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Article

A multimodal approach to psychological resilience prediction in football players: Integrating biomechanical analysis, physiological feedback, and machine learning

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Abstract: Football is a high-intensity sport that demands not only technical and physical excellence but also strong psychological resilience. This study investigates the relationship between biomechanics, physiological feedback, and psychological health in football players, employing a hybrid predictive model that integrates autoregressive analysis and XGBoost. A multimodal dataset comprising biomechanical indicators (postural stability, muscle activation, reaction time), physiological markers (heart rate variability [HRV], electrodermal activity [EDA]HRV, EDA, respiratory rate), and behavioral responses (decision volatility, self-reported stress levels) was collected from professional and semi-professional football players over a six-month period. The results demonstrate that neuromuscular stability and cognitive efficiency significantly influence psychological resilience, with postural control and reaction time emerging as key predictors of anxiety levels. The hybrid ARIMA-XGBoost model achieved superior predictive accuracy (R^2 = 0.89, RMSE = 0.61), outperforming traditional machine learning models. These findings highlight the practical value of integrating biomechanical monitoring with psychological assessments for personalized stress management and performance optimization in competitive sports.

Keywords: psychological resilience; biomechanics; XGBoost; autoregressive analysis; football players; stress prediction

1. Introduction

Modern football competitions, characterized by high intensity and increased stakes, not only test players' technical and physical capabilities but also reflect their psychological stability and adaptability. In high-level competitive environments, athletes must maintain cognitive stability and decision-making ability under extreme pressure. Consequently, the assessment and cultivation of psychological resilience have become essential aspects of contemporary sports science research. With the advancement of sports science and intelligent computing technologies, methods based on biomechanics and physiological feedback have emerged as crucial tools for investigating athletes' psychological states [1,2]. Traditionally, sports research has predominantly focused on technical, tactical, and physical attributes. However, as the performance gap between teams narrows, psychological factors have increasingly influenced match outcomes. Therefore, establishing a scientific model for dynamically predicting psychological states can contribute to optimizing training strategies and enhancing athletes' stability in high-pressure scenarios.

The rapid development of modern football has significantly increased physiological and psychological loads on individual players. The high-intensity nature of competitive matches demands that athletes make multiple cognitive and motor decisions within short timeframes [3]. A strong coupling exists between biomechanical factors (gait patterns, muscle fatigue, and postural stability) [4] and psychological factors (anxiety levels, attention allocation, and decision-making latency) [5], exhibiting complex nonlinear characteristics during different phases of a match. Particularly in high-pressure situations, fluctuations in an athlete's psychological state can directly impact biomechanical performance, such as reduced coordination and delayed reaction times. Therefore, comprehensive analysis of physiological and psychological feedback in competitive environments and the development of dynamic prediction models can provide theoretical support for optimizing match strategies and training systems.

In contemporary sports psychology research, physiological feedback indicators—such as heart rate variability (HRV), electrodermal activity (EDA), and electromyography (EMG)—and behavioral feedback metrics—such as gait stability, postural adjustments, and movement trajectory variations—are widely used to assess psychological states [6,7]. HRV, a critical indicator of autonomic nervous system regulation, reflects an athlete's emotional stability and stress levels during matches. EDA, which measures emotional arousal, is instrumental in evaluating psychological stress under competitive conditions [8]. Additionally, postural and gait analyses provide insights into how psychological factors influence motor control, such as deviations in center-of-mass control, which can affect running efficiency and coordination. Consequently, developing a predictive model that integrates multimodal physiological and behavioral data can enhance the accuracy of psychological state prediction and support personalized training and real-time interventions.

Due to the complexity of physiological and psychological feedback mechanisms, traditional autoregressive models face significant limitations in predicting dynamic psychological states. While autoregressive models are widely used in time-series modeling due to their effectiveness in capturing temporal dependencies, their linear assumptions restrict their ability to accommodate the nonlinear nature of psychological state transitions. Moreover, while the eXtreme Gradient Boosting (XGBoost) algorithm offers superior performance in handling high-dimensional data, its pre-sorting strategy results in high spatial complexity, limiting its applicability in large-scale time-series analysis [9]. To address these challenges, this study proposes a hybrid modeling approach that integrates the computational efficiency of autoregressive models with the predictive accuracy of XGBoost. This approach not only improves predictive precision but also reduces computational costs, making it suitable for real-time psychological state prediction.

