Psychology Research and Behavior Management

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Taylor & Francis Group

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ORIGINAL RESEARCH

Development and Validation of a Nomogram for Predicting Suicidal Ideation Among Rural Adolescents in China

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Purpose: Suicidal mortality is high in rural areas, and suicidal ideation, an early psychology of suicidal behavior, is particularly important for the early prevention and intervention of suicide. This study aimed to establish a nomogram model to predict high-risk groups among rural adolescents who might develop suicidal ideation.

Patients and Methods: This study conducted a cross-sectional survey of 1900 rural secondary school students in Xuzhou, China. The samples were randomly divided into a training set (1330) and a validation set (570), and a nomogram prediction model was constructed using the potential predictors of suicidal ideation screened from the training set using Lasso-Logistic regression. The model was validated using ROC, calibration, and clinical decision curves.

Results: The reported rate of suicidal ideation among rural adolescents is 18.9%. Lasso-Logistic regression found that emotional abuse, emotional neglect, hostility, subjective sleep quality, daytime dysfunction, withdrawal/escape, and depression were significant risk factors for suicidal ideation. A nomogram was built using the above 7 predictors. The area under the ROC curve (AUC) of our predictive model was 0.821 in the training set and 0.765 in the validation set, with corrected C-indices of 0.817 and 0.764, respectively. Furthermore, the calibration curves demonstrated good alignment with the ideal line ($P > 0.05$), and the decision curve analysis results indicated positive clinical utility.

Conclusion: The nomogram model constructed in this study may be an effective tool for predicting suicidal ideation in rural middle school students. It helps identify high-risk groups with suicidal ideation and provides more reliable information for the early prevention and intervention of suicide.

Keywords: suicidal ideation, nomogram, adolescent, rural, LASSO

Introduction

According to a report by the World Health Organization in 2021, over 700,000 people worldwide die by suicide each year. One in every 100 deaths is due to suicide, meaning that suicide accounts for 1% of all global causes of death.[1] More worryingly, suicide has become one of the leading causes of death (ranked fourth) among people aged 15 to 29 years,[1] and it is also the third major cause of death among the adolescent population in China.[2] Moreover, the suicide rate is higher in rural areas than in urban areas.[3] It is evident that all the above data indicate that suicide is currently one of the major public health problems worldwide. Numerous studies have shown that suicide and suicidal ideation are

Received: 29 September 2024
Accepted: 17 December 2024
Published: 25 December 2024

inextricably linked.[4–6] Individual suicide is generally considered a "thought to action" process.[5] A systematic review report indicates that the conversion rate from suicidal thoughts to suicide attempts ranges from 2.6% to 37%,[6] varying depending on the characteristics of the study population (such as the target group and psychological diagnoses). Previous studies have shown that most people who die by suicide exhibit suicidal thoughts in various ways before committing suicidal behavior.[4] Therefore, the early psychology of suicidal behavior is suicidal ideation, which can significantly predict suicidal behavior.

The three-step theory divides the development of suicidal ideation and behavior into three stages.[7] The first step occurs when an individual experiences pain (regardless of its source, typically referring to psychological or emotional pain) and hopelessness (a belief that the pain cannot improve in the future), which may lead to suicidal ideation. The second step is when the pain exceeds the individual's "connectedness" (such as relationships with others or ties to life goals), causing suicidal ideation to escalate from moderate to strong. In the third step, when an individual acquires sufficient capability for suicide, suicidal ideation may progress to suicidal behavior.

In the first step, pain and hopelessness often stem from various adverse events or emotional states, such as anxiety, depression, adverse childhood experiences, peer bullying, and sleep disturbances, all of which have been proven to be associated with suicidal ideation.[8–11] Behavioral problems such as aggression and mobile phone addiction have also been linked to suicidal ideation.[12,13] The impact of this multifactorial combination on suicidal ideation in adolescent children is unique.[14,15] Because, among further mechanisms, we believe that adolescent children are initiating a series of neuroendocrine cascades that underlie emotion regulation, and impulse control, when confronted with environmental risk factors such as life stressors that affect neurodevelopmental trajectories, impaired emotion regulation, and impulse control can significantly contribute to the emergence of psychiatric disorders, which may ultimately lead to suicidal ideation.[16] In particular, rural teenagers have "rural" characteristics, such as poorer educational resources and a higher proportion of left-behind children, which will have more significant impacts on their mental health (suffering greater pain and hopelessness), and a higher probability of suicidal ideation.[17,18] Therefore, adolescence is a critical window for early detection, prevention, and intervention of suicidal ideation and suicidal behavior, and it is crucial to establish a model that can predict suicidal ideation in adolescents.

A nomogram is a reliable predictive tool. It predicts an individual's risk of a hazardous outcome by combining various factors. Although this model is mainly used in clinical disease diagnosis and prognosis prediction, it has also been gradually applied in behavioral psychology and has shown good adaptability.[19] However, when more explanatory variables are entered into the model, the number of cases for calculating the predicted probability of a disease increases; therefore, it is usually most appropriate for a nomogram to use to 5–9 variables to identify the predicted path of a disease.[20] And Lasso-Logistic regression can simplify the number of independent variables, select the most useful predictive candidate variables in the dataset, adjust the complexity of the model, and avoid overfitting.[21]

Most of the current studies are exploring and predicting the factors of suicide and seldom predict suicidal ideation; in particular, research on the prediction of suicidal ideation among Chinese rural adolescents is lacking. We considered that all the above factors (anxiety, depression, adverse childhood experiences, etc) could influence suicidal ideation, although the magnitude of the effects varied. Therefore, the present study collected the factors that have the greatest influence on suicidal ideation among rural adolescents through LASSO regression (most of the factors were differentiated one by one from a sub-dimensional perspective to obtain a more accurate influence) and then utilized these potential predictors to establish a nomogram to identify high-risk groups for suicidal ideation. Therefore, timely interventions should be implemented to reduce suicidal ideation among rural adolescents.

Materials and Methods

Study Participants

This cross-sectional study was conducted in Jiangsu, China from September 2021 to March 2022. Four rural middle schools in Xuzhou City, Jiangsu Province, were randomly selected as the research subjects. According to the principle of school grade stratification and random selection of classes, all students within the selected classes who met the inclusion and exclusion criteria were used as research subjects for the on-site paper questionnaire survey (the first language of all

research subjects was Chinese). The process was as follows: First, we randomly selected four rural middle schools in Xuzhou City, contacted these four schools through the education department to confirm the exact time of the survey, then randomly selected six classes in each grade in each school, and finally administered an on-site paper questionnaire to all students in the selected classes who were attending school normally, voluntarily agreed to participate in the study, and did not have dyslexia. All the investigators were uniformly trained in the norms of completion to control the quality of the questionnaire. Ensure that the survey process fully respects the respondents and protects their privacy.

