J. COMBIN. MATH. COMBIN. COMPUT. 127b (2025) 5927--5940

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Detection of Mental Training Anxiety in Basketball Players in Same-Court Rivalry Centers Based on LightGBM Algorithm

Liya Yin[1,✉]

[1] UTS Business School, University of Technology Sydney (UTS), Sydney, NSW, Australia

ABSTRACT

In this study, we first collected and preprocessed data from 500 basketball players between the ages of 13-35 years old in the same-court rivalry training in Northwest China, after which we utilized the Global Chaos Bat Algorithm (GCBA) for the mental training anxiety emotion feature extraction, and analyzed the correlation between each feature and the anxiety emotion through the Pearson coefficient. Finally, the LightGBM-based emotion prediction model was constructed, and the SHAP value was introduced to evaluate the feature importance of the model. The results show that the LightGBM model performs better and has higher prediction accuracy, which is as high as 96.68%; the interpretation results of the SHAP algorithm indicate that the gender and age of the basketball players are the main real-world factors for assessing their anxiety in same-court rivalry training. In addition, their game scores, opponents' strengths and injury histories during the same-court rivalry training were the main intrinsic factors for their anxiety. In conclusion, the psychological state of basketball players can reflect the severity of their training anxiety, and it further reveals the relationship between the psychological characteristics of basketball players and their training anxiety.

Keywords: GCBA algorithm; LightGBM model; SHAP model, basketball players; anxiety detection

1. Introduction

In recent years, the fierce competition in competitive sports has led to the increasing prominence of the problem of psychological anxiety among athletes. Athletes produce psychological anxiety mostly in the process of training and the conduct of the game, the reason why anxiety is produced is because of the psychological pressure caused by the uncertainty of the results of the late game, which can be manifested psychologically as the emotions of apprehension, restlessness and fear, and physiologically as shouting and action violence [1-3]. Psychological anxiety in athletes is not regular in its characterization and has a direct correlation mainly with the intensity of the competition [4]. The

✉ Corresponding author.
E-mail address: liya_yin19@163.com (L. Yin).
Received 03 March 2024; Revised 20 April 2024; Accepted 10 November 2024; Published Online 16 April 2025.
DOI: 10.61091/jcmcc127b-325

reason why athletes develop anxiety is directly related to the fact that sports competitions have a high degree of uncertainty. In addition, the main reason for athletes' psychological anxiety is also related to the surrounding environment, such as the fear of failure can not face the coach, parents, teammates, etc., or the self, the media, the fans expect too much, afraid of their own inability to complete the game, this intangible psychological pressure, but also on the basketball players will cause great psychological anxiety [5-8]. In addition, there are some other reasons, such as the athlete's personal psychological quality, etc. If the athlete usually has psychological training or interventions, or simulation of the field of play, then the comprehensive psychological quality will be improved, and it can also moderately alleviate the situation of psychological anxiety [9-12].

Basketball is unique because of its time-limited, intense, and uncertainty of the outcome of the game, and the psychological state of the athletes fluctuates with the rhythm of the game. This fluctuation of psychological state, especially the change of emotions, can directly affect the athletes and other athletes in the whole team's competitive ability [13]. Emotional fluctuations may lead to inattention and slow reaction of the athletes and even affect their technical execution and decision-making ability, which can have a significant impact on the outcome of the game [14]. Therefore, managing and regulating emotions and maintaining a good mental state in basketball are crucial to maintaining optimal competitive performance and achieving success. There is a universal nature of this competition state anxiety in athletes, emotional intelligence and psychological resilience has been an important theme in positive psychology and post-traumatic growth, is the ability to withstand the face of setbacks, the ability to regulate emotional anxiety, as well as the ability to overcome the setbacks of the transcendence of the ability to have a certain amount of resistance to stress when an individual is faced with setbacks, the ability to keep their own psychological and behavioral normality, and have a certain degree of tolerance to setbacks,. At the same time can use psychological regulation to overcome and defeat setbacks, so that the self is transcended and success is achieved [15-18]. However, the first step to understand the athlete's psychological anxiety is to detect the anxiety state, and the traditional detection methods are carried out by scale tools, heart rate variability, EEG, etc., which have a large subjective bias in detection, a single dimension of detection, mostly pre-game or post-game detection, and lack of detection of real scenarios of confrontation matches [19-22]. Therefore, the detection technology to optimize the psychological anxiety state of basketball players has become a research focus at present.

LightGBM (Light Gradient Boosting Machine) is a gradient boosting algorithm based on decision trees, which uses decision trees based on gradient augmented trees as the basis and optimization techniques such as distributed parallel algorithms, and it can deal with a large number of sample sizes and high dimensionality data [23]. The algorithm has advantages in exploring the mental state of athletes in confrontation in basketball.

In this paper, key features such as physiological signals and behavioral performance of basketball players employed in the same game confrontation are preprocessed by the min-max normalization method. After that, the key features of the athletes in the confrontation scene are extracted under the GCBA algorithm, and then the Pearson coefficient is used to explore the correlation between the feature dimensions and filter out the features that have a significant effect on anxiety. Finally, the LightGBM mood prediction model with efficient data processing capability and good performance was constructed, and the SHAP model was introduced to interpret the results of the LightGBM mood prediction model and analyze the importance of the factors affecting basketball players' mental training anxiety in the center of the same-court confrontation.

