# Longitudinal Machine Learning Prediction of Non-Suicidal Self-Injury Among Chinese Adolescents: A Prospective Multicenter Cohort Study


**Abstract**

**Background**

Non-suicidal self-injury (NSSI) is an important public health problem among adolescents, yet traditional prediction approaches yield limited accuracy. This study aims to develop and evaluate machine learning models for predicting NSSI using longitudinal data and examine the patterns of feature importance, including risk factors and protective factors.

**Methods**

Data were obtained from the Chengdu Positive Child Development Cohort, which covers students from five primary and middle schools in China. The analysis utilized four waves of follow-up data collected from 3,483 students over a period of 2.5 years. A progressive prediction framework with three prediction windows was constructed and seven machine learning algorithms were compared. Five-fold cross-validation was used to ensure the robustness of performance evaluation. SMOTENC oversampling was used to address the class imbalance in the training set. Model performance was evaluated by area under the receiver operating characteristic curve (AUROC), accuracy, precision, recall, and F1 score. SHapley Additive exPlanations (SHAP) analysis was conducted to assess the model's interpretability.

**Results**

Random forests showed superior performance in all windows (AUROC = 0.843, 0.855, 0.853, respectively). The top predictive factors included suicide-related behaviors, depression, delinquent behaviors, and anxiety as risk factors, while spirituality, emotional competence, life satisfaction, and empathy emerged as protective factors.

**Conclusion**

The progressive prediction framework achieved robust longitudinal NSSI prediction. Positive Child Development factors, particularly spirituality and emotional competence, emerged as key protective factors against NSSI risk. These model-interpretable results provide an evidence-based foundation for developing targeted prevention strategies and early intervention programs.



*Keywords:*
Adolescents; Non-Suicidal Self-Injury; Longitudinal Cohort Study; Machine Learning


## 1. Introduction

Non-suicidal self-injury (NSSI) refers to the intentional destruction of body tissues without suicidal intent (Nock, 2009). Global prevalence ranges from 11.5% to 33.8% across different samples and study designs, with evidence suggesting an increasing trend (Mannekote Thippaiah et al., 2021). Adolescents are particularly vulnerable to NSSI, with onset typically occurring between ages 12 and 15 and peaking around 15 to 16 years. (Plener et al., 2015). Among adolescents, females demonstrated elevated NSSI rates compared to males (21.4% versus 13.7%) (Moloney et al., 2024). In China, NSSI is notably prevalent among adolescents: 19.3% in primary, 30.4% in middle, and 27.6% in senior high schools. Among Chinese adolescents, the lifetime prevalence of NSSI reaches as high as 24.7%, with minimal sex differences (Qu et al., 2023).

Research has consistently identified multiple risk factors for adolescent NSSI, including mental health disorders such as depression, anxiety, and personality disorders, alongside environmental factors including adverse childhood experiences, family dysfunction, and social isolation (Wang et al., 2022b; Cipriano et al., 2017; Wang et al., 2024a). The consequences of NSSI extend beyond immediate physical harm, encompassing long-term psychological distress, disrupted interpersonal relationships (Taylor et al., 2018), and a substantially elevated risk for future suicidal behaviors (Mars et al., 2019). These multifaceted impacts require accurate prediction models to enable targeted early intervention.

Traditional statistical approaches for NSSI prediction face limitations due to the complexity of risk factor interactions and the temporal dynamics of adolescent development (Guerry & Prinstein, 2009; Tatnell et al., 2014; Kiekens et al., 2017). Machine learning (ML) methodologies offer promising alternatives by accommodating high-dimensional data, capturing non-linear relationships between variables, and demonstrating robust predictive performance (Lin et al., 2025). Recent applications of machine learning to NSSI prediction have achieved area under the curve values ranging from 0.74 to 0.89 across diverse populations and algorithms (Zhou et al., 2024b; Castillo-Sánchez et al., 2020; Mürner-Lavanchy et al., 2024).

Current ML research in NSSI prediction encompasses various populations, including clinical samples (Chen et al., 2024a), psychiatric populations (Kappes et al., 2023), and students (Mürner-Lavanchy et al., 2024; Guo et al., 2024). Commonly employed algorithms include random forest (Burke et al., 2019), extreme gradient boosting (Xu et al., 2024a), and support vector machines (Gao et al., 2025). These studies have identified education level, childhood physical abuse experiences, emotion regulation ability, rumination and depression as factors closely associated with an increased risk of NSSI (Yang et al., 2022; Zhong et al., 2024; Mason et al., 2025; Niu et al., 2025).

However, several critical limitations persist in existing research using machine learning methodologies. Current machine learning applications in NSSI prediction have primarily utilized cross-sectional designs or short-term longitudinal data spanning less than one year (Wang et al., 2025b; Zhong et al., 2024; Zhou et al., 2024b). This temporal limitation potentially constrains the understanding of NSSI developmental trajectories and the stability of predictive factors across adolescent development. Additionally, existing prediction frameworks are unbalanced, with a predominance of risk factors with a relative scarcity of research on protective and resilience factors, limiting both model comprehensiveness and the potential for intervention development (Wang et al., 2024b).

A critical limitation of current machine learning applications involves interpretability. Many existing models function as “black boxes”, providing limited clinical interpretability and reducing practical utility for intervention planning (Xu et al., 2024a; Zhou et al., 2024b; Burke et al., 2019). Advanced explainable artificial intelligence techniques, such as SHapley Additive exPlanations (SHAP), can address this limitation by providing global assessments of variable importance and directional influence through comprehensive visualization (Lundberg & Lee, 2017; Yarkoni & Westfall, 2017). However, no studies have comprehensively applied these interpretability methods to longitudinal NSSI prediction models using extended follow-up periods. Furthermore, despite the elevated prevalence of

NSSI in Chinese adolescent populations, no research has utilized longitudinal cohort data extending beyond two years to examine dynamic changes in risk and protective factors among Chinese primary and middle school students.

Therefore, this study attempted to address the above-mentioned gaps through three primary objectives: (1) develop a progressive prediction framework utilizing 2.5-year longitudinal cohort data to capture temporal patterns in NSSI development while comparing multiple machine learning algorithms, including logistic regression, naive Bayes, random forest, support vector machines (SVM), extreme gradient boosting (XGBoost), light gradient boosting machine (LightGBM), and neural networks; (2) employ SHAP methodology to enhance model interpretability and identify key predictive factors, including both risk and protective elements; and (3) examine predictive factor interactions, particularly regarding depression as a core risk element, to inform targeted prevention strategies within the Chinese adolescent population.

