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Predictive Analysis of Post-Traumatic Stress Disorder (PTSD) in Firefighters Using a Stacking Fusion Model

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Abstract

Objective With the rapid progression of urbanization and technological advancements, firefighters increasingly face complex emergency rescue challenges, making them more susceptible to Post-Traumatic Stress Disorder (PTSD). This study aims to develop an efficient tool to predict and identify PTSD risks among firefighters, ensuring their mental well-being and enhancing rescue efficiency. **Methods** Detailed data collection and analysis were conducted across multiple fire brigades. The data underwent a series of rigorous preprocessing steps, including cleaning, normalization, and feature importance screening. The SMOTE technique was employed to enhance sample balance. Subsequently, we constructed a predictive model based on the Stacking strategy, integrating multiple algorithms such as Random Forests, Gradient Boosting, Support Vector Machines, and k-Nearest Neighbors. **Results** The model consistently exhibited outstanding performance in a series of validation tests. Its overall accuracy reached an impressive 96%, with F1 scores of 0.94 and 0.98 for non-

PTSD and PTSD categories, respectively. **Conclusion** We have successfully designed a highly precise PTSD risk prediction model for the fire safety domain. This not only aids in bolstering the psychological support for firefighters but also offers valuable insights for mental health research and public health policy formulation. This study hopes to provide value for both academic research and practical applications.

Keywords: Mendelian randomization, leukocyte telomere length, psoriasis, inflammation, causal inference

Firefighters are the guardians of the modern society. They work daily to protect people's lives and property [1]. However, this bravery and selflessness is often accompanied by great mental stress [2]. Whenever an emergency call is received, firefighters may face life-or-death decisions, extreme environmental conditions, and potential psychological trauma [3]. These experiences can leave deep traces in their minds, which may lead to post-traumatic stress disorder (PTSD) [4].

PTSD is a complex mental disorder whose symptoms include persistent fear, anxiety, avoidance, and re-experiencing the traumatic event [5]. The disease not only has profound effects on individuals, but may also harm their career, family and social activities. PTSD is particularly severe for the frontline responders like firefighters. A traumatized mind may result in slow reaction, difficult decision-making, and even operational errors in emergency situations [6].

To better support these heroes, we need to identify and process PTSD more efficiently. Traditional diagnostic methods often rely on artificial evaluation, which may be influenced by the subjectivity of [7]. Furthermore, many firefighters may be reluctant to seek help [8] because of professional pride or misunderstanding of illness.

In this context, machine learning offers a new solution. By analyzing a large amount of data, machine learning models can predict whether firefighters are likely to have PTSD, giving us an opportunity for early intervention. The goal of this study is to construct an precise predictive model for identifying and predicting PTSD risk in firefighters with a view to providing them with timely and appropriate support for [9].

1 Model Construction and Experimental Data

1.1 Construction Based on Stacking Ensemble Model

In this paper, the Stacking fusion model [10] was used to predict whether firefighters had PTSD. First, we performed data preprocessing and feature importance screening on the raw data. Subsequently, we divided the dataset into the training set and the test set [11], where the training set is used for model construction and the test set for evaluating the performance of the model. Considering that the data had fewer samples with PTSD than normal samples, we used SMOTE technology for oversampling [12], a method for generating a few classes of synthetic samples to achieve category equilibrium. Next, we defined four different machine learning models: random forest, gradient lift tree, support vector machine, and k-nearest neighbor, and set up a parameter grid for them. We found the best parameters for each model by grid search [14], [13]. Then, using these best parameters, we performed further cross-validation of each model to ensure model stability and reliability. To further improve the prediction accuracy, we used the Stacking technique where the previously trained four-trained models served as base learner and logistic regression as meta-learner. The predictions generated by the base learner are used as new features, and the meta-learner tries to learn the relationship between these predictions and the actual objective. Finally, we evaluated the performance of the Stacking model using the test set and calculated various evaluation metrics.

1.2 Experimental Data

In this study, we conducted in-depth questionnaires with multiple fire brigades designed to understand the possible risk of post-traumatic stress disorder (PTSD) for firefighters. The content of the questionnaire was based on the Event Impact Scale Revision (Impact of Event Scale-Revised, IES-R), the resilience Scale [15] (Connor-Davidson Resilience Scale, CD-RISC-10) and the Rereflection Scale [16] (Ruminative Responses Scale, RRS).