2. Anxiety Detection Method for Athletes Based on LightGBM Algorithm

2.1. Anxiety data processing and feature selection

2.1.1. Acquisition of anxiety data. This study was conducted on 500 basketball players between the ages of 13 and 35 in Northwest China. The data set was collected from the athletes' daily training sessions in the same-court rivalry center for one year from September 2023 to September 2024, and a total of 2,793 pieces of fill-in data were collected. The dataset consists of three parts: physical state anxiety, game state anxiety, and cognitive state anxiety.

2.1.2. Anxiety data processing. During the training process, the quality of the data plays an almost decisive role in the accuracy and reliability of the model. Therefore, before proceeding to the subsequent model building and realization, data preprocessing must be carried out on the original data, so as to make the data better meet the model needs and ensure that the model achieves better prediction results.

1) Data pre-processing. Data screening: The preliminary data collection work is to collect as much and comprehensive data as possible, and does not carefully consider the specific use of data. With a specific research objective, it is necessary to screen the data needed for that research objective.

Data cleaning: in this paper, the abnormal data collected from basketball players' mental training anxiety in the same-court confrontation center are processed as follows: first, if a piece of raw data is missing more than three relevant attributes, delete it; second, use the mean to fill in the raw data with missing type of numerical type, and use the plurality to fill in the raw data with missing type of string type. After the above processing, the final obtained experimental valid data 1520.

Data integration: this paper mainly uses the basketball player anxiety state tester-based physical state anxiety factors, game state anxiety factors and cognitive state anxiety factors as inputs, which need to be integrated into the data.

Data transformation: also known as data mapping processing, that is, the data need to be transformed differently in different application scenarios. In the gender attribute in the statistical information of basketball players, "male" is recorded as 1, and the gender "female" is recorded as 2; in the attribute of "body balance" in the information of mental training anxiety trait, the score is in [0,0,0], and the score is in [0,0,0]. The score is in the interval [0,1].

2) Normalization of data. Normalization of data is also known as normalization, an operation that involves scaling the data range to a specific range, usually $[0,1]$ or $[-1,1]$. In this paper, the min-max normalization method [24] is used to process the data with the following transformation function:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

where x' is the scaled value, x is the original data value, $x_{\min}$ is the minimum value of the data, and $x_{\max}$ is the maximum value of the data.

3) Data Balancing Process. Data balancing processing means that in the process of model training, in this paper, for each sample x with anxiety tendency, the Euclidean distance is used to calculate its distance to each data in the data set of the sample with anxiety tendency to get its k nearest neighbor. Secondly, based on the sample imbalance set the corresponding sampling multiplicity N, for each anxiety tendency sample x, from the k-nearest neighbor data to randomly select a number of sample data. Then assume that the selected nearest neighbors are x_n, and for each randomly selected nearest neighbor x_n, construct a new sample with the original sample data according to the formula

$x_{new} = x + rand(0,1) * |x - x_n|$. Eventually, the amount of data from the samples with and without anxiety tendency is made consistent to get a new data set of mental states.

2.1.3. Feature selection based on GCBA algorithm. Global Chaos Bat Algorithm [25] (GCBA) as a heuristic algorithm, Logistic method is a commonly used chaotic mapping method, which is characterized by its ability to generate diverse initial populations to explore the entire solution space, in this paper, an improved logistic mapping method for population initialization is used, which uses a more efficient mathematical model to overcome the traditional logistic mapping method's limitations. This new method gives better convergence results. Its mathematical model is:

$$u_i^w = \left|1 - 2 \times (u_i^{w-1})^2\right| \tag{2}$$

Where $u_i^w \left(i = 1, 2, \cdots, n, w = 1, 2, \cdots m\right)\left(u_i^w \in [0,1]\right)$ is a chaotic variable, n stands for the number of bat populations, and w stands for the initial population dimension. Next, the inverse mapping of u_i^w can be performed to obtain the position x_i^w of individual bats in the solution space, and x_i^w is calculated as:

$$x_i^w = k_i + (p_i - k_i)u_i^w \tag{3}$$

where p_i and k_i are the maximum and minimum values in the range of variables, respectively. When individual bat positions are updated, the local optimal positions of individual bats and the global optimal positions of the population are recorded. The position of the i th bat at the $t+1$ th iteration can be calculated by the following equation:

$$x_i^{t+1} = x_i^t + v_i^{t+1} F_1 c_1 (O_i - x_i^t) + F_2 c_2 (O_g - x_i^t) \tag{4}$$

where $F_1 = F_2 = 1.496$, O_i is the locally optimal position of the i th bat, and O_g is the globally optimal position of the bat population. The c_1 and c_2 are two random values within $[0,1]$.

When the global chaotic bat algorithm is applied to demographics as well as feature selection for personality trait attributes, the bat population is initialized with a matrix of size $n \times m$. Where n is the number of bat populations and m is the number of features. The bat locations are then discretized in binary using the transfer equation. The transfer equation is:

$$S(x_i^w(t)) = \frac{1}{1 + e^{-x_i^w(t)}} \tag{5}$$

where $x_i^w(t)$ represents the position of the i th bat in the wth dimension at the t th iteration. The update equation for the position of an individual bat is:

$$x_i^w(t) = \begin{cases} 0 & rand < S(x_i^w(t)) \\ 1 & rand \geq S(x_i^w(t)) \end{cases} \tag{6}$$

where $rand$ represents a random number within $[0,1]$. When the t th iteration, the i th bat is at 0 in the w-dimension, the bat is not selected; when the i th bat is at 1 in the w-dimension, the bat is selected.