## 2. Methods

### *2.1. Research design*

The data of this study were from the Chengdu Positive Child Development Cohort Study (CPCD) (Zhao et al., 2022), which is a large-scale, longitudinal tracking study in Chengdu, Sichuan Province, China. The study covers three primary schools and two middle schools located in regions with varying economic backgrounds, aiming to emphasize youth potential and developmental capability (Shek et al., 2019). The baseline survey was conducted between 23 December 2019 and 13 January 2020. The first follow-up took place between 16 June and 8 July 2020 (six months after the baseline survey). The third and fourth waves of the study were conducted from 1 to 30 June in 2021 and 2022, respectively. Information was collected through paper and electronic questionnaires completed by children and caregivers, as well as direct interviews. All procedures received approval from the Sichuan University Ethics Committee (K2020025), with written informed consent obtained from caregivers and assent from participating students.

Participants were selected using the following inclusion and exclusion criteria to ensure data quality. Students in Grades 3 and above were included, as preliminary assessment indicated younger students had difficulty comprehending questionnaire items despite appropriate cognitive development. Complete participation across all four survey waves (T1–T4) by both students and caregivers was required. Participants were excluded if (1) NSSI outcome data were missing at any wave to enable longitudinal analysis. (2) overall missing data exceeded 50% across study variables, or (3) they had documented histories of conditions potentially affecting survey validity (brain trauma, epilepsy, severe neurological disorders, schizophrenia, or intellectual disability), as verified through school records and caregiver reports.

### *2.2. Measure*

#### *2.2.1. Measure of non-suicidal self-injury (NSSI)*

Non-suicidal self-injury (NSSI) was assessed using the 9-item Deliberate Self-Harm Inventory (DSHI) (Gratz, 2001), which includes types of NSSI behaviors: cutting, burning, scratching, biting, sticking, banging, punching, and other forms. Each behavior was rated on a 4-point scale, ranging from 1 (never) to 4 (three times or more) in the past year. Participants who scored more than 1 point on any item were classified as the NSSI group. This scale has been validated in studies involving Chinese adolescents (Chen et al., 2024b; Xiong et al., 2023).

*2.2.2. Measures of Psychological Morbidity*

Several measures of psychological morbidity were used in this study:

a. Suicide-related behavior was assessed by asking participants whether they had experienced suicidal ideation, made suicide plans, or attempted suicide in the past year (Zhao et al., 2022).

b. Adolescent depression was assessed using the Center for Epidemiologic Studies Depression Scale (CES-D) (Radloff, 1977), which has been validated in China (Yu et al., 2025).

c. Adolescent anxiety was measured using the Screen for Child Anxiety Related Emotional Disorders (SCARED) (Birmaher et al., 1999), which has been validated in China (Zhang et al., 2021).

d. Internet addiction was assessed using the Young Internet Addiction Test (IAT) (Young and De Abreu, 2010), which has been validated in China (Wang et al., 2022a).

e. Student behavior was measured through self-reports by students and caregiver reports via the Child Behavior Checklist (CBCL) (Achenbach et al., 1991; Achenbach, 1991), which has been validated in China (Cui et al., 2021).

*2.2.3. Measures of Positive Youth Development and Well-Being*

a. Positive Child Development (PCD) refers to a strengths-based psychological approach that emphasizes nurturing developmental assets in children (Shek & Ma, 2010b; Lerner et al., 2005). The Chinese Positive Youth Development (CPYD) Scale was an 80-item self-report instrument, which is used to measure PCD. It comprises 15 subscales: bonding, resilience, social competence, recognition for positive behavior, emotional competence, cognitive competence, behavioral competence, moral competence, self-efficacy, clear and positive identity, beliefs in determination, beliefs in the future, prosocial involvement, prosocial norms, and spirituality (Zhao et al., 2022). The 15 subscales were used as discrete measures in this study.

b. Life satisfaction was measured by the Life Satisfaction Scale (LS) (Diener et al., 1985).

*2.2.4. Measures of Social-Psychological Attributes and Outcomes*

a. Materialism was evaluated by the Chinese Adolescent Materialism Scale (Shek et al., 2014b), and egocentrism was assessed using the Chinese Adolescent Egocentrism Scale (Shek et al., 2014a).

b. Empathy was evaluated using an 11-item scale that included items assessing behaviors such as considering others' perspectives when making decisions (Zhao et al., 2022).

c. Delinquent behavior was assessed by students' self-reports on the frequency of 12 misbehaviors in the past year, including stealing, cheating, and truancy (Shek & Zhu, 2019).

d. Academic performance was assessed through multiple dimensions, including academic intrinsic value (Zhao et al., 2022), academic utility value (Zhao et al., 2022), and academic anxiety (Shek et al., 1997). Due to the emergence of the COVID-19 pandemic after baseline data collection, COVID-19-related questions were introduced from T2. We used the 13-item Chinese version of the Children's Revised Impact of Event Scale (CRIES-13) to evaluate post-traumatic stress symptoms related to the pandemic (Lau et al., 2013).

*2.2.5. Measures of family environment*

The Chinese Family Assessment Instrument (C-FAI) was applied to measure family dysfunction, which comprises five subscales: parental control, communication, mutuality, parental concern, and conflict and harmony (Shek & Ma, 2010a). Caregivers' depression was assessed using the Zung Self-Rating Depression Scale (SDS) (Zung, 1965), and their anxiety was evaluated with the Zung Self-Rating Anxiety Scale (SAS) (Zung, 1971).

*2.2.6. Measures of Sociodemographic Characteristics*

Sociodemographic data were obtained from student and caregiver questionnaires, including children's age, sex, ethnicity, grade, number of siblings, pocket money received per week, parents' educational level, occupation, monthly income, and family conditions.

All factors in this paper are listed in **Supplementary material Table S1.**

*2.3. Analysis*

*2.3.1. Descriptive statistical analysis*

Cross-sectional characteristics were examined at each timepoint, with comparisons between adolescents with and without NSSI behaviors. Group comparisons employed chi-square tests for categorical variables and independent t-tests or Mann-Whitney U tests for continuous variables, depending on distributional assumptions. Statistical significance was set at $p<0.05$.

*2.3.2. Model development*

For missing data, stable demographic characteristics (sex, ethnicity, age) were forward-filled from baseline. Remaining missing values in continuous variables were imputed using the K-Nearest Neighbors algorithm (Su et al., 2021), while categorical variables were imputed using the mode.

