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Research paper

Machine learning-enabled mental health risk prediction for youths with stressful life events: A modelling study

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ABSTRACT

Background: Youths face significant mental health challenges exacerbated by stressful life events, particularly in the context of the COVID-19 pandemic. Immature coping strategies can worsen mental health outcomes.
Methods: This study utilised a two-wave cross-sectional survey design with data collected from Chinese youth aged 14–25 years. Wave 1 (N = 3038) and Wave 2 (N = 539) datasets were used for model development and external validation, respectively. Twenty-five features, encompassing dimensions related to demographic information, stressful life events, social support, coping strategies, and emotional intelligence, were input into the model to predict the mental health status of youth, which was considered their coping outcome. Shapley additive explanation (SHAP) was used to determine the importance of each risk factor in the feature selection. The intersection of top 10 features identified by random forest and XGBoost were considered the most influential predictors of mental health during the feature selection process, and was then taken as the final set of features for model development. Machine learning models, including logistic regression, AdaBoost, and a backpropagation neural network (BPNN), were trained to predict the outcomes. The optimum model was selected according to the performance in both internal and external validation.
Results: This study identified six key features that were significantly associated with mental health outcomes: punishment, adaptation issues, self-regulation of emotions, learning pressure, use of social support, and recognition of others' emotions. The BPNN model, optimized through feature selection methods like SHAP, demonstrated superior performance in internal validation (C-index [95 % CI] = 0.9120 [0.9111, 0.9129], F-score [95 % CI] = 0.8861 [0.8853, 0.8869]). Additionally, external validation showed the model had strong discrimination (C-index = 0.9749, F-score = 0.8442) and calibration (Brier score = 0.029) capabilities.
Limitations: Although the clinical prediction model performed well, the study it still limited by self-reported data and representativeness of samples. Causal relationships need to be established to interpret the coping mechanism from multiple perspectives. Also, the limited data on minority groups may lead to algorithmic unfairness.
Conclusions: Machine learning models effectively identified and predicted mental health outcomes among youths, with the SHAP+BPNN model showing promising clinical applicability. These findings emphasise the importance and effectiveness of targeted interventions with the help of clinical prediction model.

1. Introduction

Youths are vulnerable to stressful life events because of their immature cognitive function (Guessoum et al., 2020). This vulnerability leads to prolonged periods of poor mental health due to heightened levels of stressful life events such as depression, anxiety, and cognitive dysfunction (Racine et al., 2021; Samji et al., 2022). Coping has been identified as a significant intermediary factor between stressful life events and mental health (Cao et al., 2022), especially in the post-pandemic era (Ding et al., 2023). Adopting appropriate coping

Abbreviations: SHAP, shapley additive explanation; BPNN, backpropagation neural network; XGBoost, extreme gradient boosting; ML, machine learning; TRIPOD, Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis; Adms, Adaptive Moment Estimation.

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strategies is conducive to alleviating or eliminating the negative psychological impacts of stressful life events (Riazi et al., 2023). Immature coping strategies can lead to psychological abnormalities (Gurvich et al., 2021). Hence, it is important to detect mental health problems among youths early to prevent improper coping strategies (Looman et al., 2023).

The presence of various related factors poses a challenge for accurate prediction. A potential solution to this challenge is feature selection using machine learning (Wang et al., 2022). Principal Component Analysis (PCA) and Independent Component Analysis (ICA) are commonly used feature selection techniques in stress and mental health research, helping to remove noise and compress data, which in turn enables more efficient processing (Razavi et al., 2024). However, existing studies often exhibit several limitations that may undermine their efficacy. Many studies focus on applying a single feature selection method, which may not capture the full complexity of the data. Faizal et al. (2023) utilised filter, wrapper, and embedded methods to select features for model development from a pool of 62 features and yielded 5–30 features. While using filter, wrapper, and embedded methods separately improved model performance by reducing complexity, they may often lack generalizability across different datasets, as each method has selection biases (Faizal et al., 2023; Liang et al., 2019; Pudjihartono et al., 2022). Moreover, several studies have emphasized the benefits of integrating multiple feature selection methods, leveraging the strengths inherent in each approach (Wang et al., 2022; Spooner et al., 2023). These methods tend to produce better classification accuracy than is achieved using single feature selection methods (Pudjihartono et al., 2022). Secondly, a common limitation is the lack of comprehensive sensitivity analyses. Sensitivity analysis is crucial in feature selection to ensure that the selected features are robust and not overly influenced by specific data splits or sampling variability (Spooner et al., 2023). Unfortunately, many studies either omit this step or perform it inadequately, which can lead to overfitting and reduced model generalizability.

Nowadays, many studies have begun to explore how artificial intelligence can be applied to the field of mental health care (Graham et al., 2019). A study conducted in Japan utilised health survey data to predict the mental health of college students using various machine learning techniques, namely logistic regression, elastic net, random forest, and extreme gradient boosting (XGBoost) (Baba and Bunji, 2023). The findings demonstrated that machine learning approaches outperformed traditional statistical methods, such as logistic regression, across various performance metrics, including predictive probability (log-loss, Brier score, AUC) and confusion matrix measures (specificity, precision, recall, and Matthews correlation coefficient) (Baba and Bunji, 2023). However, these prediction models do not assess calibration, clinical benefits, or external validation, which limits their generalisability (Alba et al., 2017).

Predicting mental health outcomes in advance is beneficial for identifying and intervening in youths who cope improperly. The coping outcomes of stressful life events among the participating youths were defined based on the cut-off value of the Brief Symptom Inventory-53 (BSI-53). Moreover, the related predictors of mental health are complicated, and employing machine learning techniques facilitates the effective identification of important features for predicting outcomes and enables high-precision predictions for diverse types of data (Andriopoulos and Kornaros, 2023). In this study, we proposed a new method based on machine learning to identify important features of youth mental health and constructed a prediction model of coping outcomes for stressful life events. We used both internal and external validation to evaluate the generalisability of this method.