A total of 1920 questionnaires were returned, and based on the purpose and needs of the study, cases with missing key information (missing demographic information, missing entries more than 30%), or obvious logical errors were excluded, and the remaining cases were subjected to mean interpolation. Ultimately, 1900 valid questionnaires were deemed to be suitable for this study. The recovery rate of the effective questionnaire was 98.96%. The final age of the patients was 13–22 years.

According to the literature, the incidence of suicidal ideation among Chinese adolescents is 22.1%,[22] the allowable error was taken as 0.1, and the sample size calculated according to the following formula was 1354 at the 95% confidence level. The sample size of the present study was 1900, which fulfilled the investigation requirements of the present study.

$$n = \frac{Z^2_{\alpha/2}(1-P)}{\varepsilon^2 P}$$

The study complied with the Declaration of Helsinki, and informed consent was obtained from all the participants and their guardians.

Measures

Suicidal Ideation

In this study, suicidal ideation was measured by a widely used question: "Have you ever had suicidal thoughts in the past year?".[23–25] Answers to the questions were yes or no. When the answer is "yes", suicidal ideation is considered.[24]

Depressive Symptoms

The study used a nine-item Chinese version of the Patient Health Questionnaire (PHQ-9) to assess depressive symptoms.[26,27] Participants were asked to respond to symptoms they had experienced in the past two weeks, with scores ranging from 0 (not at all) to 3 (almost every day) for each item, and a total score ranging from 0 to 27. The criteria for major depressive disorder (MDD) were considered to be met when the total score was ≥10.[26–31] The reliability of this study was good with an alpha value of 0.882.

Anxiety Symptoms

Anxiety symptoms were assessed using the Chinese version of the 7-item Generalized Anxiety Disorder (GAD-7).[32,33] Scores ranged from 0 (not at all) to 3 (almost every day), with total scores ranging from 0 to 21. Anxiety symptoms were judged to be present when the total score was ≥5.[34] Cronbach's alpha for this study was 0.921, with good reliability.

Bullying Situations

The Chinese version of the Olweus Bullying Questionnaire was used in this study[35,36] with seven bullied items, including four dimensions: physical, verbal, relational, and cyber bullying. A 5-point scoring method was used (1 = never happened, 5 = several times a week); if any of the seven bullying items scored ≥2 points, it was judged as being bullied. In our study, the scale had good internal consistency (Cronbach's alpha = 0.776).

Adverse Childhood Experiences

The Chinese version of the short-form Childhood Trauma Questionnaire (CTQ) was used to assess adolescents' adverse experience scores.[37,38] The scale has 28 items and includes five subscales (Emotional Abuse, Physical Abuse, Sexual Abuse, Emotional Neglect, and Physical Neglect). A 5-point scoring method (1 = never, 5 = always) was used for scoring. The score for each abuse subscale was 5–25 points. The higher the score, the more serious is the abuse. This scale has good reliability and validity among Chinese adolescents. Cronbach's alpha for the total scale was 0.771.

Aggressive Behaviors

Aggressive behavior of the adolescents in this study was rated using the revised Chinese version of the aggression questionnaire (BWAQ) developed by Buss and Warren.[39,40] The aggression scale has 34 items, all of which are scored on a 5-point Likert scale, with each item ranging from 1 (not at all like me) to 5 (exactly like me). There are five subscales: physical aggression, verbal aggression, anger, hostility, and indirect aggression, with higher scores indicating greater aggression. The Cronbach's alpha for the scale was 0.896.

Sleep Problems

The Pittsburgh Sleep Quality Index (PSQI) has been used to assess the sleep status of adolescents.[41,42] It includes seven dimensions: subjective sleep quality, sleep latency, sleep duration, sleep efficiency, sleep disturbance, use of sleep medications, and daytime dysfunction. The scores for each dimension ranged from 0 to 3, and the total scores ranged from 0 to 21. The higher the score, the worse is the sleep quality. The scale has been widely used and promoted in China, and has high reliability and validity. The Cronbach's alpha of the scale in this study was 0.783.

Mobile Phone Addiction

This study used the 17-item Mobile Phone Addiction Indicator Scale (MAPI) to measure mobile phone addiction among adolescents.[43] Each item was scored on a 5-point Likert scale (1 = never, 5 = always). The scale has four dimensions: inability to control craving, anxiety and feeling lost, productivity loss, and withdrawal/escape. The higher the score, the more severe was the mobile phone dependence. Cronbach's alpha for this scale in this study was 0.921.

Other Variables

The variables in this study included age, gender (male/female), grade level (junior one/junior two/junior three/senior one/senior two/senior three), academic performance (top 20%/moderate/bottom 20%), family structure (nuclear family/single-parent family/restructured family/intergenerational family/other, the last four are summarized as non-nuclear family), only child (yes/no), parents' education level (primary school and below/middle school/high school/university and above), per capita monthly income (≤2000/2000–5999/≥6000), left-behind children (yes/no) (referring to children who remain in rural areas while one or both parents migrate to urban centers seeking employment and better economic opportunities),[44] and sexual orientation (heterosexual/non-heterosexual). BMI first needed to collect the height and weight of the subjects, and then calculated it according to the formula "BMI = Weight (kg)/Height^2(m^2)" (using the Asian population standard.[45] Normal, overweight, and obese ranges of 18.0–22.9, 23.0–24.9, and ≥25, respectively). Smoking was measured using the question "In the last month, how many days did you smoke at least one cigarette?" When the answer was ≥1 day, it was recognized as "smoking".[46] Drinking was measured using the question "In the last month, how many days did you drink at least one glass of wine?" and when the answer was ≥1 day, it was recognized as "drinking".[46]

Statistical Analysis

The training set was used to train the nomogram model. By learning the sample data in the training set, the model can adjust its own parameters to minimize prediction errors, and thus improve the accuracy of the prediction. The validation set was used to evaluate the performance of the model and to tune its hyperparameters. By evaluating the model on the validation set, the performance of the model on unseen data can be obtained to determine whether the model is overfitting or underfitting and make adjustments accordingly. Dividing the training and validation sets requires satisfying the condition that the distributions of the two parts of the data are roughly the same. This ensures that the model built using the training set also performs well on the validation set. Typically, according to the TRIPOD statement[47] and empirical practices,[46,48,49] a ratio of 7:3 provides a reasonable balance between the training and validation sets, which ensures that the model has sufficient data for training and validation of its generalization ability. Therefore, we assigned the data to the training and validation sets using random sampling at a fixed ratio of 7:3 on a computer. Then, the comparability between the two groups was assessed, and the general information of the participants was compared after grouping them according to suicidal ideation in the training set. As none of the continuous data in this study obeyed a fractional normal distribution, the count data were expressed as frequency and percentage, and the quantitative data

were expressed as median (M) and interquartile range (IQR). Chi-square or non-parametric tests were used to explore whether the distributions of the training and validation variables were consistent. At a test level of $\alpha = 0.05$, when $P > 0.05$, the training and validation sets were comparable.