Feature selection proceeded through multiple stages. Initial features were selected based on established NSSI literature and theoretical frameworks. Elastic Net regularization with cross-validation was then applied to identify the optimal L1 and L2 regularization parameters, effectively managing multicollinearity and preventing overfitting (Zou & Hastie, 2005). For highly correlated features ((Pearson's $r > 0.70$), only the feature with the highest regularization weight was retained. Continuous variables were standardized, and categorical variables were appropriately encoded.

We implemented a progressive prediction framework to examine how NSSI prediction performance and patterns of feature importance evolve with increasing longitudinal information and prediction horizons. Three temporal prediction windows were established using the same participant cohort: Window 1 utilized baseline data (T1) to predict NSSI behavior at the 6-month follow-up (T2); Window 2 incorporated cumulative data from baseline and the first follow-up (T1–T2) to predict NSSI at the 1.5-year follow-up (T3); and Window 3 used the complete longitudinal dataset (T1–T3) to predict NSSI at the 2.5-year follow-up.

Seven algorithms were compared to identify optimal predictive performance. Logistic Regression (Kleinbaum & Klein, 2002) and Naive Bayes (Perez et al., 2006) were selected for their interpretability and as baseline performance benchmarks. Ensemble methods, including Random Forest (RF) (Perez et al., 2006), eXtreme Gradient Boosting (XGBoost) (Chen & Guestrin, 2016), and Light Gradient Boosting Machine (LightGBM) (Ke et al., 2017), were employed to capture complex nonlinear feature interactions. Support Vector Machines (SVM) (Yang et al., 2022) and Neural Networks (Davis et al., 2014) were included for their capacity to model high-dimensional classification boundaries and recognize complex patterns. Class imbalance in NSSI prevalence was addressed using the Synthetic Minority Oversampling Technique for Nominal and Continuous features (SMOTENC) (Chawla et al., 2002). Five-fold cross-validation was implemented with participant-level stratification to ensure that no individual appeared in both the training and validation sets within each fold (Wang et al., 2025a).

Model performance was assessed using the Area Under the Receiver Operating Characteristic curve (AUROC), Area Under the Precision-Recall Curve (AUPRC), accuracy, precision, recall, and F1-score (Cruz-Gonzalez et al., 2025; Saito & Rehmsmeier, 2015). The best-performing model was selected based on AU-ROC across all prediction windows. SHAP was used to interpret the best-performing model by quantifying the contribution of each feature (Lundberg & Lee, 2017). SHAP analysis was conducted using Window 3 data, which includes the most comprehensive longitudinal information. SHAP dependence plots were used to examine feature interactions and their nonlinear relationships with NSSI outcomes. All analyses were performed using Python 3.8.

The detailed methodological workflow is presented in **Fig. 1**. Section (a) describes the procedures for data collection and preliminary processing. Section (b) details the steps involved in constructing the predictive models. Finally, Section (c) provides a visual representation of the analysis results for intuitive interpretation.

## 3. Results

### *3.1. Participants' characteristics*

A total of 3,483 participants were included in the analysis. The sample comprised 51.1% males, 76.7% primary school students, and 62.5% urban residents. Socio-demographic and variable characteristics are presented in **Supplementary materials Table S1**. In each wave, characteristics were compared between the non-suicidal self-injury group and the non-NSSI group, and more details are provided in **Supplementary materials Tables S2–S5**. NSSI prevalence rates across the four waves were 28.0%, 25.8%, 26.3%, and 24.2%, respectively. Dynamic NSSI transitions over the four waves are illustrated using a Sankey diagram **(Fig. 2)**.

### *3.2. Features selection result*

Seventeen features were selected through a comprehensive feature selection method using elastic net regularization to construct the machine learning models. These features include suicide-related behaviors, anxiety, spirituality, delinquent behaviors, depression, externalizing problems, family dysfunction, emotional competence, father's education level, sex, academic anxiety, materialism, life satisfaction, empathy, caregiver anxiety, father's BMI, and only child status. The elastic net regularization coefficients for each selected feature are detailed in **Supplementary materials Table S6**. Pairwise correlations between the selected features are illustrated in **Supplementary materials Figure S1.**

### *3.3. Model performance and evaluation*

#### *3.3.1. Comparisons of model performance*

The random forest model consistently outperformed all other models across the three prediction windows, as shown in **Tab. 1**. This table presented the performance metrics of the seven models across the three prediction windows. In Window 1, the random forest model achieved the highest AUROC (0.843, 95% CI: 0.828–0.857) and a solid F1 score (0.629, 95% CI: 0.604–0.654). Most models showed improved performance in Window 2, with random forest again achieving the highest AUROC (0.855, 95% CI: 0.841–0.869) and F1 score (0.647, 95% CI: 0.623–0.671). In Window 3, random forest continued to demonstrate optimal performance, with an AUROC of 0.853 (95% CI: 0.839–0.869), an

AUPRC of 0.701 (95% CI: 0.672–0.730), and an accuracy of 0.817 (95% CI: 0.804–0.829). It also maintained a strong F1 score (0.631, 95% CI: 0.605–0.658). **Supplementary materials Figure S2** visually displayed the ROC curves for each model across the three prediction windows. **Supplementary materials Figure S3** illustrated the trends in AUROC and F1 score for the seven models over the three windows.

*3.3.2. SHAP Feature Importance and Interpretation*

SHAP analysis showed the top 15 features for the three prediction windows **(Fig. 3)**. Suicide-related behavior consistently ranked as the most important factor across all windows, followed by depression, delinquent behaviors, and anxiety. These four factors maintained their top positions throughout the longitudinal analysis.

The SHAP beeswarm plots demonstrated clear directional effects for different feature types. Risk factors showed positive SHAP contributions when feature values were high (red points), indicating increased NSSI risk. Protective factors demonstrated notable importance, with spirituality and emotional competence showing strong negative associations with NSSI risk. The importance of spirituality increased from Window 1 to Window 3, suggesting its growing protective influence over time. Family dysfunction and externalizing problems occupied middle-tier importance levels, while demographic factors such as father's education level and only child status showed lower but consistent importance. The ranking remained relatively stable across windows, with minor variations in mid-tier features. The SHAP trends of the features across the three windows were shown in **Supplementary materials Figure S4.**

The stacked bar charts on the right comparing NSSI and non-NSSI groups revealed distinct patterns. Participants with NSSI showed higher mean SHAP values for risk factors (suicide-related behavior, depression, anxiety, family dysfunction) and lower values for protective factors (spirituality, emotional competence, life satisfaction).

