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Research paper

Prediction of first attempt of suicide in early adolescence using machine learning

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ABSTRACT

Background: Suicide is the second leading cause of death among early adolescents, yet the first onset of suicide attempts during this critical developmental period remains poorly understood. This study aimed to identify key characteristics associated with the first suicide attempt in early adolescence and to develop a predictive model for assessing individual risk.

Methods: We used data from the Adolescent Brain Cognitive Development Study, a longitudinal, population-based study in the US. The analysis focused on a cohort of 4,238 early adolescents (aged 11–12 years) who had no prior history of suicide attempts. To predict the onset of a first suicide attempt over the subsequent two years (2020–2022), we developed an extremely randomized tree model, incorporating 87 potential predictors from diverse bio-psycho-social domains pertinent to adolescent development.

Results: Among the 4,238 adolescents, 163 (3.8%) reported their first suicide attempt within the subsequent two years. Our predictive model demonstrated good discriminative ability, achieving an AUC of 0.82 (95% CI [0.79, 0.85]), with a sensitivity of 0.82 and a specificity of 0.69 at the optimized threshold. Key predictors included sex assigned at birth, sexual orientation, negative affect, internalizing and attention problems, and lifetime suicidal ideation, along with other significant factors from multiple domains.

Conclusions: These findings highlight the utility of machine learning algorithms in identifying predictors of suicide attempts among early adolescents. The insights gained from this study may contribute to the development of tailored screening tools and preventive interventions aimed at mitigating suicide risk in this vulnerable population.

1. Introduction

Suicide is the second leading cause of death among adolescents (CDC, 2022). According to the U.S. Centers for Disease Control and Prevention, the suicide mortality rate within this age group increased by 52.2% from 2000 to 2021, reaching an estimated rate of 11 per 100,000 in 2021 (CDC, 2022). Preventing the first suicide attempt is of vital importance, as approximately 70% of suicide deaths among adolescents occur during the first attempt (Bostwick et al., 2016). Furthermore, a suicide attempt during adolescence is associated with a significantly heightened risk of subsequent psychosocial dysfunction across various domains and is a strong predictor of future attempts (Franklin et al., 2017; Goldman-Mellor et al., 2014; Orri et al., 2022; Spirito et al., 2000), hindering healthy development.

Specifically, the incidence of suicidal behaviors begins to rise alarmingly in early adolescence (Nock et al., 2008; Nock et al., 2013; Voss et al., 2019). Early adolescents face unique developmental challenges compared to their mid or late adolescent peers (Caskey and Anfara Jr, 2007; Christie and Viner, 2005; Hamburg, 1985). The onset of puberty coincides with significant changes in educational environments (Miller and Prinstein, 2019), introducing both internal and external pressures. Furthermore, early adolescents are in the process of forming their identities and peer relationships while still developing their ability to manage social stress (Miller and Prinstein, 2019). These developmental challenges, combined with the internal struggle to regulate emotions, leave them vulnerable to intense negative experiences that

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can trigger suicidal behaviors (Kranzler et al., 2016; Lawson et al., 2022; Stein et al., 1998).

Despite this heightened vulnerability, few studies have specifically focused on this critical developmental period. Most studies tend to group early adolescents with the broader adolescent population (Carballo et al., 2020), overlooking the unique challenges youth of this phase may face. To the best of our knowledge, only a limited number of studies have investigated risk factors for suicide attempts in early adolescence. Fotti and colleagues found that depression and poor peer and parental relationships were significantly associated with suicide attempts in a cross-sectional sample of 12- to 13-year-olds (Fotti et al., 2006). Prospective studies have identified various risk factors, including psychopathology (Kelleher et al., 2013; Larsson and Sund, 2008; Ortin et al., 2019; Vander Stoep et al., 2011), recurrent suicidal ideation (Vander Stoep et al., 2011), poor somatic health (Larsson and Sund, 2008), early physical maturity (Larsson and Sund, 2008), poor self-esteem (Larsson and Sund, 2008; Martin et al., 2005), parental conflicts (Larsson and Sund, 2008), poor school adaptation (Larsson and Sund, 2008), peer victimization (Geoffroy et al., 2016), and negative life events (Larsson and Sund, 2008), while family cohesion has been identified as a protective factor (McKeown et al., 1998).

However, these studies have significant methodological limitations. Importantly, none of these studies distinguished between the first onset and recurrence of suicide attempts, despite evidence that the mechanisms behind these behaviors may differ (Abascal-Peiró et al., 2023; Ezquerra et al., 2023; Mendez-Bustos et al., 2013). Additionally, each of these studies focused on a limited set of risk factors. This contrasts with the current emphasis on the complexity of contributing factors to suicide behaviors and fails to provide a comprehensive characterization of early adolescents at risk (Franklin et al., 2017; O'Connor and Nock, 2014). Moreover, the reliance on traditional statistical methods (e.g., logistic regression) often restricts these studies from exploring non-linear relationships and interactions among variables. Emerging research advocates for the use of advanced analytical techniques, such as machine learning, to better capture the complexities of these interrelated risk factors and their potential non-linear relationships with suicide attempts, ultimately improving the identification of early adolescents at risk of suicide attempts (Burke et al., 2019; Franklin et al., 2017; Linthicum et al., 2019).

