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Psychological pain and sociodemographic factors classified suicide attempt and non-suicidal self-injury in adolescents

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ABSTRACT

This study aimed to utilize machine learning to explore the psychological similarities and differences between suicide attempt (SA) and non-suicidal self-injury (NSSI), with a particular focus on the role of psychological pain. A total of 2385 middle school students were recruited using cluster sampling. The random forest algorithm was used with 25 predictors to develop classification models of SA and NSSI, respectively, and to estimate the importance scores of each predictor. Based on these scores and related theories, shared risk factors (control feature set) and distinct risk factors (distinction feature set) were selected and tested to distinguish between NSSI and SA. The machine learning algorithm exhibited fair to good performance in classifying SA history [Area Under Curves (AUCs): 0.65–0.87] and poor performance in classifying NSSI history (AUC: 0.61–0.68). The distinction feature set comprised pain avoidance, family togetherness, and deviant peer affiliation, while the control feature set included pain arousal, painful feelings, and crisis events. The distinction feature set slightly but stably outperformed the control feature set in classifying SA from NSSI. The three-dimensional psychological pain model, especially pain avoidance, might play a dominant role in understanding the similarities and differences between SA and NSSI.

1. Introduction

Self-injurious behaviors are theoretically classified into two distinct categories: (a) non-suicidal self-injury (NSSI), involving intentional and direct harm to one's own body tissue without an aim for lethality, and (b) suicide attempt (SA), defined as the deliberate attempt to terminate one's life. Despite the intentional demarcation between NSSI and SA, clinical observations often reveal a noteworthy overlap. For example, 60.5 % of Chinese adolescents involved in SA also engaged in NSSI (Liu et al., 2018). The differentiation and prediction of individuals' self-injurious behaviors, specifically identifying those likely to engage in SA rather than solely in NSSI, remain crucial yet unresolved issues.

Although previous studies have explored the similarities and differences between the underlying mechanisms of NSSI and SA, little is known about how to determine which self-harming adolescents are most likely to engage in SA and at which point individuals' intentions change from non-lethal (i.e., NSSI) to lethal (i.e., suicide). Meta-analysis of the risk factors for NSSI and SA (Fox et al., 2015; Franklin et al., 2017) found that the predictive accuracy of self-injurious behaviors was only slightly above chance levels, suggesting that to derive accurate prediction it might be necessary to use novel risk factors and complex models. Likewise, recent studies found that simple models (univariate logistic regression) are insufficient to discriminate individuals engaged in SA from those solely with NSSI (Huang et al., 2020). To effectively distinguish SA from NSSI, it is necessary to employ complicated algorithms and consider novel risk factors.

Regarding novel risk factors, the three-dimensional psychological pain model for suicide (TDPPS) offers a potentially useful framework. Psychological pain, recognized as a complex and introspective experience of negative emotions (Shneidman, 1999), has been proven as a strong predictor for suicidality (Troister & Holden, 2010). To precisely evaluate the state of psychological pain, TDPPS divides psychological pain into cognitive (pain arousal), affective (painful feelings), and motivational (pain avoidance) components (Li et al., 2014). Specifically, pain arousal involves distress stemming from the memory of past traumatic experience; painful feelings encompass subjective feelings and somatic symptoms related to psychological pain; and pain avoidance is characterized by a strong motivation to escape unbearable psychological

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pain, coupled with the conviction that suicide is the sole means of relief. Research has demonstrated the significant role of pain avoidance in determining suicide risk in young people, both Chinese and Western (Campos et al., 2017, 2019; Li et al., 2017), outperforming a list of classical risk factors, including depression, hopelessness, and the acquired capability of suicide (Li et al., 2014; Sun et al., 2020).

TDPPS, particularly pain avoidance, might help to understand the similarities and distinctions between NSSI and SA. Longitudinal studies have found that NSSI serves as a significant and unidirectional warning sign for suicidal behavior among adolescents (Hamza et al., 2012). However, it is noteworthy that one prevalent function of NSSI is to alleviate suicidal thoughts or impulses (Czyz et al., 2021). This prompts the interesting question of whether NSSI protects against SA or acts as a risk factor. One hypothesis is that the attitude towards pain relief moderates this relationship. According to the experiential avoidance theory (Angelakis & Gooding, 2021), both NSSI and SA are avoidance and escape behaviors from the experience of unwanted heightened pain arousal and/or painful feelings. Therefore, if engaging in NSSI effectively alleviates acute psychological distress, the motivation to escape would decrease, and individuals would not feel compelled to commit suicide to achieve desired outcomes. Instead, if engaging in NSSI fails to decrease distress, individuals may perceive suicide as the only means to relieve pain (i.e., pain avoidance) and consequently engage in suicidal behavior (Hamza et al., 2012). As such, we hypothesized that pain arousal and painful feelings were closely related to both NSSI and SA, whereas pain avoidance serves as a distinguishing factor for individuals engaged in SA compared to those involved in NSSI only.