The feature dependence plots of Window 3 used the full longitudinal data, ensuring that the visualized relationships reflected the persistent dynamics of feature changes over time. The dependence plots of the top 15 features in Window 3 are displayed in **Fig. 4**. In each plot, the x-axis represents the standardized value of a given feature, and the y-axis shows the SHAP value, reflecting its impact on NSSI prediction. Each point represents one sample. The results showed that suicide-related behaviors, depression, delinquent behaviors, externalizing problems, anxiety, family dysfunction, academic anxiety, and caregiver anxiety had positive correlations with NSSI. In contrast, spirituality, emotional competence, life satisfaction, empathy, and higher father's education showed negative correlations. The only child variable displayed a categorical difference, with only children having a lower NSSI risk compared to non-only children.

SHAP interaction dependence plots were used to reveal how two features jointly interacted to influence NSSI model predictions **(Fig. 5)**. Based on the individual SHAP dependence plots, colors represented the value of the interacting feature—red for high and blue for low. The depression–anxiety interaction demonstrated synergistic effects, where combinations of high depression and high anxiety resulted in the highest NSSI risk. Low anxiety levels (blue points) clustered primarily in low depression regions, while high anxiety levels (red points) concentrated in high depression areas, indicating that these factors compounded each other's effects.

The interaction between suicide-related behavior and spirituality highlighted the moderating role of spirituality. High spirituality levels were predominantly associated with low or absent suicide-related behavior, while low spirituality values were scattered across higher levels of suicide-related behavior. The interaction between depression and emotional competence showed complementary

## 4. Discussion

This study employed ML approaches to predict NSSI among Chinese adolescents using 2.5 years of longitudinal data across four waves. There are several strengths of this study. First, longitudinal analyses based on four waves of data were employed. Second, data were collected in a non-Western context which can be used to contrast the Western studies which dominate the field. Third, machine learning approach was adopted which is a superior approach compared to the previous studies. Fourth, different machine learning models were used. Fifth, both risk as well as protective factors were considered in the model. Theoretically, the present findings can help to develop models on the risk and protective factors in NSSI. Methodologically, this study highlights the value of using machine learning approaches in identifying the factors of NSSI.

The Random Forest algorithm demonstrated superior and consistent performance across all prediction windows, achieving AUROC values ranging from 0.843 to 0.855. SHAP analysis revealed consistent patterns across all prediction windows. Suicide-related behaviors, depression, anxiety, and delinquent behaviors consistently ranked as the strongest factors. The analysis also identified important protective factors among the top 15 factors, including spirituality, emotional competence, life satisfaction, and empathy.

According to recent systematic reviews, machine learning models for NSSI prediction typically achieved AUROC values between 0.74 and 0.89 (Gao et al., 2025). The Random Forest model demonstrated robust and consistent predictive performance across all prediction windows, achieving AUROC values of 0.843, 0.855, and 0.853, respectively. Random Forest and XGBoost consistently outperformed other approaches, aligning with previous findings that ensemble methods were particularly effective for modeling complex, multifactorial NSSI data (Burke et al., 2019; Xu et al., 2024a).

Our longitudinal progressive prediction framework offered methodological advantages over the predominantly cross-sectional designs used in existing literature. While cross-sectional studies may have achieved comparable single-timepoint performance, they could not capture the temporal dynamics and developmental trajectories that our progressive windowing framework revealed (Zhong et al., 2024; Zhou et al., 2024b). The improvement from Window 1 (AUROC = 0.843) to Window 2 (AUROC = 0.855) demonstrated that accumulated longitudinal information enhanced predictive accuracy. Our multi-algorithm comparison followed best practices in machine learning applications for mental health prediction. Random Forest algorithms were particularly effective for NSSI data because they tolerated data variability and handled complex, multifactorial relationships (Burke et al., 2019). Random Forest consistently demonstrated superior performance across all temporal windows. Its capacity for feature importance ranking was compatible with SHAP analysis, making it especially valuable for longitudinal NSSI prediction. Both accuracy and clinical interpretability were essential for developing targeted interventions (Gao et al., 2025). Our findings extended this evidence by demonstrating sustained predictive accuracy across multiple longitudinal prediction windows, addressing a critical gap where most prior research relied on cross-sectional designs.

SHAP analysis revealed consistent patterns across all prediction windows, with suicide-related behaviors, depression, anxiety, and delinquent behaviors consistently ranking as the strongest factors. These findings aligned with previous machine learning studies on NSSI and suicide-related outcomes (Burke et al., 2019). Suicide-related behaviors emerged as the most influential factor due to their close interconnection with NSSI (Voss et al., 2020; Asarnow et al., 2011; Boxer, 2010). Numerous studies have found that individuals engaging in NSSI were at significantly higher risk of suicide attempts and completed suicide (Coppersmith et al., 2017; Chesin et al., 2017; Koenig et al., 2017).

However, the relationship between NSSI and suicide was complex: while NSSI might have temporarily relieved negative emotions and reduced suicidal thoughts (Klonsky, 2007; Glenn et al., 2023), it could also have increased the "acquired capability for suicide" by reducing fear of pain and death (Joiner, 2005). Although NSSI often predicted future suicide-related behaviors, longitudinal studies using cross-lagged regression showed that suicidal ideation also significantly predicted later NSSI (Xu et al., 2024b). Depression emerged as a key long-term risk factor for NSSI, aligning with prior evidence on its role in both the onset and persistence of self-injury (Valencia-Agudo et al., 2018; Guan et al., 2024; Liu et al., 2016). Our findings highlighted the frequent co-occurrence of depression and anxiety among individuals with NSSI, with SHAP analysis revealing a synergistic interaction between the two—consistent with research suggesting a distinct depression–anxiety comorbid phenotype that warranted targeted intervention (Zhou et al., 2024a). Network analyses further supported this, indicating that NSSI might have functioned both as a manifestation of depressive distress and as a mechanism to alleviate anxious tension (Guan et al., 2024). Notably, depression had a stronger predictive value than anxiety, possibly reflecting NSSI's function as a maladaptive strategy to escape pervasive negative affect, particularly sadness, hopelessness, and emotional numbness, which were core features of the depressive state (Nock, 2009). Delinquent behavior showed stable and strong contributions in our model, aligning with previous research. A meta-analysis found that problem behaviors (including bullying, smoking, and running away from home) were significantly associated with NSSI, with a pooled odds ratio of 2.36 (95% CI: 2.00–2.77). Substance abuse might have impaired adolescents' cognition, including reasoning and decision-making (Morin et al., 2019), and increased their tolerance for self-harm behaviors (Kostyrka-Allchorne et al., 2023).

