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Training Stress, Sleep Behaviour, and Recovery Self-Regulation in Elite Female Boxers: A Behavioural Pattern Analysis Using Data-Driven Methods

Worrawit Rattanasateankij

Graduate School, Srinakharinwirot University, Bangkok, Thailand

Tanormsak Senakham

Department of Sports Science, Faculty of Physical Education, Sports and Health, Srinakharinwirot University, Thailand

Sirichet Punthipayanon

Department of Sports Science, Faculty of Physical Education, Sports and Health, Srinakharinwirot University, Thailand

Thailand Association of Mixed Martial Arts, Bangkok, Thailand University, Thailand.

Thidanuch Puttasimma

Department of Computer Science, Faculty of Science and Technology, Nakhon Ratchasima Rajabhat University, Nakhon Ratchasima, Thailand.

Nutcharee Senakham*

Department of Sports Science, Faculty of Physical Education, Sports and Health, Srinakharinwirot University, Thailand.

* Correspondence concerning this article should be addressed to Nutcharee Senakham, Faculty of Physical Education, Srinakharinwirot University, 63 Rangsit-Nakhonnayok, Ongkharak, Thailand.
Email: nutcharee@g.swu.ac.th

Elite boxing performance is significantly affected by training load, sleep habits, and the regulation of recovery; however, traditional monitoring approaches tend to assess these components separately and largely depend on subjective observations from coaches. Consequently, evaluating athlete readiness solely through movement analysis is insufficient, restricting both performance enhancement and the early detection of fatigue. This study investigates behavioural patterns indicative of readiness in elite female boxers and develops a data-driven classification framework that integrates physiological and behavioural metrics with boxing action execution. Data were obtained from competitive female boxers during the pre-competition phase. Training load was quantified, sleep was assessed using wearable-derived duration and efficiency measures, and recovery regulation was evaluated through standardised recovery questionnaires. Psychological dimensions, including competitive anxiety, self-confidence, team cohesion, and perception of opponents, were also recorded. A dataset containing 5,200 labelled boxing actions underwent pre-processing involving Gaussian noise filtering and feature normalisation. Principal Component Analysis (PCA) was employed to reduce data dimensionality while preserving critical structures. To capture behavioural patterns, a Dynamic Monarch Butterfly Optimized Attention-Vision AutoEncoder (DMBO-Att-VAE) was introduced, integrating behavioural and spatiotemporal motion features, followed by SoftMax classification with a train–test split. The DMBO-Att-VAE framework, implemented in Python, successfully fused behavioural and psychological metrics with spatiotemporal features, achieving a classification accuracy of 98.76% and an F1-score of 97.52%. This data-driven approach effectively identifies behavioural indicators of readiness, providing an interpretable tool to monitor performance and optimise training strategies in elite female boxing.

Keywords: Behavioural Pattern Analysis, Boxing Performance, Training Stress, Sleep Behaviour, Recovery Self-Regulation, Action Recognition, Athlete Monitoring

Introduction

Boxing is a combat sport in which two athletes compete using gloved hands under specific rules, comprising 3-minute bouts interspersed with 1-minute recovery intervals, and relying on oxidative, glycolytic, and phosphagen energy systems (Merlo et al., 2023). Historically, boxing has been dominated by men and is considered a pinnacle of strength in the Olympic Games. Nevertheless, some argue that by blurring traditional gender distinctions, the sport empowers female athletes (Mills & James, 2022). Prolonged exposure to high training stress can negatively affect boxers, increasing the likelihood of adverse psychological responses such as depression or resistance, particularly when athletes encounter internal discomfort, mood fluctuations, or unfamiliar and uncontrollable environments (Zhang et al., 2023).

Monitoring a boxer's functional status is therefore crucial to ensure effective training and competition readiness. Optimal physiological, psychological, and emotional preparedness directly influences training quality and performance outcomes (Korobeynikov et al., 2023). In boxing, competitors are classified according to weight categories, making body composition optimisation especially important for elite athletes. Both male and female professional boxers typically maintain low body fat percentages (Gligoroski et al., 2024). In addition, upper-body muscular strength — particularly of the chest and back — has been identified as an important determinant of punching performance in elite amateur boxers (Jangphonak et al., 2025). The integration of computer vision technologies into training programmes has allowed for more precise, individualised plans and provides athletes and coaches with valuable insights through video analysis (Manoharan et al., 2025). Boxers must rapidly alternate between offensive and defensive strategies, often within 402–405 milliseconds, emphasising the importance of visual acuity and sustained concentration (Xiao et al., 2025). The sport demands strong spatial awareness and rapid response to dynamic constraints. Success depends on predicting the opponent's swift offensive actions and managing the close proximity between fighters (Limballe et al., 2024). Beyond technical and tactical demands, equipment-related factors such as elastic hand wrapping have also been shown to enhance the magnitude and precision of punch impact in elite boxers (Punthipayanon et al., 2024).

Research Aim

This study aims to investigate behavioural patterns associated with readiness in elite female boxers by integrating training load, sleep habits, recovery self-regulation, and psychological factors with the execution of boxing movements. To enhance the monitoring of performance and the optimisation of training, these combined features are classified using the Dynamic Monarch Butterfly Optimized Attention-Vision AutoEncoder (DMBO-Att-VAE) framework.

The organisation of this study is as follows: Section 1 provides an introduction to the research; Section 2 offers a review of existing literature; Section 3 details the methodology employed; Section 4 presents the results; Section 5 discusses the implications of these findings; and Section 6 concludes the study and outlines potential directions for future research.

