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Research article

Predicting non-suicidal self-injury among Chinese adolescents: The application of ten algorithms of machine learning

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ABSTRACT

Background and aims: High non-suicidal self-injury (NSSI) prevalence among adolescents is a global health issue. However, current prediction models for adolescent NSSI rely on a limited set of algorithms, resulting in biased predictions. Therefore, the aim of this study is to develop multiple machine learning models to enhance prediction accuracy and mitigate biases among Chinese adolescents.

Methods: A total of 4487 junior and senior high school students in China were recruited. Multiple algorithms were included, such as logistic regression, decision tree, support vector machine, Naive Bayes, multi-layer perceptron, K-nearest neighbors, and ensemble learning algorithm like random forest, bagging, AdaBoost, and stacking to build predictive models. Data processing techniques, including standardization and the synthetic minority oversampling technique, were employed to optimize the predictive model. The model was trained on 70 % of the data, reserving 30 % for testing.

Results: The ten prediction models achieved a good performance, with area under the receiver operating characteristic curve (AUC) scores above 0.700 in the test set. The stacking and random forest models achieved AUC scores of 0.904 and 0.898, respectively. The prediction performance of the Naive Bayes model was relatively poor. The top five important variables were resilience, bully, suicidal ideation, internet addiction, and depression.

Conclusions: The ensemble machine learning algorithm showed promising results predicting NSSI among adolescents. Such algorithms should be recommended for future NSSI research to enhance predictive accuracy. Identification of important features in NSSI prediction can help develop screening protocols and lay a foundation for clinical diagnosis and intervention in adolescent populations.

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Ethical approval

This study was approved by the Ethics Committee of University of Guizhou Normal University.

Informed consent

Informed consent was obtained from all participants in this study.

1. Introduction

Non-suicidal self-injury (NSSI) is defined as the direct and deliberate destruction of one's body tissue without suicidal intent [1]. NSSI is classified as a "condition requiring further study", which is recognized as an independent disorder in the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) [2]. NSSI has been identified as a serious public health concern worldwide and is particularly alarming among adolescents [3]. NSSI is widespread in adolescence, which is a critically vulnerable period for the onset and development of mental health problems and risky behaviors [4]. Specifically, biological models may explain why adolescence is a critical period for the emergence of NSSI [5].

Early adolescence is a significant period for brain development and neuroplasticity constitutes a possible risk and vulnerability for the onset of mental health. Concurrent changes in brain development might lead to a developmental imbalance in emotional control that resolves with the maturation of the prefrontal cortex [6,7]. The prevalence of NSSI among adolescents has been documented to range between 11.5 % and 47.1 %, with evidence suggesting a progressive increase in recent years [8–10].

1.1. Adverse effects of NSSI

The prevalence of NSSI serves not only as an indicator of immediate distress but also as a harbinger of potential long-term mental health challenges. In addition to the physical injuries it inflicts, NSSI is commonly associated with a spectrum of psychiatric disorders, including cognitive dysfunction, challenges in interpersonal relationships, and engagement in violent behaviors [11]. Prior research suggests that adolescents who engage in NSSI often enter a maladaptive coping cycle in which emotions, cognition, and self-injury behavior mutually reinforce one another [12]. Furthermore, a systematic review has highlighted the underlying mechanisms of NSSI in the context of major depressive disorder (MDD), indicating that patients with MDD and NSSI may present with specific psychosocial factors, neurobiological alterations, and hypothalamic-pituitary-adrenal (HPA) axis dysfunctions [13]. This disorder significantly impacts adolescents' lifestyles, with the high comorbidity of NSSI with other psychiatric disorders complicating the progression towards suicide. Moreover, it's estimated that around 40 % of adolescents who engage in NSSI are at risk of developing suicidal tendencies, similarly, about 60 % of adolescents with suicidal behaviors also engage in NSSI [14]. Therefore, early identification and intervention of NSSI in adolescents has crucial and positive clinical and social implications.

1.2. Factors of NSSI

At present, predicting NSSI is mainly based on regression analysis, and common predictors are as follows:

The influencing factors of NSSI predominantly encompass individual, societal, and familial dimensions. Individual factors primarily involve neurobiological elements, as well as psychological factors such as suicidal ideation, depression and emotion regulation [15–19]. According to the investigation of 9638 college students in Anhui province by Zhao et al., depression is positively correlated with NSSI, and college students with NSSI have a higher level of depression [20]. Recently, numerous scholars have started examining the risk and protective factors of NSSI from the psychological perspective, for example, Zhang et al. pointed out that psychological resilience is a protective factor for the occurrence of NSSI [19]. Family-related factors, such as the educational level of those primarily responsible for the care of teenagers and family structure—especially in single-parent and joint families, have been linked to a heightened risk of NSSI [16]. Social environmental factors mainly include experiences of school bullying and internet addiction [21–23], Hankin and Abela also showed that bullying is a risk factor for the development of repeat NSSI [24].

However, current research on predicting NSSI faces limitations in the number of variables and categories that can be analyzed concurrently. Traditional regression techniques not only significantly limit the number of predictors and their interactions that can be examined simultaneously but also assume linearity in relationships that may, in fact, exhibit more intricate patterns [25]. Machine learning (ML) techniques can make up for the shortcomings of traditional regression methods to address these limitations of conventional prediction models [26].