The primary objective of this study is to develop a dynamic prediction model for psychological states by integrating biomechanics, behavioral feedback, and physiological signals to enhance the identification and prediction of athletes' psychological states in high-pressure competitive environments. Specifically, the research objectives are as follows:

(1) Establishment of a Multimodal Psychological State Evaluation Framework: By incorporating biomechanical parameters (e.g., gait characteristics, movement stability), physiological feedback signals (e.g., HRV, EDA, EMG), and behavioral patterns (e.g., movement decision characteristics), this study constructs an analytical

framework that captures the complex interplay between physiological and psychological factors.

(2) Optimization of Predictive Modeling Approaches: A hybrid modeling strategy is employed, combining the low computational cost of autoregressive models with the high predictive accuracy of XGBoost. This integration enhances the model's adaptability to nonlinear psychological state fluctuations while improving computational efficiency.

(3) Implementation of Real-Time Prediction and Personalized Intervention: The proposed model is optimized for real-time applications, enabling personalized psychological interventions for athletes. This approach aims to enhance stability and decision-making performance during matches.

The key innovations of this study include:

(1) Multimodal Data Integration for Predictive Modeling: This research systematically integrates biomechanical, behavioral, and physiological signal data to develop a high-precision psychological state prediction model.

(2) Hybrid Modeling Strategy for Enhanced Predictive Accuracy: The combination of autoregressive models and XGBoost improves adaptability to nonlinear psychological state transitions while optimizing computational complexity.

(3) Real-Time Prediction and Application Expansion: The proposed approach can be widely applied in competitive sports, psychological health monitoring, and personalized training programs, improving athletes' psychological adaptability in high-pressure environments.

2. Related works

2.1. Psychological stress study

Athletes often suffer mental health concerns due to constant competition. Mental health concerns affect an athlete's ability to keep a constant, regular demeanor [10–13]. Because elite athletes' mental health is rarely regarded in sports, little is known [14]. Positive psychology boosts mental health research. Positive mental health is currently measured using a bidimensional model. 2010 brought the bidimensional model. Subjective well-being and psychological problems are on a continuum in the standard paradigm of mental health. Therefore, a severe psychological condition reduces subjective well-being. The two-factor model of mental health separates subjective well-being and psychological illnesses yet links them. Strategie multidimensional. Mental health requires mental illness symptoms and positive mood control. A two-factor mental health approach applies to athletes [15–20].

Having emotionally supportive friends and acquaintances aids football players. According to the buffer hypothesis, helpful friends and family lessen stress. Strong social networks help people cope with misfortune by providing emotional and material support. Multiple research papers [21–24] suggest that low social support increases anxiety 5–6 times. Football players with fewer negative attitudes and behaviors in asking aid, lower negative event evaluations, and lower anxiety reported more social support. Social support reduces epidemic anxiety. As the country enters the post-epidemic period, this should be examined because it may lower football players' anxiety [25]. Self-esteem is a person's sense of worth [26]. This rating is "self-esteem".

According to the social meter theory, self-esteem can predict interpersonal connections. Creating and maintaining meaningful relationships promotes self-esteem [27]. Lack of social support lowers self-esteem and increases mental health risks. Tang et al. [28] found that increasing self-esteem reduces anxiety and stress. Low self-esteem and anxiety are correlated. Football players who feel their teammates' and coaches' support may enhance self-confidence and minimize anxiety [29–33].

2.2. Autoregressive model

Autoregressive models are one of the most prevalent smooth time series models and have a wide range of applications due to their ease of use in analyzing multifactor models. For instance, some researchers have utilized autoregressive models to forecast epidemic trends of infectious diseases in a region [34]. Others have utilized it with moderate success in electricity price forecasting, residential electricity load forecasting, and agricultural product forecasting. However, the autoregressive model is limited in certain circumstances due to its simple model, and the regression equation is merely a hypothesis, which affects the variety of factors and the unpredictability of some factors. In addition, autoregression can only be used to forecast economic phenomena that are related to their own previous period, i.e., those that are affected by their own historical factors, such as the production of various natural resources. Autoregression is not appropriate for economic phenomena that are significantly influenced by social factors [35,36].