Related Works

Liu and Dastbaravardeh (2025) reported that a Deep Learning (DL) Sport Artificial Intelligence of Things (S-AIoT) model, which applied spatiotemporal attention to respiration, electrocardiogram (ECG), and heart rate signals, effectively classified sports activities and outperformed conventional baseline methods. Brindha et al. (2025) described boxing movements using Deep Convolutional Neural Networks (DCNNs) in combination with a wearable Inertial Measurement Unit (IMU). Their approach achieved higher accuracy and recall than alternative algorithms, enabling automated performance monitoring and adaptive training adjustments. In the context of combat sports biomechanics, Xue et al. (2025) investigated pressure sensors, including surface electromyography (sEMG) and IMUs, to analyse performance. Tsai et al. (2023) employed a hybrid Convolutional Neural Network (CNN) to examine frequency-domain Electroencephalography (EEG) brainwave data for predicting boxer performance.

While the algorithm successfully classified dynamic neural patterns, validation on larger athlete cohorts remains necessary. Loi and Moustakas (2025) simulated fatigue-induced joint torque variations using Physics-Informed Neural Networks (PINNs) coupled with a Three-Compartment Controller model to reproduce physiologically realistic movement. Afzal et al. (2025) examined the integration of Ground Reaction Forces (GRF), joint moments, and EMG during boxing via invisible video motion capture, highlighting the need for standardisation, machine learning development, and addressing challenges in coordination, validation, and data fusion.

Using IMU data, Jayakumar and Govindarajan (2025) identified six types of boxing punches through an enhanced multi-sensor fusion DCNN with sliding window pre-processing. Although the model improved efficiency and accuracy, performance may vary in larger datasets or real-match scenarios. Marquez (2025) proposed an Artificial Intelligence framework that combined IMUs with Random Forest (RF) and Support Vector Machine (SVM) algorithms to forecast boxers' fatigue and training loads, enabling a multi-objective training recommendation system with adequate predictive capability. Ozan et al. (2025), using a mixed-design repeated measures Analysis of Variance (ANOVA), found that morning High-Intensity Interval Training (HIIT) and Moderate-Intensity Continuous Training (MICT) sessions produced superior biochemical and recovery outcomes compared to evening sessions. Dalal and Rathore (2025) demonstrated via Pearson's correlation analysis that dynamic balance strongly predicted striking power and agility in elite boxers, indicating that enhanced balance contributes to improved striking performance and supports the inclusion of targeted balance training in boxing programmes.

Methodology

The Female Boxer Readiness Dataset was pre-processed using Z-score normalisation and Gaussian filtering, followed by PCA to extract the principal patterns. Subsequently, the DMBO-Att-VAE hybrid model, which integrates Attention mechanisms, VAE, and DMBO, was applied to enhance feature representation and accurately predict boxer readiness, as illustrated in Figure 1.

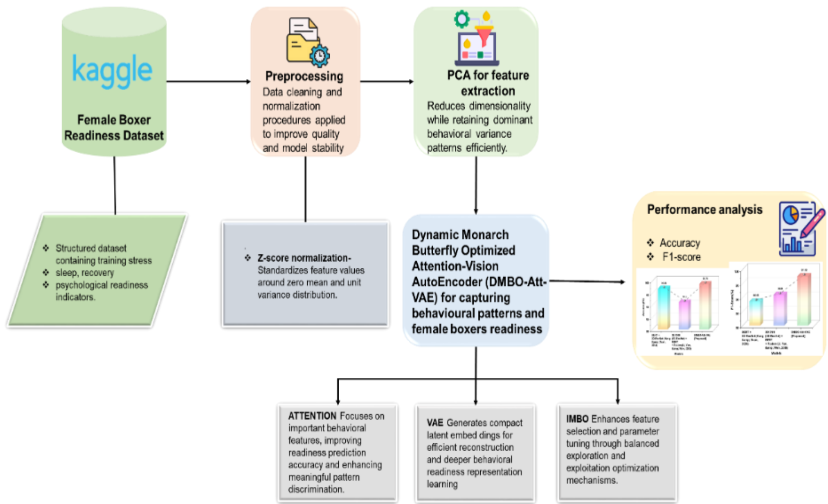

Figure 1: Methodology Design

Dataset

This dataset integrates training load, sleep habits, recovery self-regulation, and psychological factors to examine patterns of readiness in elite female boxers. It contains 5,200 pre-competition records from professional female athletes, including behavioural variables such as anxiety, self-confidence, recovery scores, sleep metrics, and indicators of training stress. This approach facilitates the identification of how these combined factors influence an athlete's readiness to perform. The dataset was partitioned into training and testing sets, comprising 80 percent and 20 percent of the data, respectively.

Z-Score-Based Feature Standardization in Pre-Processing

The pre-processing technique, Z-score normalisation, standardises pixel intensity values across boxing action frames while maintaining relative spatial relationships. This procedure enhances numerical stability during deep feature extraction by centring the data distribution around zero and scaling according to variance. The formal definition of normalisation is presented in Equation (1).

$$\mathrm{T}' = \frac{\mathrm{T}-\mathrm{min}_{\mathrm{A}}}{\mathrm{max}_{\mathrm{A}}-\mathrm{min}_{\mathrm{A}}}(\mathrm{new\_max}_{\mathrm{A}} - \mathrm{new\_min}_{\mathrm{A}}) \quad (1)$$

Where $\mathrm{max}_{\mathrm{A}}$ is the maximum value for the provided feature, T is the original value of the feature (e.g., pixel intensity, voltage, punch force, etc.), and T' is the new normalized value. $\mathrm{min}_{\mathrm{A}}$ is the minimal value for the provided characteristic, A. While $\mathrm{new\_max}_{\mathrm{A}}$ and $\mathrm{new\_min}_{\mathrm{A}}$ indicate the extreme and least values for the newly considered range A in the female readiness dataset.