Spirituality emerged as a key protective factor in our study. This concept differs from Western definitions with strong religious connotations. Instead, spirituality here is based on Shek's Chinese Positive Youth Development (CPYD) framework and is conceptualized as the pursuit of meaning, purpose, and inner fulfillment (Shek et al., 2024). Spirituality has been shown to consistently promote psychological resilience by providing inner strength and reducing problem behaviors (Shek, 2012). However, NSSI may still occur even in the presence of high spirituality, suggesting that while it is protective, a strong sense of meaning and moral values does not fully eliminate vulnerability to mental health difficulties (Ulya, 2022). Nevertheless, interventions incorporating spiritually sensitive clinical guidelines have shown promise (Dworsky et al., 2013). This finding supports building upon Positive Youth Development (PYD) theory (Zhu & Shek, 2020; Shek et al., 2019), which has proven effective in preventing and reducing NSSI among mainland Chinese adolescents. Goal setting and community participation can cultivate life meaning and purpose, while life education can enhance students' well-being and awareness of life's importance. Additionally, emotional competence emerged as a protective factor against NSSI, consistent with prior research linking emotional dysfunction to increased NSSI risk (Wolff et al., 2019). Difficulties in emotion regulation, low acceptance of emotions, and poor impulse control have been identified as key contributors. Our findings further suggest that high emotional competence may buffer the effect of depression on self-injury, highlighting its potential as a target for early intervention.

The demographic representativeness of our sample may limit the generalizability of the findings, particularly given cultural differences in NSSI risk and protective factors. Prior research has highlighted significant disparities between Western and non-Western populations in family dynamics and in the expression of psychosocial protective factors (Chen et al., 2021).

Reliance on self-report measures may have introduced bias, especially for sensitive behaviors such as NSSI. Although self-report is considered the gold standard for assessing NSSI, incorporating additional data sources, such as parent reports, clinical records, and digital biomarkers—could enhance model validity. Emerging multimodal approaches (Kline et al., 2022), including natural language processing, smartphone sensors, and social media analysis, offer promising avenues for improving prediction accuracy and clinical relevance.

The temporal prediction windows used in this study may not align with optimal intervention periods and cannot establish causal relationships. While our models performed well across multiple timeframes, tailoring prediction windows to specific intervention strategies could improve clinical utility. Short-term predictions may better support acute interventions, whereas long-term forecasts could inform preventive strategies. Finally, although SHAP analysis identified influential features, causal inference methods are needed to pinpoint modifiable risk factors with high intervention potential (Krishnadas et al., 2025).

## 5. Conclusion

This study demonstrates the effectiveness of progressive machine learning frameworks for predicting NSSI in Chinese adolescents, with the Random Forest model achieving robust performance across 2.5 years of longitudinal data. SHAP analysis identified suicide-related behaviors, depression, anxiety, and delinquent behaviors as primary risk factors, while also revealing the critical importance of Positive Youth Development elements, including spirituality, emotional competence, life satisfaction, and empathy, as protective factors. The interpretable nature of our models offers actionable insights for clinical practice and policy development. Our findings support early intervention approaches, universal screening programs, and life education initiatives. This demonstrates how longitudinal machine learning can effectively inform targeted and personalized interventions for adolescent NSSI prevention in diverse cultural contexts.

## Figures and Tables

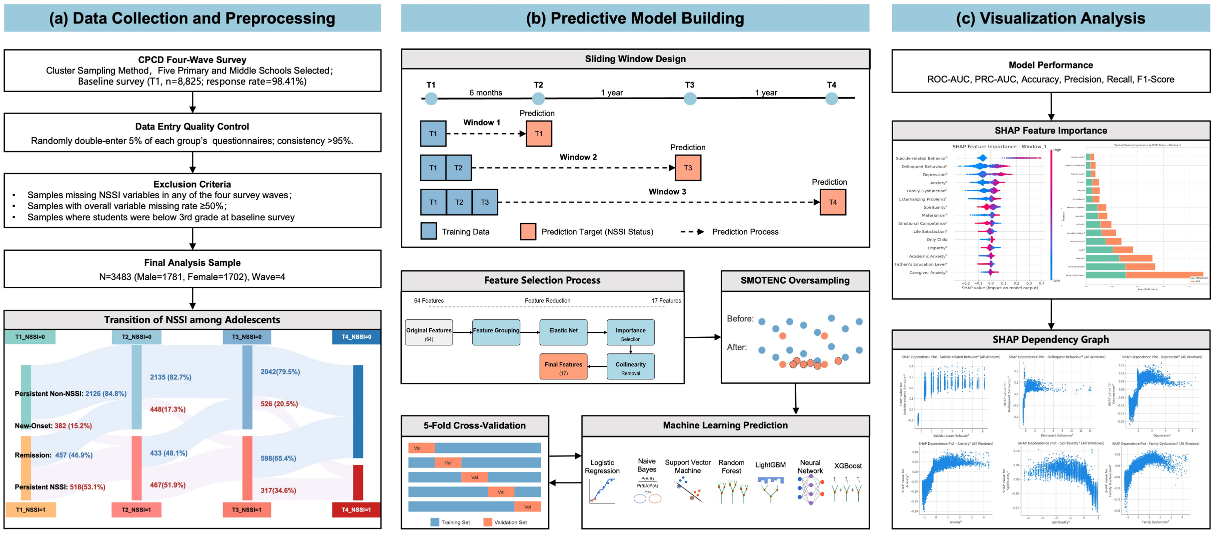


**Fig. 1.** Methodological workflow diagram.

**Notes:**
**i.** Section (a) presents the procedures for data collection and initial preprocessing.
**ii.** Section (b) outlines the construction of predictive models using Random Forest and SHAP interpretation.
**iii.** Section (c) summarizes the visualization and interpretation process of the results, emphasizing temporal dynamics and risk factor contributions.