1.3. Machine learning in predicting NSSI

ML models have brought groundbreaking advancements to NSSI research. Researchers have found that ML is capable of modeling complex variable associations and producing stronger predictive performance [27]. Research has shown that ML models are effectively applied in NSSI prediction. For instance, Zhong et al. constructed eXtreme Gradient Boosting (XGBoost) model and multivariate logistic regression model to predict NSSI, with area under the receiver operating characteristic curve (AUC) scores reached 0.830 and 0.849 respectively, and depression was found to be an important predictor of NSSI [28]. In addition, logistic regression (LR) model and random forest (RF) model have been successfully applied with a satisfactory accuracy in predicting NSSI among adolescents [29]. Fox et al. demonstrated that multiple LR models (AUCs 0.70–0.72) outperformed other models and ML model performances remained strong even after the most important factor across algorithms was removed [27].

Although numerous studies have applied ML to predict NSSI, the diversity of algorithms used has not been exhaustively explored, particularly in the context of adolescent populations. The reliance on specific algorithms for identifying predictive factors may lead to inaccuracies in predictions. A comprehensive comparison of various ML models is needed to ensure accurate prediction in predicting NSSI. Therefore, this study aims to apply multiple ML models for predicting NSSI behavior and to compare the performance of those algorithms specifically among adolescents.

2. Methods

2.1. Participants and procedures

In this study, a simple random sampling approach was employed to recruit 4506 Chinese junior and senior high school students to fill out paper questionnaires. The survey was conducted with the informed consent of students and their parents. This research protocol was reviewed and approved by the ethics committee of the School of Psychology of Guizhou Normal University, China. After excluding 19 individuals (0.4 %) due to incomplete data, the dataset comprised 4487 valid responses from junior and senior high school students. The average age of the participants in the final dataset was 16 years old, with a standard deviation of 1.75 years, and ages that ranged from a minimum of 11 to a maximum of 22 years.

2.2. Measures

2.2.1. Demographic information

In this research, demographic factors were assessed such as age, grade, only child or not, gender, place and time of residence, parents' occupation and parental level of education, monthly household income, family type, whether parents worked away from home for more than 6 months, desire for a sibling, family relationship and bullying situation.

2.2.2. Non-suicidal self-injury behavior questionnaire

The Non-Suicidal Self-Injury Behavior Questionnaire (NSSIQ), was developed by Wan et al. [30]. The questionnaire investigated whether respondents had engaged in self-harm behaviors excluding suicide and also inquired about the frequency of such behaviors over the past year. Participants were asked about their experience with eight self-harming behaviors, including intentionally hitting oneself, pulling one's hair, banging one's head or hitting other objects with a fist, pinching or scratching oneself, biting oneself, cutting or stabbing oneself, intentionally overdosing on drugs, drinking alcohol, smoking, swallowing foreign objects, and other intentional acts of self-injury.

2.2.3. Generalized anxiety Disorder-7

The Generalized Anxiety Disorder-7 (GAD-7), developed by Spitzer et al., is used to assess subjects' anxiety and severity during the last 2 weeks [31]. The scale, comprising seven items, employs a 4-point Likert scale ranging from 0 ("not at all") to 3 ("almost every day"). An increased score is associated with a higher level of anxiety severity. The scoring criteria categorize anxiety levels as follows: 0–4 points signify "no anxiety", 5–9 points denote "mild anxiety", 10–13 points suggest "moderate anxiety", 14–18 points indicate "moderate to severe anxiety", and 19–21 points are indicative of "severe anxiety" [31]. The scale's internal consistency in this investigation was substantiated by a Cronbach's alpha value of 0.912, signifying a high level of reliability.

2.2.4. Patient health Questionnaire-9

The Patient Health Questionnaire-9 (PHQ-9), developed by Kroenke et al., is used to assess subjects' depression during the last 2 weeks [32]. The scale, comprising nine items, employs a 4-point Likert scale ranging from 0 ("not at all") to 3 ("almost every day"). Higher scores on the scale correspond to greater depression severity, where scores under 5 indicate "no depression", 5–9 suggest "mild depression", 10–14 represent "moderate depression", 15–19 denote "moderate to severe depression", and scores of 20 or above indicate "severe depression" [32]. The scale demonstrated a Cronbach's alpha of 0.872.

2.2.5. The 14-item resilience scale

The 14-item Resilience Scale (RS-14) was used to assess the degree of resilience, and was a short version of the original resilience scale. The RS-14 is a 14-item instrument with a single factor structure, with a 7-point Likert scale ranging from 1("strongly disagree") to 7 ("strongly agree") [33]. Examples of questionnaire items include statements such as "I feel that I can handle many things at a time" and "I keep interested in things". The Chinese translation of the RS-14 was developed with a backtranslation procedure to ensure accuracy [33]. The Cronbach's alpha coefficient for this scale was 0.925, indicating high reliability.

2.2.6. Emotional Regulation Questionnaire

Emotional Regulation Questionnaire (ERQ) was translated into Chinese by Chen, Zhang et al., that consisted of 10 items, which were divided into two factors: cognitive reappraisal and expression inhibition, which uses a 7-point Likert scale ranging from 1 ("strongly disagree") to 7 ("strongly agree"), with higher scores reflecting a stronger tendency towards the respective strategy [34]. The Cronbach's alpha for the scale was 0.887, while the alpha coefficients for the subscales were 0.911 and 0.851, respectively.

2.2.7. A short version of Young's Internet Addiction Test

Pawlikowski et al. developed a short version of Young's Internet Addiction Test (s-IAT), that consists of 12 items and a two-factor structure (loss of control/time management and craving/social problems) [35]. Options are provided using a 5-point Likert scale ranging from 1 ("never") to 5 ("very often"). Pawlikowski et al. proposed cut-off values to differentiate between levels of internet use, categorizing scores as follows: less than 31 for normal use, 31–37 for moderate use, and above 37 for problematic use [35]. In this study, the Cronbach's alpha coefficient of the scale was 0.825.

