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RESEARCH ARTICLE

Measurement of Mental Workload Using Heart Rate Variability and Electrodermal Activity

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ABSTRACT Mental workload reflects the cognitive demands placed on individuals when performing tasks, particularly under pressure. As the esports industry continues to expand rapidly, understanding and managing the mental workload of esports athletes is crucial due to its impact on performance. While self-reported measures offer insights into players' subjective experiences, this study integrates these reports with objective physiological data—heart rate variability (HRV) and electrodermal activity (EDA)—to comprehensively assess mental workload. Data from 96 participants over 21 competitive matches were analyzed, revealing significant autonomic responses linked to cognitive demands. Key predictors of workload, such as Tonic Peak Count and Phasic Peak Count, were identified. Using machine learning models like support vector machine (SVM), workload classification achieved an accuracy of 81.97% and an AUC of 0.8824. These results underscore the value of combining physiological and subjective metrics to enable real-time monitoring and provide actionable insights for enhancing performance and well-being in high-pressure esports settings.

INDEX TERMS Mental workload, esports performance, heart rate variability, electrodermal activity, machine learning classification.

I. INTRODUCTION

The rapid ascent of electronic sports (esports) as a global phenomenon has transformed it into a dominant sector within the sports industry, characterized by highly competitive environments and significant cultural and economic influence. By 2022, esports attracted an estimated 273 million dedicated enthusiasts and 223 million casual viewers, with projections indicating that this combined audience will exceed 318 million by 2025 [1], [2]. Such exponential growth underscores the critical need to understand better the factors influencing player performance and mental well-being.

Esports athletes operate under high-stakes conditions that demand exceptional cognitive and physical capabilities. Unlike casual gaming, competitive esports involves intense scrutiny, stringent time constraints, and high-performance expectations. Players must exhibit peak concentration, rapid decision-making, strategic adaptability, and precise communication, all cumulatively heightening mental workload. Chronic exposure to such stressors has been linked to performance declines and elevated risks of fatigue, anxiety, and burnout [3], [4], [5]. Thus, effectively monitoring and managing mental workload is not merely beneficial but essential for maintaining optimal performance and safeguarding the long-term health of esports athletes [6].

Historically, the mental workload has been evaluated using self-reported instruments such as the NASA-Task Load Index (NASA-TLX) [7] and the Subjective Workload Assessment Technique (SWAT) [8], which provide insight into athletes' perceived cognitive demands during competition. However, while subjective measures offer valuable perspectives, they are inherently limited by individual perceptions and potential

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biases. Recent advancements in physiological monitoring have demonstrated the benefits of complementing self-reports with objective data, offering a more comprehensive understanding of mental workload in high-pressure contexts [9], [10], [11], [12]. Metrics such as Heart Rate Variability (HRV) [13], [14], Electrodermal Activity (EDA) [15], [16], Electromyogram (EMG) [17], [18], Electrocardiogram (ECG) [17], [19], and Electroencephalogram (EEG) [20], [21] enable the continuous measurement of mental stress and cognitive load, capturing nuanced physiological changes that may not be reflected in self-reported assessments alone.

The application of machine learning techniques has further advanced the detection of complex patterns within physiological signals, facilitating more accurate predictions of mental workload [22], [23], [24]. Despite these advancements, a substantial research gap persists in understanding esports players' unique cognitive demands [4], [25]. Unlike traditional sports or other high-pressure fields, esports presents distinct challenges and stressors, necessitating tailored approaches that integrate subjective self-reports and objective physiological measurements.

To address this gap, this study investigated the relationship between self-reported mental workload and physiological data, precisely HRV and EDA, collected from esports athletes during gameplay. Real-time fluctuations in these physiological markers are captured using wearable Photoplethysmogram (PPG) sensors, which measure HRV and EDA sensors to track skin conductivity. These devices are noninvasive, portable, and well-suited for esports' dynamic, high-pressure nature [26]. By correlating these physiological signals with athletes' self-reported workload, this research identified critical biomarkers of cognitive load specific to esports. Such insights provided a foundation for innovative strategies aimed at performance optimization, cognitive load management, and the long-term well-being of esports players.

II. METHODOLOGY

The proposed methodology, as illustrated in Figure 1, consists of several key stages: data collection, data processing, feature extraction, feature selection, classification, and evaluation. Physiological signals, including EDA and heart rate (HR), are first collected and preprocessed. Features are extracted from time-domain, non-linear, and statistical categories, with the most relevant features selected based on Spearman correlation. These features are then used to classify workload levels using machine learning models, with performance evaluated through accuracy, AUC, and log loss metrics.

A. DATASET COLLECTION

The dataset employed in this study is derived from the work of Smerdov et al. [27]. It is part of the "eSports Sensors Dataset," a comprehensive multimodal data collection from professional and amateur players during 22 League of Legends matches. Each match involved five players, totaling ten participants (five professionals and five amateurs). This dataset encompasses extensive physiological measurements, including hand and chair movements, EDA, muscle activity, EEG-based brain activity, facial temperature, oxygen saturation, HR, and eye movements, all recorded through a comprehensive sensor array. Additionally, the dataset includes post-match self-surveys and in-game performance data.

Participants, all male, were between 18 and 35 years old. The professional players had significantly higher experience levels (5,000 to 10,000 hours of play) than the amateurs (400 to 1,200 hours). This dataset provides physiological and performance metrics, enabling detailed team-level and individual analyses that strengthen the research's conclusions. Post-match surveys, stored in the player_report.json file, capture players' evaluations of their own and teammates' performance on a scale from 1 to 5. They also rate their in-game mental workload on the same scale, giving insight into team dynamics and individual responses under competitive conditions.

For analysis, the dataset was divided into training and testing sets. A "by sample" approach was applied, where data instances were randomly divided across all recorded events rather than by individual players, ensuring a robust training dataset capable of generalization across gameplay scenarios. To prevent information leakage, no data from the testing set was included in the training set.

B. PRE-PROCESSING

This study focused on three specific data types from the dataset: HR data (heart_rate.csv), EDA data (gsr.csv), and self-reported mental workload ratings (player_report.json). Data from other sensors or demographic information, such as player skill level (professional vs. amateur), were excluded to maintain a streamlined analysis aligned with the study's primary objectives.

Following data selection, the initial five-point mental workload scale was transformed into a binary classification to enhance analytical clarity and interpretability. Scores of 1, 2, and 3 were consolidated as "low workload" (coded as 0), while scores of 4 and 5 represented "high workload" (coded as 1). This binary categorization is consistent with established methodologies in workload assessment, which emphasize the benefits of reducing ordinal scale complexity to mitigate interpretational ambiguity and minimize potential noise in subjective reporting [28]. Such an approach is particularly advantageous in eliminating the ambiguity often inherent in mid-range ordinal values, thus providing a more precise delineation between low and high cognitive load levels. Furthermore, binary categorization enables a more practical and expedient assessment of workload, which is especially critical in high-stakes environments like esports, where real-time insights into workload fluctuations are essential [29], [30].