LASSO regression (Least Absolute Shrinkage and Selection Operator) achieves variable selection and model optimization by introducing L1 regularization. Its objective function is defined as follows:[50]

$$\hat{\beta}_{lasso} = \underset{\beta}{argmin} \left\{ \frac{1}{2} \sum_{i=1}^{N} \left(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right\}$$

where y_i represents the response variable for the i-th observation, x_{ij} is the corresponding predictor variable, β_0 is the intercept, β_j denotes the regression coefficient for the j-th predictor, N is the sample size, p is the number of predictors, and λ is the regularization parameter that controls the strength of the L1 penalty. The first term of the objective function (residual sum of squares) minimizes the error between the observed and predicted values to ensure model fitting accuracy, whereas the second term (L1 penalty) imposes constraints on the absolute values of the coefficients β_j, effectively reducing model complexity by driving the coefficients of less relevant variables to zero, thereby achieving feature selection. The regularization parameter λ controls the regularization strength and strikes a balance between model fitting bias and variance: smaller λ values result in weaker regularization, retaining more variables, whereas larger λ values increase regularization strength, compressing certain coefficients to zero and enhancing model sparsity and interpretability. This sparsity characteristic allows LASSO to effectively identify significant variables in high-dimensional data, avoiding overfitting and improving the model's generalization ability and interpretability.

In this study, a 10-fold cross-validation method was used to select the optimal regularization parameter, λ. The training set was randomly divided into ten equal parts, with nine parts used for model training and the remaining 1 part used for validation. This process was repeated ten times, and the average error for each λ value was calculated. The λ value corresponding to the minimum mean square error plus one standard error was selected as the optimal value to ensure the stability and generalizability of the model. Compared with traditional logistic regression, LASSO incorporates a regularization mechanism that enables automatic variable selection, eliminating the need for manual feature selection, and reducing the risk of subjective bias or omission of key variables. Unlike Ridge Regression, which uses L2 regularization and only shrinks coefficients, LASSO's L1 regularization can directly reduce irrelevant variable coefficients to zero, achieving genuine feature selection.[51] Although Elastic Net combines L1 and L2 regularization, the sparsity of predictors in this study made LASSO sufficient to meet the requirements, while maintaining a more concise model structure.[52] Machine learning methods such as random forests and support vector machines can handle non-linear relationships, but their complexity is higher, and they lack interpretability. By contrast, LASSO produces a sparse model that is more suitable for constructing nomograms.[53] Therefore, LASSO was chosen as the optimal variable selection method in this study.

For specific analyses, we included all variables in the LASSO regression model, which helped reassess their significance in a multivariate context to avoid omitting important information. First, LASSO regression was performed using the "glmnet" package in R to analyze all variables that might be related to suicidal ideation, followed by a 10-fold cross-validation method to select the optimal λ-value, based on which the strongest predictor variables associated with suicidal ideation were initially selected. These variables were included in a multifactor logistic regression, and those with statistically significant differences were selected to identify independent predictors of suicidal ideation. Finally, these factors were used to create a nomogram predictive model in the "regplot" program package in R.

After the model was constructed, its effect was verified using validation set data. The discrimination ability of this prediction model was evaluated by plotting the receiver operating characteristic (ROC) curves and calculating the area under the curve (AUC). Calibration curves were plotted, corrected C-indices were calculated, Hosmer-Lemeshow goodness-of-fit tests were performed to evaluate the calibration of the model, and decision curve analysis (DCA) was used to determine the clinical utility of the predictive model.

The present study used Excel 2016, SPSS 26.0, and R 4.2.1 to organize and statistically analyze the data.

Results

General Characteristics of Participants

Of 1900 rural adolescents, 18.9% (360/1900) reported suicidal ideation. The median age was 16 years (IQR 15–18), 817 patients (43.0%) were male, and 7.3% (139) were left-behind children. Only 12.3% (233) and 10.1% (191) of the parents had a university or higher education, respectively, and 58.3% (1108) had a family income of less than 6000 yuan. All participants were divided into training and verification sets, with 1330 in the training set and 570 in the verification set. In the comparison of the two datasets, the differences were not statistically significant except for the left-behind children ($P > 0.05$), and the distributions were roughly the same. In the training set, the groups with and without suicidal ideation differed in terms of gender, family structure, sexual orientation, smoking, drinking, depression, anxiety, aggressive behavior, and mobile phone addiction ($P < 0.05$). Except for the physical bullying dimension of bullying, the sexual abuse dimension of adverse childhood experiences, and the use of sleep medication dimension of sleep problems, the other dimensions of these three characteristics also differed between the two groups ($P < 0.05$). The characteristics of the other participants are shown in Table 1.

Screening Predictors

In the training set, 42 risk factors, including demographics and mental health, were included in the LASSO regression analysis. The optimal λ value (λ = 0.04020101) was selected through 10-fold cross-validation, compressing the coefficients of the variables with minimal impact on the dependent variable to zero to identify the most effective variables. This approach not only controls the complexity of the model but also enhances its interpretability (Figure 1). Finally, eight variables were screened using the LASSO model: emotional abuse, emotional neglect, hostility, subjective sleep quality, daytime dysfunction, withdrawal/avoidance, anxiety, and depression.

Suicidal ideation was taken as the dependent variable, and the variables selected from the LASSO regression were used as independent variables for the logistic regression analysis. Finally, seven variables with statistical significance were selected to construct the nomogram model: emotional abuse, emotional neglect, hostility, subjective sleep quality, daytime dysfunction, withdrawal/escape, and depression (Figure 2).

Development of Predictive Models

Based on the results of the multivariate logistic regression model, a nomogram for predicting suicidal ideation was developed (Figure 3). The results showed that emotional abuse contributed the most to the prediction of suicidal ideation, followed by hostility in aggression and depression.

The nomogram was assigned a specific score and the total score was used to obtain an individual's predicted probability of suicidal ideation. First, each independent predictor was projected to the first row to obtain a score for each factor, and then the scores for the seven risk factors were summed to obtain the total score. Second, an individual's risk of suicidal ideation was calculated from the total score. The higher the total score, the higher the individual's risk for suicidal ideation. For example, an individual with depressive symptoms and scores of 17, 15, 34, 1, 2, and 7 for emotional abuse, emotional neglect, hostility, sleep quality, daytime dysfunction, and escape behavior, respectively, can have each feature mapped to the "Points" axis to obtain a corresponding score. The total score of these seven items was 304. Finally, this total score was then mapped downward to obtain a predicted suicidal ideation risk of 85.5% for the individual.