2. Method

2.1. Study approval and design

De-identified data were collected in a two-wave cross-sectional study, registered prospectively, and approved by the ethics committee of our institution. This study, based on machine learning (ML) for diagnostic purposes, followed the Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis + AI (TRIPOD + AI) guidelines (Collins et al., 2024) (Supplementary TRIPOD + AI checklist).

2.2. Sample size

To ensure that the sample size was adequate for developing a clinical prediction model for binary outcomes, Riley et al. (2020) suggest considering four key aspects (eMethod-Table 1). Based on a previous investigation, the prevalence setting (i.e., outcome proportion) was determined to be 850 of 3038 (i.e. BSI-positive youths/BSI-negative youths) (Ding et al., 2023). A population of >1042 individuals was considered to have sufficient statistical power to develop a clinical prediction model in this study.

2.3. Dataset

The dataset consisted of two waves of nationwide cross-sectional online surveys of Chinese youth. Youths who met the inclusion criteria were invited to participate in this study, including those who 1) were aged 14–25 years, 2) had lived in China since the COVID-19 outbreak, and 3) could read and communicate in Chinese. We excluded youths who were clinically diagnosed with psychological or mental illness by professionals or were mentally or physically unable to communicate.

Data were collected using a structured, standardised questionnaire (Supplementary Questionnaire). Wave 1 data collection was conducted between July 1 and August 30, 2022, with 3038 participants. The mean age of the sample was 19.93 years (SD = 2.85), with 678 participants (22.3 %) aged <18 years and 1560 (51.3 %) identifying as males. Wave 2 data collection was conducted between April 30 and May 7, 2023, with 539 participants. The mean age of the sample was 19.86 years (SD = 2.69), with 154 participants (28.6 %) aged <18 years and 266 (49.4 %) identifying as males.

2.4. Features

The predictor variables (25 features in total) used in the machine learning models included demographic characteristics, stressful life events (punishment, loss, relationship pressure, learning pressure, and adaptation problems), coping strategies (task-oriented, emotion-oriented, distraction, and social diversion coping), social support (objective support, subjective support, and utilisation of support), and emotional intelligence (appraisal and expression of emotion in oneself, appraisal and recognition of emotion in others, regulation of emotion in oneself, and use of emotion to enhance performance) (features section in eMethod).

2.5. Outcome

In this modelling study, the final goal is to predict the coping outcome among youths so that the health practitioners can timely intervene. The coping outcome can be reflected as the mental health status according to the previous investigation (Ding et al., 2023). Based on the diagnosis from the Brief Symptom Inventory (BSI-53), youth with a total score of all items no <63 were considered to have poor coping outcomes of psychological distress potentially due to signifying failure to cope or limited coping strategies, which was defined as BSI-positive. Conversely, they were regarded as BSI-negative, which reflected