Recently, there has been somewhat of a paradigm shift towards machine learning (ML) in the investigation of self-injury behaviors, partially due to the inherent complexity of SA and NSSI (Fox et al., 2015; Franklin et al., 2017). Unlike traditional statistical methods, ML enables the simultaneous testing of numerous predictors and their complex relationships, determines the optimal prediction algorithm without requiring prior assumptions, and provides estimates of the relative importance of each predictor (Burke et al., 2019). Therefore, ML stands as an ideal statistical technique for addressing the complexities underlying SA and NSSI. Recent research lends support to the usefulness of Ml in aiding in the early detection of self-injurious behaviors, and identifying important risk factors (Burke et al., 2018; Fox et al., 2019; Gradus et al., 2020; Huang et al., 2020).

While ML has been increasingly employed for predicting suicide and NSSI, very little research has focused on using ML to differentiate suicide from NSSI. In a recent study employing ML algorithms (Wei et al., 2022), individual factors such as pain avoidance, pain arousal, and painful feelings were found to be more influential than environmental factors (e.g., school satisfaction) in distinguishing SA from non-suicidal adolescents. Conversely, environmental factors (peer delinquency, family togetherness, and family monitoring) outweighed individual factors in distinguishing NSSI. This study provides initial support for the utility of ML in understanding differences in psychological mechanisms between NSSI and SA. However, it does not directly identify the specific factors that can distinguish SA from NSSI.

This study aimed to employ ML to develop algorithms classifying Chinese adolescents engaged in SA from those solely involved in NSSI, and to explore the psychological similarities and differences between NSSI and SA, particularly the role of TDPPS. Given the limited application of ML in predicting SA and NSSI (Burke et al., 2019), especially in Chinese adolescents, we also sought to build algorithms to separate adolescents with a history of NSSI and SA, respectively, from those without self-harm behaviors.

This study involved a secondary analysis of a pre-existing survey on psychological crises among Chinese adolescents (Wei et al., 2022). Owing to the ability of ML to handle extensive variables, all relevant variables from this survey were included. Beyond TDPPS, these variables covered a range of factors broadly associated with NSSI and SA (Franklin et al., 2017), including crisis events (Kaess et al., 2020; Stewart et al., 2019), childhood trauma (Demirkol et al., 2020), family togetherness (Serafini et al., 2015) and peer problems (Peng et al., 2020; Wyman et al., 2019). Incorporating a comprehensive range of variables will facilitate a thorough exploration of factors that might distinguish between NSSI and SA.

Based on these variables, two algorithms were developed to classify adolescents with NSSI and SA, respectively. From these algorithms, shared factors (control feature set) and distinct factors (distinction feature set) were selected based on their importance in classification. Subsequently, algorithms distinguishing SA from NSSI were developed using these sets. Variables in the distinction set may represent the psychological mechanisms differentiating NSSI and SA if the distinction set outperforms the control set.

We hypothesized that: (i) the distinction set would achieve higher classification accuracy than the control feature set; (ii) pain avoidance would serve as a distinguishing factor between NSSI and SA, while pain arousal and painful feelings would be closely related to both NSSI and SA. For other included variables, we conduct exploratory analyses rather than formulating specific hypotheses. This study has the potential to enhance our understanding of the distinction and link between NSSI and SA, crucial for effective risk assessment and interventions.

2. Method

2.1. Participants and procedure

The present data came from an earlier survey on psychological crises in Chinese adolescents (Wei et al., 2022). The study was approved by the Institutional Review Board of the University (protocol number: IRB 20–044). A sample of 2385 adolescents was recruited from four schools in Tianjin using a convenience cluster sampling method. Informed consent, highlighting the anonymity of responses, the voluntary nature of participation, and the right to withdraw at any point, was obtained from both adolescents and schools. Additionally, passive informed consents were obtained from parents, allowing them to opt their child out of the study. Adolescents filled out paper-based questionnaires during school hours in a classroom setting. The enrollment period ran from July 2019 to September 2020.

2.2. Measures

To alleviate participant burden, abbreviated questionnaires with established reliability and validity were selected whenever feasible. This study involved a variety of factors broadly associated with NSSI and SA (Franklin et al., 2017), including both relatively stable, distal factors (e.g., childhood trauma) and variable, proximal factors (e.g., recent crisis events). The assessment also covered theoretically relevant constructs with suicide and NSSI, such as the TDPPS (Li et al., 2014), coping style (Liu et al., 2016), and peer support (Van Orden et al., 2010).