Predictive Effectiveness of the Model

The AUC values of the ROC curves for the nomogram were 0.821 (0.792–0.850) for the training set and 0.765 (0.710–0.819) for the validation set, indicating that the nomogram had good discrimination. There was no statistically significant difference in the AUC values between the two groups ($P > 0.05$) (Figure 4A).

The calibration curves for the training and verification sets are shown in (Figure 4B). The calibration and ideal lines fit well with corrected C-indices of 0.817 and 0.764, respectively. The Hosmer-Lemeshow test also showed that the fit of the model was good (training set, $P = 0.388$; validation set, $P = 0.300$), which indicated that the predicted probability of

Table 1 Distributional Differences Between the Training and Validation Sets and General Characteristics of Participants with/Without Suicidal Ideation in the Training Set

Characteristics	All (1900)	Data Set		Z/χ^2	*P*-value	Suicidal Ideation (Training Set)		Z/χ^2	*P*-value
		Training Set (1330)	Validation Set (570)			Yes (261)	No (1069)		
Suicidal ideation (n, %)				1.322	0.250				
No	1540(81.1)	1069(80.4)	471(82.6)						
Yes	360(18.9)	261(19.6)	99(17.4)						
Age (M, IQR)	16(15,18)	16(15,18)	16(15,18)	0.826	0.502	16(15,18)	16(15,18)	0.383	0.999
Gender (n, %)				0.487	0.485			8.502	0.004
Male	817(43.0)	565(42.5)	252(44.2)			90(34.5)	475(44.4)		
Female	1083(57.0)	765(57.5)	318(55.8)			171(65.5)	594(55.6)		
Grade (n, %)				2.176	0.824			1.488	0.914
Junior one	327(17.2)	224(16.9)	103(18.1)			50(19.2)	174(16.3)		
Junior two	369(19.4)	252(18.9)	117(20.5)			49(18.8)	203(19.0)		
Junior three	127(6.7)	87(6.5)	40(7.0)			17(6.5)	70(6.5)		
Senior one	538(28.3)	388(29.2)	150(26.3)			72(27.6)	316(29.6)		
Senior two	442(23.3)	311(23.4)	131(23.0)			61(23.4)	250(23.4)		
Senior three	97(5.1)	68(5.1)	29(5.1)			12(4.6)	56(5.2)		
Academic performance (n, %)				0.709	0.702			3.315	0.191
Top 20%	506(26.6)	353(26.5)	153(26.9)			61(23.4)	292(27.3)		
Moderate	1190(62.6)	829(62.3)	361(63.3)			164(62.8)	665(62.2)		
Bottom 20%	204(10.8)	148(11.1)	56(9.8)			36(13.8)	112(10.5)		
Family structure (n, %)				0.032	0.857			7.429	0.006
Nuclear	1656(87.2)	1158(87.1)	498(87.4)			214(82.0)	944(88.3)		
Non-nuclear	244(12.8)	172(12.9)	72(12.6)			47(18.0)	125(11.7)		
Only child (n, %)				0.152	0.697			0.547	0.459
No	1698(89.4)	1191(89.5)	507(88.9)			24(9.2)	115(10.8)		
Yes	202(10.6)	139(10.5)	63(11.1)			237(90.8)	954(89.2)		
Father's education (n, %)				0.497	0.920			5.884	0.117
Primary school and below	129(6.8)	89(6.7)	40(7.0)			65(6.1)	24(9.2)		
Middle school	903(47.5)	635(47.7)	268(47.0)			524(49.0)	111(42.5)		
High school	635(33.4)	447(33.6)	188(33.0)			357(33.4)	90(34.5)		
University and above	233(12.3)	159(12.0)	74(13.0)			123(11.5)	36(13.8)		
Mother's education (n, %)				2.375	0.498			0.239	0.971
Primary school and below	269(14.2)	185(13.9)	84(14.8)			149(13.9)	36(13.8)		
Middle school	975(51.3)	691(52.0)	284(49.8)			553(51.7)	138(52.9)		
High school	465(24.5)	315(23.7)	150(26.3)			256(23.9)	59(22.6)		
University and above	191(10.1)	139(10.4)	52(9.1)			111(10.4)	28(10.7)		

(*Continued*)

https://doi.org/10.2147/PRBM.S498396

https://doi.org/10.2147/PRBM.S498396

Table 1 (Continued).

Characteristics	All (1900)	Data Set		Z/χ^2	*P*-value	Suicidal Ideation (Training Set)		Z/χ^2	*P*-value
		Training Set (1330)	Validation Set (570)			Yes (261)	No (1069)		
Per capita monthly income (n, %)				3.292	0.193			0.287	0.867
≥6000	792(41.7)	540(40.6)	252(44.2)			104(39.8)	436(40.8)		
2000–5999	912(48.0)	644(48.4)	268(47.0)			126(48.3)	518(48.5)		
≤2000	196(10.3)	146(11.0)	50(8.8)			31(11.9)	115(10.8)		
Left-behind children (n, %)				6.937	0.008			3.246	0.072
No	1761(92.7)	1219(91.7)	542(95.1)			232(88.9)	987(92.3)		
Yes	139(7.3)	111(8.3)	28(4.9)			29(11.1)	82(7.7)		
Sexual orientation (n, %)				0.255	0.613			35.427	<0.001
Heterosexuality	1553(81.7)	1091(82.0)	462(81.1)			181(69.3)	910(85.1)		
Non-heterosexual	347(18.3)	239(18.0)	108(18.9)			80(30.7)	159(14.9)		
BMI (n, %)				0.573	0.751			0.112	0.946
Normal	1532(80.6)	1078(81.1)	454(79.6)			211(80.8)	867(81.1)		
Overweight	175(9.2)	121(9.1)	54(9.5)			23(8.8)	98(9.2)		
Obesity	193(10.2)	131(9.8)	62(10.9)			27(10.3)	104(9.7)		
Smoking (n, %)				0.537	0.464			9.075	0.003
No	1838(96.7)	1284(96.5)	554(97.2)			244(93.5)	1040(97.3)		
Yes	62(3.3)	46(3.5)	16(2.8)			17(6.5)	29(2.7)		
Drinking (n, %)				0.862	0.353			25.059	<0.001
No	1769(93.1)	1243(93.5)	526(92.3)			226(86.6)	1017(95.1)		
Yes	131(6.9)	87(6.5)	44(7.7)			35(13.4)	52(4.9)		
Depression (n, %)				0.433	0.510			230.408	<0.001
No	1492(78.5)	1039(78.1)	453(79.5)			113(43.3)	926(86.6)		
Yes	409(21.5)	291(21.9)	117(20.5)			148(56.7)	143(13.4)		
Anxiety (n, %)				0.184	0.668			129.030	<0.001
No	1134(59.7)	798(60.0)	336(58.9)			76(29.1)	722(67.5)		
Yes	766(40.3)	532(40.0)	234(41.1)			185(70.9)	347(32.5)		
Bullying									
Physical bullying (n, %)				0.058	0.810			1.322	0.250
No	1846(97.2)	1293(97.2)	553(97.0)			251(96.2)	1042(97.5)		
Yes	54(2.8)	37(2.8)	17(3.0)			10(3.8)	27(2.5)		
Verbal bullying (n, %)				0.116	0.734			21.325	<0.001
No	1697(89.3)	1190(89.5)	507(88.9)			213(81.6)	977(91.4)		
Yes	203(10.7)	140(10.5)	63(11.1)			48(18.4)	92(8.6)		