We collected multiple features associated with the risk of PTSD in firefighters. Among them, the work experience involves the actual working years of firefighters. Experienced firefighters tend to be more effectively responsive to all types of stress and trauma, so their PTSD risk may be relatively low. In addition, we recorded the number of traumatic events experienced by firefighters in the past year, which is also an important factor affecting the risk of PTSD.

Beyond this, we considered other factors associated with PTSD risk. There are 15 features, specifically as follows:

(1) Work experience: indicates the actual working years of a firefighter.
(2) Past traumatic experience: the number of traumatic events experienced in the past year.
(3) Family support: mark whether there is family support (1 means yes, 0 means no).
(4) Training level: a "basic", "intermediate", or "advanced" firefighter training level.
(5) Physical health status: a physical health index of 0 to 100.
(6) Mental health history: identify whether there were any mental health problems in the past (1 means yes, 0 means no).
(7) Average working hours: It represents the average working hours per week.
(8) Exposure to trauma: indicates the number of trauma types.
(9) Job satisfaction: A 0 to 10 job satisfaction score.
(10) Team cohesion: a cohesion score between a 0 to 10 team.
(11) Physical fitness score: a physical fitness level score of 0 to 100.
(12) Number of counseling sessions: indicates the number of psychological counseling sessions attended in the past year.
(13) Type: Describes a firefighter's regular shift, such as "day", "night" or "early / night".
(14) Equipment familiarity: a 0 to 10 equipment familiarity score.
(15) Number of monthly exercises: indicates the number of fire drills per month.

These characteristics comprehensively consider the variety of situations and stresses that firefighters may face in their work and life, and give us a comprehensive framework for assessing their PTSD risk. To ensure the accuracy of the prediction, we set a critical value to determine whether firefighters have PTSD. Preliminary data analysis showed that the reliability of our collected information was very high, which laid a solid foundation for subsequent in-depth research.

2 Data Preprocessing

2.1.1 Missing Value Statistics

First of all, we used Python to sort out the questionnaire and deleted the missing and missing information to ensure the integrity of the data.

2.1.2 Data Cleaning

Noise and inaccurate information in the data may affect the model performance. Data cleaning ensures that the data is accurate and reliable, thus providing a solid foundation for analysis and modeling. First, we detect and fix the errors and inconsistencies in the data to ensure the quality of the data. By drawing the boxplot of numerical features, we can intuitively understand the distribution of the data [17]. As shown in Figure 2. We can observe that there are a small number of outliers in the feature of work experience. In order to increase the authenticity of the analysis, we keep this part of the outliers.