Finally, a completeness check was conducted on the selected files, excluding match folders with missing data, to ensure data integrity. Only complete entries were retained for consistency and reliability. The distribution of the binary mental workload categories was then examined to evaluate balance and guide model training strategy, helping to ensure robust analysis and accurate interpretation of cognitive and physiological responses under competitive esports conditions.

C. FEATURE EXTRACTION

1) HRV

This study's HR data was sourced from a dataset that recorded HR in beats per minute (bpm), providing averaged HR values over each second. Since this dataset lacks raw PPG or ECG signals, direct RR intervals necessary for precise HRV feature extraction are unavailable. Consequently, HRV metrics such as the Standard Deviation of NN intervals (SDNN), the Root Mean Square of Successive Differences (RMSSD), and the Coefficient of Variation (CV), which traditionally require raw RR intervals, cannot be directly calculated from this data.

To address the absence of direct RR interval data, we converted HR values into approximate RR intervals using a standard transformation. This conversion is based on Fridericia's correction formula for QT interval adjustment, which relates HR and RR intervals, as in (1).

$$RR\ Interval\ (ms) = \frac{60,000}{Heart\ Rate\ (bpm)} \tag{1}$$

Fridericia's correction suggests that heart rate is inversely proportional to RR intervals, as in (2).

$$Hear\ Rate\ (bpm) = \frac{60}{RR\ Interval\ (s)} \tag{2}$$

This formula allows the derivation of RR intervals in milliseconds from averaged HR values in bpm, enabling the estimation of HRV features. Although this approach provides an estimated RR interval rather than raw variability data, it enables the analysis of HRV metrics to a reasonable degree. HRV estimates derived from bpm data may only partially capture true heart rate variability as accurately as direct RR intervals from raw signals. However, they provide a feasible approximation for HRV feature analysis.

Time-domain features, as shown in (3), (4), and (5), were derived from RR intervals to capture HRV and reflect autonomic nervous system (ANS) activity [31]

$$SDNN = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(RR_i - \overline{RR})^2} \tag{3}$$

where N is the total number of $RR\ interval$, RR_i the i^{th} $interval$, and $\overline{RR}$ the mean RR.

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{n-1}(RR_{i+1} - RR_i)^2} \tag{4}$$

$$CV = \frac{SDNN}{MeanRR} \tag{5}$$

Non-linear HRV features, particularly entropy-based measures such as Shannon Entropy (ShEn) as in (6), Renyi Entropy (REn) as in (7), and Tsallis Entropy (TEn) as in (8), offer valuable insights into the complexity of heart rate patterns, thereby reflecting underlying physiological processes involved in heart rate regulation [32].

$$ShEn = -\sum_{\mathrm{i}} p(i)log^2\,(p(i)) \tag{6}$$

where $p(i)$ is the probability of each outcome in the $RR\ interval$ distribution.

$$REn = \left(\frac{1}{1-\alpha}\right) log^2\left(\sum_{\mathrm{i}} p(i)^{\mathrm{a}}\right) \tag{7}$$

where α is the order parameter ($\alpha \neq 1$),

$$TEn = \left(\frac{1}{(q-1)}\right)\left(1 - \sum_{\mathrm{i}} p(i)^{\varphi}\right) \tag{8}$$

where q is the entropic index ($q \neq 1$).

2) EDA

The EDA signal is known to be affected by motion artifacts and noise, potentially masking physiological information crucial for assessing mental workload [33]. To mitigate these issues, we applied a wavelet-based denoising technique for artifact removal [34].

We used the Stationary Wavelet Transform (SWT) with Haar wavelets, which maintains signal alignment and stability during denoising, making it suitable for artefact suppression in physiological data. The signal was decomposed into phasic and tonic components post-denoising using the cvxEDA algorithm [35]. This convex optimization-based approach accurately separates rapid responses (phasic) and slower baseline trends (tonic) in EDA data. The model is defined as (9).

$$y = r + t + \epsilon \tag{9}$$

where y is the observed signal, r is the phasic component, t is the tonic component, and ϵ is Gaussian noise.

Key statistical features, as shown in (10), (11), (12), (13), (14) and (15) were extracted from the denoised and decomposed EDA signal components to capture workload-relevant characteristics.

$$Mean\ (\boldsymbol{\mu}) = \frac{1}{N}\sum_{i=1}^{N} X_i \tag{10}$$

where X_i is the i^{th} data point, and N is the total number of points.

$$Standard\ deviation\ (\boldsymbol{\sigma}) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(xi - Mean)^2} \tag{11}$$

$$Range = max(x) - min(x) \tag{12}$$

$$skewness = \frac{\frac{1}{N}\sum_{i=1}^{N}(Xi - Mean)^3}{(\sqrt{\frac{1}{N}\sum_{i=1}^{N}(Xi - Mean)^2})^3} \tag{13}$$

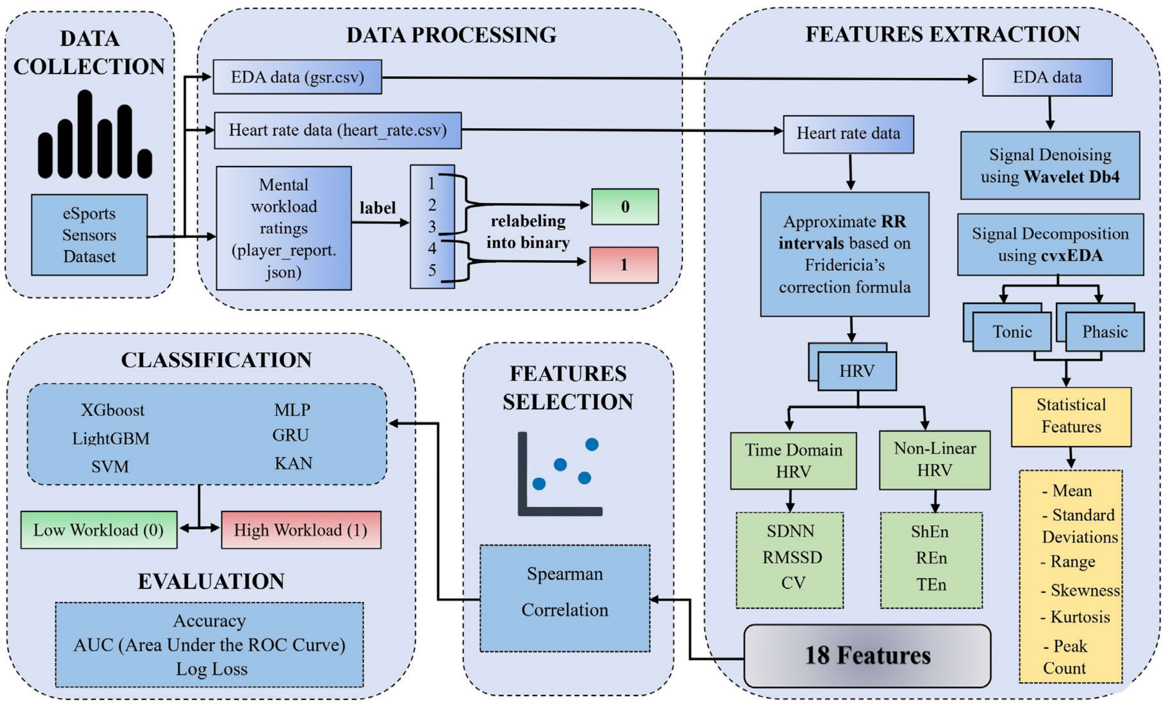

FIGURE 1. Block diagram of the proposed mental workload classification scheme using HRV and EDA.