After the above steps of feature extraction for mental health data, the optimal features are selected sequentially. Next, these features are combined and scored and the optimal feature combination is selected. The combination of features in three psychological states:

1) When predicting the presence of physical state anxiety factors in the population, there are four feature attributes in the optimal feature combination, which are body balance, injury history, muscle strength, and workout load.

2) When predicting whether there is a competition state anxiety factor in the population, there are four feature attributes in the optimal feature combination, which are technical errors, competition venue comfort, venue humidity, and competition rules.

3) When predicting the presence of cognitive state anxiety in the population, the optimal feature combination had four feature attributes, which were opponent strength, self-regulation, match score, and spectator atmosphere.

2.1.4. Method of correlation analysis of anxiety scale dimensions. The scale used to obtain data for this assessment was a categorical scale of training anxiety emotional states in basketball players, consisting of 3 training anxiety emotional problems and 12 dichotomous traits. Personality traits usually develop gradually during an individual's growth and development and remain relatively stable in adulthood. Training anxiety mood, anxiety, and stress are major mental health concerns that are closely related to personality traits. In order to analyze the correlation between the dimensions, this paper uses Pearson's coefficient to explore the correlation between the trait dimensions.

2.2. Model for Detecting Anxiety in Basketball Players' Mental Training

2.2.1. Predictive Modeling of Psychological Training Anxiety. A prediction model of basketball players' anxiety during same-court rivalry training based on the LightGBM algorithm [26-27] was used and combined with the SHAP algorithm to interpret the model results in order to increase the interpretability of the model.

2.2.2. Introduction to the LightGBM algorithm. The LightGBM algorithm is an efficient gradient boosting decision tree framework, and its efficiency stems from two main aspects: first, the histogram-based decision tree algorithm is used, which reduces the number of feature values to be considered by constructing a feature histogram and dividing it into discrete bins, accelerating the computation speed and reducing the memory footprint; Second, a gradient one-sided sampling technique is used, which reduces the number of instances to be considered in each iteration, speeds up convergence and avoids overfitting problems by identifying instances with large gradients and then sampling instances with small gradients based on a threshold.

The LightGBM algorithm is a summation function consisting of k basis models as follows:

$$\hat{y}_i = \sum_{t=1}^{k} f_t(x_i) \tag{7}$$

Where: x_i represents the input features of the i th sample; f_t represents the t th base model; and $\hat{y}_i$ represents the predicted value of the i th sample. The loss function can be represented by the predicted value and the true value as follows:

$$L = \sum_{i=1}^{n} l(y_i, \hat{y}_i) \tag{8}$$

Where: n represents the sample capacity; l represents the loss function of the i th sample; y_i represents the true value of the i th sample. The objective function is established on this basis as follows:

$$Obj(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{t=1}^{k} \Omega(f_t) \tag{9}$$

Where: Ω represents the regularization term; θ is the model parameter. The probability of each category can be obtained through the Softmax function. Specifically, let the model has trained a total of k trees, and the output of the m th tree is $f_m(x)$, then the probability that the sample point x belongs to the category c is:

$$p_c(x) = \frac{\sum_{m=1}^{k} w_m \cdot I\left(f_m(x) = c\right)}{\sum_{m=1}^{k} w_m} \tag{10}$$

Where: w_m is the weight of the m th tree; I is the indicator function. The Softmax function can understand the probability distribution of each category and can classify the borrowing customers, and the classification accuracy of LightGBM algorithm can be improved to a certain extent by continuously optimizing the objective function.

2.2.3. Indicators for assessing the importance of SHAP features. The SHAP algorithm is a method for interpreting the predictive results of machine learning models. By providing an importance score, or shapley value, for each feature, the extent to which each feature contributes to the model's prediction results can be quantified, helping researchers to understand the extent to which each feature influences the model. As a result, the SHAP algorithm has been widely used in finance, healthcare, natural language processing, and other fields.

In the SHAP algorithm, all features are considered as “contributors”, and their influence on the final output is measured by calculating the Shapley value of each “contributor” with the following formula:

$$y_i = y_{base} + f(x_{i,1}) + f(x_{i,2}) + \cdots + f(x_{i,k}) \tag{11}$$

Where: $x_{i,k}$ represents the k th feature of the i th sample; $f(x_{i,k})$ represents the Shapley value of $x_{i,k}$; y_{base} represents the baseline of the whole model; and y_i represents the predicted value of the i th sample. Intuitively, when $f(x_{i,k}) > 0$, it means that the feature has a positive effect on the prediction results; conversely, when $f(x_{i,k}) < 0$, it means that the feature has a negative effect on the prediction results.