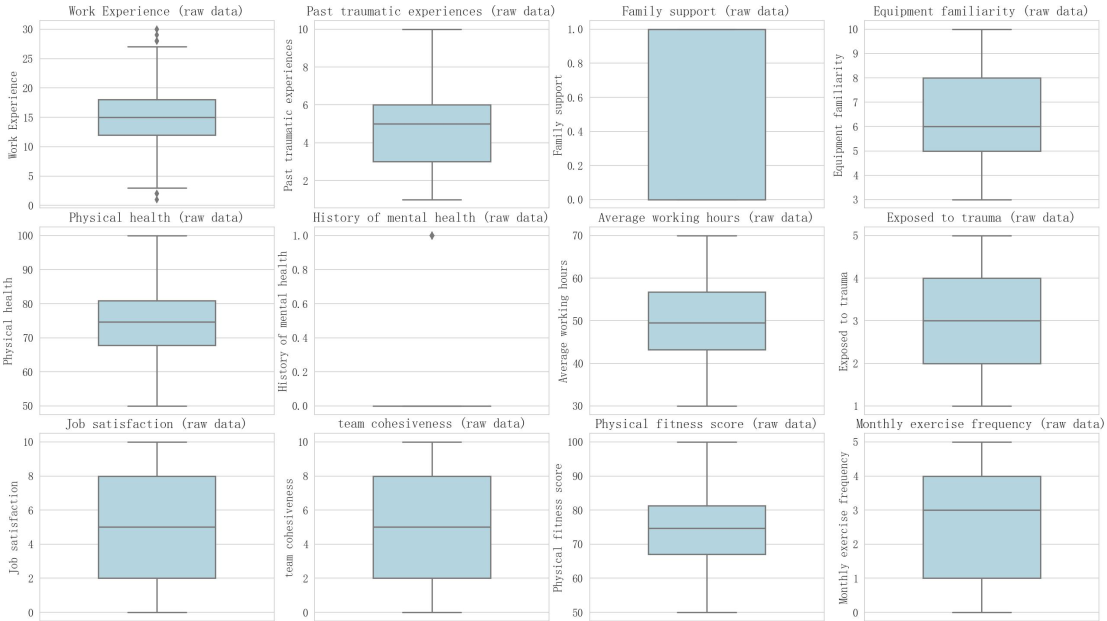

Figure 1 Box type diagram

2.1.3 Standardization

The classification algorithm is sensitive to the scale and distribution of the features. Data transformation can ensure that features are at the same scale, thereby improving model performance. In this paper, it aims to adjust the scale of each feature to have a mean of 0 and a standard deviation of 1. This ensures that all features have the same weight in the machine learning model, especially when using algorithms that require distance measures (e. g., support vector machines, K-nearest neighbor, and logistic regression).

$$z = \frac{x - \mu}{\sigma} \tag{1}$$

among:

z： Normalized values

x： The original eigenvalue

μ： Mean of features

σ： Standard deviation of features

Draw density maps before and after normalization using Python, as shown in Figure 3. It can be seen that the standardized data is more suitable for the use of machine learning.

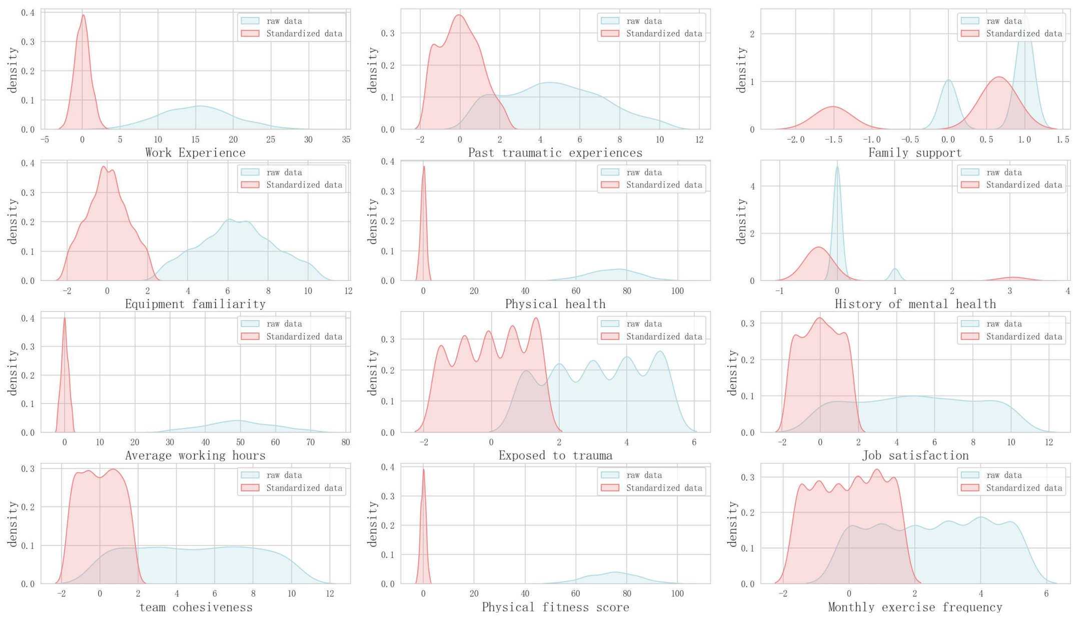

Figure 2 A density contrast plot

2.1.4 Label code

The training level is an indication of a firefighter's training level, which is a categorical variable whose value can be "basic", "intermediate", or "advanced". This indicates the depth and level of training that firefighters receive. For example, firefighters receiving advanced level training may have completed more advanced and complex training courses. Its presence is related to firefighters' ability to manage emergencies, and firefighters with more or higher training may be more experienced and able to handle stress and traumatic events, thus potentially reducing their risk of developing PTSD.