$$kurtosis = \frac{\frac{1}{N}\sum_{i=1}^{N}(Xi - Mean)^4}{\left(\sqrt{\frac{1}{N}\sum_{i=1}^{N}(Xi - Mean)^2}\right)^4} - 3 \quad (14)$$

$$Peak\ Count = |t : Sx(t) is\ a\ local\ maximum| \quad (15)$$

where $Sx(t)$ represents the signal, and peaks were detected using SciPy's find_peaks function [36].

D. FEATURE SELECTION

Eighteen features were extracted, consisting of 6 features from HRV and 12 from EDA. To enhance model performance and reduce dimensionality, feature selection was applied to this set using the Spearman correlation coefficient to identify the most significant features.

Based on their ranks, the Spearman correlation coefficient ρ quantifies the strength and direction of a monotonic relationship between two variables, x and y. The Spearman correlation between variables x_i and y_j is calculated as in (16),

$$\rho x_i, y_j = 1 - \frac{6\sum d_i^2}{n\left(n^2 - 1\right)} \quad (16)$$

where d_i is the difference between the ranks of each observation x_i and y_j and n is the number of observations.

This approach measures the monotonic relationship between each feature and the target variable, allowing for the selection of the ten most relevant features for inclusion in the machine learning model.

E. CLASSIFICATION

For classification, we employed six machine learning models: Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), Support Vector Machine (SVM), Multilayer Perceptron (MLP), Gated Recurrent Unit (GRU), and the Kolmogorov Arnold Network (KAN).

To address the class imbalance, we applied the Synthetic Minority Over-sampling Technique (SMOTE), which creates synthetic instances in the feature space to balance the class distribution [37]. After resampling, we used StandardScaler to normalize the features as in (17)

$$X_{scaled} = \frac{X - X_{mean}}{X_{std}} \quad (17)$$

where X_{scaled} is the standardized value, X is the original value, X_{mean} the feature mean, and X_{std} the standard deviation.

StratifiedKFold cross-validation with five folds was used for model training and testing, preserving class distribution in each fold.

XGBoost was configured for binary classification with a "binary" objective function, combining decision trees in a regularized gradient-boosted ensemble [38]. The model's prediction for an instance i as in (18).

$$\hat{y}_i = \phi\left(\Sigma_k = 1^t f_k(x_i)\right) \quad (18)$$

where $\hat{y}_i$ is the predicted probability, ϕ is the sigmoid function, t is the number of trees, f_k represents the k^{th} tree, and x_i is the feature vector of the i^{th} instance.

Equation (19) is the objective function optimized by XGBoost,

$$L(\phi) = \Sigma_i l(y_i, \hat{y}_i) + \Sigma_k \Omega(f_k) \tag{19}$$

where l is the binary cross-entropy loss, y_i is the true label, $\hat{y}_i$ the predicted probability, and $\Omega(f_k)$ the regularization term.

LightGBM grows trees leaf-wise instead of level-wise, as in XGBoost [39]. For binary classification, LightGBM minimizes the following objective function as in (20),

$$L = \sum_i l(y_i, \hat{y}_i) + \lambda \sum_{j=1}^{J} \Omega(T_j) \tag{20}$$

where λ is a regularization parameter, J denotes the number of leaves, and $\Omega(T_j)$ controls the complexity of each leaf.

SVM aims to find the optimal hyperplane separating two classes [40]. For binary classification, this decision boundary is defined as in (21),

$$w^T x + b = 0 \tag{21}$$

where w is the weight vector, x the feature vector, and b the bias term. Equation (22) is the optimization problem solved by SVM,

$$min_{\omega,b} \frac{1}{2} \|\omega\|^2 \ subject\ to\ y_i \left(\omega^T x_i + b\right) \geq 1 \ \forall i \tag{22}$$

where y_i is the true label. We used the Radial Basis Function (RBF) kernel for nonlinear separable data as in (23),

$$K\left(x_i, x_j\right) = exp(-\gamma \ \|x_i - x_j\|^2) \tag{23}$$

where γ controls the kernel width.

MLP is a fully connected neural network that approximates non-linear mappings through multiple layers [41]. For an input x, the output y of a single hidden layer with ReLU activation is computed as in (24) and (25),

$$h = \sigma(W^{(1)}x + b^{(1)}) \tag{24}$$

$$y = W^{(2)}h + b^{(2)} \tag{25}$$

where σ is the ReLU activation function, $W^{(1)}$ is the weight matrix for the first layer, and $b^{(1)}$ is the bias vector

For binary classification, a sigmoid activation is applied to the output to yield a probability as in (26).

$$\hat{y} = \frac{1}{1 + e^{-y}} \tag{26}$$

GRU, a type of recurrent neural network, are effective in capturing temporal dependencies in time-series data [42]. GRU utilize gating mechanisms to manage the flow of information, as in (27), (28), (29), and (30).

1. Update Gate

$$z_t = \sigma(W_z x_t + U_z h_{t-1}) \tag{27}$$

where z_t is the update gate at time t, x_t the input, h_{t-1} is the hidden state, and σ is the sigmoid function.

2. Reset Gate

$$r_t = \sigma(W_r x_t + U_r h_{t-1}) \tag{28}$$

where r_t is the reset gate.

3. Current Memory Content:

$$\widetilde{h_t} = tanh(W_h x_t + U_h(r_t \odot h_{t-1})) \tag{29}$$

where $\widetilde{h_t}$ is the candidate hidden state, and $\odot$ denotes element-wise multiplication.

4. Final Hidden State

$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot \widetilde{h_t} \tag{30}$$

KAN is a neural network architecture leveraging RBF layers and KAN Layers [43]. The output y for an input x through an RBF layer is given as in (31),

$$RBF(x) = exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \tag{31}$$

where μ and σ represent the RBF center and spread, respectively.

In the KAN Layer, transformed inputs are aggregated via a spline basis, providing flexible non-linear approximations as in (32),

$$KAN(x) = W_{spline} \cdot RBF(x) + b \tag{32}$$

where W_{spline} is the weight matrix for the spline layer, and b is the bias term.