Relational bullying (n, %)				1.786	0.181			18.197	<0.001
No	1809(95.2)	1272(95.6)	537(94.2)			237(90.8)	1035(96.8)		
Yes	91(4.8)	58(4.4)	33(5.8)			24(9.2)	34(3.2)		
Cyber bullying (n, %)				0.241	0.624			12.062	0.001
No	1880(98.9)	1317(99.0)	563(98.8)			253(96.9)	1064(99.5)		
Yes	20(1.1)	13(1.0)	7(1.2)			8(3.1)	5(0.5)		
ACEs (M, IQR)									
Emotional abuse	5(5,7)	5(5,7)	5(5,7)	0.786	0.567	7(5,9)	5(5,6)	4.877	<0.001
Physical abuse	5(5,5)	5(5,5)	5(5,5)	0.395	0.998	5(5,6)	5(5,5)	1.899	0.001
Sexual abuse	5(5,5)	5(5,5)	5(5,5)	0.235	1.000	5(5,5)	5(5,5)	0.876	0.427
Emotional neglect	6(5,9)	6(5,9)	6(5,9)	0.696	0.718	8(5,13)	6(5,9)	3.534	<0.001
Physical neglect	9(9,10)	9(9,10)	9(9,10)	0.736	0.651	10(9,11)	9(9,10)	2.449	<0.001
Aggression (M, IQR)									
Physical aggression	12(9,15)	11(9,15)	12(9,15)	0.586	0.883	14(11,17)	11(9,14)	3.669	<0.001
Verbal aggression	12(9,14)	12(9,14)	12(9,14)	0.531	0.941	13(10,15)	12(9,14)	1.796	0.003
Anger	15(12,19)	15(12,19)	14(12,19)	0.846	0.471	18(14,22)	14(12,18)	4.395	<0.001
Hostility	17(13,22)	17(13,22)	17(13,22)	0.546	0.927	22(18,27)	16(13,20)	5.751	<0.001
Indirect aggression	11(9,14)	11(9,14)	11(9,14)	0.636	0.814	13(11,16)	11(8,13)	3.498	<0.001
PSQI (M, IQR)									
Sleep duration	1(0,2)	1(0,2)	1(0,1)	0.441	0.990	1(1,2)	1(0,1)	2.590	<0.001
Sleep efficiency	0(0,0)	0(0,0)	0(0,0)	0.125	1.000	0(0,0)	0(0,0)	1.397	0.040
Sleep latency	1(1,2)	1(1,2)	1(1,2)	0.561	0.912	2(1,2)	1(0,2)	3.475	<0.001
Sleep disturbance	1(1,1)	1(1,1)	1(1,1)	0.481	0.975	1(1,2)	1(1,1)	2.597	<0.001
Subjective sleep quality	1(0,1)	1(0,1)	1(0,1)	0.240	1.000	1(1,2)	1(0,1)	2.901	<0.001
Use of sleep medications	0(0,0)	0(0,0)	0(0,0)	0.135	1.000	0(0,0)	0(0,0)	1.060	0.212
Daytime dysfunction	2(1,3)	2(1,3)	2(1,3)	0.305	1.000	3(2,3)	2(1,3)	4.014	<0.001
MPA (M, IQR)									
Inability to control craving	15(11,20)	16(11,21)	14(11,20)	1.286	0.073	19(14,24)	15(11,20)	3.146	<0.001
Feeling anxious and lost	6(4,10)	6(4,10)	6(4,9)	0.746	0.634	8(5,13)	6(4,9)	2.739	<0.001
Withdrawal/Escape	6(3,9)	6(3,9)	6(3,9)	0.736	0.651	8(5,12)	6(3,9)	3.433	<0.001
Productivity loss	8(5,10)	8(5,10)	7(5,10)	0.851	0.464	9(7,12)	7(5,10)	3.183	<0.001

Abbreviations: BMI, Body mass index; ACEs, Adverse childhood experiences; PSQI, Pittsburgh sleep quality index; MPA, Mobile phone addiction.

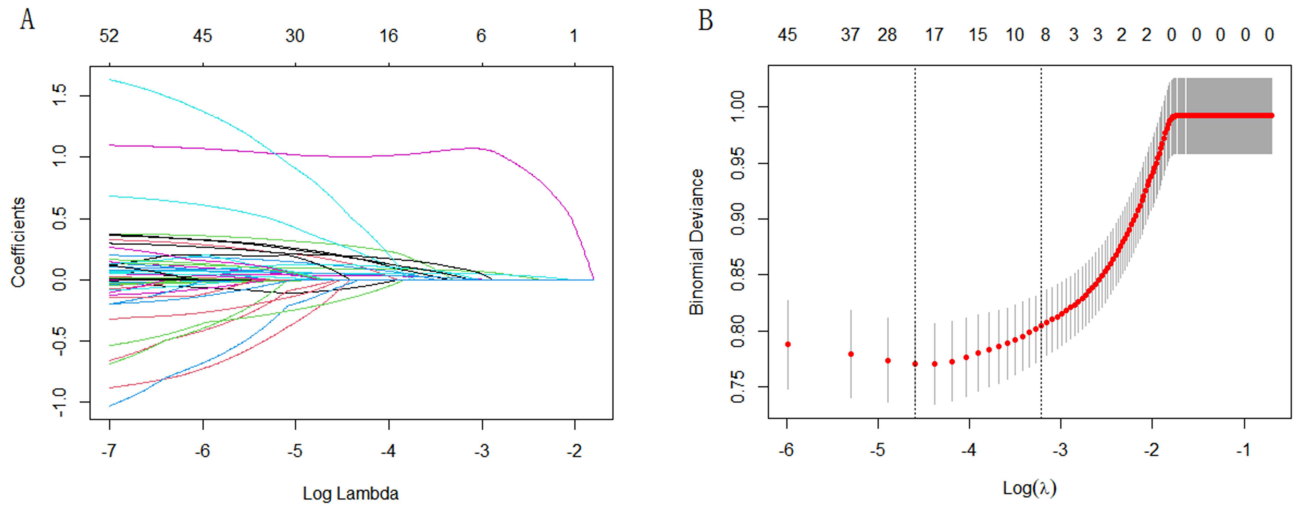

Figure 1 The process of selecting predictor variables for Lasso regression. (**A**) Lasso coefficient profiles of the candidate features. Each curve represents the regression coefficient of a feature variable. As the λ value increases, the regularization strength of the model also increases, resulting in more feature coefficients being compressed to zero. (**B**) The selection of optimal parameters (lambda) by 10-fold cross-validation. The red dots indicate the error corresponding to each λ value, and the gray lines represent the standard deviation range of the error. The left vertical line represents the λ value that minimizes the error, while the right vertical line represents the maximum λ value selected within the error range.