Dimensionality Reduction Using Principal Component Analysis (PCA)

PCA serves as a dimensionality reduction technique that condenses the high-dimensional behavioural patterns observed in elite female boxers. The initial female boxer's readiness dataset $Z_{s\times t}$ is structured as a matrix consisting of s rows and t columns, shown in Equation (2).

$$Z_{s\times t} = \begin{pmatrix} x_{11} \cdots & x_{1t} \\ \vdots \quad \ddots & \vdots \\ x_{s1} \quad \cdots & x_{st} \end{pmatrix} \quad (2)$$

Prediction results can be substantially affected by considerable differences in the scale ranges of features such as sleep regulation and training load. The component $Z_{s\times t}$ is standardized to employ the better use of PCA and transformed into a standardized matrix $Z_{l,m}{}^{*}$ in a female boxer's readiness dataset, represented in Equation (3).

$$Z_{l,m}{}^{*} = \frac{Y_{l,m} - \mu_m}{\sigma_m}, l = 1,2, \dots, s; m = 1,2, \dots, t \quad (3)$$

The standardized value is denoted as $Z_{l,m}{}^{*}$, s denotes the number of observations (female boxers' readiness records). μ_m and σ_m are represent both the average and variance of the original data m. Equation (4) represents the effectiveness rate of each primary component (η).

$$\eta_k = \frac{\lambda_k}{\sum_{k=1}^{s} \lambda_k} \quad (4)$$

Where η_k is the effectiveness rate of the k-th major component, $\lambda_k$is the eigenvalue corresponding to the k-th principal component,$\sum^{s}_{\text{and } k=1} \lambda_k$ is the sum of all eigenvalues, representing the total variance across principal components.

Dynamic Monarch Butterfly Optimized Attention-Vision Autoencoder (DMBO-Att-VAE) for Capturing Behavioural Patterns and a Female Boxer's Readiness

The proposed hybrid approach integrates an Attention Mechanism to emphasise key features, a Vision AutoEncoder (VAE) to generate a compact latent representation, and Dynamic Monarch Butterfly Optimization (DMBO) to optimise parameters and features. This combination enhances classification accuracy, reconstruction efficiency, and overall model performance on the female boxers' dataset.

Attention Mechanism for Improved Player Performance

An attention mechanism is employed to enhance behavioural pattern classification by focusing on the most salient spatiotemporal motion features extracted from boxing action sequences. Let U be the number of frames or time steps, and let I be a matrix made up of feature vectors $[I_1, I_2, \dots I_U]$. These features are assigned weights through the attention mechanism, which emphasises the frames and behavioural cues most relevant to athlete readiness. To accentuate meaningful variations, the spatiotemporal and behavioural features are subjected to a nonlinear transformation before the attention calculation, as represented in Equation (5).

$N = \tanh(I)$ (5)

Where I is the feature matrix of spatiotemporal and behavioural (sleep behaviour, recovery self-regulation, and psychological characteristics) embeddings, N depicts the non-linearly transformed feature matrix emphasizing important variations, $tanh()$ denotes the hyperbolic tangent function for non-linear scaling. This stage enables the model to focus on critical movements and behavioural indicators that exert the greatest influence on performance, as illustrated in Equation (6).

$\alpha = softmax\ (x^U N)$ (6)

Where x^U is the trainable attention parameter vector, α denotes the attention weight vector (1 × T) indicating the importance of each frame/feature, $softmax()$depicts the normalized weights to sum to 1. To create a single representative vector, the feature vectors are combined using the attention weights. This provides an overview of the sequence's most illuminating behavioural and spatiotemporal patterns, represented in Equation (7).

$s = I\alpha^U$ (7)

Where α^U is the transposed attention weights vector, s denotes the weighted sum of feature vectors summarizing the sequence. The attention weights are employed to consolidate the feature vectors into a single composite vector, as shown in Equation (8).

$i^* = tanh(s)$ (8)

Where i^* is the final attentive representation used for boxers' readiness classification.

Vision-Based Autoencoder (VAE): Encodes Data into Compact Latent Representations for Efficient Reconstruction and Generation

VAE is employed to extract behavioural and spatiotemporal patterns from boxing action videos and physiological indicators. In the absence of labels, VAE learns latent embeddings that reflect different levels of readiness.

Masked Input: To ensure that the encoder focuses on critical motion and behavioural information, a portion of the behavioural patches is randomly masked, as illustrated in Equation (9).

$Y^* = n(Y)$ (9)

Where Y^* represents the visible patches after masking, and Y is the original boxing or motion volume, and $n(.)$ denotes the random masking function.

Reconstruction of Encoder-Decoder: MASK tokens were utilised to encode the visible patches and reconstruct the complete video sequence, including the masked regions, as illustrated in Equation (10).

$\hat{Y} = E(F(Y^*), MASKtokens)$ (10)

$E(\cdot)$is the encoder network that extracts latent spatiotemporal and behavioural embeddings from visible patches, $D(\cdot)$denotes the decoder network that reconstructs the full input volume from latent embeddings and MASK tokens, $MASKtokens$ represent the positional tokens representing the missing patches in Y^*, and $\hat{Y}$ represents the reconstructed player 3.