For the model evaluation, three metrics were used: Accuracy, AUC (Area Under the ROC Curve), and Log Loss.

- Accuracy measures the proportion of correct classifications, as in (33).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{33}$$

- AUC quantifies the model's ability to distinguish between classes by integrating the true positive rate (sensitivity) and false positive rate over varying thresholds.
- Log Loss: The harmonic mean of precision and sensitivity, calculated as in (34).

$$Log\ loss = -\frac{1}{N} \sum_{i=1}^{N} \left(\begin{array}{c} (y_i log\,(p_i) + \\ (1 - y_i)\, log\,(1 - p_i)) \end{array} \right) \tag{34}$$

where y_i True label for instance and p_i is predicted probability.

III. RESULT

A. DATA COMPLETENESS AND DISTRIBUTION ASSESSMENT

Preprocessing confirmed complete data across all matches, with no missing entries at the match level. The original dataset comprised 21 matches, each involving 5 players, for a total of 105 player entries (21 matches × 5 players). However, only 96 player entries had complete data across all required metrics EDA, heart rate, and player reports. Entries with missing data in any of these metrics were excluded to ensure consistency and accuracy in the analysis.

For example:

- Player 2 lacked heart rate data in Matches 1, 2, 7, and 8.
- Player 3 was missing heart rate data in Matches 14, 15, and 16.

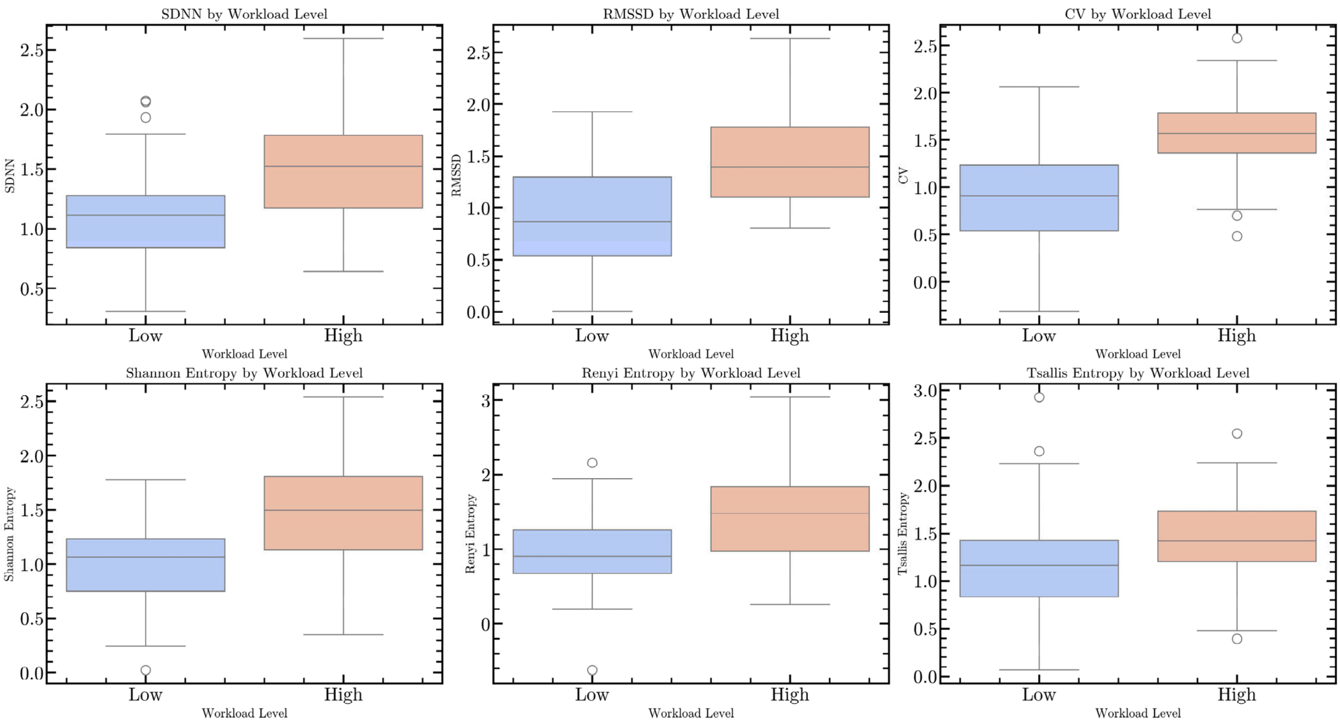

FIGURE 2. Distribution of HRV features across different mental workload levels.

- Player 4 had one missing heart rate sample from Match 19.

These inconsistencies in data availability were carefully handled by removing entries with incomplete data to maintain the robustness of workload assessments. Player report files were nearly complete, with only one missing sample for Player 0 in Match 8. The final dataset used in the analysis includes 96 players with full EDA, heart rate, and workload data.

Initial analysis of the workload class distribution revealed a significant imbalance, with Class 0 comprising 69.6% and Class 1 comprising 30.4% of the dataset. To mitigate potential bias in model training, we implemented the SMOTE. This resampling method successfully balanced the class distribution to a 1:1 ratio.

B. HRV ANALYSIS: AUTONOMIC PATTERNS

HRV metrics offer valuable insights into the autonomic nervous system's response to cognitive demands, particularly in esports. By examining the distributional changes of key HRV features between low and high workload conditions, we can discern significant autonomic responses to varying cognitive loads. Figure 2 illustrates these shifts, forming the basis for our discussion.

The SDNN, which reflects the variability in heartbeat intervals, exhibits a significant increase under high workload conditions. Statistical analysis yields a Mann-Whitney U statistic of 598.0 ($p < 0.00001$) and a large effect size (Cohen's $d = 0.998$). This increase suggests heightened sympathetic activity during tasks with elevated cognitive demands, aligning with previous findings that indicate increased sympathetic activation in esports players during intensive gameplay [13].

Similarly, the RMSSD, an indicator of parasympathetic (vagal) activity, shows a significant increase under high workload, with a Mann-Whitney U statistic of 473.0 ($p < 0.0000001$) and a large effect size (Cohen's $d = 1.304$). This robust change reflects the expected reduction in vagal modulation during periods of high cognitive load, consistent with studies demonstrating decreased parasympathetic activity during challenging cognitive tasks [44].

Contrary to previous expectations, the CV demonstrates significant sensitivity to workload changes. The difference between low and high workload conditions is evident ($U = 416.0$, $p < 0.00000001$) with a large effect size (Cohen's $d = 1.389$). These finding highlights CV's potential as a sensitive marker of cognitive stress and its dynamic impact on autonomic regulation, supporting research that shows CV variability during demanding cognitive tasks [45].