3. Analysis of the results of training anxiety detection in basketball players

3.1. Descriptive statistics of mental training anxiety in basketball players

The experiments in this paper mainly use the LightGBM package of Python and the SHAP-based tree interpretation model TreeExplainer. The data are the psychological training anxiety data of 500 basketball players labeled with training anxiety (light/medium/heavy) in the same-court confrontation. Descriptive statistics were used to understand the distribution of athletes' gender, age, psychological and training anxiety. The results showed that this athlete data included 241 females and 259 males. The percentage of the number of different training anxiety moods was 25.34% mild, 36.98% moderate, and 37.68% severe. The average age of the athletes was 23 years old, of which 327 athletes aged 15-19 years old accounted for the largest proportion. The descriptive statistical results of training anxiety emotional state of basketball players are shown in Table 1. It can be seen that there are large individual differences in the four anxiety mood states of injury history, technical errors, opponent strength and game score, especially game score, whose mean value reaches 0.5743, which has the greatest impact on the training anxiety of basketball players, and also has more commonality among other factors.

Table 1. The description of the anxiety state of basketball athletes training

Training anxiety	Factors	Mean	Standard deviation	Variance
A: Physical anxiety factors	A1: Physical balance	0.1216	0.1273	0.0222
	A2: Injury history	0.3573	0.0943	0.0203
	A3: Muscle power	0.1626	0.1265	0.0077
	A4: Exercise load	0.1534	0.1246	0.0078
B: State anxiety factor	B1: Technical error	0.3313	0.1593	0.0273
	B2: Comfort level	0.0689	0.0948	0.0085
	B3: Site humidity	0.1717	0.1537	0.0036
	B4: Rules of the game	0.0421	0.1293	0.0271
C: Cognitive state anxiety factors	C1: Rival strength	0.4244	0.1315	0.0322
	C2: self-control	0.2718	0.1021	0.0321
	C3: Game score	0.5743	0.1366	0.0136
	C4: Audience atmosphere	0.2145	0.141	0.0122

3.2. LightGBM model performance testing

In this section, LightGBM of this paper is compared with six existing models based on logistic regression (LR), KNN, SVM, random forest (RF), decision tree (CART), and Xgboost. In order to improve the fairness and reliability of the comparison between the models, the cross-validation method was used in the experiment for performance evaluation, and the results of the accuracy comparison of different models are shown in Figure 1. Preliminary view of the distribution of prediction accuracy shows that the LightGBM model is more accurate than all the six compared models.

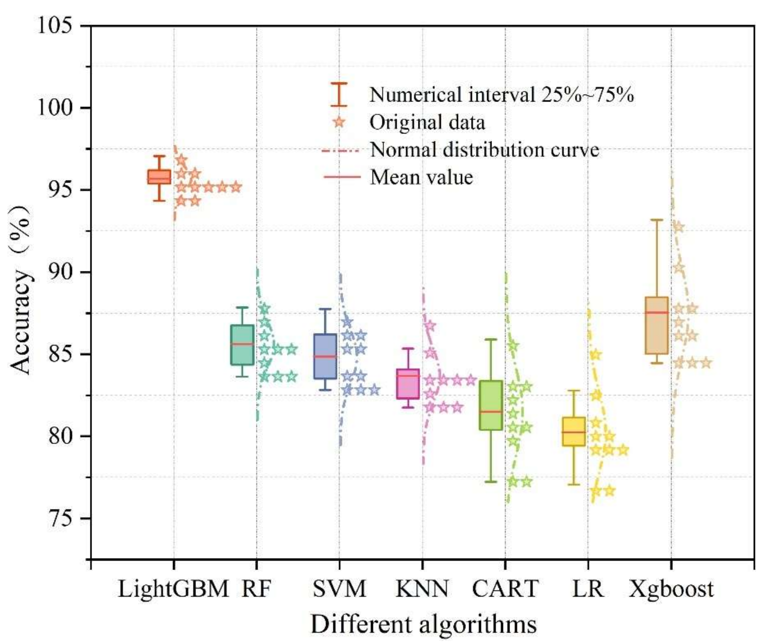


Fig. 1. Comparison results of different models

Five commonly used evaluation metrics, namely, accuracy, precision, recall, F1 value and AUC value, were used to assess the strengths and weaknesses of the models. The results of model performance comparison are shown in Table 2. According to the experimental results, it can be seen that, among them, the LightGBM model has an accuracy rate of more than 95% for the remaining four indicators, except for the recall rate of 94.29% which is less than 95%. Compared with other machine learning algorithms, the integrated class algorithms RF, Xgboost, and LightGBM perform better in prediction accuracy, and their accuracy ranges from 90.92% to 96.68%, which reflects the superiority of the integrated algorithms.The Xgboost algorithm is the closest to the algorithm LightGBM in this paper in terms of various performances, but the latter performs better, with performance improvement of about 5.43%-11.4%, because LightGBM retains the information gain of small samples and also has the advantage of supporting efficient parallelism.

The pre-sorting algorithm of Xgboost is different from the GOSS sampling strategy, which needs to traverse each feature value, and each traversal will carry out a split gain calculation according to the need, and after pre-sorting, it also needs to record the feature values and their corresponding samples' statistics indexes, whereas LightGBM uses a histogram algorithm to transform the feature values into bin values, and no longer needs to record the feature-to-sample indexes, and uses mutual exclusion during the training process. And it uses mutually exclusive feature bundling algorithm to reduce the number of features in the training process, which greatly reduces the memory consumption. It can be seen that among the seven algorithms, LightGBM has more accurate results, consumes less memory, runs faster, and has better stability than the other algorithms.