2.2.1. Demographic information

Demographic information was collected through self-reported measures, including age, gender, sexual orientation, parental educational level, parental marital status (divorced or not), family structure, place of growing up, being the only child or not, and boarding at school or not.

2.2.2. Self-injury

NSSI was assessed using a global question (“Have you ever intentionally hurt yourself without the intention of death?”), with common forms of NSSI provided as examples (e.g., hit, pinch, and bite). Responses were recorded on a 3-point Likert scale (1 = never; 2 = have once; 3 = have twice or more). For ease of comparison and interpretation, the responses were dichotomized as no or yes.

Suicide ideation was assessed through a global question (“Have you ever thought about or planned suicide?”). Participants indicated their responses on a 3-point Likert scale (1 = never; 2 = once had, with a mild desire to die/without a detailed plan; 3 = once had, with a moderate to strong desire to die/with a detailed plan).

SA was assessed using a single-item scale ("Have you ever attempted to kill yourself?"), with participants making a two-alternative forced choice (0 = no; 1 = yes). Additionally, the time of occurrence was assessed after participants reported experiencing NSSI, SA, or suicide ideation: within a month, within 6 months, within a year, and more than one year ago. The approach to measuring self-injury using a global question can be seen in previous studies (e.g., Barzilay et al., 2017).

2.2.3. Psychological pain

The three-dimensional psychological pain scale is a 17-item self-report instrument that measures the level of current and worst psychological pain and contains pain arousal, painful feelings, and pain avoidance subscales (Li et al., 2014). Each item was rated on a 5-point Likert-type scale ranging from 1 (not at all) to 5 (extremely), with higher scores indicating more severe psychological pain. The Cronbach's α for the current sample was 0.958.

2.2.4. Childhood trauma history

The physical abuse and sexual abuse subscales of the Personal Report of Childhood Abuse (PRCA) were used to measure participants' childhood trauma history (Zhu et al., 2006). Each item was rated both on the frequency and severity from 0 (never/caused no harm at all) to 5 (always/caused me great harm). If either the frequency or severity score is 0, the item's final score is set to 0; otherwise, the item score is calculated as the average of the frequency and severity scores. The Cronbach's α for the current sample was 0.720.

2.2.5. Crisis events

To measure crisis events, a Crisis Events Questionnaire for Adolescents (CEA) was developed. CEA is a 27-item scale with items on family conflict (5 items), academic pressure (5 items), conflict with teachers (3 items), sex-related events (4 items), peer conflict (5 items), and major crisis events (5 items). Participants indicated the occurrence of each event in the previous 12 months (0 = never happened, 1 = happened) and the degree of impacts (1 = not at all, 5 = a lot). The sum of the product of occurrence and impact was computed as the final score. The Cronbach's α for the current sample was 0.827.

2.2.6. Coping style

The Simplified Coping Style Questionnaire (SCSQ) is a 20-item self-report instrument that assesses participants' coping styles (Xie, 1998). Each item was rated on a 4-point Likert scale ranging from 0 (never) to 3 (often), with a higher score indicating a more positive coping style. The Cronbach's α for the current sample was 0.896.

2.2.7. Cognitive flexibility

The Chinese version of the Cognitive Flexibility Instrument (CFI) was used to measure cognitive flexibility (Wang et al., 2016). The items were rated on a 5-point Likert scale ranging from 1 (never) to 5 (always), with higher scores indicating better cognitive flexibility. The Cronbach's α for the current sample was 0.892.

2.2.8. Bullying and being bullied

Participants were asked four questions to measure the frequency of bullying other children and being bullied by others (Bao et al., 2020). Responses were made on a 5-point Likert scale (1 = not at all, 5 = several times a week). The response "only once or twice" was used as the cut-off point, and participants were then coded as involved in bullying/being bullied or not.

2.2.9. Perceived discrimination

The Secondary School Students' Perceived Discrimination Questionnaire (SDPQ) was utilized to assess adolescents' perceived discrimination (Wang et al., 2020). Each item was rated on a 5-point Likert scale ranging from 1 (not at all) to 5 (extremely), with higher scores indicating greater perceived discrimination. The Cronbach's α for the current sample was 0.943.

2.2.10. Perceived marital conflict

The revised Children's Perception of Marital Conflict Scale (CPIC) was used to measure participants' perceived severity and threat of marital conflict, as well as self-blame due to the conflict (Chi & Xin, 2003). All items were rated on a 4-point Likert scale ranging from 1 (not at all) to 4 (extremely), with higher scores indicating more severe marital conflict and more frequent self-blame. The Cronbach's α for the current sample was 0.908.