Loss of Pixel-Wise Reconstruction: The accuracy of the reconstruction is evaluated to preserve motion and behavioural features, including punch dynamics, footwork, and physiological as well as behavioural cues, as demonstrated in Equation (11).

$\boldsymbol{\mathcal{L}_{rec}} = \left\| Y - \hat{Y} \right\|_2$ (11)

$\boldsymbol{\mathcal{L}_{rec}}$ is the pixel-wise mean squared error loss between original and reconstructed data, Y represents the original data volume, and $\|.\|_2$ represents the $L2$ norm measuring the difference between original and reconstructed features.

The Function of Total Loss: Robust embeddings representing training load, sleep behaviour, and recovery patterns are learned through the integration of reconstruction, perceptual, edge, and contrastive loss functions, as depicted in Equation (12):

$\boldsymbol{\mathcal{L} = \mathcal{L}_{rec} + \lambda_1 \mathcal{L}_{per} + \lambda_2 \mathcal{L}_{edge} + \mathcal{L}_{CL}}$ (12)

L stands for VAE training's total loss, λ_1, λ_2 are the coefficients for perceptual and edge losses that are weighted to limit their influence on the overall loss, $\mathcal{L}_{per}$ denotes a feature-level perceptual consistency loss that preserves meaningful behavioural relationships within latent representations, $\mathcal{L}_{edge}$ denotes the edge loss that was calculated using 3D Sobel filters to retain punch trajectories and motion gradients, $\mathcal{L}_{CL}$ denotes that the robustness of behavioural pattern representations is increased by using contrastive loss to ensure consistency between embeddings from two randomly masked viewpoints, as illustrated in Figure 2.

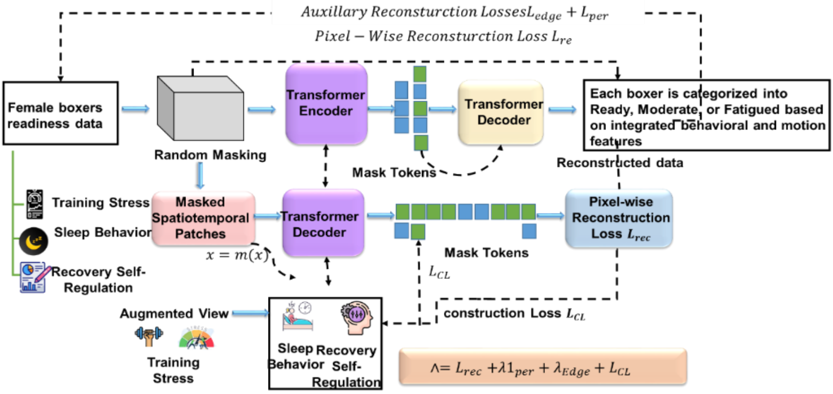

Figure 2: VAE Framework for Female Boxers' Readiness Assessment

Dynamic Monarch Butterfly Optimization (DMBO): Optimizes Parameters or Feature Selection for Faster and More Accurate Solutions

The spatiotemporal and behavioural feature embeddings within the DMBO-Att-VAE framework are optimised using the DMBO algorithm. By incorporating quasi-oppositional learning and chaotic local search, the approach balances exploration (identifying new regions) and exploitation (refining promising solutions), thereby enhancing search efficiency.

Step 1: Initialization

Considering attributes related to readiness, including training load, sleep behaviour, and recovery parameters of female boxers, the complete set of candidate solutions, OQ, is categorised into two groups, as illustrated in Equations (13) and (14).

$$OQ_1 = ceil\ (q \times OQ)\ (13)$$

$$OQ_2 = OQ - OQ_1\ (14)$$

Where OQ is the total number of candidate solutions (boxing actions, training stress, etc.), q denotes the exploration ratio, OQ_1 and OQ_2 are the exploration and exploitation-focused candidates, and $ceil$ () rounds up to the nearest integer.

Step 2: Improvements on Migration

To effectively explore and exploit the behavioural and motion feature space, two populations of monarch butterflies are maintained separately. The migration update is illustrated in Equation (15).

$$y_{j,l}^{u+1} = \begin{cases} y_{s1,l}^{u}, s \leq q \\ y_{s2,l}^{u},\ \ s > q \end{cases}\ (15)$$

Where $y_{j,l}^{u+1}$ is the updated value of feature l for butterfly j at iteration $u+1$, $y_{s1,l}^{u}$, and $y_{s2,l}^{u}$ denote the positions of randomly selected butterflies from exploration and exploitation groups, and s is the uniform random number [0,1] to select the migration source.

Step 3: Elite Substitute

The parent solution is substituted with the new candidate if it enhances the elite female boxer's performance; otherwise, a randomly selected exploratory individual is chosen. This process preserves high-quality information for classification, as indicated in Equation (16).

$$y_{j,l}^{u+1} = \begin{cases} y_{Best,l}^{u}, & if\ the\ trial\ solution\ improves\ fitness \\ y_{s3,l}^{u}, & otherwise \end{cases} \quad (16)$$

Where $y_{Best,l}^{u}$ is the best-performing feature l in the current population at iteration u, $y_{s3,l}^{u}$ represents a randomly selected butterfly, where the newly generated solution improves the player's performance.

Step 4: Levy Walk Butterfly Adjustment

Stochastic exploration is facilitated through a Levy flight step, preventing the algorithm from being trapped in local optima within the feature space of elite female boxers, as shown in Equations (17) and (18).

$$y_{j,l}^{u+1} = y_{j,l}^{u} + b.(ey_l - 0.5) \quad (17)$$

$$ey = Levy\left(y_j^u\right), \qquad b = \frac{tn}{2} \quad (18)$$

Where ey is the step size for feature l from the Levy distribution, $Levy\left(y_j^u\right)$ denotes the Levy flight function applied to butterfly j's current position, b is the weighting coefficient controlling the magnitude of female boxers' readiness features, and tn is the maximum step length for exploration.