Entropy-based metrics provide additional insights into the complexity of HRV responses to cognitive load. ShEn shows a significant increase ($U = 559.0$, $p < 0.000002$) with a large effect size (Cohen's $d = 1.102$), suggesting that higher cognitive load induces greater complexity in heart rate patterns, reflecting adaptive shifts in autonomic control mechanisms. REn also exhibits significant increases under high workload conditions ($U = 695.0$, $p < 0.00013$) with a large effect size (Cohen's $d = 0.864$), capturing the

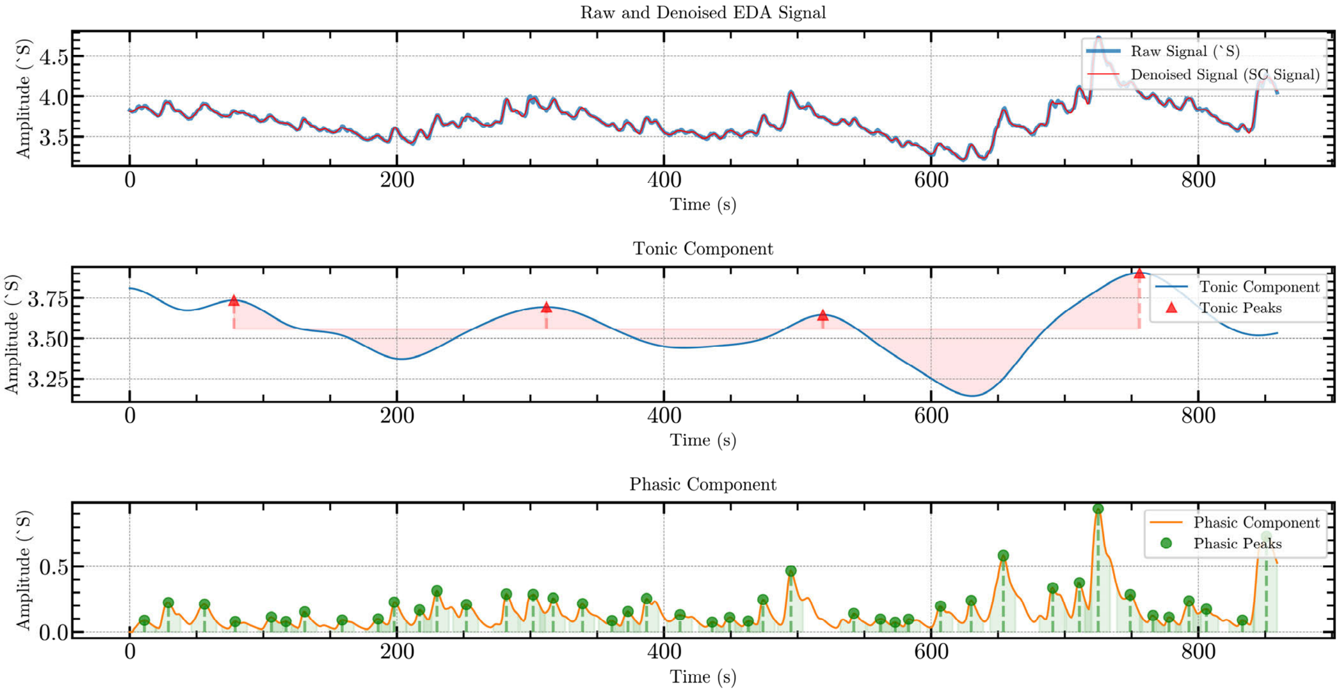

FIGURE 3. **Denoising and decomposition of EDA signal: visualization of raw signal, denoised output, tonic and phasic components.**

nuanced interplay between cognitive demand and autonomic responses. TEn, while showing a more minor yet significant increase ($U = 839.0$, $p < 0.0047$) with a moderate effect size (Cohen's $d = 0.525$), remains valuable as an indicator of structured patterns in HRV that correlate with sustained cognitive effort.

These findings challenge traditional assumptions about HRV metrics and their discriminative power in assessing mental workload. The significant shifts observed across all features particularly RMSSD, CV, and ShEn underscore their utility in capturing the nuanced interplay between cognitive load and autonomic regulation. This multifaceted approach to HRV analysis offers a promising path for developing refined, adaptive models for cognitive workload assessment, paving the way for real-time monitoring and tailored interventions in high-demand environments.

C. EDA

1) EDA SIGNAL DENOISING AND DECOMPOSITION

EDA signals are often contaminated by noise from motion artefacts and environmental factors, as depicted in Figure 3. We employed wavelet-based denoising using the Daubechies 4 (db4) wavelet, which offers an optimal balance between frequency and temporal resolution. This method effectively attenuated noise while preserving essential physiological patterns, resulting in the enhanced signal shown in Figure 3.

Following denoising, we applied the cvxEDA algorithm to decompose the EDA signal into its tonic and phasic components. The tonic component reflects slow baseline shifts associated with general arousal levels, while the phasic component captures rapid, transient peaks linked to immediate physiological responses. This decomposition, illustrated in Figure 3, allows for a more detailed analysis of autonomic responses.

D. EDA FEATURE EXTRACTION AND STATISTICAL ANALYSIS BY WORKLOAD LEVEL

By examining phasic and tonic EDA features, we can discern distinct patterns of sympathetic activation that correspond to different levels of cognitive demand. Figures 4 and 5 illustrate these variations, serving as a foundation for our analysis.

In high workload scenarios, a notable increase in mean EDA values indicates elevated baseline arousal. This rise is statistically significant for both phasic ($U = 1587.0$, $p < 0.042$, Cohen's $d = -0.27$) and tonic ($U = 963.0$, $p < 0.042$, Cohen's $d = 0.27$) components, suggesting enhanced sympathetic activity. However, the modest effect sizes imply that mean EDA alone may not be sufficient to effectively differentiate between workload levels, highlighting the need to consider additional variability and dynamic features.

The phasic EDA's standard deviation (SD) demonstrates heightened sensitivity to cognitive load. Under increased workload, SD significantly rises ($U = 1625.0$, $p < 0.022$, Cohen's $d = -0.34$), reflecting more frequent and pronounced arousal fluctuations. This pattern aligns with findings in esports research, where players exhibit increased physiological arousal during intense gameplay [46]. Conversely, tonic SD remains relatively unchanged ($U = 1206.0$, $p < 0.654$, Cohen's $d = -0.03$), indicating that sustained