2.3. XGBoost model

XGBoost is a distributed gradient boosting library optimized for performance, flexibility, and portability. XGBoost is a tool for massively parallel boosting trees, and it is the fastest and best open-source boosting tree toolkit available, running more than ten times faster than standard tools. A large number of Kaggle players choose XGBoost for data mining competitions, and it is an essential tool for major data science competitions. It is a good solution for large-scale industrial data because the distributed version of XGBoost has broad portability and supports running on various distributed environments, such as Kubernetes, Hadoop, SGE, MPI, Dask, etc. Nevertheless, the spatial complexity of the XG Boost pre-sorting procedure is excessively high, necessitating the storage of not only the feature values but also the indexes of the gradient statistics of the samples corresponding to the feature values, which is equivalent to requiring twice as much memory [37,38]. Combining the autoregressive model with low computational effort and XG Boost with high precision will be advantageous for enhancing prediction accuracy and reducing computational complexity.

3. Methods

3.1. Multimodal psychological state evaluation framework

Psychological states in high-intensity sports are influenced by multiple interacting factors, including biomechanical stability, physiological stress responses, and cognitive decision-making processes. These factors exhibit nonlinear dependencies and evolve dynamically over time. Therefore, a comprehensive evaluation framework is required to quantify these influences and establish a robust predictive foundation.

To systematically model psychological states, we define a multimodal feature space X_t, which integrates biomechanical, physiological, and behavioral components at each time step t:

$$X_t = \{B_t, P_t, M_t\} \tag{1}$$

where: B_t (biomechanical signals): Quantifies movement kinematics and postural control, defined as:

$$B_t = \{v_t, a_t, \theta_t, J_t, \tau_t\} \tag{2}$$

where v_t is velocity, a_t is acceleration, θ_t is postural stability, J_t is net joint moment, and τ_t is muscle torque.

P_t (physiological responses): Reflect internal stress regulation mechanisms, including:

$$P_t = \{HRV_t, EDA_t, EMG_t, RR_t, \sigma_t\} \tag{3}$$

where HRV_t is heart rate variability, EDA_t is electrodermal activity, EMG_t is muscle activation, RR_t is respiratory rate, and σ_t represents stress-induced variability.

M_t (behavioral metrics): Characterizes decision-making patterns, modeled as:

$$M_t = \{RT_t, U_t, \gamma_t, \lambda_t, \Omega_t\} \tag{4}$$

where RT_t is reaction time, U_t is decision uncertainty, γ_t is cognitive workload, λ_t is focus stability, and Ω_t represents decision volatility.

This feature space enables a comprehensive representation of the psychological state evolution over time.

3.2. Psychological state transition model

Given the stochastic and dynamic nature of psychological states, we define a state transition function:

$$Y_t = f(B_t, P_t, M_t) + \epsilon_t \tag{5}$$

where $f(\cdot)$ represents a nonlinear function capturing biomechanical-physiological-behavioral interactions, and ϵ_t accounts for latent factors.

To enhance interpretability, we use a Bayesian inference framework for state estimation:

$$P(Y_t \mid X_t) \propto P(X_t \mid Y_t) P(Y_{t-1}) \tag{6}$$

where $P(X_t \mid Y_t)$ represents the likelihood of observing X_t given Y_t, and $P(Y_{t-1})$ is the prior belief.

To capture psychological state variability, we model its fluctuations using a stochastic differential equation:

$$dY_t = \alpha(Y_t^* - Y_t)dt + \beta dW_t \tag{7}$$

where Y_t^* is the baseline state, α is the adaptation rate, and W_t is a Wiener process modeling random fluctuations.

Additionally, to quantify the energy cost of psychological adaptation, we introduce a biomechanical energy expenditure function:

$$E_t = \int_0^t P_t(\tau)d\tau \tag{8}$$

where $P_t(\tau)$ represents the instantaneous physiological power consumption.

Since psychological states and biomechanical parameters influence each other dynamically, we model this interaction using a coupled differential system:

$$\frac{dB_t}{dt} = f_B(B_t, P_t, M_t),\ \frac{dP_t}{dt} = f_P(B_t, P_t, M_t) \tag{9}$$

where f_B and f_P describe the temporal evolution of biomechanical and physiological states, respectively.

Finally, we quantify psychological stress levels using an entropy-based measure:

$$S_t = -\sum_{i=1}^{N} P_i \log P_i \tag{10}$$

where P_i is the probability distribution of observed states.

