 W) and the longest RT (0.23 ± 0.05 s). Substantial differences were observed in muscle power (95.4% between C3 and C2) and RT (30.2% between C3 and C2), emphasising the importance of profiling individual performance in sports. Despite these insights, several limitations must be acknowledged. The small sample size, particularly in C1 with only four participants, limits the generalisability of the findings. Additionally, the cross-sectional design precludes determination of causal relationships between training interventions and performance outcomes. The lack of long-term follow-up and fatigue assessments also prevents evaluation of the stability of performance profiles over time. Future research should aim to expand the sample size, incorporate longitudinal study designs, and include fatigue-related measurements to further refine and validate the identified performance profiles.

7. References

Chottidao, M., Kuo, C.-H., Tsai, S.-C., Hwang, I.-S., Lin, J.-J., & Tsai, Y.-S. (2022). A comparison of plyometric and jump rope training programs for improving punching performance in junior amateur boxers. *Frontiers in bioengineering and biotechnology*, *10*, 878527.

Finlay, M. J., Greig, M., Bridge, C. A., & Page, R. M. (2024). Post-activation performance enhancement of punch force and neuromuscular performance in amateur boxing: toward a more individualized and “Real-World” approach. *The Journal of Strength & Conditioning Research*, *38*(6), 1063-1071.

Hausen, M., Taylor, L., Bachini, F., Freire, R., Pereira, G., & Itaborahy, A. (2024). Physical capacities and combat performance characteristics of male and female Olympic boxers. *Research Quarterly for exercise and Sport*, *95*(4), 813-823.

Jianjun, Q., Isleem, H. F., Almoghayer, W. J., & Khishe, M. (2025). Predictive athlete performance modeling with machine learning and biometric data integration. *Scientific reports*, *15*(1), 16365.

Kozin, V. Y., Boychuk, Y. D., Skaliy, A., Zelenskiy, R., & Honcharenko, V. I. (2021). Individual factorial structure of biomechanical and psychophysiological indicators as a basis for determining the fighting style of qualified veteran boxers. *Health, sport, rehabilitation*, *7*(3), 8-30.

Kozin, V. Y., Falova, O. Y., Cretu, M., & Cieślicka, M. (2021). Determination of fighting styles of qualified veteran boxers based on cluster analysis of biomechanical and psychophysiological indicators. *Health, sport, rehabilitation*, *7*(4), 19-34.

Liu, P., Liu, Y., Hao, X., Cheng, N., Kang, J., Xiao, Z., He, P., & Yan, J. (2025). The impact of an 8-week integrated neuromuscular training on strength, speed, and agility in military personnel: a randomized controlled trial. *BMC Sports Science, Medicine and Rehabilitation*, *17*(1), 127.

Liu, Y., Zhu, Z., Chen, X., Deng, C., Ma, X., & Zhao, B. (2022). Biomechanics of the lead straight punch of different level boxers. *Frontiers in physiology*, *13*, 1015154.

Manoharan, S., Warburton, J., Hegde, R. S., Srinivasan, R., & Srinivasan, B. (2025). An active machine learning framework

for automatic boxing punch recognition and classification using upper limb kinematics. *PLoS One*, *20*(5), e0322490.

Pinto, M., Crisóstomo, J., Kirk, C., Abián-Vicén, J., & Monteiro, L. (2025). Influence of Anthropometric Characteristics and Muscle Performance on Punch Impact. *Sports*, *13*(8), 281.

Reis, F. J., Alaiti, R. K., Vallio, C. S., & Hespanhol, L. (2024). Artificial intelligence and Machine Learning approaches in sports: Concepts, applications, challenges, and future perspectives. *Brazilian journal of physical therapy*, *28*(3), 101083.

Satılmış, N., Söyler, M., & Kılınçarslan, G. (2023). Comparison of Anthropometric Characteristics and Biomotor Ability Variables of Athletes in Different Combat Sports. *The Online Journal of Recreation and Sports*, *12*(4), 829-837.

Söyler, M., Gürkan, A. C., Kayantaş, İ., Aydın, S., Karataş, B., Eraslan, M., Şahin, M., Küçük, H., Badau, A., & Badau, D. (2025). Investigation of the effects of different plyometric training protocols on punching force and muscle performance in male boxers. *Applied Sciences*, *15*(12), 6532.

Stewart, C., Cornett, R., Baker, J. S., Gu, Y., Dutheil, F., & Ugbolue, U. C. (2025). The Role of Lower Limb Kinetics in Boxing Punches and the Impact of Fatigue on Biomechanical Performance. *Bioengineering*, *12*(12), 1355.

Van der Zwaard, S., De Ruiter, C. J., Jaspers, R. T., & De Koning, J. J. (2019). Anthropometric clusters of competitive cyclists and their sprint and endurance performance. *Frontiers in physiology*, *10*, 1276.

Venckunas, T., Bruzas, V., Snieckus, A., Stasiule, L., Kniubaite, A., Mickevicius, M., Kamandulis, S., & Stasiulis, A. (2024). Anaerobic performance profiling in elite amateur boxers. *Sports*, *12*(9), 231.

Yi, W., Chen, C., Zhou, Z., Cui, W., & Wang, D. (2022). Acute effects of ballistic versus heavy-resistance exercises on countermovement jump and rear-hand straight punch performance in amateur boxers. *BMC Sports Science, Medicine and Rehabilitation*, *14*(1), 161.