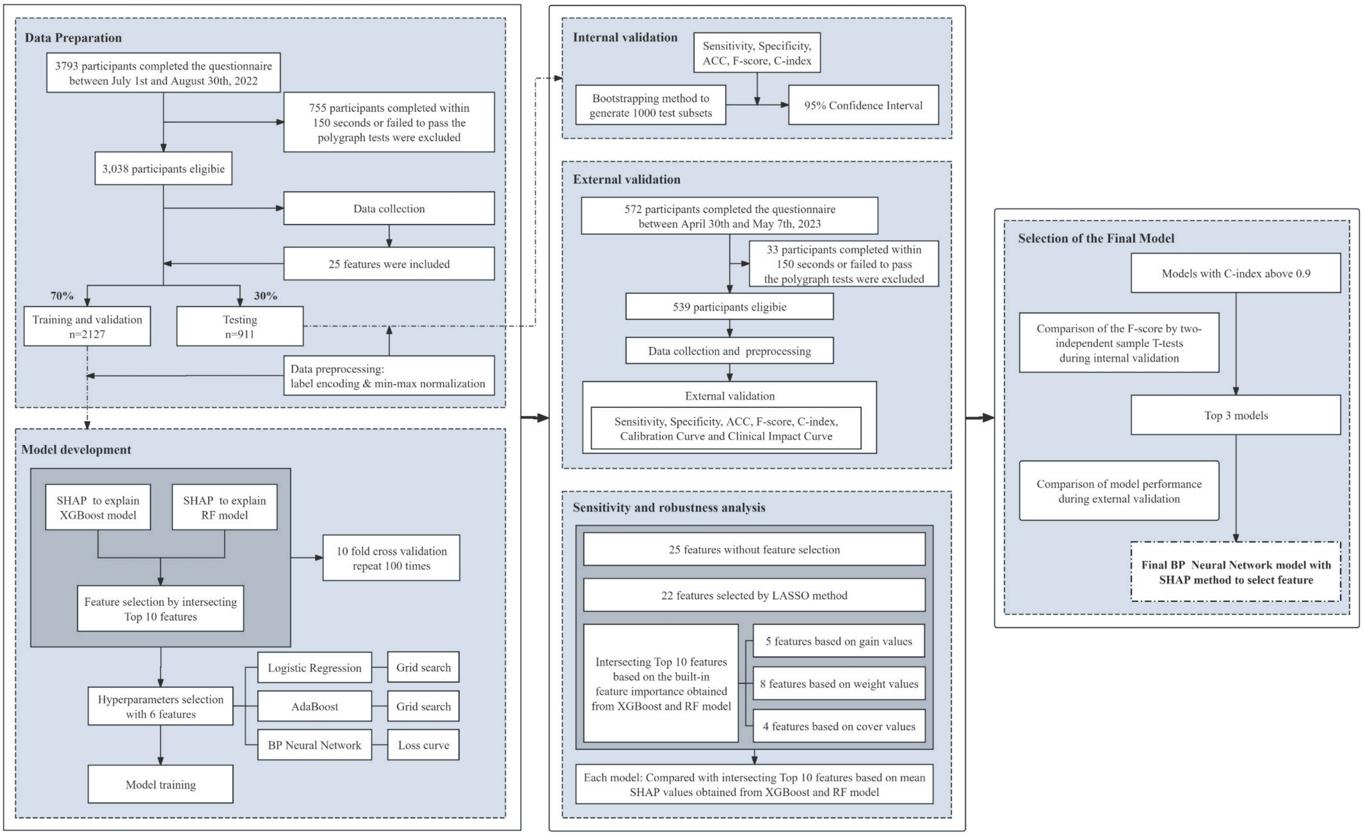

Fig. 1. Modelling process of the study.
This figure showed the whole modelling processes in the study. Containing the data preparation, model development, internal validation, external validation, model evaluation, and sensitivity analysis.

effective coping outcomes (Ding et al., 2023; Richmond et al., 2023).

2.6. Statistical analysis

A *P*-value of <0.05 was considered statistically significant. IBM SPSS Statistics version 26 was used to perform descriptive statistics, which are presented as mean [SD] or number (%), as appropriate. Additionally, chi-square tests and two-sample independent *t*-tests were performed to assess the disparities between Wave 1 and Wave 2, as well as within each subgroup (BSI-positive and BSI-negative). R 4.3.3 and Python 3.9 were utilised for data processing and modelling, as shown in Fig. 1 and eMethod-Table 3.

2.7. Data pre-processing

Respondents who completed their questionnaires within 150 s or failed the polygraph test were excluded from Waves 1 and 2. No missing values were handled after exclusion. In the process of model development, 70 % of Wave 1 data was allocated for feature selection and model training (90 % of the data is allocated to the training set and 10 % to the validation set in accordance with the 10-fold cross-validation method), while the remaining 30 % (test set) was solely utilised for internal validation purposes. Wave 2 data was exclusively reserved for external validation (eMethod-Figs. 1 and 2). Then, we encoded the categorical variables as numerical values and normalised the continuous variables using Min-Max normalization (eMethod-Fig. 1, eMethod-Table 4).

2.8. Feature selection

Shapley additive explanations (SHAP) derived from cooperative game theory were computed to elucidate the impact of each risk factor (feature importance) on the feature selection process (Lundberg and Lee, 2017). The 10-fold cross-validation method was iterated 100 times to enhance robustness and compute the 95 % confidence interval of the SHAP value. The ranking of each variable was determined using the mean of 1000 SHAP values obtained through cross-validation. We employed the random forest and XGBoost models to assess feature importance within the training set. The overlapping features among the top 10 identified by the mean SHAP values from each algorithm were recognised as the most influential predictors of mental health state (BSI-positive and BSI-negative) (eMethod-Fig. 3). A grid-search method was implemented for hyperparameter tuning.

2.9. Model development

We trained three different machine learning models to predict the outcome: Adaboost, Back Propagation Neuron Network (BPNN), and logistic regression. The variables that remained after the feature-selection process were used to develop the prediction model. To expedite the convergence process of BPNN and enhance the training efficiency, we employed Adaptive Moment Estimation (Adms) as an accelerator to construct the model. A 10-fold cross-validation was applied to the training data to determine optimal model hyperparameters. A grid search and loss curves were used for model tuning. The model composition and best hyperparameters after tuning are displayed in eMethod-Tables 5 and 6.

2.10. Internal and external validation of all models

The internal validation utilised the test set prepared during the data preprocessing phase. Employing the bootstrapping method, we generated 1000 subsets to ensure the robustness of the results and calculated

Table 1
Detailed information about demographics, stressful life events, coping strategies, social supports and emotional intelligence among the youths of all participants.