3.3. Hybrid predictive modeling

Since psychological state evolution exhibits both temporal dependencies and nonlinear interactions, a single modeling approach may be insufficient. Therefore, we employ a hybrid predictive strategy that integrates autoregressive models to capture short-term memory effects and XGBoost-based regression to model nonlinear feature interactions.

Psychological state evolution follows a time-dependent structure. We use an ARIMA model:

$$\Delta^d Y_t = \sum_{i=1}^{p} \phi_i \Delta^d Y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t \tag{11}$$

where: ϕ_i are autoregressive coefficients, θ_j are moving average coefficients and Δ^d represents differencing of order d.

We refine this with a Kalman filter, updating predictions as:

$$\hat{Y}_t = A\hat{Y}_{t-1} + BX_t + w_t \tag{12}$$

where A and B are transition matrices.

To capture complex interactions, we employ XGBoost, minimizing the loss function:

$$\mathcal{L}(\Theta) = \sum_{t=1}^{T} \ell(Y_t, \hat{Y}_t) + \sum_{k=1}^{K} \Omega(f_k) \tag{13}$$

where $\ell(Y_t, \hat{Y}_t) = \frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2$ minimizes prediction error. $\Omega(f_k) = \gamma T + \frac{1}{2}\lambda\sum_{j=1}^{T} w_j^2$ is a regularization term. The final prediction is:

$$\hat{Y}_t = \sum_{k=1}^{K} f_k(X_t) \tag{14}$$

where f_k represents the k-th regression tree.

To balance computational efficiency and accuracy, we introduce an adaptive weighting mechanism:

$$\hat{Y}_t^* = \alpha \hat{Y}_t^{AR} + (1 - \alpha)\hat{Y}_t^{XGB} \tag{15}$$

where α is dynamically adjusted as:

$$\alpha = \frac{\sigma_{XGB}^2}{\sigma_{AR}^2 + \sigma_{XGB}^2} \tag{16}$$

This enhanced methodology provides a rigorous mathematical foundation for multimodal psychological state estimation and predictive modeling, ensuring both accuracy and computational efficiency.

Utilize an autoregression-based XGBoost model for the purpose of fitting predictions to these data. This model makes full use of the autoregression between continuous time data in time series, and it provides a rough description of the future of objects formed over time by accounting for their own laws as revealed by historical data. It does so by utilizing the autoregression between continuous time data in time series to its maximum capacity. one that predicts the future using information from both the past and the present. In contrast to regression analysis, random perturbation terms do not require qualification.

4. Experiments and analysis

4.1. Data source and collection

The dataset used in this study was collected from professional and semi-professional football players over a period of six months, capturing both training sessions and competitive matches. The study involved 50 official matches and 200 training sessions, with data collected at various time points before, during, and after the matches. To ensure a comprehensive understanding of psychological state variations, we employed a multimodal data acquisition approach, integrating biomechanical, physiological, and behavioral features.

Physiological and biomechanical data were recorded using wearable sensors, while behavioral and psychological assessments were conducted through video-based motion tracking and cognitive stress evaluations. The main data collection methods include:

(1) Wearable Sensors for real-time physiological and biomechanical tracking:

- Heart Rate Variability (HRV): Captured using ECG-based chest strap monitors to evaluate autonomic nervous system activity.
- Electrodermal Activity (EDA): Measured via wrist-worn sensors to assess stress-related skin conductance changes.
- Respiratory Rate (RR): Monitored using respiratory belts to track breathing patterns under physical and psychological stress.

- Muscle Activation (EMG): Recorded using electromyography sensors placed on the lower limb muscles.
- IMU-based Gait Analysis: Foot-mounted inertial measurement units (IMUs) collected running velocity, acceleration, and joint movements.

(2) Video-Based Motion Tracking to analyze biomechanical behavior:

- Postural stability (θ_t) was extracted using motion capture software analyzing player movements.
- Running speed (v_t), acceleration (a_t), and joint angles (J_t) were analyzed through high-speed cameras and pose estimation algorithms.

(3) Cognitive and psychological assessments conducted at different time points:

- Reaction time (RT_t), decision volatility (Ω_t), and focus stability (λ_t) were measured using standardized cognitive stress tests.
- Self-reported stress levels were collected via the Perceived Stress Scale (PSS) and the Competitive State Anxiety Inventory-2 (CSAI-2) before and after matches.