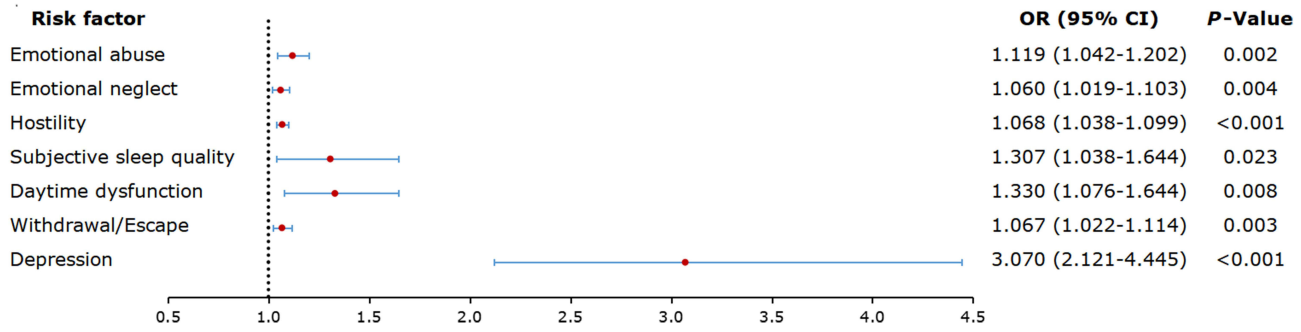

Figure 2 Odds Ratio forest plot for multivariate logistic regression in the training set.

the model was highly consistent with the observed probability. The decision curve analysis showed that nomogram prediction produced more net benefit at a threshold probability of 3–84% (Figure 4C). This finding suggests that our nomogram has a good clinical utility.

Discussion

This study utilized survey data from rural adolescents in Xuzhou, China to establish, for the first time, a nomogram prediction model for suicidal ideation among rural adolescents to identify those at high risk for suicidal ideation among rural adolescents. The reported rate of suicidal ideation among rural adolescents in this study was 18.9%, far exceeding the global 12-month prevalence of adolescents (14.2%).[54] Our nomogram showed that childhood emotional abuse, emotional neglect, depressive symptoms, and the hostility dimension of aggression were better predictors of suicidal ideation among adolescents. Although anxiety and bullying were not included, the results were broadly consistent with our prior assumptions.

In terms of childhood trauma factors, a systematic review of the literature showed that both dimensions of emotional abuse and emotional neglect were independent predictors of adolescent suicidal ideation.[55] The same consistent conclusion was reached in this study, and emotional abuse emerged as the most significant contributing factor to the prediction of suicidal ideation. Past evidence also suggests that among the five sub-dimensions of childhood trauma, emotional abuse is the most detrimental factor for adolescents.[56] First, trauma may negatively affect brain development,

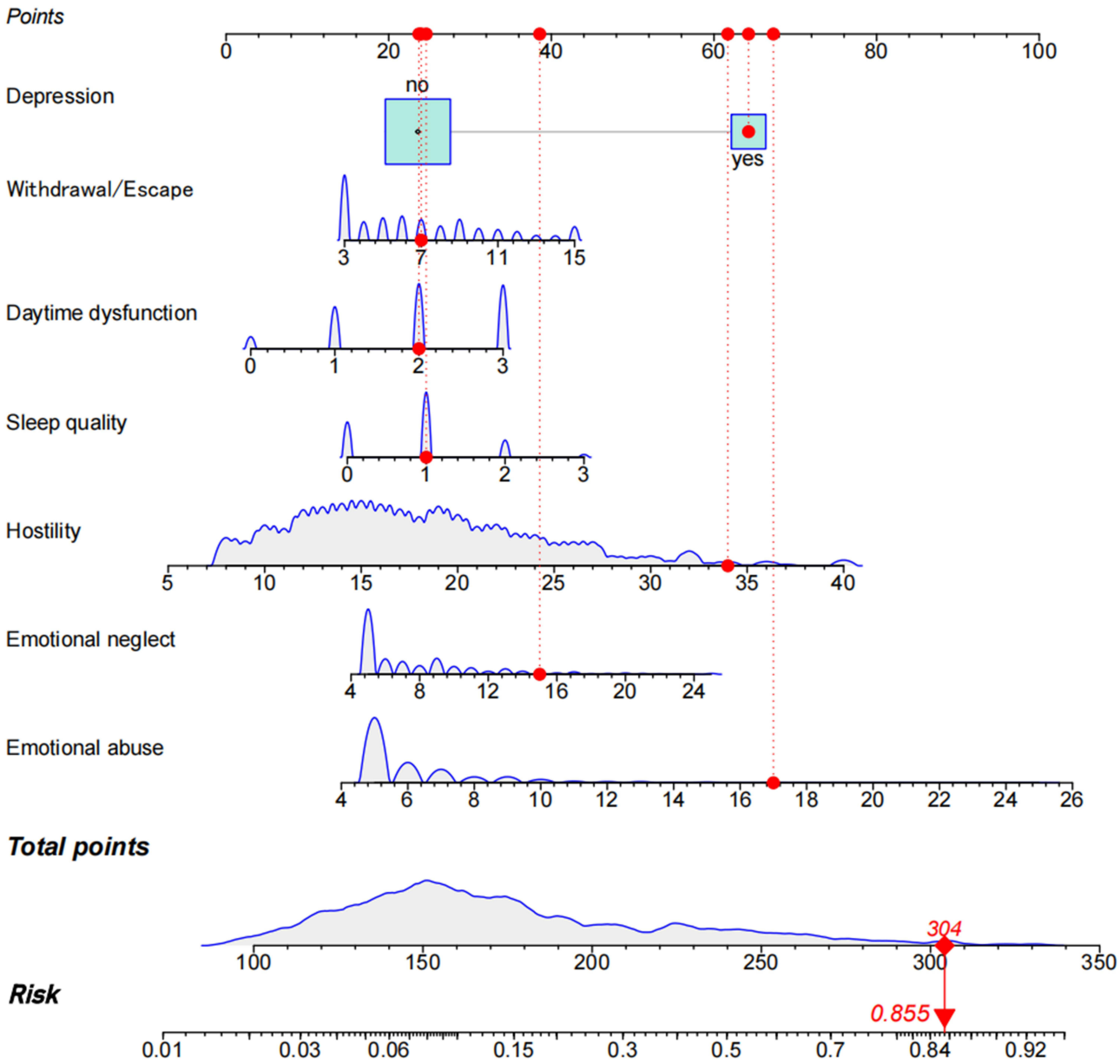

Figure 3 Predictive nomogram model of suicidal ideation. In the nomogram, quantitative features are depicted as density profiles to visualize the distribution, and qualitative features (such as depression) are presented as boxes. The size of the boxes indicates the proportion of each characteristic.