Step 5: Anti-Oppositional Education

To enhance diversity in the search space and accelerate convergence, quasi-opposite solutions are generated. Equations (19) and (20) allow the model to explore previously unvisited regions.

$$OQ_j^{'} = M_j + V_j - OQ_j \quad (19)$$

$$OQ_j^{d} = rand\left(\frac{M_j+V_j}{2}, OQ_j^{'}\right) \quad (20)$$

Where OQ_j and $OQ_j^{'}$ are the current and updated candidate solutions, $M_j, V_j$are the minor and higher bounds of the search space for feature j, and OQ_j^{d} is the quasi-opposite candidate solution.

Step 6: The Unorganized Local Search employs chaotic perturbations to improve exploration of complex behavioural patterns in elite female boxers and to avoid premature convergence, as represented in Equation (21).

$$h_{o+1} = v.h_o.(1 - h_o), \quad y_{j,l}^{u+1} = y_{j,l}^{u} + t_{p,o,r}.(ey_l - 0.5) \ (21)$$

Where $h_o$is the chaotic sequence value at iteration o, h_{o+1} is the next value of the chaotic sequence, v denotes the chaotic map control parameter, $t_{p,o,r}$ represents the chaotic perturbation coefficient applied to feature update, and $y_{j,l}^{u}$ denotes the final updated feature value including chaotic adjustment, as illustrated in Figure 3.

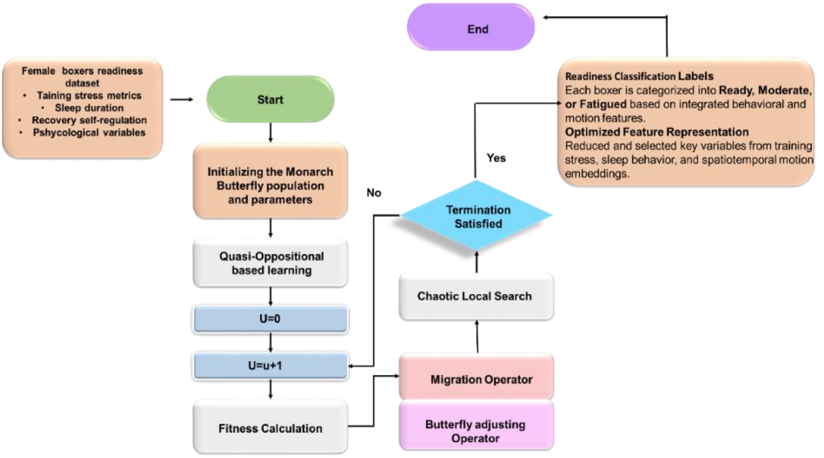

Figure 3: DMBO Flow

The proposed hybrid framework utilises DMBO for optimal feature selection, VAE for compact latent encoding, and the Attention Mechanism to prioritise the most significant features, thereby enhancing classification of structured boxing readiness data. Adaptive optimisation strategies are applied to mitigate overfitting and maintain model generalisation.

Result

The relationships among behavioural, physiological, and psychological readiness indicators were examined using a combination of statistical validations and multidimensional visual analytics through a comprehensive performance assessment. The study further benchmarks the proposed DMBO-Att-VAE framework against existing models to evaluate classification performance and reliability. All experiments were conducted using Python alongside TensorFlow and PyTorch deep learning libraries, with statistical analyses performed via Scikit-learn. Model training was executed on a desktop system equipped with an NVIDIA RTX-series GPU (24GB VRAM), an Intel i9 processor, and 64GB RAM, ensuring efficient optimisation and robust multimodal feature learning.

Multidimensional Data Visualization Analysis

Figure 4(a) shows predominantly weak linear correlations among the majority of features, exemplified by a negative correlation of 0.06 between the TRIMP score and self-confidence. This relative independence of variables enables the DMBO-Att-VAE framework to effectively capture diverse behavioural representations. Moreover, Figure 4(b) illustrates distinct separation between readiness groups based on features such as TRIMP score and sleep duration, with participants exhibiting high readiness reporting lower fatigue and higher self-confidence. Such variability enhances the DMBO-Att-VAE model's learning capability, producing high performance metrics of 98.76% classification accuracy and a 97.52% F1-score.

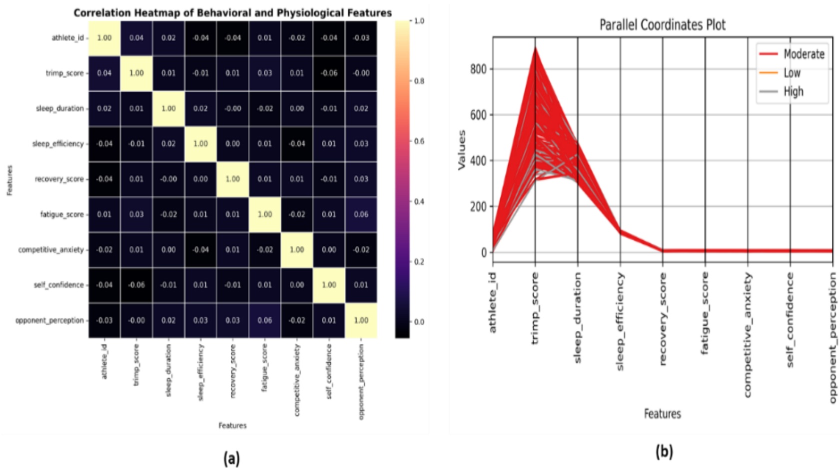

Figure 4: Behavioural and Physiological Pattern Analysis (a) Feature Correlation Heatmap Visualization and (b) Parallel Readiness Feature Distribution