Variables	Wave 1				Wave 2				P value[c]
	All participants	BSI-positive	BSI-negative	P value[a]	All participants	BSI-positive	BSI-negative	P value[b]	
	(n = 3038)	(n = 850)	(n = 2188)		(n = 539)	(n = 93)	(n = 446)		
Demographics									
Age	19.93 (2.85)	20.12 ± 2.61	19.86 ± 2.93	0.016	20.15 ± 2.06	19.80 ± 2.80	19.80 ± 2.80	0.168	0.618
14–17 years	678 (22.32)	150 (17.65)	528 (24.13)	<0.001	11 (11.83)	101 (22.65)	101 (22.65)	0.019	0.428
18–26 years	2360 (77.68)	700 (82.35)	1660 (75.87)		82 (88.17)	345 (77.35)	345 (77.35)		
Sex				<0.001				0.011	0.392
Men	1560 (51.35)	530 (62.35)	1030 (47.07)		57 (61.29)	209 (46.86)	209 (46.86)		
Women	1478 (48.65)	320 (37.65)	1158 (52.93)		36 (38.71)	237 (53.14)	237 (53.14)		
Education level				0.020				0.077	0.060
Junior middle school or below	242 (7.97)	73 (8.59)	169 (7.72)		4 (4.30)	25 (5.61)	25 (5.61)		
Senior middle school	963 (31.70)	268 (31.53)	695 (31.76)		32 (34.41)	125 (28.03)	125 (28.03)		
Undergraduate	1660 (54.64)	478 (56.24)	1182 (54.02)		56 (60.22)	260 (58.30)	260 (58.30)		
Postgraduate	173 (5.69)	31 (3.65)	142 (6.49)		1 (1.08)	36 (8.07)	36 (8.07)		
Social role				<0.001				0.183	<0.001
Students	2655 (87.39)	724 (85.18)	1931 (88.25)		84 (90.32)	406 (91.03)	406 (91.03)		
Employed	368 (12.11)	115 (13.53)	253 (11.56)		9 (9.68)	29 (6.50)	29 (6.50)		
Unemployed	15 (0.49)	11 (1.29)	4 (0.18)		0 (0.00)	11 (2.47)	11 (2.47)		
City size[d]				<0.001				<0.001	<0.001
Megacity	1089 (35.85)	357 (42.00)	732 (33.46)		49 (52.69)	129 (28.92)	129 (28.92)		
Supercity	1209 (39.80)	311 (36.59)	898 (41.04)		37 (39.78)	259 (58.07)	259 (58.07)		
Others	740 (24.36)	182 (21.41)	558 (25.50)		7 (7.53)	58 (13.00)	58 (13.00)		
Father's occupation				<0.001				<0.001	<0.001
Long-term employee	2037 (67.05)	391 (46.00)	1646 (75.23)		38 (40.86)	372 (83.41)	372 (83.41)		
Worker	408 (13.43)	122 (14.35)	286 (13.07)		8 (8.60)	42 (9.42)	42 (9.42)		
Precarious employment	269 (8.85)	198 (23.29)	71 (3.24)		37 (39.78)	17 (3.81)	17 (3.81)		
Self-employed	324 (10.66)	139 (16.35)	185 (8.46)		10 (10.75)	15 (3.36)	15 (3.36)		
Mother's occupation				<0.001				<0.001	0.544
Long-term employee	2030 (66.82)	440 (51.76)	1590 (72.67)		31 (33.33)	345 (77.35)	345 (77.35)		
Worker	443 (14.58)	128 (15.06)	315 (14.40)		20 (21.51)	53 (11.88)	53 (11.88)		
Precarious employment	359 (11.82)	206 (24.24)	153 (6.99)		34 (36.56)	26 (5.83)	26 (5.83)		
Self-employed	206 (6.78)	76 (8.94)	130 (5.94)		8 (8.60)	22 (4.93)	22 (4.93)		
Having medical staffs in family				<0.001				<0.001	<0.001
Yes	738 (24.29)	291 (34.24)	447 (20.43)		47 (50.54)	35 (7.85)	35 (7.85)		
No	2300 (75.71)	559 (65.76)	1741 (79.57)		46 (49.46)	411 (92.15)	411 (92.15)		
Willingness to mental health consulting				<0.001				<0.001	0.097
Yes	2148 (70.70)	408 (48.00)	1740 (79.52)		33 (35.48)	327 (73.32)	327 (73.32)		
No	774 (25.48)	355 (41.76)	419 (19.15)		47 (50.54)	114 (25.56)	114 (25.56)		
Uncertain	116 (3.82)	87 (10.24)	29 (1.33)		13 (13.98)	5 (1.12)	5 (1.12)		
Social support									
Objective support	5.55 ± 2.81	3.95 ± 1.92	6.17 ± 2.86	<0.001	4.10 ± 2.46	5.97 ± 3.50	5.97 ± 3.50	<0.001	0.520
Subjective support	22.72 ± 4.08	20.50 ± 3.55	23.59 ± 3.94	<0.001	20.24 ± 4.48	23.47 ± 3.96	23.47 ± 3.96	<0.001	0.327
Utilisation of social support	8.88 ± 2.00	7.36 ± 1.91	9.46 ± 1.70	<0.001	6.99 ± 1.83	9.03 ± 1.66	9.03 ± 1.66	<0.001	0.023
Emotional intelligence									
Appraisal and expression of emotion in oneself	21.46 ± 4.30	19.31 ± 5.02	22.30 ± 3.66	<0.001	18.29 ± 5.92	22.63 ± 2.74	22.63 ± 2.74	<0.001	0.021
Appraisal and recognition of emotion in others	21.09 ± 4.58	18.33 ± 5.40	22.16 ± 3.70	<0.001	17.67 ± 5.76	21.91 ± 3.92	21.91 ± 3.92	<0.001	0.682
Regulation of emotion in oneself	21.51 ± 3.83	18.74 ± 4.41	22.58 ± 2.95	<0.001	18.09 ± 5.42	22.37 ± 3.45	22.37 ± 3.45	<0.001	0.502
Use of emotion to facilitate performance	21.43 ± 4.14	18.97 ± 4.57	22.38 ± 3.53	<0.001	17.91 ± 5.71	21.47 ± 5.06	21.47 ± 5.06	<0.001	0.019
Stressful life events									
Being punished	9.55 ± 8.14	19.76 ± 7.79	5.58 ± 3.47	<0.001	28.95 ± 6.96	11.66 ± 2.58	11.66 ± 2.58	<0.001	<0.001
Loss	9.52 ± 7.15	17.37 ± 6.20	6.47 ± 4.78	<0.001	26.00 ± 4.97	12.48 ± 5.04	12.48 ± 5.04	<0.001	<0.001

(continued on next page)

Table 1 (*continued*)