2.2.11. Family monitoring

The Secondary School Students' Family Monitoring Questionnaire (SFMQ) was used to assess the level of family monitoring (Wei et al., 2022). Each item was rated on a 3-point Likert scale ranging from 1 (never) to 3 (always), with higher scores indicating stricter family monitoring. The Cronbach's α for the current sample was 0.773.

2.2.12. Family togetherness

To assess their sense of emotional closeness and bonding with parents (Williams & Anthony, 2015), participants were presented with five items such as "My parents and I support each other during difficult times" rated on a 3-point Likert scale (1 = not like me, 3 = a lot like me) (Bao et al., 2020). Higher scores indicated greater family togetherness. Cronbach's α was 0.933 for the current sample.

2.2.13. Peer support

The Secondary School Students' Peer Support Questionnaire (SPSQ) was used to assess participants' perceptions of peer support (Wei et al., 2022; Williams & Anthony, 2015), typified by phrases such as "I can trust my friends". Participants responded on a 3-point Likert scale (1 = not like me, 3 = a lot like me), with higher scores indicating greater peer support. The Cronbach's α for the current sample was 0.937.

2.2.14. Deviant peer affiliation

The Secondary School Students' Delinquent Peer Questionnaire (SDPQ; Teevale et al., 2016; Wei et al., 2022) was employed to assess the frequency and degree of delinquent behaviors within the peer group, such as "How many of your friends skip school?". Each item was rated on a 5-point Likert scale (1 = none of my friends, 5 = almost all my friends), with higher scores indicating greater exposure to the delinquent behaviors of peers. The Cronbach's α for the current sample was 0.861.

2.3. Analytic plan

2.3.1. Missing data

Missing values of continuous variables were regarded as missing at random, and a maximum likelihood approach was used at the item level (Schafer & Graham, 2002). Missing values of categorical variables were replaced by a new class (i.e., 99), and participants with missing values of dependent variables (i.e., SA or NSSI) were excluded from the corresponding analysis (see Table S1). Considering the high comorbidity of NSSI and suicide risk, participants with a history of suicide ideation/SA were excluded from the analysis of NSSI [lifetime: $n = 290$ (72.32 %); 1-year: $n = 135$ (53.79 %); 6-month: $n = 83$ (44.62 %); 1-month: $n = 36$ (34.95 %)].

2.3.2. Distinguish NSSI and SA from no self-injury

Datasets were constructed for NSSI and SA, respectively. To maximize information utilization, models were created to predict occurrences of NSSI (SA) at different intervals: in the past 1 month, past 6 months, past 1 year, and over the lifetime. This approach allows for assessing our model's performance in identifying both recent and lifetime self-harm behaviors, as well as facilitating an examination of the robustness of the TDPPS effect.

Models were built using random forest, an ensemble learning algorithm widely accepted in the ML community. Recognized for its efficiency and robustness, this algorithm effectively addresses feature selection issues, tackles classification problems, and handles outliers and noisy data (Jaiswal & Samikannu, 2017). It provides an estimation of the relative importance of each predictor, with a higher score indicating greater relevance for accurate clarification. Random forest has been extensively employed in predicting self-injury behaviors (Burke et al., 2019).

In the current study, a random forest comprising 1000 trees was constructed. The Gini coefficient was used to measure the quality of a split in each decision tree. The maximum depth of the decision tree was restricted to three levels, and the minimum number of samples required to split an internal node was set to 6. Given the imbalance in labeling, where the proportion of individuals with SA or NSSI was relatively small, we opted to set the class_weight parameters as "balanced" to amplify the influence of SA and NSSI samples. The dataset was randomly divided with 70 % allocated for constructing models (training set) and 30 % for evaluating model performance (test set).

2.3.3. *Distinguish between NSSI and SA*

Two feature sets were chosen based on the rank of average feature importance scores in the previous step: (i) the control feature set, consisting of features with high importance scores in predicting both NSSI and SA, i.e., ranked in the top five for classifying both; (ii) the distinction feature set, comprising features with a high importance score in predicting one behavior but relatively less important for the other, i.e., ranked in the top five for classifying NSSI or SA, with an absolute difference in importance ranking between SA and NSSI $\geq$5. These two feature sets were employed respectively to construct a classifier distinguishing SA from NSSI. To robustly estimate and compare model performance, we utilized five additional ML methods alongside random forest: multilayer perceptron classifier, stochastic gradient descent classifier, AdaBoost classifier, support vector machine classifier, and gaussian naive bayes classifier (Hastie et al., 2016). The evaluation of model fitness was conducted using repeated stratified 10-fold cross-validation, repeated 50 times.