Figure 5 depicts the relationship between training stress and sleep behaviour. Panel (a) presents TRIMP scores (ranging from 300 to 900) alongside sleep efficiency values (80–96%), revealing a nonlinear interaction associated with psychological variability. Figure 5(b) compares sleep efficiency across High, Moderate, and Low readiness groups, showing that athletes with high readiness predominantly achieve sleep efficiencies above 90%, whereas those with low readiness are more dispersed within the 80–88% range. The Dendrogram in Figure 5(c) identifies two principal behavioural clusters at a linkage distance of approximately 850. Recovery score distributions, as illustrated in Figure 5(d), exhibit moderate variability among athletes, highlighting generally stable recovery patterns with distinct peaks. These observations underscore the importance of recovery self-regulation in readiness modelling and contribute to the optimisation of the DMBO-Att-VAE framework.

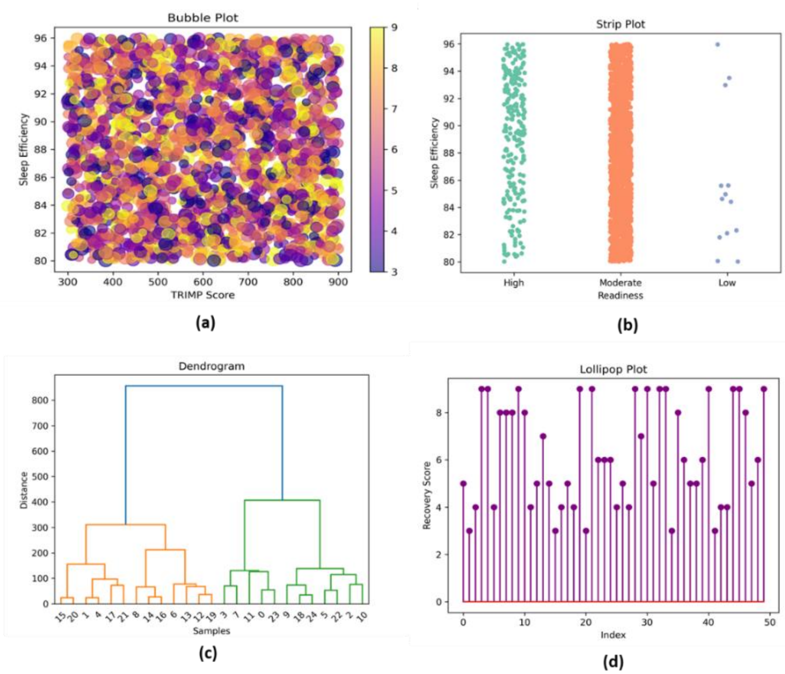

Figure 5: Multidimensional Behavioural Pattern Visualization (a) Training Stress Sleep Interaction, (b) Sleep Efficiency Readiness Distribution, (c) Hierarchical Behavioural Cluster Structure, and (d) Recovery Score Distribution Pattern

Statistical Validation and Significance Testing

Based on the Wilcoxon Signed-Rank Test results (Table 1), changes in recovery scores and the associated physiological variables are statistically significant ($p < 0.001$). The Z-values indicate notable directional associations, with the TRIMP score showing a negative correlation and sleep-related variables showing a positive correlation with recovery. Overall, these findings indicate that training stress and sleep behaviour are substantially linked to recovery status in elite female boxers (Zhang et al., 2026)..

Table 1

Wilcoxon Signed-Rank Test Consequences for Balancing Physiological Variables (N = 5200)

Feature Pair	Median (Var1)	Median (Var2)	Z-Value	P-Value	Effect Size (r)
TRIMP Score vs Recovery Score	158.4	7.6	-6.32	<0.001	0.41
Sleep Duration vs Recovery Score	421.3	7.6	5.18	<0.001	0.36
Sleep Efficiency vs Recovery Score	89.7	7.6	4.74	<0.001	0.33

The Independent Samples t-test (Table 2) demonstrates that comparisons between High and Low readiness groups reveal statistically significant differences across all psychological variables ($p < 0.001$). Athletes in the High-readiness group exhibit lower levels of fatigue and competitive anxiety, alongside higher self-confidence, compared with those in the Low-readiness group. The 95% confidence intervals exclude zero, confirming the robustness of these differences.

Table 2

Independent Sample T-Test Between High and Low Readiness Groups

Feature	Readiness Group	Mean ± SD	95% CI of Difference	T-Value	P-Value
Fatigue Score	High	3.21 ± 0.88	[-3.39, -3.13]	-9.42	<0.001
	Low	6.47 ± 1.02			
Competitive Anxiety	High	2.94 ± 0.76	[-3.30, -3.06]	-10.18	<0.001
	Low	6.12 ± 1.15			
Self-Confidence	High	8.12 ± 0.91	[3.61, 3.89]	11.04	<0.001
	Low	4.37 ± 1.08			
Opponent Perception	High	3.56 ± 0.72	[-2.44, -2.22]	-8.63	<0.001
	Low	5.89 ± 0.95			

Model Performance Evaluation

A performance evaluation was conducted to compare the effectiveness of the proposed framework with established multimodal boxing recognition models. The comparative methods include Bidirectional Encoder Representations from Transformers (BERT) combined with Three-Dimensional Residual Network (3D-ResNet) (Kong & Duan, 2024) and Three-Dimensional Convolutional Neural Network (3D CNN) integrated with BERT and feature fusion (Li et al., 2026), both of which incorporate psychological and spatiotemporal video features. Accuracy and F1-score, key evaluation metrics reflecting overall consistency and classification balance, were employed throughout the assessment.