2.2.8. The University of California at Los Angeles Post-traumatic Stress Disorder Reaction Index

The University of California at Los Angeles Post-traumatic Stress Disorder Reaction Index (UCLA PTSD Reaction Index, PTSD-RI) is a widely used tool to detect PTSD in children and adolescents, and this study used the trauma history section, which corresponds to Criterion A (Severe Traumatic Experience) in the PTSD diagnostic criteria [36]. There are 15 questions in this section. The initial 14 questions inquire whether participants have encountered such events. The 15th item requires participants to identify which of the preceding 14 items poses the greatest personal distress and to indicate their age at the time of the event's occurrence. The survey encompasses a range of 14 distinct traumatic experiences, spanning from natural disasters and catastrophic accidents to instances of warfare, domestic violence and sexual assault.

2.2.9. The Youth Self-Report

The Youth Self-Report (YSR), designed by Achenbach, employs a standardized format to assess adolescents' self-reported competencies and behavioral concerns [37]. This instrument utilizes a 3-point Likert scale, scored from 0 ("none") to 2 ("marked"), to quantify the presence of specific feelings or behaviors [37]. This study only used problems, including thinking problems, problematic behaviors, aggressive behaviors, attention deficits, and disciplinary violations. The scale exhibited a high internal consistency with a Cronbach's alpha of 0.922, and the respective alpha coefficients for its subscales were 0.711, 0.825, 0.852, and 0.706.

2.2.10. Suicide probability scale

The Suicide Probability Scale (SPS), a standardized self-report instrument, was developed and subsequently revised by Cull and Gill. It employs a 4-point Likert scale, scored from 1 ("strongly disagree") to 4 ("strongly agree"), to assess the frequency of subjective feelings and behaviors related to suicidal ideation [38]. The higher the score, the greater the risk of suicide. 36-item self-report measure of SPS with four clinical subscales (Hopelessness, Negative Self-evaluation, Suicide Ideation, and Hostility), and only the dimension of Suicide Ideation was used in this study. The Cronbach's alpha coefficient for this scale was 0.875.

2.3. Statistical analysis

Data analysis used SPSS version 25.0 and Python version 3.0. Continuous numerical variables were presented as the mean ± standard deviation. Given the non-normal distribution of the continuous data, as evidenced by the normality test results depicted in Table 1, non-parametric tests were employed for group comparisons. Categorical variables were represented by frequency counts and compared between groups using the χ^2 test. All tests were two-sided, and results were considered statistically significant for p values $<$ 0.05.

2.3.1. Data preprocessing

An individual was identified as engaging in NSSI if they had engaged in the behavior more than once. Categorical variables with missing values were replaced by the mode of the frequency count and the missing values of continuous variables were replaced by the mean. In order to improve the model performance and reduce excessive prediction errors that can arise from significant differences in the values of various continuous variables, standardization was applied to process the data.

The smaller subset (NSSI) was oversampled by using synthetic minority oversampling technique (SMOTE) to address the imbalanced distribution of the NSSI/non-NSSI [39]. Moreover, the model was trained using 70 % of the data, with the remaining 30 % reserved for testing (Fig. 1). Dividing the data can facilitate the assessment of a model's performance on new datasets and mitigate the risk of overfitting.

2.3.2. Data analysis

The predictive model's performance was assessed through the computation of several metrics, such as accuracy, precision/positive predictive value (PPV), sensitivity/recall, specificity, negative predictive value (NPV), F1-score, and the area under the receiver operating characteristic (ROC) curve (AUC). The ROC curve was constructed, utilizing the false positive rate as the x-axis and the true positive rate as the y-axis. An AUC value of 0.5 indicates no discriminative ability, whereas an AUC greater than 0.70 is considered clinically useful [40]. Additionally, the F1-score effectively balances precision and sensitivity, striving to achieve the optimal value for both metrics.

We utilized multiple ML algorithms, including logistic regression (LR), decision tree (DT), support vector machine (SVM), Naive Bayesian (NB), multi-layer perceptron (MLP), K-nearest neighbors (KNN), and ensemble learning algorithms like random forest (RF), bagging, AdaBoost, and stacking. to build predictive models. The aim was to identify the most optimal model for the test dataset and subsequently rank the importance of predictive features of NSSI.

Table 1
Descriptive statistics of categorical variables, with p values from the χ^2 test.

Total ($N = 4487$)	Non-NSSI	NSSI	p-value
gender			0.612
male	1883	655	
female	1459	490	
only child or not			0.955
yes	200	68	
no	3142	1077	
grade			<0.001
1	161	115	
2	117	58	
3	498	185	
4	749	269	
5	807	252	
6	1010	266	
place of residence			<0.001
urban	676	283	
rural	2666	862	
wanbro			<0.001
yes	650	284	
no	2692	861	
faedu			0.286
primary school	1069	358	
junior high school;	1759	586	
senior high school	394	148	
university	120	53	
moedu			0.288
primary school	2011	653	
junior high school;	1067	390	
senior high school	208	79	
university	56	23	
fajob			<0.001
administration	115	53	
enterprise	515	226	
individual business	239	102	
agriculture	548	174	
unemployed	124	35	
others	1801	555	
mojob			<0.001
administration	66	23	
enterprise	549	222	
individual business	215	106	
agriculture	579	186	
unemployed	144	66	
others	1789	542	
income			0.085
<3000 yuan	714	227	
3000–6000 yuan	1722	558	
6000–9000 yuan	606	236	
9000–12,000 yuan	205	84	
>12,000 yuan	95	40	
family type			<0.05
core family	2983	1002	
divorced, living with father	138	43	
divorced, living with mother	87	31	
reconstituted family	88	52	
death of mother	8	5	
death of father	38	12	
pwo6m			0.710
parents work outside	944	335	
father works outside	371	139	
mother works outside	182	66	
parents don't work outside	1845	605	
bully			<0.001
yes	1297	654	
no	2045	491	
parloc			<0.05
both parents are	2851	938	
only the father is	110	61	
only the mother is	104	46	