2.3.4. *Model fit indices*

The area under the receiver operating characteristic curve (AUC) is a classic indicator of the model's synthetical performance (Walsh et al., 2017). AUCs of 0.50 to 0.59 indicate extremely poor classification, 0.60 to 0.69 poor classification, 0.70 to 0.79 fair classification, 0.80 to 0.89 good classification, and above 0.90 excellent classification (Šimundic, 2008). However, given the low base rate of NSSI and SA, the AUCs can be misleading. As such, we additionally reported three other important performance metrics: precision (true positives divided by the sum of true positives and false positives), recall (true positives divided by the sum of true positives and false negatives), and accuracy (sum of true positives and true negatives divided by all the conditions). Furthermore, the Brier score was used as a calibration index to evaluate how the predicted probability of the current model matched the actual probability. Brier scores range from 0 to 1, with lower scores indicating better performance.

Data preparation, including data reduction and missing value imputation, was conducted using SPSS version 25. Subsequent data analyses were performed utilizing Python version 3.8, with relevant Python libraries, including *scikit-learn*, *NumPy*, and *Pandas* (Pedregosa et al., 2011; Van Der Walt et al., 2011).

3. Results

3.1. *Sample characteristics*

Participants were gender-matched (51.6 % female), with age ranging from 11 to 15 years ($M = 15.23$, $SD = 1.56$). The majority of participants (94.5 %) identified as Han Chinese, and 62.7 % were only children. Additionally, 19.4 % reported having divorced parents, and 58.2 % grew up in rural areas. Regarding parental education, a significant proportion had an education level lower than high school, with 83.8 % for mothers and 81.3 % for fathers. Table 1 presents the self-reported rates of NSSI and SA. Among adolescents with a history of NSSI, 72.3 % ($n = 290$) reported having considered or attempted suicide previously.

3.2. *Distinguish NSSI and SA from no self-injury*

The model fit indices are presented in Table 2. In classifying SA, the random forest model yielded fair to good AUCs (0.70–0.87) across various time intervals, excluding the one-year classification model (AUC = 0.65). The models yielded high accuracy across time, ranging from 0.93 (lifetime) to 0.99 (1 month). Brier score ranged from 0.01(1 month) to 0.07 (lifetime), indicating that the model is close to "perfect" (Walsh et al., 2017). The precision scores ranged from 0.18 (1 year) to 0.50 (1 month), and recall scores ranged from 0.33 (1 year) to 0.75 (6 months).

In classifying NSSI, the algorithm yielded poor AUCs across time, ranging from 0.61 (1 month) to 0.68 (lifetime). The precision scores ranged from 0.08 (1 month) to 0.14 (lifetime), and the recall scores ranged from 0.35 (1 month) to 0.55 (lifetime). The accuracy ranged from 0.80 (lifetime) to 0.86 (1 month), with Brier scores ranging from 0.14 (1 month) to 0.20 (lifetime).

Features were ranked by the average feature importance score across time (see Table 3). Painful feelings and pain arousal were ranked in the top five for both SA and NSSI classifications. The pain avoidance was high in classifying SA but not in classifying NSSI. Feature importance scores for NSSI and SA models at various time intervals are listed in Tables S2 and S3, respectively.

3.3. *Distinguish between NSSI and SA*

The control feature set comprised painful feelings, pain arousal, and crisis events, while the distinction feature set included family togetherness, pain avoidance, and deviant peer affiliation.

The performance of the distinction and the control feature set in classifying lifetime SA from lifetime NSSI is summarized in Table 4. Regardless of the ML algorithms used, the distinction feature set exhibited slightly superior performance compared to the control feature set. The model performances of the distinction feature set were as follows: fair AUCs ranging from 0.73 to 0.79, precision from 0.72 to 0.81, recall from 0.61 to 0.71, accuracy from 0.75 to 0.81, and Brier from 0.19 to 0.25. In comparison, the control feature set exhibited poor to fair AUCs ranging from 0.64 to 0.73, precision from 0.57 to 0.75, recall from 0.50 to 0.64, accuracy from 0.68 to 0.77, and Brier from 0.24 to 0.32. Similar results were observed in the models of 1-year, 6-month, and 1-month (see Table S4).

4. Discussion

The present study utilized ML to classify SA from NSSI in a community sample of Chinese adolescents. Based on the average feature importance scores, two feature subsets were chosen and evaluated for

Table 1
Rates of NSSI and SA.

	NSSI	SA
Lifetime	401(16.81 %)	67(2.81 %)
1-year	251(10.52 %)	39(1.64 %)
6-month	186(7.80 %)	28(1.17 %)
1-month	103(4.28 %)	18(0.75 %)

Note. NSSI = non-suicidal self-injury; SA = suicide attempt.

Table 2
Model performance in predicting NSSI and SA.