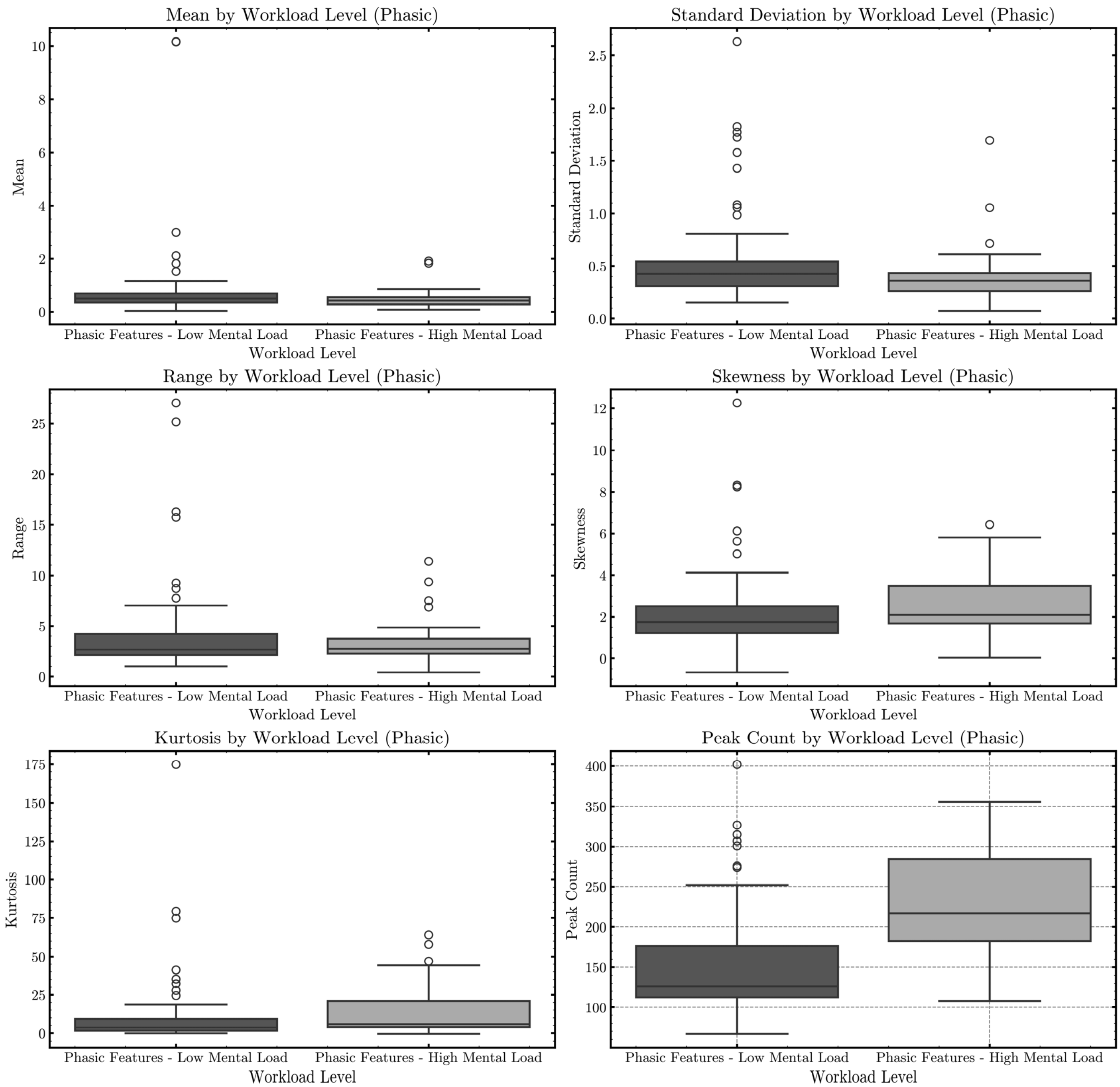

FIGURE 4. **Phasic EDA feature distributions by mental workload level.**

arousal states may be less responsive to immediate workload changes.

Metrics such as range, skewness, and kurtosis offer additional perspectives on EDA signal characteristics. The range does not show significant differences between workload conditions for either phasic ($U = 1305.0$, $p < 0.847$, Cohen's $d = -0.19$) or tonic ($U = 1138.0$, $p < 0.372$, Cohen's $d = -0.04$) data, suggesting limited utility in distinguishing cognitive states. Phasic skewness trends toward significance ($U = 992.0$, $p < 0.065$, Cohen's $d = 0.23$), indicating a potential shift toward higher EDA values under stress. In contrast, phasic kurtosis approaches significance ($U = 975.0$, $p < 0.050$, Cohen's $d = 0.16$), suggesting sharper peak arousal responses. However, these features exhibit limited effect sizes and may serve better as supplementary metrics within a comprehensive model. Tonic skewness ($U = 1255.0$, $p < 0.899$, Cohen's $d = 0.14$) and kurtosis ($U = 1231.0$, $p < 0.776$, Cohen's $d = -0.20$) remain unchanged, reinforcing their limited sensitivity to workload variations.

Notably, peak count emerges as a robust indicator of sympathetic activation. The frequency of transient, phasic