Variables	Wave 1				Wave 2				*P* value[c]
	All participants	BSI-positive	BSI-negative	*P* value[a]	All participants	BSI-positive	BSI-negative	*P* value[b]	
	(n = 3038)	(n = 850)	(n = 2188)		(n = 539)	(n = 93)	(n = 446)		
Relationship pressure	7.49 ± 4.69	12.33 ± 4.15	5.61 ± 3.34	<0.001	17.87 ± 3.06	8.12 ± 2.80	8.12 ± 2.80	<0.001	<0.001
Learning pressure	7.2 ± 4.76	11.70 ± 4.16	5.45 ± 3.72	<0.001	17.76 ± 2.87	9.19 ± 3.60	9.19 ± 3.60	<0.001	<0.001
Adaptation problem	8.03 ± 5.72	14.30 ± 5.43	5.59 ± 3.56	<0.001	21.28 ± 4.61	10.06 ± 3.22	10.06 ± 3.22	<0.001	<0.001
Coping strategies									
Task-oriented coping	25.83 ± 5.06	23.34 ± 5.07	26.79 ± 4.71	<0.001	24.85 ± 5.03	26.56 ± 4.65	26.56 ± 4.65	0.002	0.062
Emotion-oriented coping	13.12 ± 5.27	17.32 ± 3.99	11.49 ± 4.78	<0.001	18.67 ± 2.45	13.46 ± 6.20	13.46 ± 6.20	<0.001	<0.001
Distraction coping	14.41 ± 2.80	13.66 ± 2.96	14.69 ± 2.68	<0.001	14.69 ± 2.92	14.21 ± 2.91	14.21 ± 2.91	0.151	0.394
Social diversion coping	10.81 ± 2.44	9.76 ± 2.55	11.22 ± 2.27	<0.001	10.08 ± 2.37	11.17 ± 2.25	11.17 ± 2.25	<0.001	0.117

Note: Data are shown as mean ± SD or n (%).
[a] The comparison group is BSI-positive and BSI-negative in Wave 1.
[b] The comparison group is BSI-positive and BSI-positive in Wave 2.
[c] The comparison group is all participants in Wave 1 and all participants in Wave 2.
[d] According to the State Council of the People's Republic of China, Megacity was defined as a city which has a population of 10million or more people; Supercity was defined as a city which has a population of 1million or more people. Others included the city which has a population of less than 1million.

95 % confidence intervals. Wave 2 data were utilised for external validation. We calculated the ACC, F-score, C-index, sensitivity, specificity, bias-corrected calibration curve, Brier score, and clinical impact curve to evaluate our clinical prediction models (Alba et al., 2017) (model validation section in eMethod).

2.11. Sensitivity and robustness analysis

In this study, SHAP was utilised as the primary method for analysing feature importance and guiding feature selection during model construction. However, to explore the sensitivity and robustness of the pruning method, we employed various alternative techniques to compute feature importance. These alternative methods were used in the same manner for model construction and performance evaluation (eMethod-Table 7).

2.12. The selection of the final model

The prediction models both in primary analysis and sensitivity & Robustness analysis were included in model evaluation. First, models with a C-index below 0.90 in both the internal and external validation phases were excluded. Second, we conducted a two-sample independent *t*-test to compare the 1000 F-scores obtained through bootstrap sampling in the internal validation for each prediction model. The prediction models with the top three F-scores were retained. The top three prediction models were subjected to further evaluation based on the external validation results. The model with the highest F-score, along with the most satisfactory bias-corrected calibration curve, Brier score, and clinical impact curve, was selected as the final model.

3. Results

3.1. Summary statistics

Table 1 summarises the distribution of the predictor variables across Waves 1 and 2. The results revealed a significant increase in various stressful life events among youths during Wave 2. Notably, the frequency of experiencing punishment rose sharply (Wave 1: 9.55 [8.14]; Wave 2: 28.95 [6.96]; $p < 0.001$), as did experiences of loss (Wave 1: 9.52 [7.15]; Wave 2: 26.00 [4.97]; $p < 0.001$) and adaptation issues (Wave 1: 8.03 [5.72]; Wave 2: 21.28 [4.61]; $p < 0.001$). Additionally, the use of emotion-oriented coping strategies increased in Wave 2 (18.67 [2.45]) compared to Wave 1 (13.12 [5.27]; $p < 0.001$).

There was a decrease in the utilisation of social support in Wave 2 (Wave 1: 8.88 [2.00]; Wave 2: 6.99 [1.83]; $p = 0.023$). Emotional intelligence also deteriorated, particularly in the appraisal and expression of emotions (Wave 1: 21.64 [4.30]; Wave 2: 18.29 [5.92]; $p = 0.021$) and the use of emotion to facilitate performance (Wave 1: 21.43 [4.14]; Wave 2: 17.91 [5.71]; $p = 0.019$).

3.2. Prevalence of outcome

According to the investigation, the prevalence of BSI-positive cases declined in Wave 2 (93/539, 17.3 %) compared to Wave 1 (850/3038, 28.0 %). The overall BSI-positive prevalence among surveyed youths decreased, with some groups experiencing reductions of over 10 % (Supplementary Table 1). However, youths with medical staffs in the family showed an increase in BSI-positive prevalence from Wave 1 (39.43 %) to Wave 2 (57.32 %).

3.3. Feature selection

The final model incorporated six features identified by intersecting the top 10 features ranked by both random forest and XGBoost (Fig. 2A, Supplementary Fig. 2). These features include punishment, adaptation issues, self-regulation of emotions, learning pressure, use of social support, and recognition of others' emotions. The importance of each selected variable was assessed using the SHAP values. Table 2 displays the selected predictors and their corresponding final mean SHAP values, providing a detailed description of the primary analysis. We also employed various methods to calculate the feature importance to ensure the robustness of our proposed SHAP-based method (Supplementary Fig. 1, Supplementary Tables 2–6).