		AUC	Accuracy	Precision	Recall	Brier
SA	lifetime	0.70	0.93	0.20	0.45	0.07
	1-year	0.65	0.96	0.18	0.33	0.04
	6-month	0.87	0.98	0.33	0.75	0.02
	1-month	0.70	0.99	0.50	0.40	0.01
NSSI	lifetime	0.68	0.80	0.14	0.55	0.20
	1-year	0.64	0.81	0.13	0.46	0.19
	6-month	0.63	0.84	0.12	0.39	0.16
	1-month	0.61	0.86	0.08	0.35	0.14

Note. AUC represents the area under the receiver operating curve. Accuracy represents the sum of true positives and true negatives divided by all conditions. Precision represents the number of true positives divided by the sum of true and false positives. Recall refers to the number of true positives divided by the number of true positives and false negatives. Brier score assesses the alignment between predicted probability and real-world probability, with scores closer to 0 indicating better calibration. NSSI = non-suicidal self-injury; SA = suicide attempt.

Table 3
The average feature importance scores in classifying the history of SA and NSSI.

Variable	SA		NSSI	
	Score	Rank	Score	Rank
Painful feelings	0.188	1	0.122	3
Pain avoidance	0.152	2	0.040	8
Pain arousal	0.117	3	0.128	1
Family togetherness	0.084	4	0.036	9
Crisis events	0.063	5	0.126	2
Childhood trauma history	0.059	6	0.027	12
Coping style	0.055	7	0.082	6
Perceived marital conflict	0.044	8	0.083	5
Deviant peer	0.032	9	0.088	4
Cognitive flexibility	0.030	10	0.052	7
Family monitoring	0.030	11	0.018	14
Perceived discrimination	0.027	12	0.035	10
Age	0.025	13	0.017	16
Being bullied	0.020	14	0.006	21
Peer support	0.015	15	0.017	17
Father's level of education	0.012	16	0.031	11
Gender	0.011	17	0.013	19
Sexual orientation	0.010	18	0.016	18
Boarding at school	0.006	19	0.007	20
Family structure	0.005	20	0.003	25
Mother's level of education	0.004	21	0.020	13
Bullying	0.003	22	0.004	23
Place of growing-up	0.003	23	0.018	15
Only child	0.003	24	0.004	24
Parents' marital status	0.002	25	0.005	22

Note. NSSI = non-suicidal self-injury; SA = suicide attempt. The scores are averaged across models predicting NSSI/SA occurrence in the past 1 month, past 6 months, past 1 year, and over the lifetime.

performance: the distinction feature set, including family togetherness, pain avoidance, and deviant peer affiliation; and the control feature set, comprising painful feelings, pain arousal, and crisis events. The distinction feature set slightly but consistently outperformed the control feature set, suggesting its potential utility in distinguishing SA from NSSI. The three-dimensional psychological pain model, especially pain avoidance, might play a role in understanding the psychological similarities and differences between NSSI and SA.

The random forest models effectively differentiated adolescents with SA history from those without such history, exhibiting fair to good classification (AUC: 0.70–0.87), except for the 1-year SA model (AUC: 0.65), and high accuracy across time (0.93–0.99). Nevertheless, the precision (0.18–0.50) and recall (0.33–0.75) were relatively low and variable in the SA model. Previous ML studies in community adolescents and young adults (Miche et al., 2020; Navarro et al., 2021; Shen et al., 2020; Su et al., 2020) reported AUCs ranging from poor to extremely good (0.62–0.93) and yielded similarly low and variable precision and recall score (precision: 0.02–0.62, recall: 0.36–0.87). The relatively low precision and recall may be attributed to the low prevalence of SA in community adolescents, posing a challenge for prediction (Su et al., 2020). The Brier score, an important but rarely reported metric (Christodoulou et al., 2019), ranged from 0.01 to 0.07 in this study, indicating high accuracy of probability estimation in our model. As one of the few studies predicting SA among Chinese adolescents, our developed model demonstrated acceptable and reasonable performance.

Table 4
Model performance in classifying lifetime SA from lifetime NSSI.