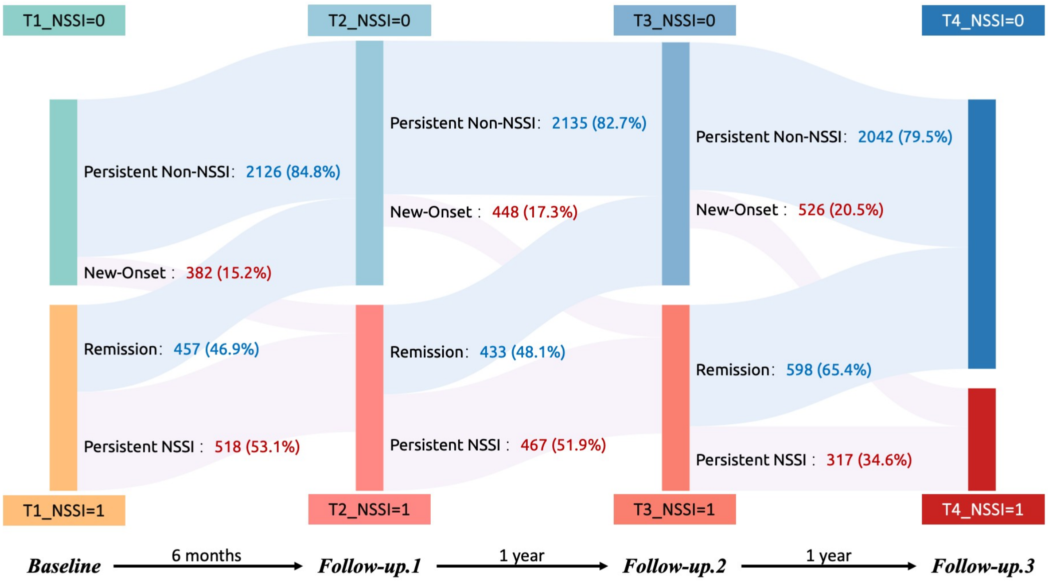


**Fig. 2.** Sankey diagram of dynamic transformation of adolescent NSSI.

**Tab.1.** Model Performance Across Prediction Windows.

| Windows | Model | AUROC (95% CI) | AUPRC (95% CI) | Accuracy (95% CI) | Precision (95% CI) | Recall (95% CI) | F1 Score (95% CI) |
|---|---|---|---|---|---|---|---|
| 1 (T1-T2) | Logistic Regression | 0.841 (0.826–0.855) | **0.691 (0.662–0.719)** | 0.788 (0.773–0.801) | 0.573 (0.545–0.602) | **0.707 (0.677–0.735)** | **0.633 (0.608–0.656)** |
| | Naive Bayes | 0.832 (0.818–0.847) | 0.673 (0.646–0.703) | 0.801 (0.788–0.814) | 0.637 (0.603–0.671) | 0.536 (0.505–0.569) | 0.582 (0.555–0.610) |
| | Random Forest | **0.843 (0.828–0.857)** | 0.672 (0.640–0.704) | 0.806 (0.792–0.818) | 0.620 (0.588–0.650) | 0.639 (0.608–0.672) | 0.629 (0.604–0.654) |
| | XGBoost | 0.830 (0.814–0.845) | 0.672 (0.642–0.702) | **0.812 (0.799–0.824)** | **0.651 (0.614–0.682)** | 0.588 (0.556–0.620) | 0.618 (0.591–0.643) |
| | LightGBM | 0.823 (0.806–0.839) | 0.657 (0.626–0.689) | 0.799 (0.785–0.812) | 0.621 (0.588–0.653) | 0.568 (0.536–0.600) | 0.593 (0.565–0.619) |
| | SVM | 0.771 (0.751–0.789) | 0.545 (0.508–0.582) | 0.759 (0.744–0.773) | 0.531 (0.500–0.561) | 0.579 (0.547–0.612) | 0.554 (0.528–0.580) |
| | Neural Network | 0.782 (0.764–0.798) | 0.587 (0.554–0.621) | 0.752 (0.737–0.766) | 0.516 (0.487–0.546) | 0.634 (0.604–0.666) | 0.569 (0.545–0.595) |
| 2 (T1T2-T3) | Logistic Regression | 0.843 (0.828–0.857) | **0.712 (0.684–0.741)** | 0.780 (0.767–0.794) | 0.562 (0.535–0.590) | **0.741 (0.714–0.771)** | 0.639 (0.617–0.664) |
| | Naive Bayes | 0.837 (0.821–0.852) | 0.696 (0.667–0.724) | **0.821 (0.808–0.833)** | **0.732 (0.699–0.768)** | 0.499 (0.468–0.530) | 0.594 (0.566–0.622) |
| | Random Forest | **0.855 (0.841–0.869)** | 0.710 (0.682–0.740) | 0.809 (0.795–0.822) | 0.628 (0.599–0.658) | 0.668 (0.638–0.698) | **0.647 (0.623–0.671)** |
| | XGBoost | 0.849 (0.835–0.863) | 0.709 (0.681–0.737) | 0.818 (0.805–0.830) | 0.664 (0.632–0.697) | 0.621 (0.591–0.654) | 0.641 (0.616–0.667) |
| | LightGBM | 0.846 (0.832–0.861) | 0.707 (0.679–0.735) | 0.810 (0.796–0.822) | 0.648 (0.615–0.680) | 0.604 (0.572–0.633) | 0.626 (0.600–0.650) |
| | SVM | 0.789 (0.772–0.808) | 0.596 (0.565–0.630) | 0.766 (0.752–0.780) | 0.546 (0.520–0.577) | 0.647 (0.616–0.679) | 0.592 (0.570–0.620) |
| | Neural Network | 0.793 (0.775–0.812) | 0.635 (0.605–0.670) | 0.761 (0.747–0.775) | 0.538 (0.511–0.568) | 0.637 (0.608–0.667) | 0.583 (0.560–0.610) |
| 3 (T1T2T3-T4) | Logistic Regression | 0.845 (0.830–0.862) | 0.690 (0.660–0.722) | 0.796 (0.783–0.810) | 0.565 (0.535–0.598) | 0.689 (0.659–0.721) | 0.621 (0.595–0.649) |
| | Naive Bayes | 0.833 (0.817–0.849) | 0.662 (0.630–0.695) | **0.817 (0.804–0.829)** | **0.679 (0.641–0.718)** | 0.465 (0.434–0.498) | 0.552 (0.523–0.581) |
| | Random Forest | **0.853 (0.839–0.869)** | **0.701 (0.672–0.730)** | **0.817 (0.804–0.829)** | 0.617 (0.586–0.651) | 0.645 (0.615–0.678) | 0.631 (0.605–0.658) |
| | XGBoost | 0.843 (0.829–0.859) | 0.677 (0.647–0.710) | 0.796 (0.783–0.809) | 0.566 (0.535–0.598) | 0.681 (0.650–0.713) | 0.618 (0.591–0.644) |
| | LightGBM | 0.844 (0.829–0.861) | 0.684 (0.654–0.715) | 0.800 (0.786–0.813) | 0.570 (0.540–0.601) | **0.708 (0.678–0.740)** | **0.632 (0.606–0.658)** |
| | SVM | 0.776 (0.757–0.796) | 0.552 (0.514–0.589) | 0.765 (0.750–0.780) | 0.512 (0.480–0.545) | 0.595 (0.562–0.632) | 0.550 (0.522–0.580) |
| | Neural Network | 0.773 (0.756–0.793) | 0.608 (0.575–0.640) | 0.742 (0.728–0.757) | 0.475 (0.446–0.506) | 0.632 (0.600–0.668) | 0.542 (0.515–0.569) |

**Notes:**
i. Window 1: T1–T2 each model evaluation.
ii. Window 2: T1T2–T3 each model evaluation.
iii. Window 3: T1T2T3–T4 each model evaluation.