Accuracy (%): Accuracy (Equation 22) represents the proportion of correctly classified boxing actions relative to all predictions generated by the model, reflecting the overall effectiveness and precision of the action classification framework.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (22)$$

True Positive (TP) represents correctly predicted positive actions, while True Negative (TN) denotes accurately predicted negative actions. False Positive (FP) accounts for incorrectly predicted positives, and False Negative (FN) reflects missed positive cases. The DMBO-Att-VAE framework achieved an accuracy of 98.76%, surpassing BERT + 3D-ResNet (96.86%) and 3D CNN + BERT + Fusion (91.2%).

F1-Score (%): The F1-score is the harmonic unkind of precision and recall, ensuring a balance between FPs and FNs (Equation 23). It is particularly useful in evaluating classification robustness across multiple action categories.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{23}$$

Recall refers to the proportion of correctly predicted positive actions relative to all actual positive actions. The proposed DMBO-Att-VAE model achieved an F1-score of 97.52, outperforming the baseline models, with BERT + 3D-ResNet scoring 88.55 and the fusion-based model reaching 90.9. This indicates higher recall accuracy and reduced misclassification across all action classes.

Table 3

Performance Contrast of Recognition Models

Models	Accuracy (%)	F1-Score (%)
BERT + 3D-ResNet (Kong & Duan, 2024)	96.86	88.55
3D CNN + BERT + Fusion (Li et al., 2026)	91.2	90.9
DMBO-Att-VAE (Proposed)	98.76	97.52

These results demonstrate that the proposed framework is the most stable, robust, and effective method for boxing action recognition within the context of this study, as presented in Table 3 and Figure 6.

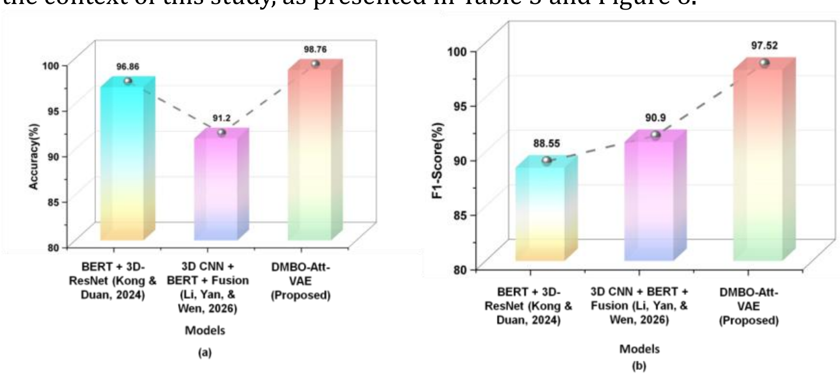

Figure 6: Evaluation Examination of (a) Accuracy (%) and (b) F1-Score (%) Comparison of the Proposed and Existing

For fair benchmarking, all existing methods were reimplemented and retrained using the current Female Boxer Readiness Dataset. Differences in model performance were observed due to the behavioural and physiological complexity inherent in the dataset. The baseline approaches achieved accuracies of 94.38% and 92.16%, respectively. In contrast, the proposed DMBO-Att-VAE framework consistently demonstrated superior performance, attaining an accuracy of 97.94% and an F1-score of 96.31%, indicating enhanced generalisation and more effective learning of readiness patterns on the retrained task, as presented in Table 4.

Table 4

Re-Implemented the Existing Methods Using Female Boxer Readiness Dataset

Models	Accuracy (%)	F1-Score (%)
BERT + 3D-ResNet (Kong &Duan, 2024)	94.38	86.74
3D CNN + BERT + Fusion (Li et al., 2026)	92.16	88.03
DMBO-Att-VAE [Proposed]	97.94	96.31

Discussion

Advanced modelling of behavioural patterns in elite female boxers demonstrates that the integration of training load, sleep habits, and recovery self-regulation significantly enhances the reliability of readiness classification. The proposed DMBO-Att-VAE framework utilises dynamic meta-heuristic optimisation, attention-based feature weighting, and variational latent encoding to capture complex nonlinear interactions among physiological and psychological indicators. Kong and Duan (2024) proposed a boxing behaviour recognition framework facilitated by sports psychology features using CNN. However, their model primarily relied on CNN-based feature extraction without advanced optimisation or deep latent representation, limiting its ability to manage the complex variability of readiness. Similarly, Li et al. (2026) introduced a multimodal model combining psychological profiling with 3D-ResNet and BERT-based feature fusion, but the strategy remained at the feature concatenation level without automated optimisation and did not generalise effectively when retrained on behaviour-oriented datasets. In contrast, the DMBO-Att-VAE framework integrates variational latent learning, attention-guided feature refinement, and dynamic meta-heuristic optimisation, enabling it to capture nonlinear relationships between stress, sleep, and psychological readiness.