Feature set	Algorithms	AUC	Accuracy	Precision	Recall	Brier
Control feature set	MLP	0.73	0.77	0.75	0.59	0.24
	SGD	0.64	0.68	0.57	0.54	0.32
	AdaBoost	0.68	0.72	0.69	0.50	0.28
	SVC	0.73	0.75	0.68	0.64	0.25
	RF	0.68	0.72	0.68	0.53	0.28
	Gaussian NB	0.73	0.76	0.71	0.61	0.24
Distinction feature set	MLP	0.78	0.81	0.81	0.65	0.19
	SGD	0.73	0.75	0.72	0.65	0.25
	AdaBoost	0.76	0.79	0.81	0.61	0.21
	SVC	0.76	0.78	0.74	0.67	0.22
	RF	0.79	0.80	0.77	0.71	0.20
	Gaussian NB	0.77	0.80	0.79	0.64	0.20

Note. AUC represents the area under the receiver operating curve. Accuracy represents the sum of true positives and true negatives divided by all conditions. Precision represents the number of true positives divided by the sum of true and false positives. Recall refers to the number of true positives divided by the number of true positives and false negatives. Brier score assesses the alignment between predicted probability and real-world probability, with scores closer to 0 indicating better calibration. AdaBoost = AdaBoost classifier; Gaussian NB = gaussian naive bayes classifier; MLP = multilayer perceptron classifier; NSSI = non-suicidal self-injury; RF = random forest classifier; SA = suicide attempt; SGD = stochastic gradient descent classifier; SVC = support vector machine classifier.

For NSSI classification, the random forest model yielded poor AUCs (0.61–0.68). Contrastingly, prior ML studies predicting NSSI in high-risk adults achieved excellent AUCs (0.87–0.90; Fox et al., 2019). Among studies conducted on youth, most did not report model performance (e.g., Ammerman et al., 2017; Ammerman, Jacobucci, Kleiman, et al., 2018; Ammerman, Jacobucci, McCloskey, et al., 2018), except for Zhou et al. (2024), who presented an AUC of 0.835, precision of 0.248, and a Brier score of 0.074. The relatively poor performance of our model in NSSI classification may stem from excluding adolescents with both NSSI and suicide ideation/SA in the analysis. Given the frequent co-occurrence of NSSI and suicidality (Liu et al., 2018), excluding this subgroup would significantly decrease the incidence of NSSI and compromise the sample's representation. Furthermore, removing NSSI adolescents with a history of suicide ideation/SA, who often exhibit more frequent and severe self-injurious behaviors (Stewart et al., 2017), might also make it harder to distinguish between cases with NSSI and those without. However, to explore the psychological differences between NSSI and SA, we chose to exclude adolescents with both behaviors from the NSSI model and combined them with those who only have SA (Huang et al., 2020). Future research should enhance our study by including all adolescents engaged in NSSI to improve NSSI classification.

The model, derived from the distinction feature set, solely utilized three independent factors and produced fair classifications between NSSI and SA (AUC: 0.73–0.79), comparable to a prior model with 33 variables (AUC = 0.72, 95 % CI = 0.63, 0.82; Huang et al., 2020). In contrast, the model using the control feature set exhibited poor to fair classification power (AUC: 0.64–0.73). Despite a modest difference, there was a stable tendency for the distinction feature set to outperform the control feature set, indicating the non-random significance of factors in the distinction set (i.e., pain avoidance, family togetherness, and deviant peer affiliation). These factors might shed light on the mechanism distinguishing SA from NSSI and could facilitate efficient SA screening and intervention. Although the distinctions between NSSI and SA tend to be complex (Huang et al., 2020), our findings suggest the feasibility of developing a relatively accurate model with only a small number of variables.

Our findings highlighted the prominent role of TDPPS in elucidating the distinctions and similarities between NSSI and SA. Specifically, pain avoidance emerged as a crucial factor distinguishing adolescents engaged in SA from those solely engaged in NSSI, whereas pain arousal and painful feelings were closely related to both NSSI and SA. Prior research has rarely pinpointed specific factors separating SA from NSSI (Stewart et al., 2017) and this study addresses this gap by introducing pain avoidance, a novel and promising factor specific to suicide. The perspective of pain avoidance may also contribute to debates on whether engaging in NSSI increases or reduces suicide risk (Bryan et al., 2015). Specifically, for individuals with low pain avoidance, NSSI may function as a protective mechanism due to its pain-relieving function (Taylor et al., 2018). Conversely, for those with high pain avoidance, NSSI might be risky as it not only fails to effectively alleviate psychological pain but may also amplify individuals' ability to enact suicide by reducing fear of death (Joiner, 2005). Hence, pain avoidance might moderate the relationship between NSSI and suicide.

The roles of painful feelings and pain arousal align with previous research, where internalizing symptoms and mental distress were identified as common risk factors for both NSSI and SA (Fox et al., 2015; Franklin et al., 2017). Moreover, TDPPS were among the most important predictors for differentiating adolescents engaged in SA from those not. In line with previous studies utilizing traditional statistical methods (Ducasse et al., 2018; Sun et al., 2020), the current study supported the dominant role of TDPPS in identifying suicide risk using ML algorithms.