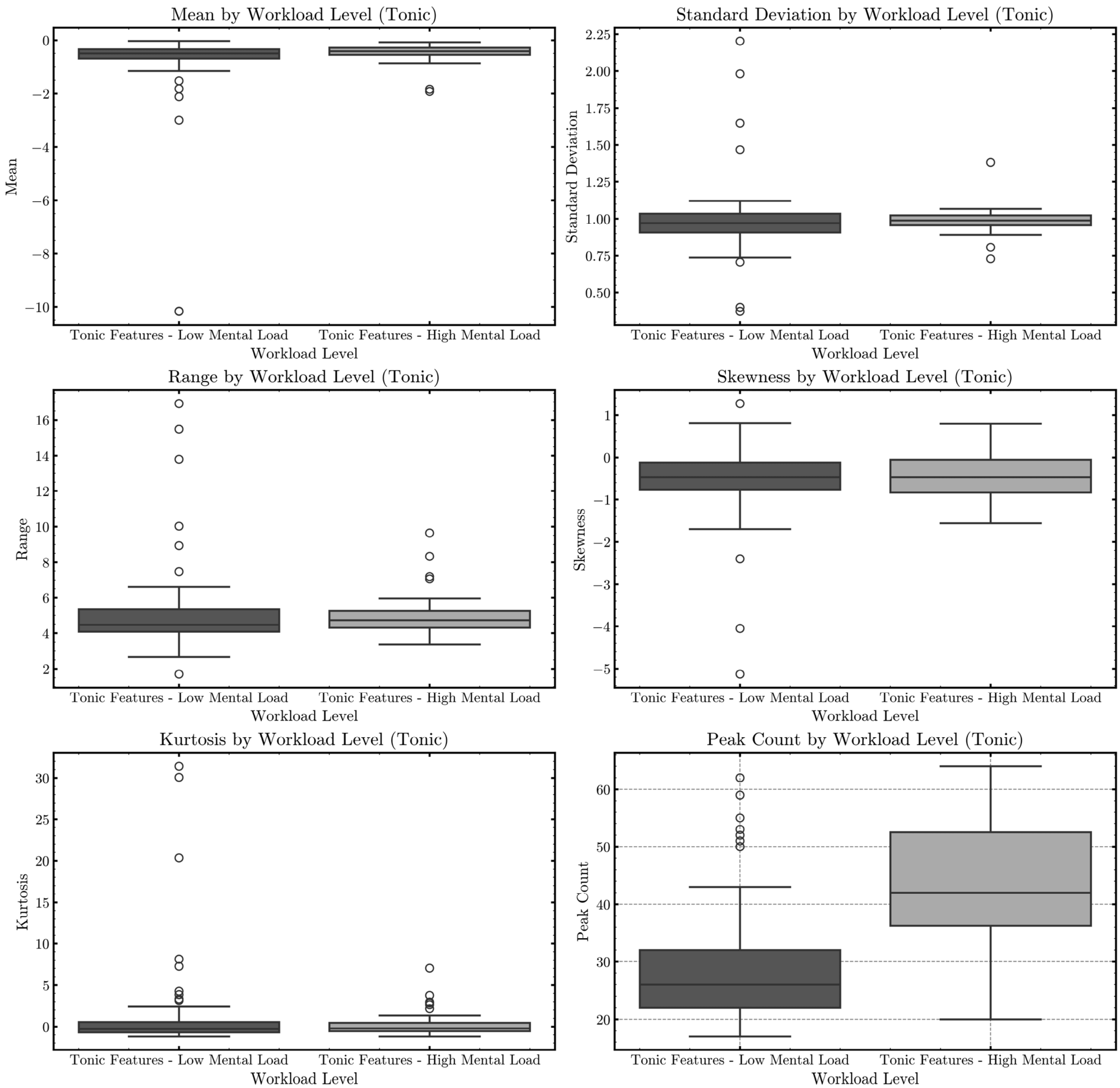

FIGURE 5. **Tonic EDA feature distributions by mental workload level.**

EDA events increases significantly under high workload for both phasic (U = 423.0, $p < 0.000000025$, Cohen's d = 1.18) and tonic (U = 390.0, $p < 0.000000007$, Cohen's d = 1.38) data, reflecting a marked rise in arousal responses. This finding is consistent with studies showing that esports players experience heightened physiological responses during competitive play. Specifically, tonic EDA represents sustained, baseline changes in sympathetic nervous system activity, which ongoing cognitive or emotional stressors can influence, while phasic events capture transient responses to immediate challenges.

Both peak counts in these components are sensitive to fluctuations in mental workload, with the increased demands of the task leading to a rise in physiological arousal. The sensitivity of peak count to these fluctuations may be particularly pronounced in esports, where rapid shifts in mental workload occur in short time frames, often in response to in-game events. As workload demands intensify, the frequency of peaks increases, reflecting the heightened emotional and cognitive engagement of the player. The substantial effect sizes underscore peak count's strong discriminative capability, making it a critical marker for

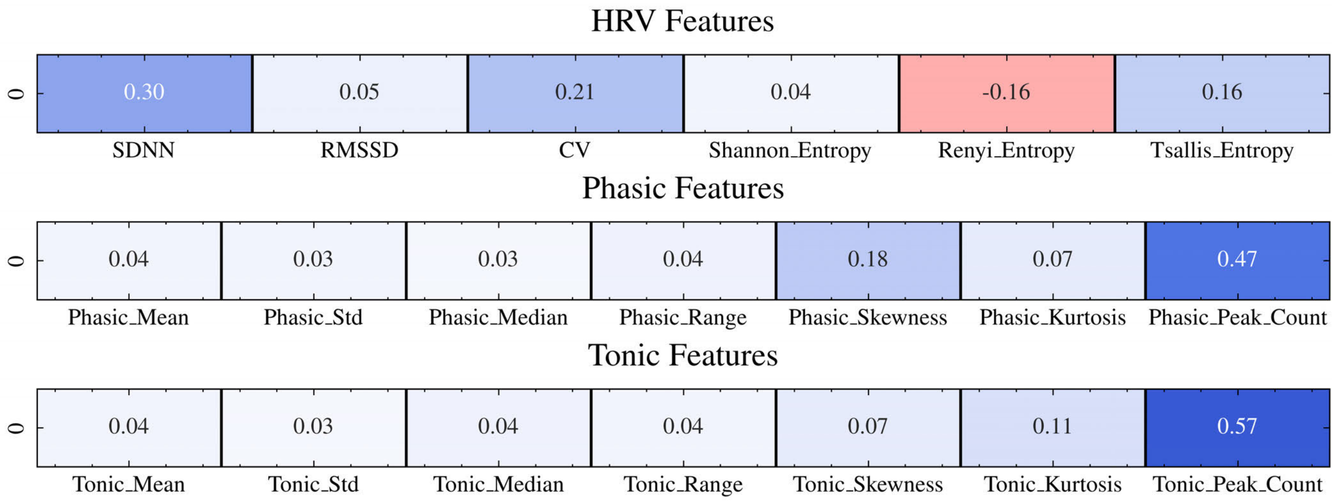

FIGURE 6. HRV, phasic, and tonic feature correlations with mental workload.

assessing mental workload in dynamic environments such as esports.

In summary, while mean EDA provides a general overview of arousal levels, features such as peak count offer more nuanced insights into the dynamic nature of sympathetic responses to cognitive demands. These findings underscore the importance of a multifaceted approach to EDA analysis in understanding autonomic regulation in high-performance esports settings.

E. CORE FEATURE SELECTION

In the feature selection process, Spearman's rank correlation was utilized to quantify the strength and direction of monotonic relationships between each feature and the target variable (Figure 6). From the HRV features shown, SDNN emerges as the most strongly correlated feature, with a Spearman correlation of approximately 0.30, highlighting its potential importance in predicting the target variable. CV follows with a correlation of 0.21, indicating a moderate association. Interestingly, REn exhibits a negative correlation (−0.16), Similar to phasic features, Tonic Mean, Tonic SD, Tonic Median, and Tonic Range have relatively weaker correlations, ranging from 0.03 to 0.04.

This analysis underscores the utility of peak count metrics, both phasic and tonic, as key predictors due to their strong associations with the target variable. In contrast, other features exhibit moderate to weak correlations, highlighting the need for a more focused feature selection strategy that balances predictive power with model complexity. This targeted approach improves interpretability and enhances the robustness of predictive models by emphasizing the most informative features.

Therefore, the top 10 features we selected for further analysis are Tonic Peak Count, Phasic Peak Count, SDNN, CV, REn, TEn, Phasic Skewness, Tonic Kurtosis, Phasic Range, and Tonic Mean. This selection captures high-impact predictors and features that add complementary value for nuanced workload assessment.

F. MODEL PERFOMANCE OVERVIEW

Among the models (Figure 7), XGBoost and LightGBM demonstrate consistently strong performance. LightGBM edges out XGBoost with a slightly higher accuracy of 81.23% compared to 79.63%, reflecting its ability to generalize effectively. However, XGBoost's AUC of 0.8739 signifies excellent discrimination between classes, closely matched by LightGBM's 0.8536. Both models also exhibit low log loss values, indicating well-calibrated predictions that balance overconfidence and underconfidence.