3.4. Model development

The selected features were incorporated into three models: logistic regression, AdaBoost, and BPNN. Internal and external validation

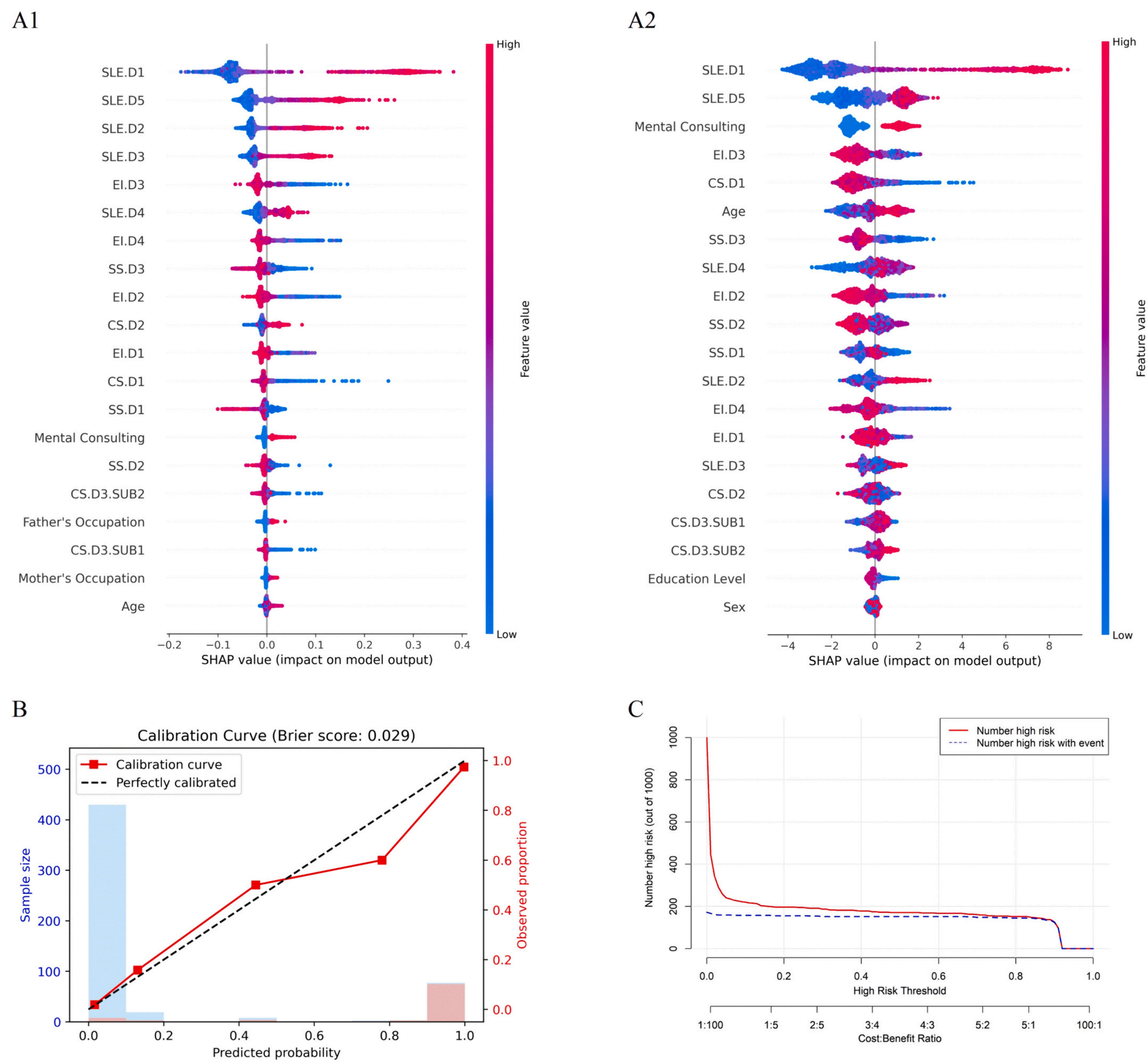

Fig. 2. SHAP summary plot, bias-adjusted calibration curve and clinical impact curve of the final model.
[A1] Top 20 feature importance rankings by Shapley Additive Explanations (SHAP) for the Random Forest model. [A2] Top 20 feature importance rankings by SHAP for the eXtreme Gradient Boosting (XGBoost) model. [B] Bias-adjusted calibration curve for the Back Propagation Neural Network model, built using six features identified by intersecting the top 10 features ranked by mean SHAP values from both the XGBoost and Random Forest models during external validation. [C] Clinical impact curve for the Back Propagation Neural Network model, built using six features identified by intersecting the top 10 features ranked by mean SHAP values from both the XGBoost and Random Forest models during external validation.

demonstrated that the feature selection process assessed using SHAP values achieved the best performance. The Back Propagation Neural Network (BPNN) was chosen as the final model for this study, showing strong performance with high F-scores (Internal validation [95 % CI]: 0.8861 [0.8853, 0.8869]; External validation: 0.8442) and good C-indices (Internal validation [95 % CI]: 0.9120 [0.9111, 0.9129]; External validation: 0.9749) (Table 3, Supplementary Tables 7 and 8, and Supplementary Figs. 3 and 4).

3.5. Mental health status prediction

Although the discrimination of the final six-feature model for predicting mental health status (BSI-positive) was slightly reduced compared with the original 25-feature model in the internal validation, it exhibited significantly better performance in the external validation (Table 3, Supplementary Table 7). BPNN demonstrated enhanced discrimination (C-index = 0.9749, F-score = 0.8442) and calibration (Brier score = 0.029). The clinical impact curve indicated an incremental net benefit when the final model was implemented in clinical practice (Fig. 2B and C).

3.6. Sensitivity analysis

To evaluate the effectiveness of the proposed feature selection

Table 2
Description of the selected features in our youth's mental health prediction model with the Final Mean SHAP Values.