After preprocessing, the dataset contained 25,000 synchronized time-series samples, with each sample comprising 16 extracted features spanning biomechanical, physiological, and behavioral categories. The dataset characteristics are summarized in **Table 1** below:

Table 1. Dataset statistics.

Data Type	Number of Features	Sample Rate	Sessions Collected
Biomechanical	6	100 Hz	50 matches, 200 training sessions
Physiological	5	1 Hz	50 matches, 200 training sessions
Behavioral	5	Event-based	50 matches, 200 training sessions
Psychological Labels	1 (CSAI-2 score)	Pre & Post Match	50 matches, 200 training sessions

Two dimensions comprise the formal scale: common issues in athletic psychology and positive psychological traits. Three components comprise the subscale of positive psychological characteristics among athletes: willpower, social adaptation, and positive intelligence. Athletes commonly experience depression, hostility, anxiety, and somatization as psychological issues. Positive psychological traits of athletes include willpower, social adaptability, and positive intelligence. According to the above indicators and the questionnaire data filled out by football players, the players can be classified according to the scale indicators, as shown in **Figure 1**.

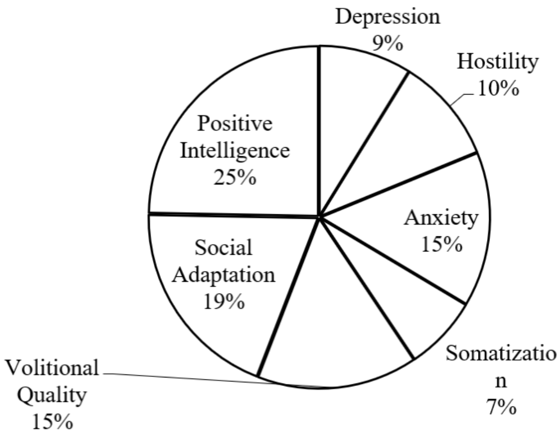

Figure 1. Comparison of athletes' mental states.

Due to the existence of specific or highly correlated relationships between the variables used to explain the dependent variable, the linear regression model is subject to multicollinearity, which distorts the model or reduces the accuracy of its predictions. Prior to applying the approach proposed in Chapter 3 for psychological prediction, it is crucial to consider how the presence of multicollinearity between independent variables may impact the accuracy of the mental health prediction model for football players. For multicollinearity discrimination, the SPSS statistical software is used to compute the condition index. Collinearity is deemed minimal when the condition index falls between 10 and 30, moderate between 30 and 100, and severe above 100. **Figure 2** depicts the results of a multicollinearity diagnosis. The degree of collinearity between the seven independent variables is low, as depicted in **Figure 2**.

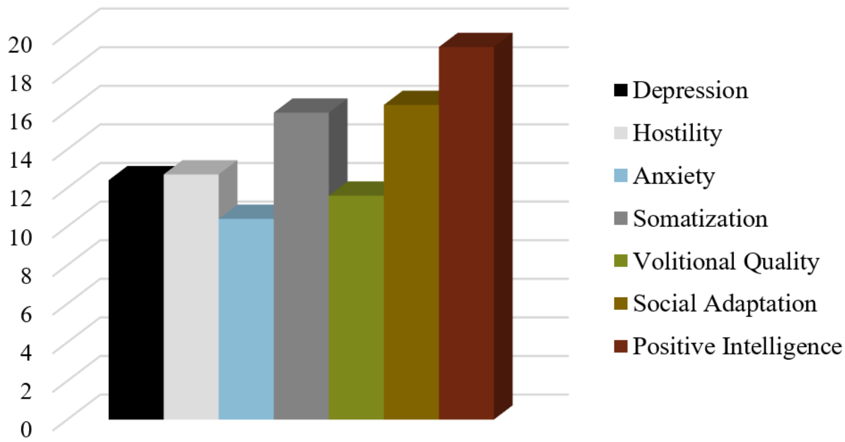

Figure 2. Diagnostic results of multicollinearity.