In addition to TDPPS, deviant peer affiliation, family togetherness, and crisis events may contribute to understanding the characteristics of NSSI and SA. Concerning similarities, the current study identified the relationship between crisis events and both NSSI and SA, in line with previous studies where stressful life events were regarded as a risk factor for self-injury (Baetens et al., 2021; Franklin et al., 2017).

Furthermore, we found that deviant peer affiliation played a more important role in classifying NSSI, while family togetherness was more important in classifying SA. In support, previous studies have found that perceived family support was independently related to adolescent suicide ideation and SA but peer support was not (Miller et al., 2015; Moller et al., 2021). Additionally, peer delinquency has been closely related to NSSI rather than SA in Chinese adolescents using decision tree models (Wei et al., 2022). The initiation of NSSI is often prompted by social modeling (Jarvi et al., 2013) and can be reinforced by delinquent and impulsive behaviors within peer groups (Grigoryan & Jurcik, 2020), particularly the NSSI behaviors exhibited by one's closest friends (You et al., 2013). On the other hand, suicide represents an escalation of NSSI in both intention and consequences, driven by the intent to end one's life. Family issues, in comparison to peer issues, tend to be more stable and long-term among young people (Moller et al., 2021), possibly leading individuals to perceive unending psychological distress and prompting suicide as the only way out. It is crucial to note that while this study indicates the separate importance of peers and family in classifying NSSI and SA, it does not suggest that family issues are unrelated to NSSI or that peer issues are unrelated to SA. These findings should be considered exploratory, and further research is needed to examine the role of family and peers in predicting NSSI and SA.

Although the ultimate clinical relevance awaits future verification, our study suggests several potential clinical implications. We demonstrated the potential utility of a simple and short feature set, including pain avoidance, family togetherness, and deviant peer affiliation, to distinguish adolescents at high risk for SA from those solely engaged in NSSI. Screening for pain avoidance and family togetherness might facilitate the identification of adolescent self-injurers at elevated risk for suicide, enabling the implementation of tailored prevention or intervention efforts, such as psychological pain theory-based cognitive therapy (Zou et al., 2017) and family therapy (Waraan et al., 2023). However, the classification efficacy of our distinction feature set needs to be validated through prospective studies with larger sample sizes. Additionally, our models demonstrated reasonable accuracy in classifying both lifetime and short-term SA. Despite relatively poor classification ability in the NSSI model, our study preliminarily demonstrated the feasibility of ML in predicting SA and NSSI in adolescents. We hope this research is a starting point for additional studies exploring accurate and efficient prediction of suicide and NSSI through ML.

The present study has several limitations. First, this study is a secondary analysis of existing data and might have overlooked certain variables crucial for distinguishing SA from NSSI, such as NSSI severity (Stewart et al., 2017). Nevertheless, we included numerous variables associated with SA and NSSI (Franklin et al., 2017; Valencia-Agudo et al., 2018), along with the theoretically important pain avoidance score for distinguishing SA from NSSI. Second, the predictors identified as “important” in the ML model should be interpreted with caution due to potentially limited generalizability (Fox et al., 2019). Additionally, differences in classification power of the distinction and control feature sets were relatively small and merely descriptive, with the presence of a statistical difference remaining unclear. Therefore, the current results require cautious interpretation. Third, the participants were from local schools in Tianjin and the findings may not be generalizable to clinical populations and adolescents in other cities. The age range of the current sample (11 to 15 years) might overlook crucial developmental differences (Lee et al., 2019). Further, the measurement of SA and NSSI in this study relies on self-rating scales, introducing the potential for recall and social desirability bias. While similar self-assessment tools are commonly used in NSSI and SA studies (e.g., Shen et al., 2020; Zhou et al., 2024), incorporating parent-reported assessments, clinical interviews, and medical records may enhance measurement accuracy. Finally, a cross-sectional design precludes concluding the causal relationship between psychological indicators and NSSI/SA. Longitudinal and experimental investigation is required in future studies.

5. Conclusions

The present study utilized ML techniques to investigate psychological indicators for classifying adolescents with SA from those only engaged in NSSI, with a particular focus on the three-dimensional psychological pain model for suicide. The findings indicated that pain avoidance, deviant peer affiliation, and family togetherness might help distinguish between SA and NSSI. In particular, the observed specific role of pain avoidance in identifying SA has potential clinical relevance, which might provide a screening tool to reliably identify adolescents at high risk for SA, but not NSSI.

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PSYCInfo codes

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CRediT authorship contribution statement

Jiamin Bao: Writing – original draft, Methodology, Formal analysis.

Jiachen Wan: Visualization, Formal analysis, Data curation. **Huanhuan Li:** Writing – review & editing, Supervision, Project administration, Investigation, Funding acquisition, Conceptualization. **Fang Sun:** Writing – original draft, Methodology.

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

Data availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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