(*continued on next page*)

Table 1 (*continued*)

Total ($N = 4487$)	Non-NSSI	NSSI	*p*-value
neither parent	277	100	
time of residence			0.407
<1 year	114	38	
1–3 years	163	67	
4–7 years	181	70	
>7years	2120	694	
unclear	764	276	
PTSD-RI			<0.001
no	808	145	
yes	2534	1000	

Note: The grade levels are categorized as "1–3" for junior high school students and "4–6" for senior high school students.

Table 2
Descriptive statistics of continuous numerical variables, with *p* values from nonparametric test.

NSSI		Mean	Standard deviation	Normality test	Nonparametric test
				p-value	*p*-value
Non-NSSI group	age	16.00	1.752	<0.001	<0.001
	s-IAT	25.47	7.984	<0.001	<0.001
	thinkpro	2.03	2.268	<0.001	<0.001
	attende	3.84	3.289	<0.001	<0.001
	violation	1.69	2.109	<0.001	<0.001
	aggrebe	4.55	4.461	<0.001	<0.001
	PHQ-9	5.39	4.518	<0.001	<0.001
	GAD-7	3.04	3.857	<0.001	<0.001
	suicidepossi	10.95	3.878	<0.001	<0.001
	ERQ-1	27.61	8.451	<0.001	<0.001
	ERQ-2	16.67	6.079	<0.001	<0.001
	resilience	61.54	16.388	<0.001	<0.001
NSSI group	age	15.7	1.839	<0.001	<0.001
	s-IAT	27.52	8.340	<0.001	<0.001
	thinkpro	3.74	2.871	<0.001	<0.001
	attende	5.73	3.889	<0.001	<0.001
	violation	2.77	2.579	<0.001	<0.001
	aggrebe	7.66	5.566	<0.001	<0.001
	PHQ-9	8.32	5.272	<0.001	<0.001
	GAD-7	5.67	4.777	<0.001	<0.001
	suicidepossi	14.1	5.475	<0.001	<0.001
	ERQ-1	26.73	8.087	<0.001	<0.001
	ERQ-2	18.18	5.957	<0.001	<0.001
	resilience	58.7	15.819	<0.001	<0.001

Note: **s-IAT** means internet addiction; **thinkpro** means thinking problems; **attende** means attention deficit; **violation** means disciplinary violations; **aggrebe** means aggressive behaviour; **PHQ-9** means depression; **GAD-7** means anxiety; **suicidepossi** means the suicidal ideation; **ERQ-1** means disciplinary violations; **ERQ-2** means expression inhibition.

3. Results

3.1. Descriptive analysis

In the final analysis, a total of 4487 participants were included, with 1145 (25.5 %) reported an act of NSSI and 3342 (74.5 %) reported no such instances within the preceding 12 months. Among the 1145 participants who reported NSSI, 655 (57.2 %) were male and 490 (42.8 %) were female (Table 1). A heat map (Fig. 2) was used to illustrate the correlations between variables.

The χ^2 tests conducted on categorical variables revealed significant differences in grade ($p < 0.001$), place of residence ($p < 0.001$), desire for a sibling ($p < 0.001$), father's occupation ($p < 0.001$), mother's occupation ($p < 0.001$), family type ($p < 0.05$), bully ($p < 0.001$), whether the parents are local or not ($p < 0.05$) and whether has experienced a traumatic event or not ($p < 0.001$) (Table 1). The distribution of continuous variables significantly differs between the NSSI and non-NSSI groups (Table 2).

3.2. Evaluation the performance of multiple prediction models

Multiple prediction models have AUCs above 0.700, indicating a good model fit. Details are presented in Table 3. In terms of AUC value, the classification order of the models is as follows: Stacking (AUC = 0.904) > AdaBoost (AUC = 0.903) > RF (AUC = 0.898) > Bagging (AUC = 0.891) > KNN (AUC = 0.854) > SVM (AUC = 0.849) > LR (AUC = 0.816) > MLP (AUC = 0.811) > NB (AUC = 0.775) > DT (AUC = 0.704). The ROC curves of the top four models, ranked by AUC values, are presented in Fig. 3. The F1-scores, which