Table 2. Model performance comparison results

Model	Accuracy	Precision	Recall	F1-score	AUC
LR	0.8491	0.7872	0.744	0.7664	0.9167
KNN	0.8296	0.7325	0.7439	0.7305	0.8587
SVM	0.8259	0.7897	0.6951	0.7532	0.9009
RF	0.9092	0.8335	0.7913	0.8449	0.9035
CART	0.8417	0.8211	0.7928	0.7846	0.8564
Xgboost	0.9125	0.8354	0.8289	0.8685	0.9267
LightGBM	0.9668	0.9543	0.9429	0.9579	0.9998

3.3. Explanation of SHAP model on athletes' psychological training anxiety

3.3.1. Feature Importance Analysis. The average effect of SHAP values on the size of the model output is shown in Figure 2. The 4 most important features in the LightGBM-based model for predicting training anxiety in basketball players are game score, opponent strength, injury history, and technical errors. In addition to these 4 features were identified as the primary psychological factors that distinguish training anxiety in basketball players. The order of importance of the characteristics of training anxiety varied among basketball players. For mild/severe training anxiety, the cognitive state anxiety factor was the most critical criterion; while for moderate training anxiety, the physical state anxiety factor and the game state anxiety factor were the two most important criteria.

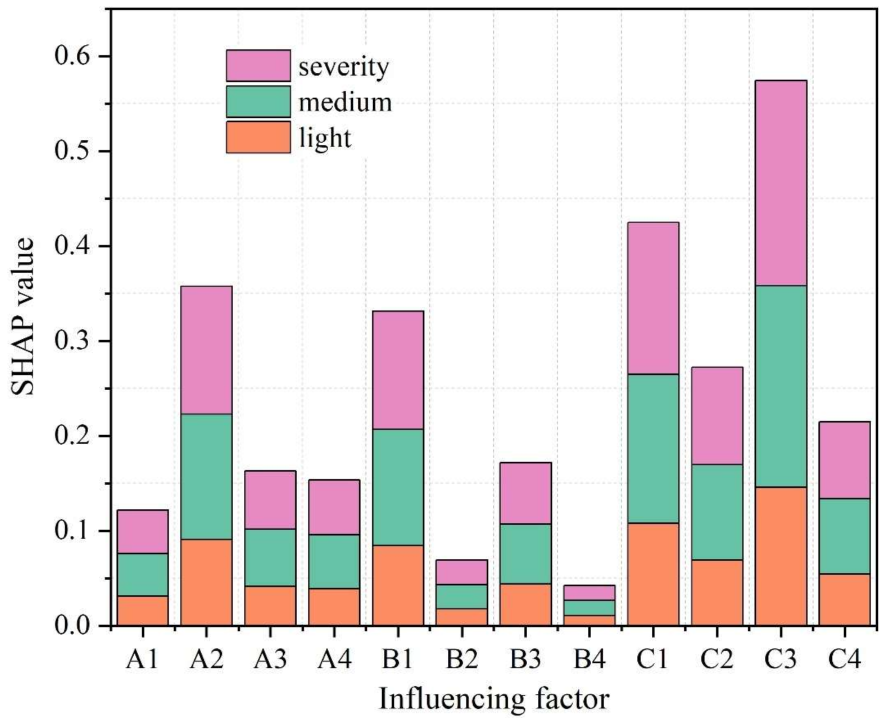


Fig. 2. The average effect of SHAP values on the output size of the model

3.3.2. Main effects analysis of characteristic variables. The influence of SHAP value on the main effect of model output feature variables is shown in Figure 3, where each color point represents a sample and the horizontal coordinate shows the SHAP value of the feature variables, and the distribution of the color points shows the influence of each feature variable on the target variable.

The cognitive state anxiety factor in the training process of basketball players is analyzed as an example. The figure highlights the importance of the two elements of game score and opponent strength in the prediction, and they have a significant impact on the prediction of heavy training anxiety. At the same time, a significant negative correlation between opponent strength, match size and athletes' state of anxiety is shown, i.e., athletes with higher scores (indicated by red dots) may have extremely high or low training anxiety.

On the characteristic of the physical state anxiety factor, despite the fact that the majority of basketball players scored low, some of those who scored high still presented high levels of training anxiety.

In addition, the analysis of the game state anxiety factor revealed that a moderate percentage of the group of basketball players with severe training anxiety scored low (indicated by blue dots). The game size factor, however, revealed that athletes with low scores faced a higher risk of training anxiety than those with high scores.