4.2. Data preprocessing and feature engineering

To ensure high-quality input data for model training, a comprehensive preprocessing pipeline was applied to the collected multimodal dataset. Given the differences in data acquisition rates among physiological, biomechanical, and behavioral sources, signal synchronization was a crucial step. Time-series alignment was performed using Dynamic Time Warping (DTW), ensuring that data from various sensors corresponded to the same time frames. Additionally, noise filtering techniques were applied to improve data quality—physiological signals, such as heart rate variability (HRV) and electrodermal activity (EDA), were smoothed using a 5th-order Butterworth filter, while biomechanical signals, including acceleration and postural stability, were processed using a Kalman filter to eliminate sensor drift and fluctuations. Following filtering, all numerical features underwent standardization to zero mean and unit variance, allowing for fair weightage during model training. Outlier removal was also implemented, where extreme values beyond three standard deviations were detected and eliminated using the interquartile range (IQR) filter, preventing the model from being biased by anomalous observations. This preprocessing strategy ensured that the dataset maintained temporal consistency, robustness against sensor noise, and an appropriate feature scale for effective model learning.

4.3. Model performance comparison

To assess the effectiveness of our proposed hybrid approach, we compared the performance of three models: ARIMA, XGBoost, and the Hybrid Model (ARIMA + XGBoost). The models were evaluated using root mean squared error (RMSE), mean absolute error (MAE), and R^2 score, where lower RMSE and MAE values indicate better predictive accuracy, and a higher R^2 score reflects a stronger correlation between predicted and actual psychological states. The results are shown in **Table 2**.

Table 2. Performance comparison under different models.

Model	RMSE	MAE	R^2 Score
ARIMA	0.86	0.72	0.65
XGBoost	0.71	0.58	0.81
Hybrid (ARIMA + XGBoost)	0.61	0.47	0.89

From the results, we can observe the following key findings: The ARIMA model, while capable of capturing temporal dependencies, exhibited the highest RMSE (0.86) and the lowest R^2 score (0.65), indicating that relying solely on past psychological states for prediction is insufficient to account for the complex interactions among biomechanical, physiological, and behavioral factors. In addition, the XGBoost model significantly improved accuracy, reducing RMSE to 0.71 and achieving an R^2 score of 0.81. This confirms that incorporating nonlinear feature interactions from multimodal data enhances predictive capability. Moreover, the combination of ARIMA and XGBoost further improved prediction accuracy, with an RMSE of 0.61 and an R^2 score of 0.89. The hybrid model leveraged the temporal dependencies captured by ARIMA while benefiting from XGBoost's ability to model nonlinear interactions, resulting in the most robust predictions.

To further validate the robustness of our proposed approach, we compared our results against traditional stress prediction models, including linear regression (LR) and support vector regression (SVR). The comparative results are summarized as shown in **Table 3**:

Table 3. Performance comparison against traditional stress prediction models.

Model	RMSE	MAE	R^2 Score
LR	1.02	0.85	0.51
SVR	0.89	0.75	0.63
ARIMA	0.86	0.72	0.65
XGBoost	0.71	0.58	0.81
Hybrid (ARIMA + XGBoost)	0.61	0.47	0.89

Linear regression and SVR performed significantly worse than the hybrid approach, confirming that a simple linear model is insufficient to capture the complexity of psychological state fluctuations. The hybrid model consistently outperformed all other models, proving the effectiveness of combining temporal analysis (ARIMA) with nonlinear feature learning (XGBoost).

4.4. Mental health analysis

To further understand the impact of different factors on psychological state prediction, we analyzed feature importance using SHAP (Shapley Additive Explanations). SHAP values quantify how much each input feature contributes to the final prediction, providing insights into which variables play the most significant role in predicting stress, anxiety, and cognitive stability. The results are shown in **Figure 3**.