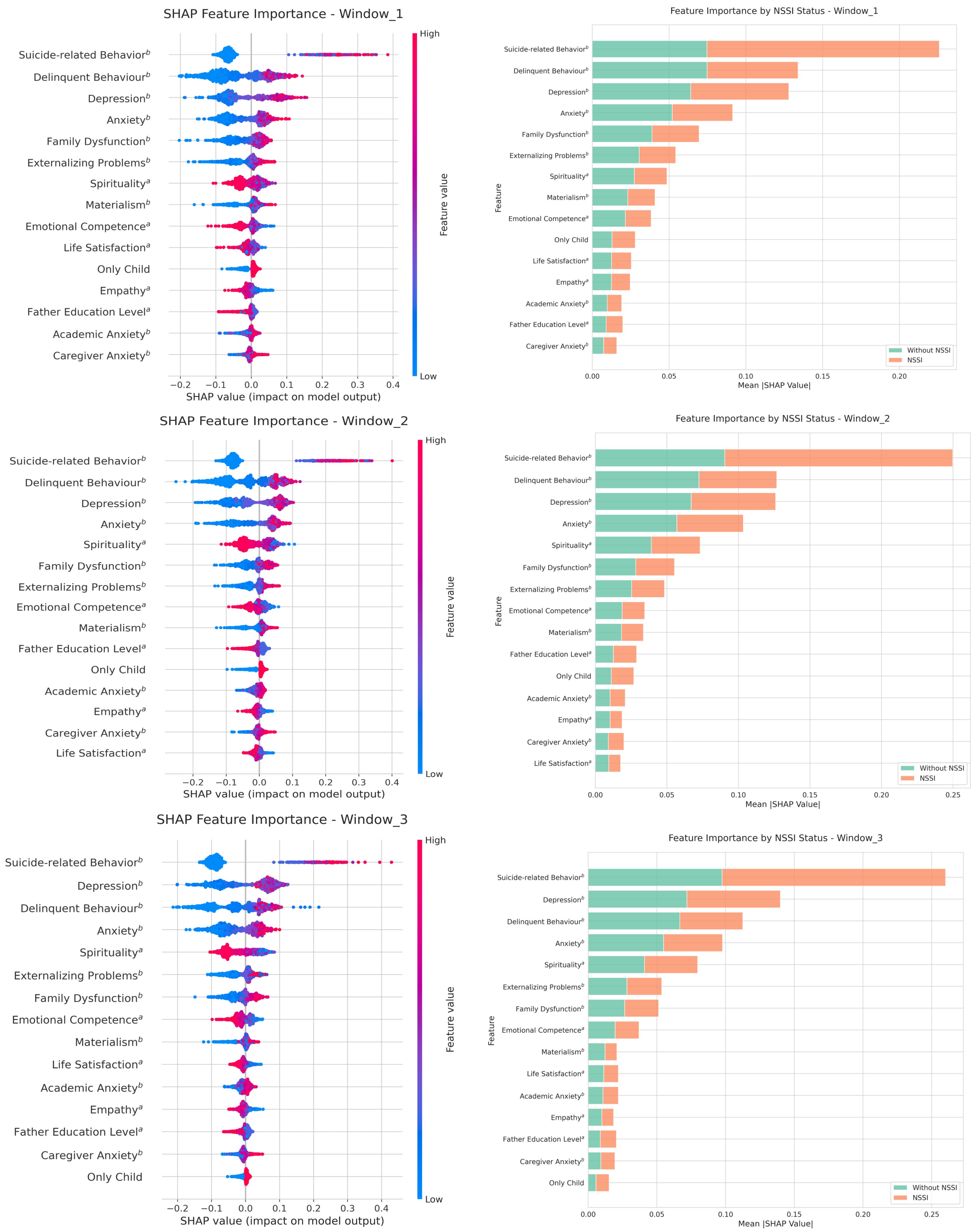


**Fig. 3.** SHAP feature importance of 3 windows

**Notes:**

i. "a" Higher scores indicate more favorable outcomes.

ii. "b" Lower scores indicate more favorable outcomes.