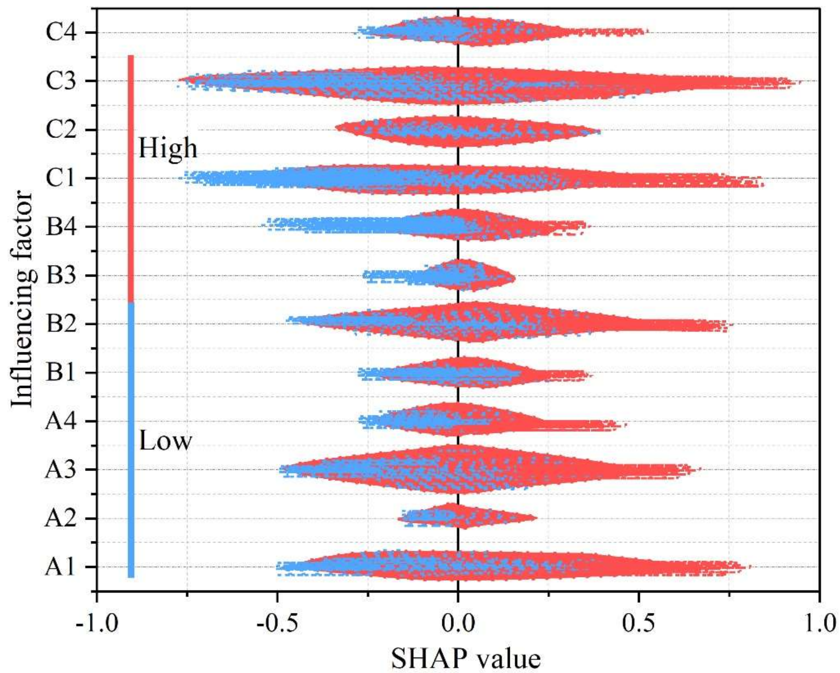


Fig. 3. The effect of SHAP value on the main effect of the characteristic variable

3.3.3. Analysis of interaction effects. This study explored the relationship between physical state anxiety, game state anxiety, and cognitive state anxiety traits and the risk of developing training anxiety in heavy basketball players by using a dependency plot of SHAP values. A SHAP dependency plot is a scatterplot in which each point represents a specific sample, the horizontal axis represents the observed trait Fx, and the vertical axis represents the SHAP value of Fx; interactions with the Fx feature Fy is represented by color shades. In this study, gender and age characteristics were used as Fy, while the 12 psychological characteristics were used as Fx.

The correlations between physical fitness status and training anxiety in basketball players of different genders are shown in Figure 4. There was a more significant negative correlation between physical fitness status and training anxiety in basketball players of different genders, i.e., the lower the score of physical fitness status, the higher the training anxiety. In contrast, the effect of physical fitness status on training anxiety in males seems to be insignificant. In the region of higher training anxiety, i.e., the region with SHAP values greater than 0.2. It was observed that the scores for the physiological traits corresponding to the blue dots were generally low. This finding emphasizes the importance of gender differences as well as physical fitness status when considering the risk of training anxiety mood disorders, especially for female basketball players.

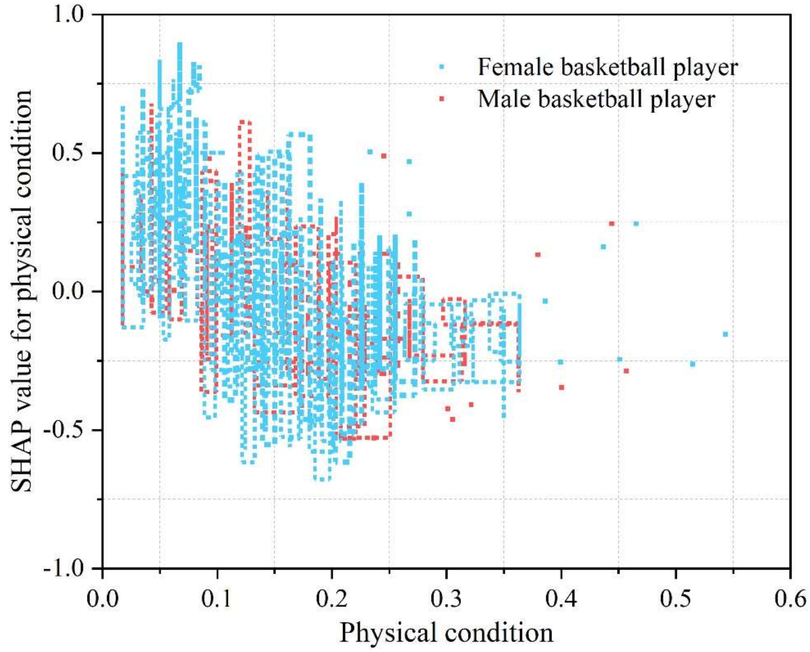
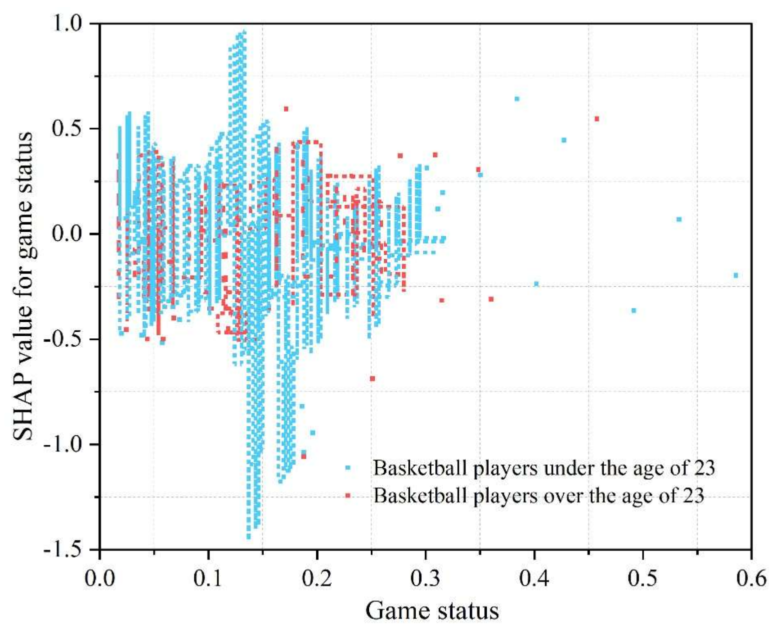