On the other hand, the shift type indicates the firefighter's regular shift, which is also a categorical variable whose value can be "day", "night" or "early / night alternation". This indicates the day. For example, the "day" shift refers to the 7 am to 4 pm time period, while the "night" shift is from 10 pm to 6 am. Different shifts may be related to different stress and work environment. For example, firefighters on night shifts may face more emergency calls and less breaks, which can increase their stress and fatigue and thus increase their risk of PTSD.

Finally, the PTSD label was our target variable, representing whether a firefighter had PTSD. A value "1" represents a firefighter with PTSD, while "0" means a firefighter not having PTSD. This provides us with an explicit classification for training and evaluating our predictive model. Understanding and predicting which firefighters are more likely to have PTSD can help us identify in advance and provide them with appropriate support and intervention to protect their mental health.

2.2 Characteristic importance

To better understand the importance of individual features in the dataset for predicting whether firefighters will have post-traumatic stress disorder (PTSD), we used a random forest model for feature selection. Random Forest is an ensemble learning method that is able to provide us with a score [18] for the importance of each feature to the model prediction.

First, we applied the random forest model on the normalized and labeled datasets and trained it using 100 decision trees. After the training, we used the characteristics of the random forest model to obtain the importance score of each feature.

To visually demonstrate the importance of individual features, feature importance was visualized by Python, as shown in Figure 4.

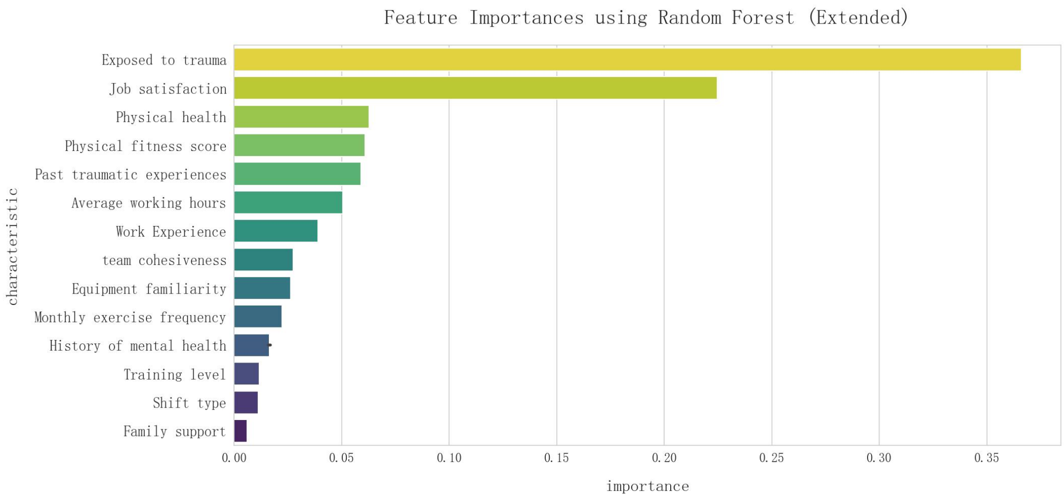

Figure 3. Feature importance

By observing the bars, we found relatively low importance scores for some features. To improve the prediction effect and simplify the model, we decided to remove three less important features from the feature list: "family support", "training level" and "shift type". With this feature selection method, we were able to focus more on those features that had the greatest impact on the prediction results, thus improving the accuracy and efficiency of the model.

2.3 SMOTE

SMOTE ("Synthetic Minority Over-sampling Technique") is an oversampling technique for unbalanced classes of data sets. In practice, the number of samples for one category of a data set is often smaller than the others. This imbalance can cause the machine learning models to bias the majority class and ignore the minority class. To address this issue, SMOTE is designed to balance categories by generating synthetic minority class samples.

In this study, due to the category imbalance in the dataset, we applied SMOTE for oversampling processing to ensure that the model had good predictive performance on all categories. By using SMOTE, we balanced the number of samples between categories, creating a more equitable environment for model training. This not only improves the prediction accuracy of the model for the minority classes, but also enhances its overall generalization ability. In brief, SMOTE helps our model to better cope with the challenge of category imbalance.

2.4 Model building

2.4.1 The determination of hyperparameters

In order to more accurately predict whether firefighters are at risk of PTSD, the choice of appropriate hyperparameters is crucial for model building. The hyperparameters are those determined before the start of the model training and are different from the optimized parameters during the training process. Appropriate selection of hyperparameters can significantly improve the prediction accuracy of the model [19].