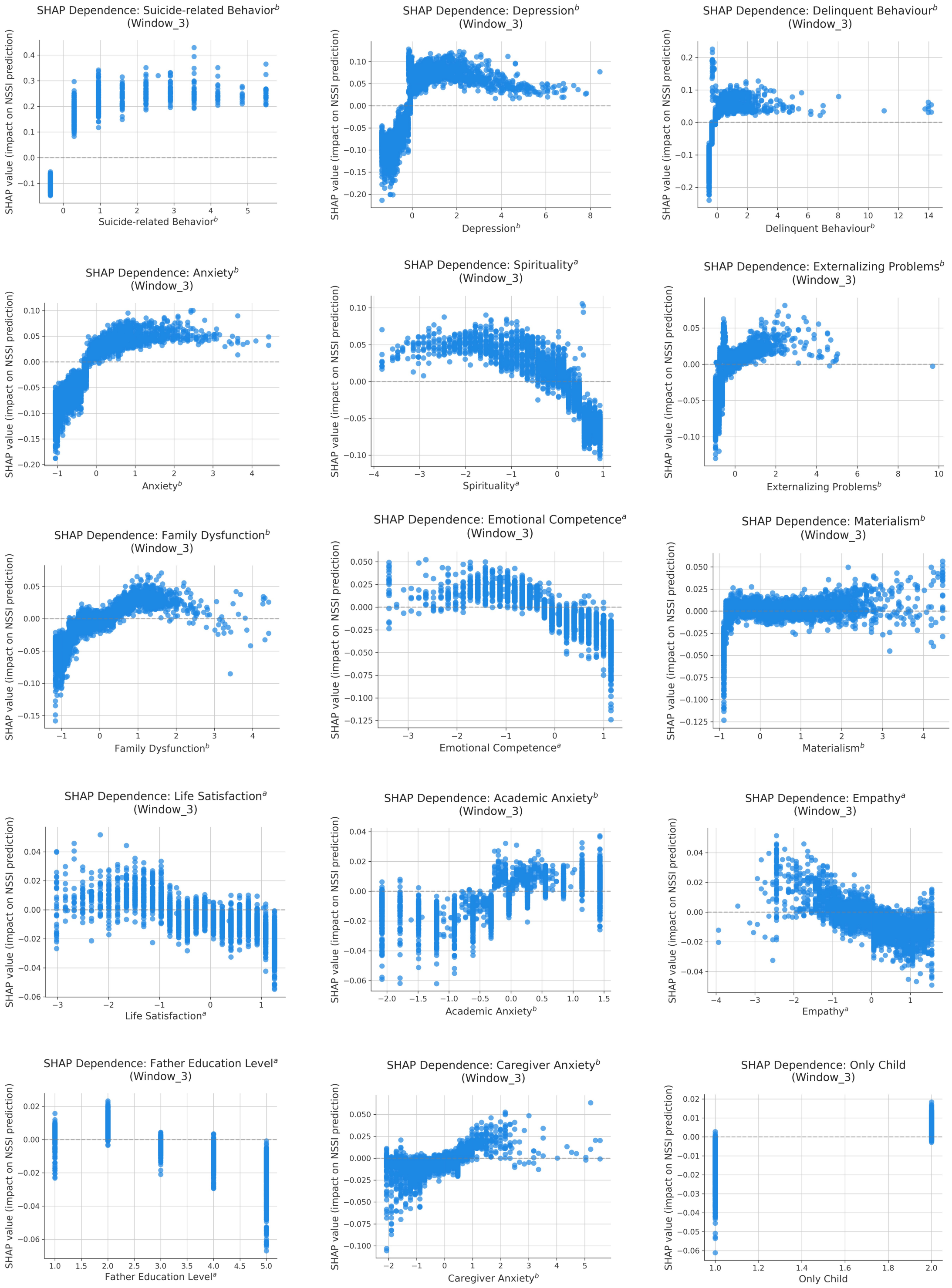


**Fig. 4.** SHAP independence plots for top 15 features.

**Notes:**

i. The horizontal axis represents the standardized feature scores, and the vertical axis represents SHAP values, indicating the contribution to the outcome.

ii. In the labels of the pictures, “a” means the higher the score, the more beneficial it is to people, and “b” means the lower the score, the more beneficial it is to people.

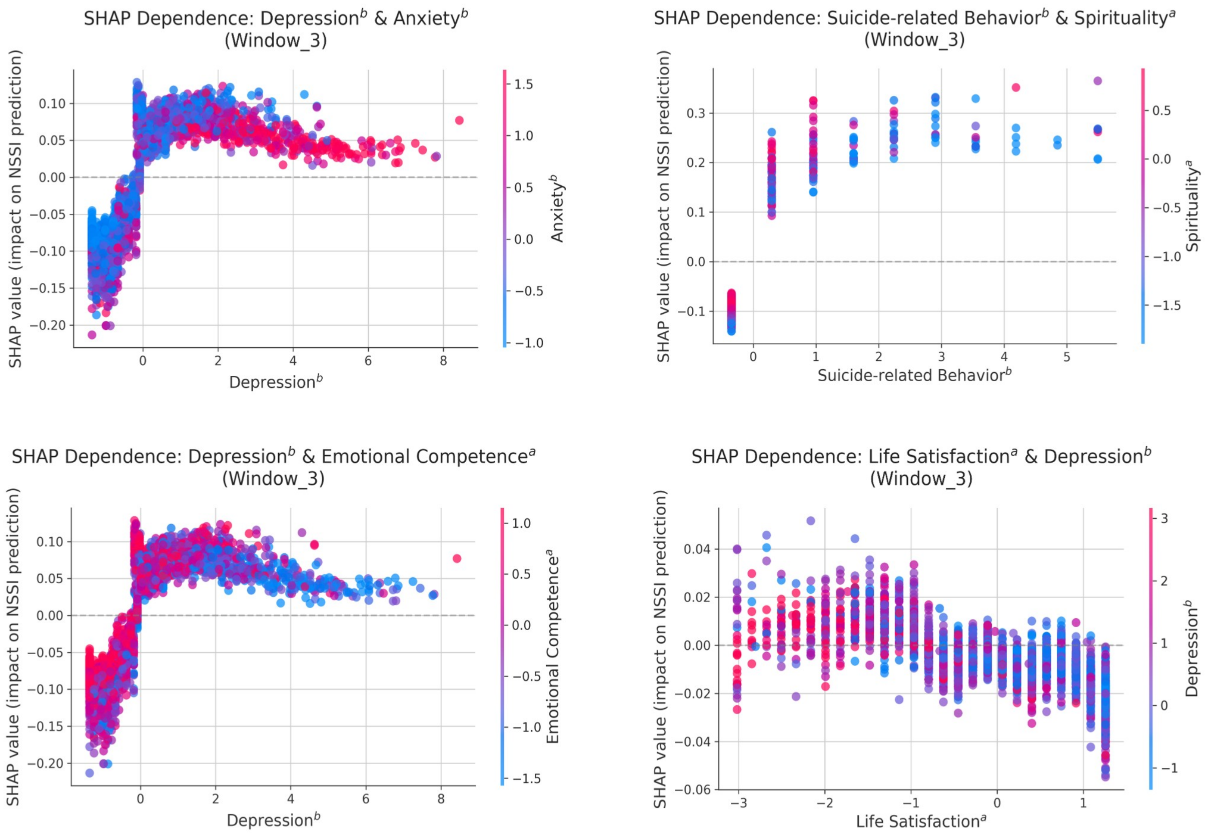


**Fig. 5.** SHAP interaction independence plots of partial features.

**Notes:**

i. The color represents the value of the second feature that is not on the x-axis, red indicates high values and blue indicates low values.

ii. "a" means the higher the score, the more beneficial it is to people, and "b" means the lower the score, the more beneficial it is to people.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Data sharing

The datasets generated and/or analyzed during this study are not publicly available due to the sensitive nature of the data, such as involving human participants. However, anonymized data may be available from the corresponding author upon reasonable request.

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