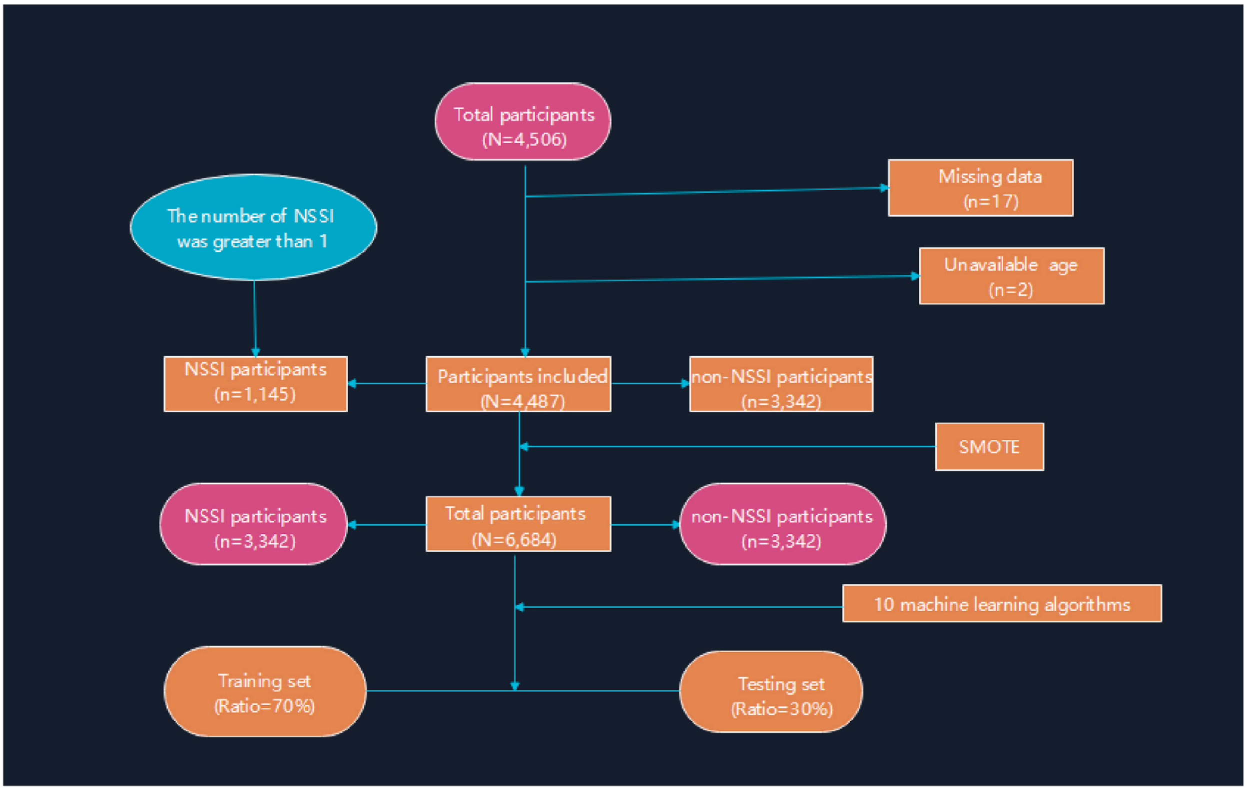

Fig. 1. Flow chart of the study.

effectively balances precision and sensitivity, were high, indicating good classification performance. This score aims to achieve the optimal value for both metrics (Table 3).

In terms of PPV, RF and Stacking tied for the highest PPV at 82 %, followed by AdaBoost and Bagging at 80 %. RF (PPV = 82 %) = Stacking (PPV = 82 %) > AdaBoost (PPV = 80 %) = Bagging (PPV = 80 %), the remaining models are ordered as: SVM (PPV = 78 %), LR (PPV = 75 %), MLP (PPV = 74 %) = NB (PPV = 74 %), KNN (PPV = 73 %), DT (PPV = 71 %). Furthermore, NPV spans from 67 % to 83 %, sensitivity extends from 64 % to 87 %, and specificity varies between 67 % and 81 %. Additionally, all accuracy values in this study are 70 % or higher.

We assessed the importance of 28 predictive factors using the RF model. The feature importance plot (Fig. 4) shows that the top five important variables are "resilience" (importance = 0.089), "bully" (importance = 0.084), "suicidal ideation" (importance = 0.079), "internet addiction" (importance = 0.067), "depression" (importance = 0.066).

4. Discussion

This study utilized multiple ML models to predict NSSI among Chinese adolescents. Feature importance was ascertained through permutation importance, a method that quantifies the rise in prediction error following the random shuffling of a feature's values. This approach was applied to the test dataset, thereby pinpointing the features that enhance the model's capacity to generalize. Models such as DT, RF, and AdaBoost can estimate feature importance.

In this study, given the superior performance of the RF model in identifying adolescent NSSI, the RF algorithm, which employs bootstrap sampling to construct an ensemble of decision trees [41], was utilized for ranking feature importance. The feature importance plot of the RF model provides novel insights into the predictors of NSSI. Additionally, multiple evaluation metrics were used to thoroughly assess the model's predictive performance for NSSI behavior. Notably, the PPV obtained, ranging from 71 % to 82 %, indicate a favorable outcome, this result is significantly higher than the 14 % value reported by Marti-Puig et al. [42].

4.1. Multiple model comparison

In this study, ensemble learning algorithms such as RF, Bagging, AdaBoost, and Stacking predicted NSSI relatively well and more ML ensemble learning algorithms should be applied to the NSSI field in the future. Ensemble learning algorithms are not a single ML algorithm but combine multiple ML algorithms to complete the learning task. It can be said that it gathers the strengths of various schools and integrates the thoughts of many scholars, potentially achieving high accuracy rates in classification algorithms for ML, as