Order	Predictor	Variable description	FMSV[a]
1	SLE.D1 (Being punished)	As one of the dimensions of ASLEC[b], includes 6 items: Family squabbles; Lost election; Criticism and punishment; Transfer/Drop out of school; Fight with others; Beaten and scolded by parents (0, Unhappen; 1, Not at all; 2, Mild; 3, Moderate; 4, Severe; 5, Extremely severe)	1.000000
2	SLE.D5 (Adaptation problem)	As one of the dimensions of ASLEC[b], includes 4 items: Changes in living habits; Away from family members; Be seriously ill; Others (0, Unhappen; 1, Not at all; 2, Mild; 3, Moderate; 4, Severe; 5, Extremely severe)	0.418345
3	EI.D3 (Regulation of emotion in oneself)	As one of the dimensions of WLEIS[c], it refers to the ability to understand and evaluate deep-seated self-emotions, and to express them naturally, including 4 items: I have a good sense of why I have certain feelings most of the time; I have good understanding of my own emotions; I really understand what I feel; I always know whether or not I am happy (1, Strongly disagree; 2, Disagree; 3, Somewhat disagree; 4, Not quite sure; 5, Kind of agree; 6, Agree; 7, Strongly agree)	0.251194
4	SLE.D4 (Learning pressure)	As one of the dimensions of ASLEC[b], includes 5 items: Fail the exam; The heavy burden of study; Financial difficulties of family; Lost election; Pressure of entering a higher school (0, Unhappen; 1, Not at all; 2, Mild; 3, Moderate; 4, Severe; 5, Extremely severe)	0.206707
5	SS.D3 (Utilisation of social support)	As one of the dimensions of SSRS[d], it refers to the ability to actively seek and reasonably apply social support, including 3 items	0.194754
6	EI.D2 (Appraisal and recognition of emotion in others)	As one of the dimensions of WLEIS[c], it refers to the ability to appraise and recognize of emotion in others, including 4 items: I always know my friends' emotions from their behavior; I am a good observer of others' emotions; I am sensitive to the feelings and emotions of others; I have good understanding of the emotions of people around me (1, Strongly disagree; 2, Disagree; 3, Somewhat disagree; 4, Not quite sure; 5, Kind of agree; 6, Agree; 7, Strongly agree)	0.181345

Note: The predictors are shown in decreasing order of FMSV.
[a] FMSV (Final Mean SHAP Value), refers to the average of mean SHAP value in each variable gained by min-max normalization in Random Forest and XGBoost models.
[b] ASLEC, Adolescent Self-rating Life Events Checklist.
[c] WLEIS, Wong and Law EI Scale.
[d] SSRS, Social Support Rating Scale.

method and the selected final model, we conducted sensitivity analyses using various feature selection methods and prediction models. These analyses were performed during the internal validation phase and involved pairwise comparisons of each model using independent *t*-tests (Supplementary Tables 9–11). The results confirmed the reliability of our feature selection method and demonstrated the superior performance of the final model.

4. Discussion

Using two-wave data obtained from a nationwide online survey, we developed machine learning-based prediction models using important features identified by intersecting the top 10 features from both models. We ranked the feature importance by SHAP analysis to explore the predictive effect of sociodemographic characteristics, stressful life events, social support, emotional intelligence, and coping strategies on mental health states. The findings underscored the promising capabilities of this feature selection method, while demonstrating that the BPNN model performed more effectively than AdaBoost and logistic regression in terms of discrimination, calibration, and clinical use. This prediction model will be beneficial for monitoring mental health and identifying those at risk for timely interventions aimed at helping youths adjust effectively to stressful life events in the post-pandemic world. External validation using data across different geographic areas in China and time points (before and after the COVID-19 pandemic) added confidence to the generalisation performance of the final prediction model and proved the robustness of the feature selection. Notably, the final model we proposed surpasses the performance of previous similar studies, with our SHAP+BPNN model yielding a higher F-score in both internal and external validation, outperforming the previous research's 0.81 ± 0.19 (Gokten and Uyulan, 2021). A meta-analysis of depression treatment outcomes revealed that the eight adequate-quality studies included in the analysis reported a mean accuracy of 0.63 [95 % CI: 0.56–0.71], whereas our final model consistently outperformed these results (Sajjadian et al., 2021). Furthermore, our study offers a more exhaustive assessment of the model, thereby guaranteeing its generalizability and minimizing the risk of overfitting.

Primarily, we developed two machine learning models based on the XGBoost and random forest algorithms and performed a SHAP analysis to rank the importance of features from each model. Important features were extracted by intersecting the top 10 features from the XGBoost and random forest models. The effectiveness of feature selection in enhancing learning efficiency and prediction accuracy and simplifying outcomes is well-established (Koller and Sahami, 1996). Our study employed feature selection using XGBoost and random forest separately based on bagging and boosting techniques. Bagging, or bootstrap aggregation, involves perturbing training sets multiple times using bootstrapping, with predictors combined through simple voting or averaging. Random forest, by randomly selecting features at each node, limits the generalisation error and demonstrates speed and accuracy. Álvarez-Estévez explored ensemble methods using various wrapper and filter techniques, noting differences between the union and intersection approaches (Álvarez-Estévez et al., 2011). Although the intersection approach may yield a more restrictive set of features, it can add robustness to feature selection. Hybrid and ensemble feature selection methods have gained prominence by leveraging the outputs of multiple algorithms to overcome limitations and enhance reliability (Ang et al., 2016). Studies have shown that ensemble methods generally outperform individual techniques in terms of classification accuracy (Wang et al., 2022; Huang, 2021).

In particular, SHAP values offer an extensive overview of the impact of each variable and the range of their values on the outcome. The predictor variables identified after the intersection included three aspects: stressful life events, emotional intelligence, and social support. Table 2 provides detailed information regarding these features. Our findings showed that the top predictive factors for mental health state included three types of stressful life events: punishment, adaptation problems, and learning pressure. These results align with previous findings which show that stressful life events, such as changes in living habits, the death of a family member, experiencing violence, or parental divorce, can lead to serious long-term mental health problems (Hughes et al., 2017). This consistency highlights the importance of the timely

Table 3
Details about the performance of the models developed with different algorithms in primary analysis.