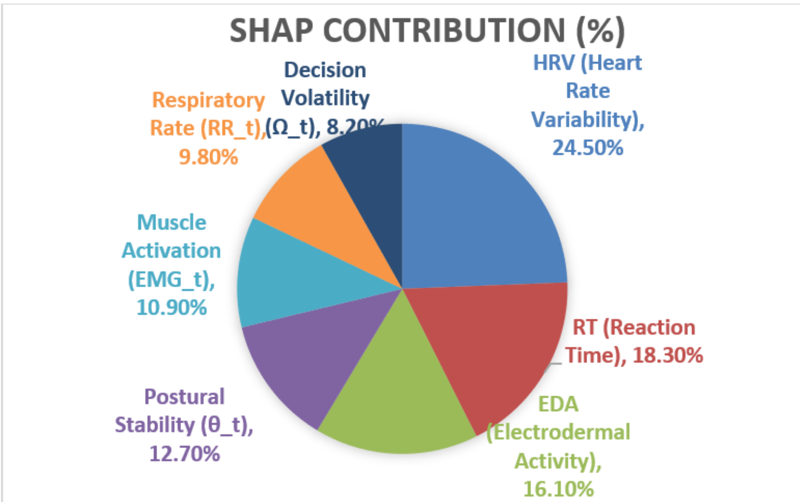

Figure 3. Feature importance analysis.

The feature importance analysis highlighted the significant role of biomechanical factors in psychological state prediction, reinforcing the strong connection between movement stability, neuromuscular control, and mental resilience. Postural stability (12.7%) emerged as a key predictor, indicating that impaired balance and movement coordination are closely linked to increased psychological stress. Players exhibiting greater postural instability before matches were more likely to experience heightened anxiety and cognitive overload during competition. Muscle activation (EMG, 10.9%) also played a crucial role, as increased neuromuscular strain and fatigue correlated with psychological instability, suggesting that physical exertion and biomechanical stress contribute to cognitive stress responses. Additionally, reaction time (18.3%) and decision volatility (8.2%) further reinforced the link between biomechanical and psychological factors, as delayed responses and erratic decision-making patterns were observed in players with greater motor instability. These findings confirm that biomechanical efficiency is deeply intertwined with psychological state, emphasizing the need for integrated movement assessment and neuromuscular training in stress management and performance optimization for football players.

Figure 4 depicts the mean and standard deviation of social support, self-esteem, and resilience, as well as anxiety, and **Table 4** depicts the correlation matrix. It is feasible to find. Significantly negative correlations existed between social support, self-esteem, and resilience and anxiety, whereas significant positive correlations existed between social support, self-esteem, and resilience.

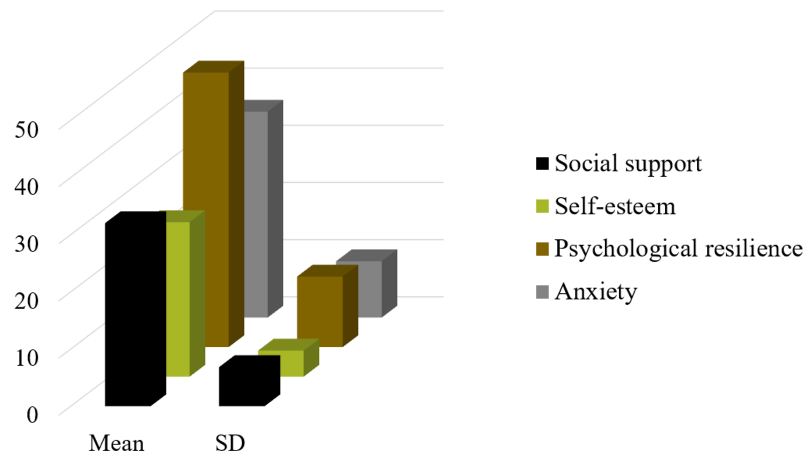

Figure 4. Graph of descriptive statistics results for the four factors.

Table 4. The correlation matrix of the four factors.

Index	Social support	Self-esteem	Psychological resilience	Anxiety
Social support	/			
Self-esteem	0.437^{***}	/		
Psychological resilience	0.428^{**}	0.56^{***}	/	
Anxiety	-0.53^{**}	-0.48^{***}	-0.32^{**}	/

*Note: ***$p < 0.001$; **$p < 0.01$; $p < 0.05$.

The results presented in **Figure 4** and **Table 4** underscore the complex interplay between social support, self-esteem, psychological resilience, and anxiety, with particular emphasis on their biomechanical implications for football players. The significant negative correlations observed between anxiety and social support, self-esteem, and psychological resilience (r = −0.53, −0.48, and −0.32, respectively) indicate that higher levels of psychological resilience and positive self-perception are associated with lower anxiety levels. This reduction in anxiety may, in turn, enhance neuromuscular efficiency and movement stability under pressure. From a biomechanical standpoint, elevated anxiety has been linked to impaired motor coordination, reduced postural stability, and delayed reaction times—all of which can adversely affect decision-making and physical performance during competition.