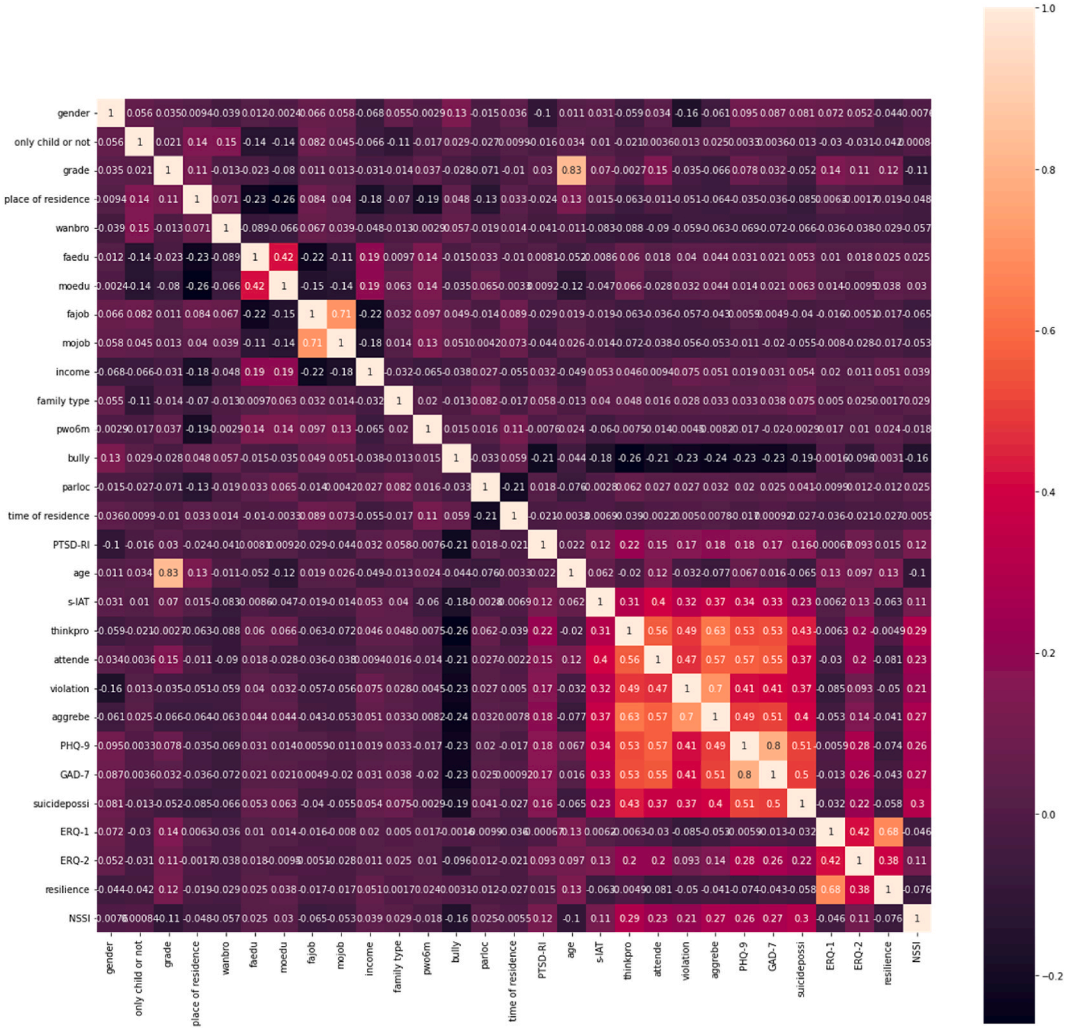

Fig. 2. Heat map displaying the relationship between machine learning features.

Note: **wanbro** means desire for a sibling; **faedu** means father's level of education; **moedu** means mother's level of education; **fajob** stands for the father's occupation; **mojob** represents the mother's occupation; **income** represents the monthly household income; **pwo6m** represents whether parents worked away from home for more than 6 months; **parloc** means whether the parents are local or not; **PTSD-RI** refers to whether has experienced a traumatic event or not; **s-IAT** means internet addiction; **thinkpro** means thinking problems; **attende** means attention deficit; **violation** means disciplinary violations; **aggrebe** means aggressive behaviour; **PHQ-9** means depression; **GAD-7** means anxiety; **suicidepossi** means the suicidal ideation; **ERQ1** means disciplinary violations; **ERQ-2** means expression inhibition.

Table 3
Prediction scores of multiple machine learning algorithms.

ML	Precision (PPV) %	Sensitivity (Recall) %	Specificity%	Accuracy%	NPV%	F1-score	AUC
NB	74	64	77	70	67	0.69	0.775
DT	71	72	69	70	70	0.72	0.704
MLP	74	75	74	73	73	0.75	0.811
LR	75	72	74	73	72	0.73	0.816
KNN	73	87	67	77	83	0.80	0.854
SVM	78	77	77	77	76	0.77	0.849
RF	82	84	81	82	83	0.83	0.898
Bagging	80	82	79	80	80	0.81	0.891
AdaBoost	80	85	77	81	83	0.82	0.903
Stacking	82	84	80	82	83	0.83	0.904

Note: NB = Naive Bayesian; DT = decision tree; MLP = multi-layer perceptron; LR = logistic gegression; KNN = K-nearest neighbors; SVM = support vector machine; RF = random forest.