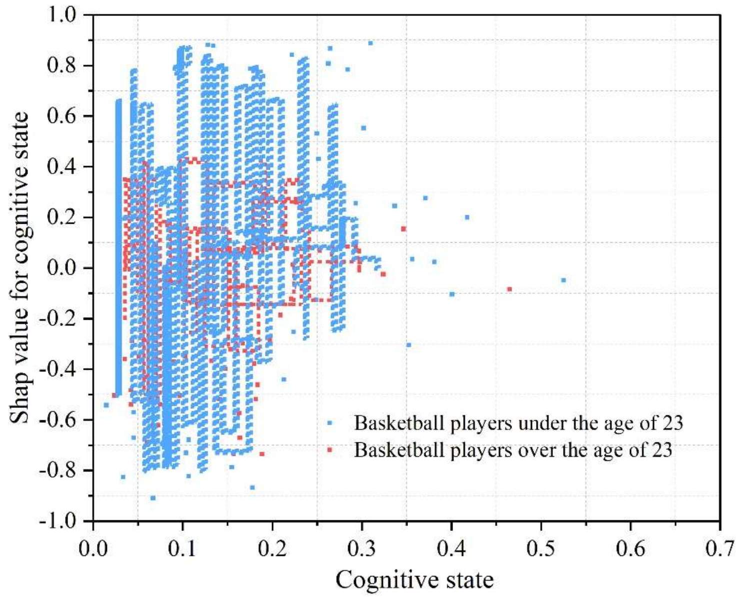
Fig. 4. The correlation between athlete's physical condition and training anxiety

The correlations between psychological characteristics and training anxiety of basketball players of different ages are shown in Figure 5, where (a) and (b) represent the game state anxiety factor and cognitive state anxiety factor, respectively. From the game state anxiety factor, it can be seen that the SHAP values of basketball players over 23 years of age are concentrated in the [-0.50, 0.41] range, and the distribution of athletes under 23 years of age has a wider range of -1.48-0.98, which suggests that the game state has a greater impact on the training anxiety of basketball players over 23 years of age.

Similarly, the effect of cognitive status varied across age groups. The training emotions of basketball players over 23 years of age showed a wider distribution in SHAP values, which indicates that cognitive state has a more significant effect on training anxiety emotions of basketball players over 23 years of age. In contrast, the game state affective factor was weakly associated with training anxiety mood at most ages, i.e., SHAP values showed lower or negative values.



(a)State anxiety factor



(b)Cognitive state anxiety factors

Fig. 5. The correlation between psychological characteristics and training emotions

4. Conclusion

In this paper, a prediction model for basketball players to develop anxiety in same-court rivalry training was established based on the lightGBM algorithm, and the SHAP algorithm was introduced to interpret the prediction results of the model.

The LightGBM model's accuracy precision rate and other indexes are improved by 5.43% to 11.4% than the Xgboost algorithm, and compared with other algorithms, it performs better in prediction accuracy, occupies less memory, and operates at a faster rate.

Women are at high risk of developing anxiety with athletes under the age of 23 during mental training in a co-competitive center. Cognitive state was the primary factor distinguishing the severity of training anxiety; different gender and age of basketball players led to different effects of anxiety generation in same-court rivalry training, and in particular the physical state of females had a greater impact on their ability to generate training anxiety. Cognitive state is an important reason for basketball players under the age of 23 to develop anxiety in same-court rivalry training; game state is the main factor that triggers anxiety in athletes over the age of 23.

In summary, the factors that produce anxiety in basketball players' same-court rivalry training are complex in nature, and the effects of different game states and cognitive states on the occurrence of training anxiety vary by age and gender.

References

[1] Rice, S. M., Gwyther, K., Santesteban-Echarri, O., Baron, D., Gorczynski, P., Gouttebarge, V., ... & Purcell, R. (2019). Determinants of anxiety in elite athletes: a systematic review and meta-analysis. British journal of sports medicine, 53(11), 722-730.

[2] Castro-Sánchez, M., Zurita-Ortega, F., Chacón-Cuberos, R., López-Gutiérrez, C. J., & Zafra-Santos, E. (2018). Emotional intelligence, motivational climate and levels of anxiety in athletes from different categories of sports: Analysis through structural equations. International journal of environmental research and public health, 15(5), 894.

[3] Pons, J., Viladrich, C., Ramis, Y., & Polman, R. (2018). The mediating role of coping between competitive

anxiety and sport commitment in adolescent athletes. The Spanish journal of psychology, 21, E7.

[4] de Arruda, A. F. S., Aoki, M. S., Drago, G., & Moreira, A. (2019). Salivary testosterone concentration, anxiety, perceived performance and ratings of perceived exertion in basketball players during semi-final and final matches. Physiology & behavior, 198, 102-107.

[5] Freire, G. L. M., da Cruz Sousa, V., Alves, J. F. N., de Moraes, J. F. V. N., de Oliveira, D. V., & do Nascimento Junior, J. R. A. (2020). Are the traits of perfectionism associated with pre-competitive anxiety in young athletes? Perfectionism and pre competitive anxiety in young athletes. Cuadernos de Psicología del Deporte, 20(2), 37-46.