It is well-established that the interplay of training load, sleep, and recovery self-regulation is a key determinant of performance optimisation in elite athletes, particularly in physically demanding and high-intensity sports such as boxing. Elite female boxers undergo rigorous training regimens that impose additional burdens on both physiological and psychological systems. Aydın et al. (2026) highlighted that variations in internal and neuromuscular performance directly influence readiness to train. Their findings suggest that traditional monitoring approaches, which rely solely on isolated physiological metrics or performance outcomes, are insufficient to capture the multidimensionality of athlete preparedness. They advocate for monitoring systems that combine objective physiological measurements with subjective self-reports to provide a comprehensive assessment of performance readiness. This limitation in conventional methods underscores the need for multidimensional models that incorporate behavioural, physiological, and psychological data (Temm et al., 2022).

The present study aligns with this perspective by offering a data-driven approach that integrates multiple indicators to provide deeper insight into athlete dynamics. Sleep, in particular, has emerged as a critical factor for recovery and performance optimisation. Doherty et al. (2021) emphasised that sleep is an active physiological process essential for muscle recovery, cognitive restoration, and hormonal balance. Poor or insufficient sleep impairs reaction time, diminishes cognitive performance, and creates a perception of fatigue, adversely affecting athletic performance. Moreover, suboptimal sleep quality can increase training-induced physiological load, with cumulative negative effects on both immediate performance and long-term health (Poucher et al., 2021). The interaction among training load, sleep, and recovery self-regulation presents a complex challenge requiring integrative approaches such as the DMBO-Att-VAE framework proposed in this study.

Recovery strategies are particularly crucial in high-impact sports where athletes experience repeated high-intensity physical activity and psychological pressure. Kużdżał et al. (2025) demonstrated that rapid weight-loss practices, common in combat sports, negatively affect sleep quality, disrupt metabolic function, and hinder recovery. This creates a cycle in which inadequate recovery increases fatigue and performance decrements, thereby raising training stress. These observations are supported by Kaczmarek et al. (2025), who reviewed physiological and molecular interactions between sleep and performance, showing that sleep disturbances impair muscle recovery, immune function, and hormonal balance, ultimately reducing performance.

In addition to physiological factors, psychological dimensions are increasingly recognised as critical in recovery and performance models. Proietti et al. (2024) reported that self-regulation training enhances stress resilience in athletes. Interventions such as mindfulness, cognitive restructuring, and goal-setting improve athletes' capacity to manage psychological pressures in high-performance environments, counteracting fatigue effects and enhancing responsiveness to stress. Psychological factors, including competitive anxiety, self-confidence, and perceived stress—which are central to the present study—provide insight into an athlete's mental state and motivation, complementing physiological measures to offer a more comprehensive understanding of readiness.

Mental fatigue has also become a focus in sports science. Wu et al. (2024) demonstrated that extensive cognitive load contributes to decreased decision-making accuracy, slower reaction times, and reduced motivation, which are particularly detrimental in fast-paced sports such as boxing where rapid and precise actions are essential. The interplay of mental and physical fatigue further complicates readiness evaluation, highlighting the importance of integrated models that consider both domains. Norouzi and Shojaei (2025) analysed the relationships among sleep quality, mental health, and perceived stress, showing that stress, anxiety, and depressive symptoms are strongly associated with poor sleep and negatively influence performance. Scott et al. (2021) corroborated this, finding that improved sleep quality is linked to enhanced mental health outcomes, underlining the importance of prioritising sleep in both physical and psychological recovery. The psychological model of locus of control, as described by Holden et al. (2019), further explains individual differences in stress perception and response. An internal locus of control encourages proactive problem-solving and adaptive coping, whereas an external locus may increase vulnerability to stress and reduce motivation. These findings emphasise the value of fostering a positive psychological climate and adaptive coping strategies to enhance athlete preparedness and performance.

Collectively, the literature highlights the interdependence of training load, sleep, recovery self-regulation, and psychological well-being in shaping athletic performance. This study contributes to the field by unifying these variables into a coherent, data-driven methodology. The DMBO-Att-VAE framework enables precise analysis of the interactions among physiological, behavioural, and psychological factors, offering a nuanced understanding of athlete readiness. This integrative model supports performance optimisation in elite female boxing and provides practical value for coaches, sports scientists, and practitioners. The integration of physiological, behavioural, and psychological indicators represents a significant advancement over traditional, one-dimensional monitoring methods, capturing the true complexity of elite athletic performance. This interdisciplinary approach not only enhances knowledge of athlete preparedness but also informs the development of individualised training and recovery programmes. In an environment of evolving competitive demands, employing innovative, data-driven methodologies is essential to ensure optimal performance while safeguarding long-term health.

Practical and Theoretical Implications

In application, the proposed framework provides coaches and sports psychologists with an AI-driven instrument to assess athlete readiness by incorporating combined physiological and cognitive indicators. It facilitates the early detection of fatigue or psychological strain, supporting performance optimisation and injury prevention.

Conclusion

Elite female boxers exhibit complex behavioral and physiological patterns that reflect their readiness for high-performance competition. The spatiotemporal action features extracted by the DMBO-Att-VAE framework effectively integrated behavioral and psychological variables with spatiotemporal motion features, achieving a classification accuracy of 98.76% and an F1-score of 97.52%. These results surpass those of existing multimodal models and demonstrate strong generalisation on the retrained dataset. Despite these strengths, the study has limitations, including the relatively small dataset, class imbalance, and context-specific issues, which may affect generalisability and complicate the optimisation of the model's complex structure. Future research could expand the dataset to encompass diverse competitive scenarios, incorporate longitudinal tracking of adaptive training, and develop real-time readiness assessments, ultimately enhancing AI-driven strategies for performance optimisation and injury prevention in elite female boxing.

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