leading to psychopathic symptoms and psychological problems such as depression, anxiety, and impulsivity.[57] It is well known that the risk of suicidal ideation is significantly increased after experiencing these adverse psychological conditions.[58] Additionally, self-abandonment and self-loathing after abuse can contribute to suicidal ideation.[59] Thus, is an emotional neglect. Because the family is the most dependent living environment for teenagers and their psychology is not mature enough, experiencing parents' neglect of their emotions will cause anxiety,[60] leading to suicidal thoughts. In China, rural adolescents are more likely to suffer from emotional abuse and neglect than urban adolescents,[61,62] and psychologically endure greater pain and hopelessness. Therefore, these two factors are worthy of attention. Parents should pay timely attention to their children in their daily lives to fulfill their need to correspond to their emotions.

Among the various dimensions of aggressive behavior, hostility has a significant predictive effect on suicidal ideation. Hostility reflects an individual's intrinsic aggressive tendency, which may be associated with the accumulation of negative emotions and environmental stress.[63,64] Rural adolescents, due to factors such as economic hardship,

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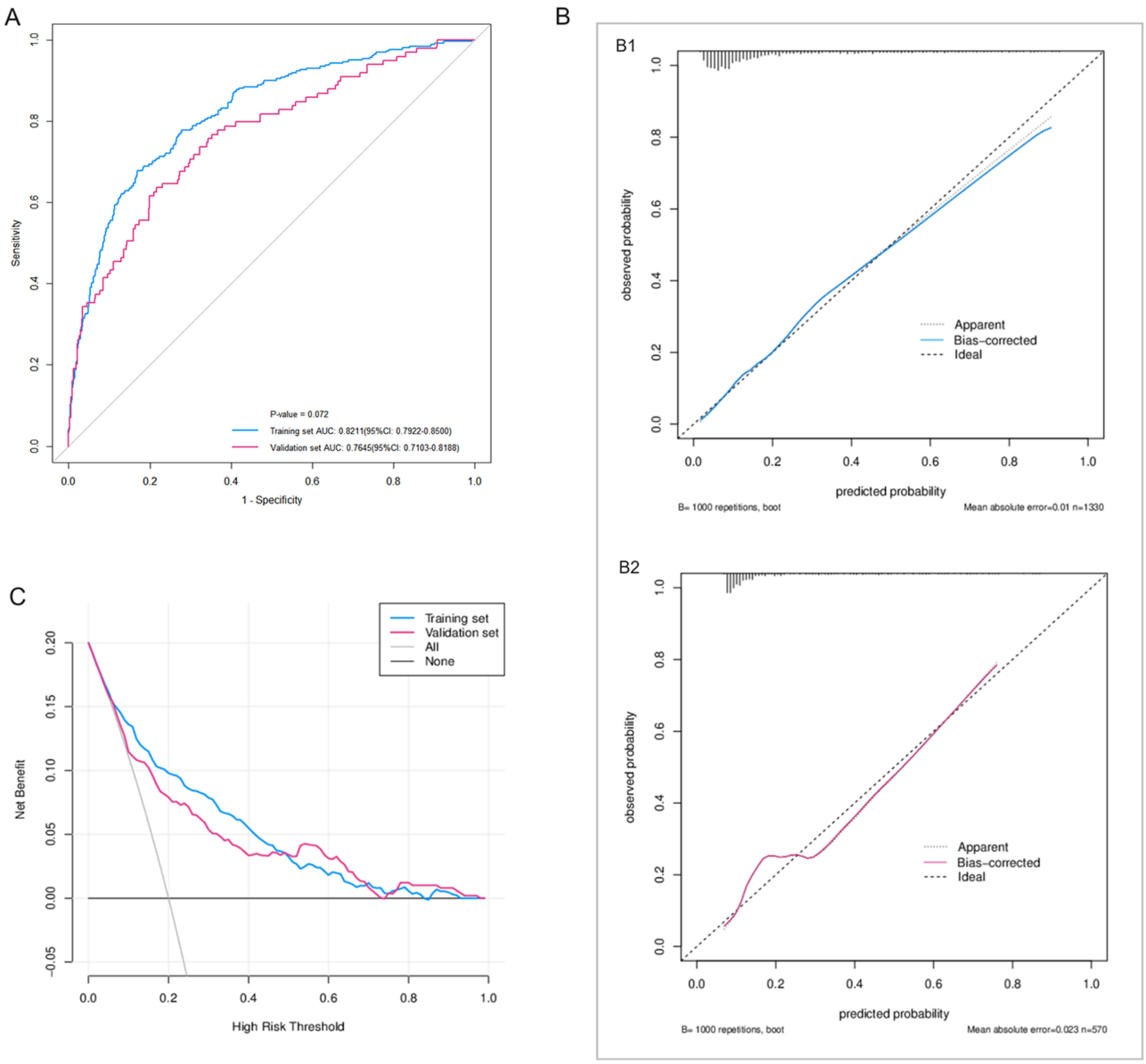

Figure 4 (**A**) ROC curve of the nomogram. The AUC being greater than 0.7 indicates good model performance. A P-value of 0.072 (>0.05) suggests that the model's performance is consistent between the training and validation sets. (**B**) Calibration curves of the nomogram. B1 Calibration curve for the training set; B2 Calibration curves for the validation set. The Hosmer-Lemeshow test results showed that P > 0.05 for both the training and validation sets. (**C**) Decision curve analysis for the nomogram. The blue and pink curves are both higher than the gray and black lines, indicating that the model's predictions have greater clinical value compared to "screening everyone" or "screening no one". At different thresholds, the model performs consistently, and the net benefit curves for the validation and training sets show similar trends, suggesting that the model has a wide range of applicability and high clinical utility.

dysfunctional families, or a lack of educational resources, are more likely to develop hostile emotions.[65] The psychological stress brought about by these external environments may lead them to engage in negative behaviors, such as verbal conflicts or attacking others, and even turn to self-directed aggression, manifesting as self-harm or suicidal ideation.[55] Studies have shown that the emergence of hostility in adolescents is often related to impaired emotional regulation or early adverse experiences.[66,67] Therefore, helping adolescents effectively express and manage negative emotions and enhancing psychological resilience may be key measures for reducing hostility levels. Parents and schools should improve communication and guidance and provide adolescents with a more supportive environment for psychological growth, thereby mitigating the negative impact of hostile emotions on mental health.