In our study, the grid search (GridSearchCV) method, an automated search for the optimal hyperparameter combination. We defined a range of possible parameter values for each algorithm and evaluated the performance of each parameter combination by cross-validation. The following are the hyperparameters required to optimize for each base model that we consider:

For the random forest model, we considered the parameters of random forest including the number of trees (n_estimators), the maximum depth (max _ tap), the minimum number of samples required for internal node repartition (min_samples_split), the minimum number of samples required for leaf nodes (min_samples_leaf), and the number of features considered when finding the optimal segmentation (max_features).

The gradient lift parameters include the number of lift stages to be performed (n_estimators), the learning rate narrowing the contribution of each tree (learning_rate), the maximum depth of the tree (max_depth), the proportion of samples (subsample) for fitting each lift, the number of features considered when finding the best segmentation (max_features), and the minimum weighted score of the weights of leaf nodes (min_weight_fraction_leaf).

The parameters of the SVM involve the penalty parameter (C) of the error term, the coefficient of the kernel function (gamma), the kernel function type used (kernel), and the degree of the polynomial kernel function (degree).

The parameters of K nearest neighbor include the number of nearest neighbors for the query (n_neighbors), the weight function of voting (weights), the power parameter (p) for calculating the Minkowski distance measure between points, the algorithm for calculating the nearest neighbor (algorithm) and the leaf size passed to BallTree or KDTree (leaf_size).

By 5-fold cross-validation, we found the best hyperparameter combination for each algorithm. The following are the selected optimal parameters of each model：

Table 1: Optimum parameters

model	hyperparameter	Optimal value
RF	n_estimators，max_depth，min_samples_split，min_samples_leaf，max_features	50，40，4，2，auto
Gradient	n_estimators，learning_rate，max_depth，subsample，max_features，min_weight_fraction_leaf	200，0.2，5，0.9，sqrt，0.0
SVM	C，gamma，kernel，degree	1，0.5，rbf，2
k-NN	n_neighbors，weights，p，algorithm，leaf_size	2，distance，1，auto，10

2.5 Test of the model

In our study, the model was tested to ensure the robustness and accuracy of the model to ensure the reliability of the predictions. This not only facilitates the timely identification and intervention of firefighters living with PTSD, but also helps to ensure their work efficiency and safety.

2.5.1 Evaluating indicator

The performance of the prediction model can be quantified by multiple evaluation indicators. The following are the main evaluation indicators used in this study:

Accuracy rate (Accuracy): It is the proportion of the sample number that the model predicts correctly to the total sample number.be defined as:

$$\text{Accuracy} = \frac{\text{Predict the number of samples}}{\text{Total sample size}} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Specifically, TP, TN, FP and FN indicate the number of true, true negative, false positive and false negative, respectively.

Recall (Recall): Also known as true rate, representing the proportion of samples correctly predicted for all positive samples.be defined as:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{2}$$

Accuracy (Precision): the proportion of samples that are predicted to be positive.be defined as:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{3}$$

The F1 score (F1-score): it is the harmonic average of the precision rate and the recall rate, which provides us with the overall performance of the model.be defined as:

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

2.5.2 Single-model performance evaluation

Through the above evaluation metrics in detail, we evaluated the performance of each base model on the test set, and the index values are shown in Table 6. From the results, the random forest model performed best in predicting firefighters at risk of PTSD, with high accuracy and F1 scores. In contrast, the SVM and k-nearest neighbor models perform relatively performance.

Figure 4 Table of Model Performance

Model	Accuracy	Precision: PTSD/PTSD	Recall: PTSD/PTSD	F1-score: PTSD/PTSD
RF	95%	0.88 / 0.99	0.96 / 0.95	0.92 / 0.97
Gradient	94%	0.91 / 0.95	0.87 / 0.97	0.89 / 0.96
SVM	82%	0.88 / 0.81	0.40 / 0.98	0.55 / 0.89
k-NN	79%	0.60 / 0.89	0.73 / 0.81	0.66 / 0.85

2.5.3 Stacking Model evaluation

The Stacking model improves the accuracy of prediction by integrating the prediction results of multiple base models, the index values are shown in Table 7 and the confusion matrix is shown in Figure 5. On our test set, the Stacking model had 98% accuracy, a result significantly higher than the accuracy of a single model. This suggests that by comprehensively utilizing the advantages of multiple models, the Stacking model has higher accuracy and stability in predicting whether firefighters at risk of PTSD.