[6] Gómez-López, M., Chicau Borrego, C., Marques da Silva, C., Granero-Gallegos, A., & González-Hernández, J. (2020). Effects of motivational climate on fear of failure and anxiety in teen handball players. International journal of environmental research and public health, 17(2), 592.

[7] Pluhar, E., McCracken, C., Griffith, K. L., Christino, M. A., Sugimoto, D., & Meehan III, W. P. (2019). Team sport athletes may be less likely to suffer anxiety or depression than individual sport athletes. Journal of sports science & medicine, 18(3), 490.

[8] Pascoe, M., Pankowiak, A., Woessner, M., Brockett, C. L., Hanlon, C., Spaaij, R., ... & Parker, A. (2022). Gender-specific psychosocial stressors influencing mental health among women elite and semielite athletes: a narrative review. British Journal of Sports Medicine, 56(23), 1381-1387.

[9] Mi, S., Lei, M., & Hui, B. (2022). THE STABILITY OF ATHLETES'PSYCHOLOGICAL QUALITY IN MAJOR BASKETBALL GAMES. Revista Brasileira de Medicina Do Esporte, 29, e2022_0393.

[10] Glass, C. R., Spears, C. A., Perskaudas, R., & Kaufman, K. A. (2019). Mindful sport performance enhancement: Randomized controlled trial of a mental training program with collegiate athletes. Journal of Clinical Sport Psychology, 13(4), 609-628.

[11] Ong, N. C., & Chua, J. H. (2021). Effects of psychological interventions on competitive anxiety in sport: A meta-analysis. Psychology of Sport and Exercise, 52, 101836.

[12] Kamis, H., Radzi, J. A., & Kassim, A. F. M. (2021). Does Coaching Effectiveness and Coach-Athlete Relationship Moderate the Anxiety Among Athletes?. Jurnal Sains Sukan & Pendidikan Jasmani, 10(2), 19-25.

[13] Nanda, F. A., & Dimyati, D. (2019). The psychological skills of basketball athletes: Are there any differences based on the playing position?. Jurnal keolahragaan, 7(1), 74-82.

[14] Dereceli, Ç. (2019). An Examination of Concentration and Mental Toughness in Professional Basketball Players. Journal of Education and Training Studies, 7(1), 17-22.

[15] Li, T., & Ma, Y. (2022). Relations between psychological quality and training in basketball players. Revista Brasileira de Medicina do Esporte, 29, e2022_0354.

[16] Sniras, S. A., & Uspuriene, B. A. (2018). Assessment of pre-competition emotional states of different mastery women-basketball players. Physical education of students., 22(3), 151-158.

[17] Ercis, S. (2018). Effects of Physical Fitness and Mental Hardness on the Performance of Elite Male Basketball Players. Journal of Education and Training Studies, 6(n9a), 56-60.

[18] Pinto, J. C. B. D. L., Menezes, T. C. B., Fortes, L. D. S., & Mortatti, A. L. (2018). Monitoring stress, mood and recovery during successive basketball matches. Journal of Physical Education and Sport, 18(2), 677-685.

[19] Cheng, M. Y., Yu, C. L., An, X., Wang, L., Tsai, C. L., Qi, F., & Wang, K. P. (2024). Evaluating EEG neurofeedback in sport psychology: a systematic review of RCT studies for insights into mechanisms and performance improvement. Frontiers in psychology, 15, 1331997.

[20] Sopa, I. S., & Pomohaci, M. (2020). Discovering the anxiety level of a basketball team using the SCAT questionnaire. Timisoara Physical Education & Rehabilitation Journal, 13(25).

[21] Bosma, N., & Van Yperen, N. W. (2020). A quantitative study of the impact of functional classification on competitive anxiety and performance among wheelchair basketball athletes. Frontiers in Psychology, 11, 558123.

[22] García-Ceberino, J. M., Fuentes-García, J. P., & Villafaina, S. (2022). Impact of basketball match on the pre-competitive anxiety and HRV of youth female players. International Journal of Environmental research and public health, 19(13), 7894.

[23] Zhang, C., Deng, J., & Yi, W. (2024). Data-driven online tracking filter architecture: A LightGBM implementation. Signal Processing, 221, 109477.

[24] Kim Hyun Jin,Baek Ji Won & Chung Kyungyong. (2021). Associative Knowledge Graph Using Fuzzy Clustering and Min-Max Normalization in Video Contents. IEEE ACCESS,9,74802-74816.

[25] Li Ying,Cui Xueting,Fan Jiahao & Wang Tan. (2022). Global chaotic bat algorithm for feature selection. The Journal of Supercomputing,78(17),18754-18776.

[26] Haiyang Zhang,Wenwen Li,Guolong Wang,Fanfan Song,Zhaoqi Wen,Hengyuan Zhang... & Shaozhong Kang. (2025). Predicting stomatal conductance of chili peppers using TPE-optimized LightGBM and SHAP feature analysis based on UAVs' hyperspectral, thermal infrared imagery, and meteorological data. Computers and Electronics in Agriculture,231,110036-110036.

[27] Chukwuemeka Daniel. (2024). A robust LightGBM model for concrete tensile strength forecast to aid in resilience-based structure strategies. Heliyon,10(20),e39679-e39679.