The MLP model, with its accuracy of 82.03%, further highlights its capability to capture intricate patterns within the data. Although its AUC of 0.8396 is lower than that of LightGBM and XGBoost, MLP's strength lies in its flexibility and capacity for complex pattern recognition. The slightly higher log loss value of 0.6068 suggests room for fine-tuning its confidence scores but does not detract from its overall competitiveness.

SVM boasts the highest AUC at 0.8824, indicating its superior ability to distinguish between positive and negative cases. Coupled with an accuracy of 81.97% and a low log loss of 0.4289, SVM's performance underscores its precision in setting clear decision boundaries. This makes it particularly valuable in contexts where precise class differentiation is essential.

In contrast, GRU shows a dip in performance with an accuracy of 71.11% and an AUC of 0.7697. While its metrics trail behind the leading models, GRU's recurrent architecture may still offer advantages for specific temporal data patterns, even if its broader classification performance could be more robust. The log loss of 0.6186 further indicates some inconsistency in its predictive confidence.

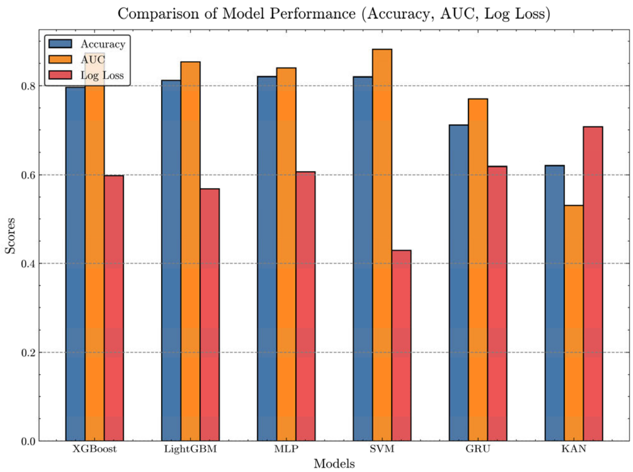

FIGURE 7. **Comparison of model performance.**

At the other end of the spectrum, KAN exhibits the weakest performance, with an accuracy of 62.05%, a relatively low AUC of 0.5308, and the highest log loss at 0.7071. These metrics indicate substantial difficulties in accurately and confidently classifying the data, suggesting that KAN may require significant adjustments or be better suited for this dataset.

Ultimately, SVM emerges as the top performer, with its standout AUC demonstrating superior discriminative power and clear decision boundaries, making it highly effective for precise class differentiation. LightGBM and XGBoost also show balanced and robust performance, serving as reliable alternatives. MLP offers a strong option with excellent accuracy, while GRU and KAN illustrate the challenges of model tuning and the importance of selecting algorithms that align with data characteristics and classification objectives.

IV. DISCUSSION

This study provided valuable insights into how esports athletes experience and manage mental workload by analyzing HRV and EDA data. By combining subjective self-reports with objective physiological measurements, we explored the complex interplay of cognitive demands faced by players in competitive, high-pressure gaming environments.

In our EDA analysis, we utilized cvxEDA for signal decomposition due to its robust performance in detecting workload variations, particularly in high-stress end-of-game scenarios. cvxEDA's scientifically validated strengths in sensitivity and accuracy make it well-suited for capturing both phasic and tonic components of the EDA signal, which are critical for understanding transient and sustained cognitive demands. This choice aligns closely with the study's focus on precise and reliable workload detection in esports environments. Key findings include HRV features like SDNN and CV as indicators of autonomic regulation shifts in response to varying cognitive loads. Additionally, decomposing EDA into tonic and phasic components revealed details regarding sustained and transient arousal states, with phasic and tonic peak counts emerging as a strong predictor of cognitive load, capturing rapid sympathetic responses to gameplay challenges.

For practical applications, this research offers insights that could benefit players, coaches, and the esports industry. Coaches can use continuous monitoring to understand how players respond to various cognitive loads, allowing individualized training programs that optimize performance without causing excessive mental fatigue. Additionally, coaches could leverage these metrics to guide recovery strategies and implement cognitive resilience training, supporting players in managing stress during high-stakes competitions. For game developers, understanding cognitive load responses could inform the design of adaptive gameplay elements or training modes that align with players' mental states, enhancing player engagement and skill development.

Despite these promising results, several limitations inform potential directions for future research. Firstly, our sample included only male esports athletes within a limited age range, potentially restricting the generalizability of our findings. Physiological responses to cognitive load may vary across gender and age; thus, a more diverse participant pool would provide broader insights into mental workload across various demographic groups.

Moreover, while our StratifiedKFold cross-validation approach ensured balanced class distribution, the resulting models are personalized as they may use data from the same subject in both training and testing sets. This approach, while effective for within-subject analysis, limits the generalization of the model across individuals. Future research should consider implementing Leave-One-Subject-Out (LOSO) cross-validation, which ensures that data from any single subject is used exclusively for testing, thereby providing a more rigorous assessment of model generalizability and applicability across diverse populations.

Furthermore, our binary classification of mental workload as "low" or "high" simplifies a complex spectrum of cognitive states. While this categorization improves analytical clarity, it may overlook nuanced fluctuations in cognitive load throughout gameplay. Future research could benefit from adopting multi-class or continuous workload scales, offering a more comprehensive view of cognitive load dynamics.

Further exploration of additional physiological metrics, such as respiratory rate or multimodal sensor data, could enhance the model's accuracy and depth, capturing more subtle variations in physiological states. Additionally, newer EDA decomposition algorithms (e.g., SparsEDA) could provide alternative methods to refine the extraction of workload-relevant features, warranting further investigation in future studies. While the machine learning models in this study proved effective, their performance depends on the training data's size and representativeness. Although robust, our dataset may be subject to data collection and preprocessing biases. Techniques like SMOTE were utilized to address imbalances, but future studies would benefit from more extensive and diverse datasets to improve the robustness and generalizability of predictive models.

Finally, implementing continuous workload monitoring in esports presents practical challenges, including sensor reliability, data consistency, and integration into dynamic gaming environments. Real-world applications will require high-fidelity, non-intrusive monitoring solutions that capture accurate physiological data without disrupting gameplay, supporting esports athletes' long-term performance and well-being.

V. CONCLUSION

This study provided a foundational understanding of the potential of physiological metrics, particularly HRV and EDA, for assessing mental workload in esports athletes. Using the SVM model, our approach achieved a robust classification performance, with an accuracy of 81.97% and an AUC of 0.8824, identifying tonic and phasic peak counts as highly influential features with significant Spearman correlations of 0.57 and 0.47, respectively. Additionally, core HRV features like SDNN and CV proved vital in distinguishing autonomic responses to mental workload.

These results underscore the value of integrating objective physiological data with self-reported workload assessments to enhance real-time cognitive monitoring. Such insights are not only applicable to optimizing performance in high-stress esports environments but also open pathways to tailored interventions for athlete well-being. This research thereby sets a foundation for innovative approaches in cognitive load management, potentially benefiting both short-term performance and the long-term health of competitive players.

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