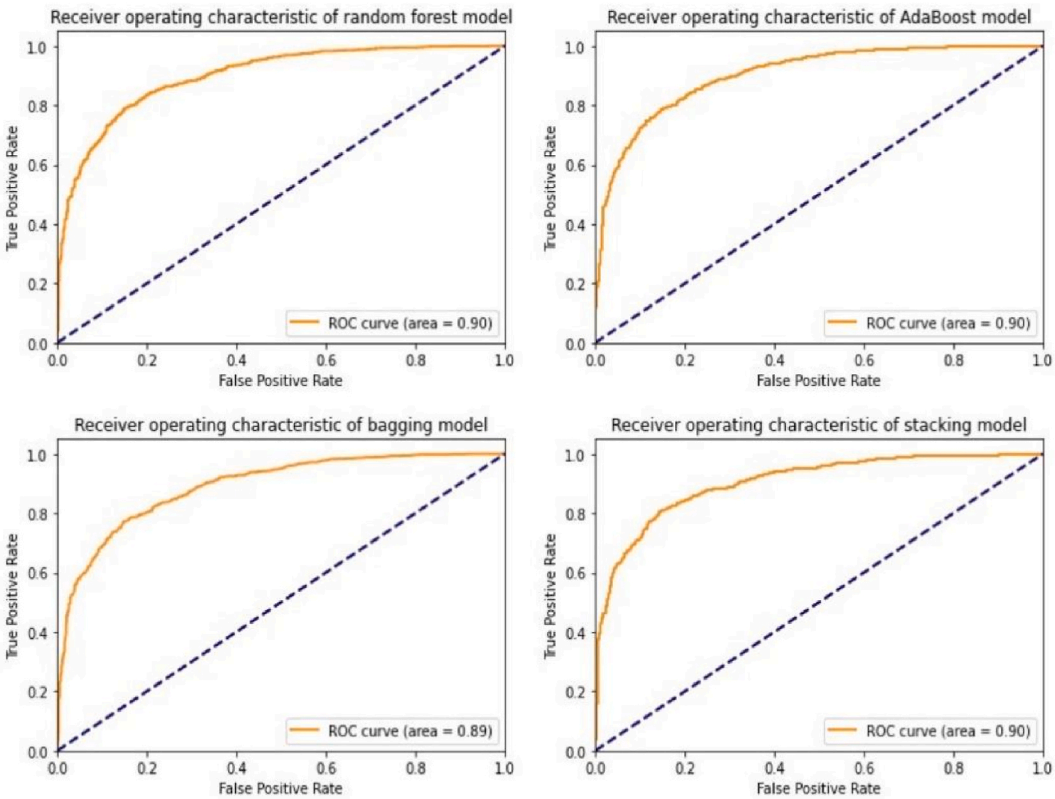

Fig. 3. ROC curve of random forest, AdaBoost, bagging and stacking model.
Note: The figure's purple diagonal dashed line serves as a reference, indicating the outcome of a classifier employing a random chance strategy for sample classification. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

the saying goes, "two heads are better than one". However, the disadvantage is that the training process of the model may be more complex and less efficient. This is also fully confirmed the "no free lunch theorem", indicating that no single algorithm is consistently superior to the others [43]. That is why this study applied multiple ML algorithms to predict NSSI among adolescents, compared with many previous studies that used a single algorithm [16,28,42].

The NB model showed relatively poor prediction accuracy, which may be due to the fact that the NB algorithm requires the independence of feature conditions, a criterion difficult to meet in most practical problems [44]. To mitigate the conditional independence assumption of the Naive Bayes algorithm and improve the accuracy and precision of NSSI behavior prediction for adolescents, future studies can consider algorithms like the Probabilistic Optimization Naive Bayes (PONB), which incorporates conditional probability weighting and prior probability compensation mechanisms.

4.2. Features importance

Consistent with many other studies, resilience is found to be a protective predictor of NSSI in this study [18,19,45,46]. Resilience can cultivate protective mechanisms that act as a safeguard against NSSI. High resilience in individuals facilitates calm and responsible responses to stress, concurrently mitigating the propensity for risk-taking behaviors, such as NSSI. Moreover, individual resilience can decrease the likelihood of NSSI after experiencing controllable negative life events [47]. Therefore, it becomes imperative for educators and parental figures to proactively fortify the psychological resilience of adolescents within their daily interactions thus reducing the incidence of NSSI.

School bullying, to be specific, who experienced, witnessed, or repeatedly subjected to bullying at school. In this study, emerged as one of the crucial predictors of NSSI among adolescents, further providing evidence for previous studies [22]. Victims of bullying may engage in NSSI behavior as a means to seek help, inflict self-punishment, or release stress. The meta-analysis conducted by Van Geel et al. showed that adolescents who had been bullied were 2.1 times more likely to exhibit NSSI behaviors than those who had not been bullied [48]. Furthermore, the younger the victim, the more NSSI behaviors they had, reflecting that bullying could be an independent risk factor for NSSI behaviors in adolescents. Therefore, it is imperative to strengthen the management of bullying. Since teenagers spend most of their time in school, schools should be vigilant in investigating bullying behavior. Teachers and parents should also be attentive to signs of emotional or behavioral issues in teenagers, such as emotional distress, difficulties in peer communication, or conduct problems, and intervene promptly when abnormalities are detected.