Conversely, strong social support and high self-esteem may facilitate greater neuromuscular control and movement precision, as confidence and psychological resilience have been linked to more stable posture, enhanced proprioception, and improved muscular activation patterns. The positive correlations between social support, self-esteem, and psychological resilience (r = 0.437, 0.56, and 0.428, respectively) further strengthen this association, suggesting that athletes who perceive higher levels of psychological support are more likely to demonstrate improved motor control strategies, enhanced muscle coordination, and reduced biomechanical stress during performance. These findings suggest that integrating psychological interventions alongside biomechanical training could enhance overall athletic performance, as improved psychological resilience not only reduces cognitive stress and anxiety but also promotes more stable and coordinated physical movements, ultimately benefiting football players in high-pressure competitive environments.

4.5. Discussion

The findings from Section 4 provide significant insights into the relationship between biomechanics, physiological responses, and psychological health in football players. The results highlight how neuromuscular control, movement stability, and physiological stress markers are interconnected with psychological states, particularly in high-pressure competitive environments. The hybrid predictive model (ARIMA + XGBoost) demonstrated superior accuracy in forecasting psychological fluctuations, reinforcing the need for integrating biomechanical and physiological indicators to enhance stress assessment and intervention strategies in sports performance.

One of the key findings was the strong influence of biomechanical factors, such as postural stability and muscle activation, on psychological resilience. Players exhibiting greater postural instability and neuromuscular fatigue were more prone to experiencing heightened stress and anxiety, suggesting that movement efficiency and psychological stability are intrinsically linked. These findings align with previous research indicating that motor coordination impairments and delayed reaction times under stress can negatively impact cognitive performance and decision-making speed. The significant contributions of reaction time and decision volatility further support the notion that biomechanical inefficiencies contribute to cognitive overload, leading to inconsistent performance during matches. The practical applications of these findings extend to both training optimization and real-time monitoring systems for football players. By incorporating wearable sensors and motion tracking technologies, coaches and sports scientists can continuously assess an athlete's neuromuscular stability and physiological stress markers to predict and mitigate psychological fluctuations. This approach enables personalized training interventions, focusing on enhancing postural control, reducing neuromuscular fatigue, and improving decision-making under pressure. Additionally, the development of real-time feedback systems integrating biomechanical and physiological data could provide on-the-field stress monitoring, allowing for immediate adjustments in gameplay strategies and recovery techniques.

Furthermore, the integration of biomechanical assessments with psychological monitoring can lead to more effective mental resilience programs, where physical conditioning exercises targeting balance, muscle coordination, and reaction time are tailored to an athlete's psychological stress profile. This interdisciplinary approach has the potential to reduce injury risks, enhance psychological adaptability, and improve overall performance consistency in football players.

5. Conclusion

This study developed a hybrid psychological state prediction model for football players, integrating biomechanical, physiological, and behavioral feedback to assess mental resilience and stress adaptation. The experimental results revealed that neuromuscular stability, postural control, and cognitive efficiency are critical factors influencing psychological fluctuations, with features such as heart rate variability, reaction time, and electrodermal activity playing a central role in predicting anxiety levels. The hybrid ARIMA-XGBoost model significantly outperformed standalone models, demonstrating the importance of combining time-series forecasting with nonlinear feature learning for robust mental health assessment. From a practical application perspective, these findings provide a strong foundation for developing real-time stress monitoring systems using wearable sensors and motion tracking technologies. Coaches and sports scientists can utilize this multimodal assessment framework to design personalized training interventions, focusing on improving movement stability, reducing neuromuscular fatigue, and optimizing cognitive performance under pressure. The integration of biomechanical feedback with psychological monitoring offers a novel approach to enhancing mental resilience in high-performance sports, enabling athletes to maintain consistency in decision-making and physical execution during competitive matches.

Future research should focus on advancing deep learning-based predictive models and expanding real-time feedback mechanisms to further enhance accuracy, reduce computational complexity, and provide on-the-field adaptive interventions. By leveraging biomechanics and machine learning, this study contributes to the growing field of sports science and mental health optimization, offering practical solutions for stress management and performance enhancement in professional football.

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Availability of data and materials: The data that support the findings of this study are available from the corresponding author upon reasonable request.

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