The final prediction graph revealed that depression played a crucial predictive role in the overall model. Social, family, school, residential environment, and psychological and genetic factors all contribute to depression;[68] however, rural adolescents may be worse off due to parental neglect or lack of psychotherapeutic resources, among other reasons. Depression can maintain adolescents in a state of prolonged loss and pain, making them feel that their life is meaningless. With the constant stimulation of such extreme thoughts, suicidal ideation in adolescents follows.[69] To reduce the incidence of this situation, attention should be paid to the mental health of rural adolescents in all aspects. Notably, previous studies have shown a significant association between adolescent depression and mobile phone addiction, poor sleep quality, and increased aggression.[70,71] However, in our study, these were also risk factors for suicidal ideation in adolescents.

Undoubtedly, mobile phone addiction and sleep disorders increase the risk of suicidal ideation in teenagers.[72] Escape, an important negative manifestation of mobile phone addiction, was associated with suicidal ideation in this study. Escape implies the social withdrawal of teenagers, which in the long run may eventually lead to a lack of communication in social situations in real life, resulting in loneliness.[73] On the one hand, this can aggravate mobile phone dependence among adolescents, a phenomenon that is more pronounced among rural adolescents,[74] and on the other hand, this loneliness in daily life increases the risk of depression and suicide.[75] Additionally, sleep problems should not be neglected. Two subdimensions, subjective sleep quality and daytime dysfunction, independently predicted the development of suicidal ideation. Teenagers can experience various negative emotions due to poor sleep quality,[72] which can lead to suicidal ideation. Moreover, when teens have daytime dysfunction, such as academic inefficiency, decreased energy, and fatigue,[76] this can add to the psychological burden on teens and worsen sleep deprivation, which can eventually lead to the development of paranoid thoughts and suicidal ideation.[77] Mobile phone addiction and sleep problems in teenagers have many adverse consequences. Helping teenagers control problematic mobile phone use and developing scientific and healthy sleep habits can promote positive growth.

Implication

To minimize the occurrence of suicidal ideation among adolescents, it is crucial to address their overall healthy development from multiple perspectives. For example, rural adolescents should be provided with a safe and stable family and school environment, while being encouraged to develop healthy mobile phone usage habits and maintain regular sleep routines. The COVID-19 pandemic has exacerbated mental health issues among adolescents, especially those in rural areas and marginalized groups, who face higher risks of suicidal ideation due to resource shortages and social isolation. Additionally, negative public opinion and social discrimination against China and other countries during the pandemic may have intensified psychological stress among adolescents, further contributing to suicidal ideation. Therefore, intervention measures should consider regional disparities and social contexts to provide more targeted psychological support. In addition to preventive measures, attention should be paid to providing timely and personalized interventions for adolescents who have already exhibited suicidal ideation, such as psychological counseling and support services, family support, and school-based mental health education, to effectively reduce the risk of suicide. Through multi-level intervention measures, it is possible to significantly reduce suicidal ideation among adolescents and its severe consequences it may bring.

Limitations

This study had several limitations. First, this was a cross-sectional study, and it was difficult to draw causal inferences owing to design flaws inherent in the method. Second, this study involved only Chinese people, and the sample representation was somewhat limited; however, the situation in other countries was different, and the results may differ. Third, we used data from rural adolescents to develop the model, which might not be applicable to urban adolescents. Fourth, all symptoms in the present study were assessed using a self-reported assessment questionnaire, which is somewhat subjective, and subsequent studies should use more objective diagnostic results. Fifth, our results may have been influenced by the frequency and duration of suicidal ideation, the season in which the data were collected, and the COVID-19 pandemic at that time. Sixth, the LASSO regression method may oversimplify the model, potentially ignoring the important variables involved in interactions or nonlinear relationships. Additionally, although the selection of the

regularization parameter λ is supported by cross-validation, the results may vary across different datasets or parameter adjustments. Finally, we only analyzed some risk factors for adolescent suicidal ideation, and further multifactorial studies should be conducted in the future to explore the risk factors for adolescent suicidal ideation at a deeper level to reduce suicidal ideation and suicide risk.

Conclusion

This study developed a LASSO-based nomogram model to predict suicidal ideation among rural adolescents in China, demonstrating strong predictive performance. The findings indicate that key factors, such as poor subjective sleep quality, emotional neglect, depression, and hostility, significantly increase the risk of suicidal ideation. The model is simple in design and easy to use, making it particularly suitable for applications in rural areas with limited healthcare resources. By integrating this tool into school and community settings, educators and healthcare providers can collect individual characteristic values based on the model, and assess the risk probability of suicidal ideation without relying on complex diagnostic tools. This approach enhances early identification and prevention, reduces the incidence of suicidal ideation among adolescents, and mitigates the impact of mental health issues in resource-limited areas. In the future, the applicability of the model can be validated in different populations and the integration of other predictive algorithms can be explored to further enhance the model's performance and generalizability.

Data Sharing Statement

As the data involve adolescent mental health information, we are currently unable to share the raw data to ensure ethical and privacy protection.

Ethics Approval

The Ethics Committee of Xuzhou Medical University and its affiliated hospitals approved this study (XYFY2020-KL219-01), which was conducted in accordance with the Declaration of Helsinki.

Informed Consent

All participants and their guardians provided written informed consent before the implementation of the survey.

Acknowledgments

The authors would like to thank all those who participated in this survey.

Author Contributions

Wei Wang and Caiyi Zhang contributed equally as co-corresponding authors. All the authors contributed substantially to this work. Wei Wang conceived the study. Yunjiao Luo and Yuhao Wang contributed to data curation and drafted the original manuscript. Yingxue Wang, Yihan Wang, Na Yan, Blen Dereje Shiferaw, Louisa Esi Mackay, and ZiYang Zhang supervised the study and validated the results. Wei Wang and Caiyi Zhang participated in the manuscript's review and editing. All authors were involved in study design, data acquisition, analysis, and interpretation. They all participated in drafting, revising, and critically reviewing the article. All authors approved the final version to be published, agreed on submission to the journal, and are accountable for all aspects of the work.

Disclosure

The author(s) report no conflicts of interest in this work.

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