In conclusion, the Stacking model demonstrated excellent performance in our study, providing a highly accurate mental health warning tool for firefighters. This will help in the timely identification and intervention of those firefighters at risk for PTSD to ensure their mental health and thus improve their work efficiency and safety.

Figure Figure 5 Stacking Model performance table

Model	Accuracy	Precision: PTSD/PTSD	Recall: PTSD/PTSD	F1-score: PTSD/PTSD
Stacking	96%	0.91 / 0.99	0.96 / 0.97	0.94 / 0.98

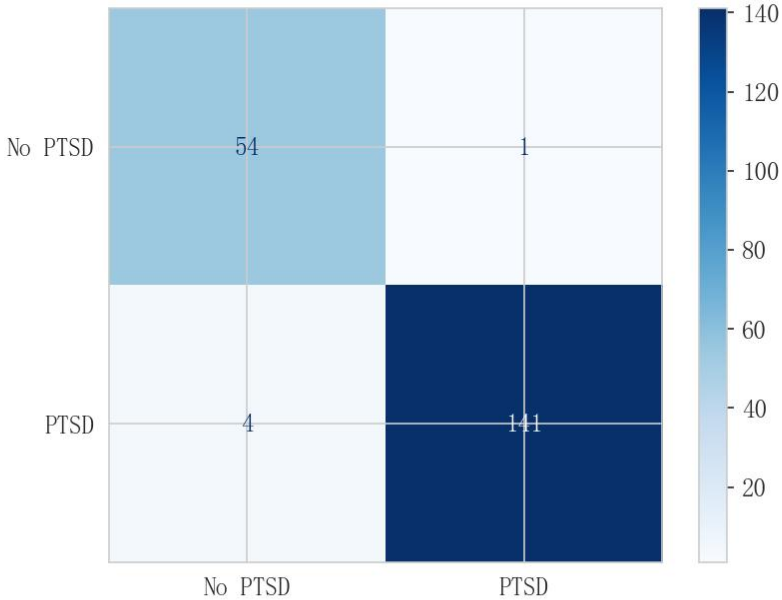

Figure 6 confounding matrix

2.6 Conclusions and Outlook

Conclusions: This study systematically explored the risk of post-traumatic stress disorder (PTSD) in firefighters. During the data collection phase, we developed specific questionnaires based on the Event Impact Scale Revision (IES-R), the resilience Scale (CD-RISC-10) and the Ruminant Scale (RRS), and successfully conducted extensive surveys for multiple fire brigades. This process ensures the comprehensiveness and accuracy of the data. After this analysis, we identified 15 features closely associated with the risk of PTSD. In particular, factors such as exposure to trauma, job satisfaction, and physical health status showed significant associations in the model. Using the Stacking strategy, we integrated multiple machine learning algorithms to successfully construct a highly accurate PTSD risk prediction model. This model not only makes accurate predictions of the overall PTSD risk of firefighters, but also shows detailed analysis ability in specific risk factors, providing strong technical support for firefighters' mental health assessment and intervention.

Outlook: For future research, we plan to further refine and expand the content of data collection, especially more deeply into specific traumatic events experienced by firefighters, involving the nature, intensity and frequency of events. At the same time, firefighters' psychological coping mechanisms, emotional regulation strategies, and specific interaction patterns with families and colleagues will also be considered to more fully capture the risk factors of PTSD. Furthermore, we see the potential of the model in other high-risk occupations, such as police, healthcare and military personnel, will validate and perform the necessary optimization for the applicability of the model in these contexts. As technology advances, new machine learning and AI approaches will also be explored and integrated into the models. At the same time, we expect to work more deeply with fire departments and mental health institutions to develop precise prevention and intervention strategies based on the prediction of the model, and establish a feedback mechanism in the practical application of the model to collect real-time feedback from users, so as to power the continuous optimization of the model. This series of programs and efforts aims to provide more comprehensive and precise support for the mental health of firefighters and other high-risk professionals.

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