Model	Sensitivity (%)	Specificity (%)	Accuracy (%)	F-score (%)	C-index (%)
Internal validation (mean [95%CI])					
LR[a]	86.66 [86.54, 86.79]	94.91 [94.85, 94.96]	92.53 [92.47, 92.58]	86.98 [86.88, 87.07]	95.20 [95.14, 95.26]
AdaBoost[b]	85.53 [85.40, 85.67]	96.76 [96.72, 96.80]	93.52 [93.47, 93.57]	88.38 [88.28, 88.47]	95.29 [95.23, 95.34]
BPNN[c]	83.29 [83.14, 83.45]	98.10 [98.04, 98.15]	93.81 [93.77, 93.86]	88.61 [88.53, 88.69]	91.20 [91.11, 91.29]
External validation					
LR[a]	91.40	94.17	93.69	83.33	98.02
AdaBoost[b]	88.17	95.52	94.25	84.10	96.11
BPNN[c]	90.32	95.07	94.25	84.42	97.49

Note: Models are all built with six features determined by intersecting the top 10 features ranked by mean SHAP values obtained from both the XGBoost model and the Random Forest model.
[a] LR, Logistic Regression.
[b] AdaBoost, Adaptive Boosting.
[c] BPNN, Back Propagation Neural Network.

detection and treatment of mental health problems among youths and that it can escalate to severe mental illness and give rise to behavioural issues (Bai et al., 2022). Other noteworthy factors among the intersection of the top 10 features are the utilisation of social support, regulation of emotion in oneself, and appraisal and recognition of emotion in others. Studies have shown that social support and emotional intelligence are protective factors for youth mental health (Azpiazu et al., 2023). The identification of these top-ranked features suggests their potential role in preventing and intervening in mental health problems among youth. Rather than evaluating the mental health state with 25 features, the final BPNN model with the SHAP method selected six features that outperformed traditional statistical methods (e.g. logistic regression with LASSO regression) and achieved the best performance. Using this simple and efficient self-assessment model, students can monitor their mental health state, and psychological consultation mentors can easily identify at-risk individuals by evaluating the selected features.

The findings of the present study show that youths experienced a considerable rise in a variety of stressful life events during Wave 2, indicating that mental health problems appear to have become prominent among youths in China (Qiao et al., 2021). Stressors such as academic pressure, family issues, and relationship problems may contribute to poor mental health among school youths. Considering the multiple sources of stress, developing multilevel strategies that most notably engage the health and education sectors and the wider community, including youths and their families, is vital for strengthening monitoring and implementing prevention (Chen et al., 2024). According to the consistent changes from Wave 1 to Wave 2, different levels of social support, coping strategies, and emotional intelligence led to different mental health states. Prevention programs can be implemented at both the school and family level (Li et al., 2021). Knowledge on improving emotional intelligence and utilisation of social support should also be provided by school (Luo et al., 2022). Furthermore, schools are supposed to monitor students' mental health states, which could be realised by assessing emotional intelligence and social support (Gray et al., 2022). Moreover, stressors that arise in families cannot be ignored; it is critical to support family functioning because it may affect adolescents' coping with stressful experiences (Bai et al., 2022). For youths already at a high risk of mental health problems, the intersecting features in this study may serve as intervention targets to mitigate the occurrence of severe mental health disorders. Youths may be reluctant to seek help or utilise social support for mental health problems, as they may be unaware of the knowledge and resources of mental health issues or may experience mental health symptoms (e.g. depressive symptoms) (Azpiazu et al., 2023). To enhance the state of mental health among this population, it may be essential to raise the public's awareness of the assistance and resources that are accessible, as well as to implement screening procedures for mental distress in school and primary care settings (Qiao et al., 2021).

5. Limitations

The limitations of this study include the use of only self-reported data. In the future, objective indicators should be considered. Future studies should also explore neurofunctional predictors and information from clinical files, laboratory examinations, and images to help implement early screening and diagnosis of mental health status among youths. The intrinsic mechanism for selecting the features of different algorithms suggests different sets of features. However, the six selected features are likely to be robust because of the intersection of the top 10 variables, which indicates the high rankings of these features and the results of the sensitivity analysis. Also, we conducted a cross-sectional study with a large sample size in China, while data cover is limited in covering the minority nationality, which may lead to the problem of unfairness of algorithms. Finally, it is important to note that these findings only suggest associations between factors and the outcome and do not establish causal relationships, which are inherent to the nature of the machine learning model used in this study.

6. Conclusion

Machine learning models effectively identified and predicted mental health outcomes among youths, with the SHAP+BPNN model showing promising results in clinical applicability. These findings emphasise the importance of targeted interventions focusing on coping strategies, social support, and emotional intelligence to enhance youths' mental health when facing stressful life events.

Code availability

The code will be available in GitHub by accessing this web page. https://github.com/226LiNa622/YStitch.git.

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Ethics approval statements

This study was registered prospectively on ClinicalTrials.gov (ID: NCT05435469), and ethically approved by the Ethics Committee of the

School of Nursing, Sun Yat-sen University (ID: L2022SYSU-HL-044).

CRediT authorship contribution statement

Hexiao Ding: Writing – review & editing, Writing – original draft, Visualization, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Na Li:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Lishan Li:** Writing – review & editing, Writing – original draft, Conceptualization. **Ziruo Xu:** Writing – review & editing, Writing – original draft, Visualization, Conceptualization. **Wei Xia:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

This manuscript has not been published or presented elsewhere in part or in entirety and is not under consideration by another journal. All study participants provided informed consent, and the study design was approved by the appropriate ethics review board. There are no conflicts of interest to declare.

Data availability

The dataset of this study is all derived from the anonymous online survey results of our research group in the past. These data have already been safely stored in a database. We will make the dataset publicly available, but please contact the corresponding author by email to inform us of your purpose before using it. We will authorize the usage according to ethical principles after rigorous discussion.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jad.2024.09.111.

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