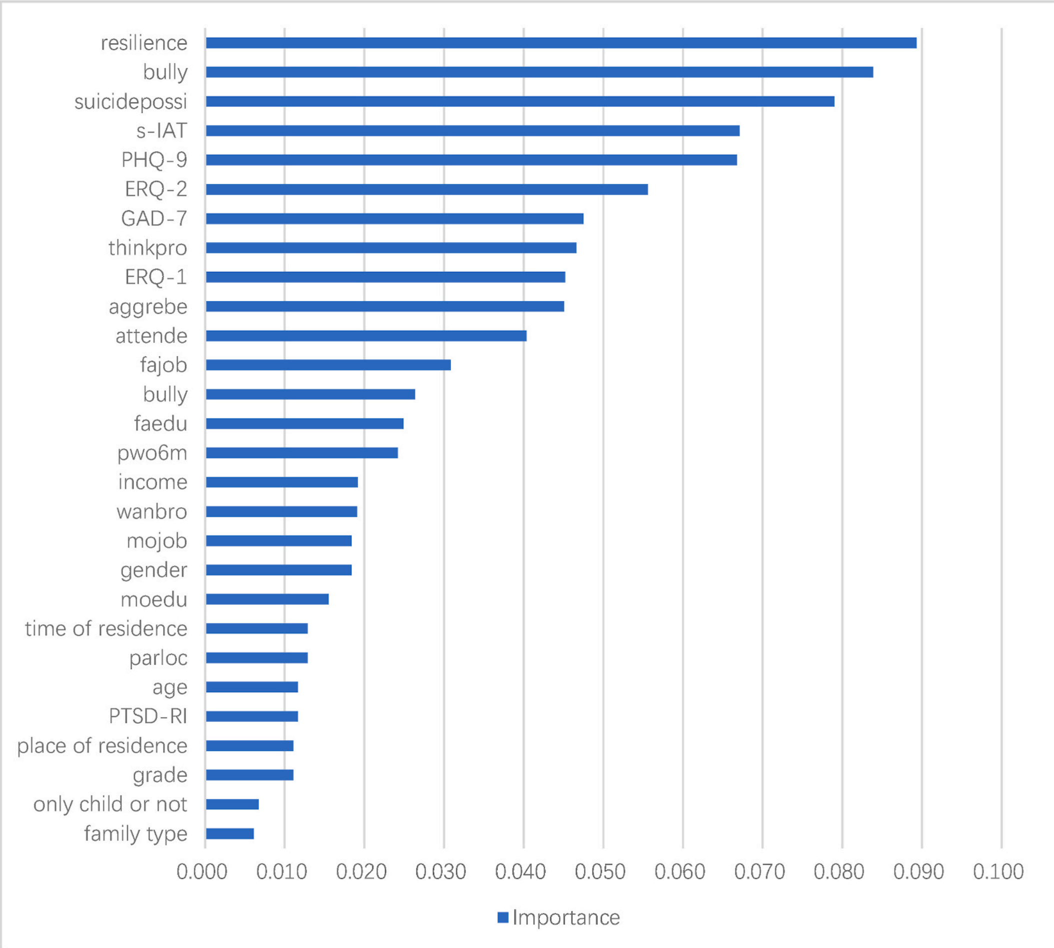

Fig. 4. Importance order of features in predicting NSSI.
Note: Feature importance plot illustrates the importance of features in predicting NSSI using the random forest model.

Internet addiction has been identified as a significant predictor of NSSI, a finding that corroborates the results of prior research [23]. Numerous factors contribute to the online behaviors of adolescents who engage in NSSI, with one potential reason being the heightened probability that those with internet addiction or who are heavily engaged in online activities encounter NSSI-related content. This is due to the extended periods they spend online [23]. For instance, existing literature has reported that youth can be exposed to various NSSI websites containing graphic content, which is considered a potential trigger for NSSI behaviors [49]. Consequently, evaluating the risk of NSSI among adolescents exhibiting addictive internet behaviors is crucial. The study's results also highlight the necessity for further research. Specifically, additional studies are required to ascertain the existence of a causal link and to explore potential gender disparities in the relationship between internet addiction and NSSI.

In this study, suicidal ideation and depression were both identified as important predictors of NSSI, consistent with findings from prior research. Previous studies have found that the presence of suicide ideation may increase an individual's risk of NSSI behavior, and NSSI behavior may be a precursor to suicide attempts [50]. Some individuals also report engaging in NSSI as a means to alleviate suicidal thoughts or urges, which could be an unintended consequence of NSSI's mood-regulating effects [51].

Depression is an important predictor of NSSI behavior in adolescents, and depressed adolescents exhibit more frequent and persistent NSSI behaviors than their non-depressed peers. The prevalence of NSSI in adolescents with higher scores on depression evaluations may be related to the dysfunction of the hypothalamic-pituitary-adrenal (HPA) axis. Additionally, it may be due to the fact that NSSI can promote the secretion of endogenous opioid peptides. These peptides can reduce the pain associated with NSSI and produce feelings of pleasure, potentially leading to recurrent NSSI in depressed adolescents [52,53].

4.3. Limitations and future directions

Our research illustrates the efficacy of ML as a robust analytical approach for examining behavioral issues that are driven by a variety of intricate factors. However, first, all the variables included are derived from survey questionnaires, which largely rely on subjective judgments. In the future, it is recommended to integrate these findings with objective indicators, including laboratory tests, imaging data, or genomic information.

Second, the unique attributes of this cross-sectional dataset render the external and longitudinal validation of the models in other datasets challenging. Consequently, future studies should undertake external and longitudinal validation efforts.

Finally, future research will consider incorporating more comprehensive data sources, such as smartphones and social media, to more accurately and holistically predict NSSI among adolescents. Although data-driven risk prediction is prone to high false positive rates for infrequent events like NSSI, ML remains a promising tool for complementing traditional assessment methods.

Ethics declarations

The study follows the ethical standards of the 2013 Declaration of Helsinki and was approved by the Committee of the School of Psychology of Guizhou Normal University, China (GZNUPSY.LL.N2211021) on November 11, 2022. Written informed consent was obtained from all the participants. The questionnaires were anonymized, and patients were free to opt out of participation in the study whenever they were uncomfortable.

Data availability statement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

CRediT authorship contribution statement

Wei Chen: Writing – review & editing, Validation, Funding acquisition, Conceptualization. **Yujing Gao:** Writing – original draft, Methodology, Data curation. **Shiyin Xiao:** Validation, Methodology.

Declaration of competing interest

The authors declare that they have no conflict of interest that could have appeared to influence the work reported in this paper.

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