Using data from a large U.S. population-based longitudinal study, this study aims to identify key factors prospectively associated with the first onset of suicide attempts in early adolescence. Our investigation encompasses a broad range of characteristics in early adolescents (aged 11–12 years), covering diverse bio-psycho-social aspects pertinent to their development. We employed a machine learning approach to capture complex patterns and interactions among these factors, while effectively addressing the challenge of class imbalance resulting from the low incidence of suicide attempts. To the best of our knowledge, this is the first study to investigate factors associated with the first suicide attempt in early adolescence.

2. Methods

2.1. Sample

Data were drawn from the Adolescent Brain Cognitive Development (ABCD) study, the largest longitudinal, population-based study of brain development and adolescent health in the United States. The study recruited 11,880 pre-adolescents, all aged 9–10 years, from 21 research sites across the country between 2016 and 2018. Participants are scheduled to be assessed annually for non-imaging data and biannually for imaging and bioassays over a span of 10 years.

This study utilized data from the ABCD Study Curated Annual Release 5.1, covering the period from baseline to the 4-year follow-up (2016–2022). As the 4-year follow-up assessments were still ongoing when the data were frozen for this release, only 4,754 participants who had completed these assessments were included. To focus on early adolescence while ensuring access to a broader range of measures—such as more comprehensive mental health assessments (e.g., impulsivity and BIS/BAS) at the 2-year follow-up compared to the 1-year or 3-year follow-ups—we restricted our analysis to adolescents who were 11–12 years old at the 2-year follow-up. Moreover, as we aimed to examine factors associated with a first suicide attempt, we included only adolescents who had not reported any suicide attempts prior to this time point, resulting in a final sample of 4,238. The participant selection procedure is illustrated in Fig. 1.

2.2. Measures

2.2.1. Outcome variable

Suicide attempts were self-reported annually by youths using the computerized Kiddie Schedule for Affective Disorders and Schizophrenia for DSM-5 (K-SADS-5). At each yearly assessment, youths who reported any form of present or past suicidal behaviors—including preparatory actions toward imminent suicidal behavior, aborted attempts, interrupted attempts, and actual suicide attempts—were classified as having endorsed a lifetime suicide attempt. Participants without a lifetime suicide attempt by the 2-year follow-up but developed one between the 2-year and 4-year follow-ups (aged 11–14 years) were identified as the first-onset group (n = 163). Those who did not develop a suicide attempt across all waves were assigned to the never-onset group (n = 4,075). The characteristics of both the first-onset and never-onset groups are detailed in Table 1.

2.2.2. Predictor variables

Based on previous literature regarding risk factors for suicidal thoughts and behaviors (Ati et al., 2021; Carballo et al., 2020; Cha et al., 2018; Fotti et al., 2006; Franklin et al., 2017; Geoffroy et al., 2016; Kelleher et al., 2013; Larsson and Sund, 2008; Martin et al., 2005; McKeown et al., 1998; Ortin et al., 2019; Vander Stoep et al., 2011), we selected a total of 87 predictors covering eight domains: demographics, physical health, gender identity and sexual development, disposition, psychopathology, developmental history, social environment, and cognitive functioning. Detailed definitions and assessments of each predictor are provided in Table S1 (see Fig. S1 for a visualization of the relationships between predictor variables and the suicide attempt outcome). The majority of these predictors were evaluated using data from the 2-year follow-up, with a few exceptions noted below.

First, demographic variables, specifically sex assigned at birth and race/ethnicity, were obtained from baseline data to ensure completeness. Second, variables related to developmental history were also

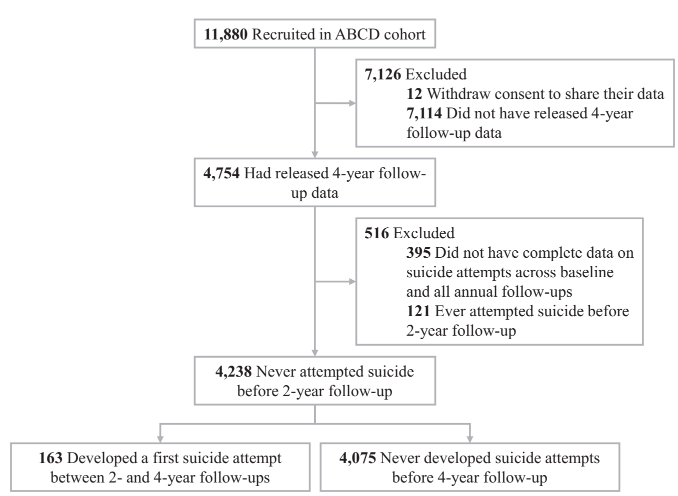

Fig. 1. Study flowchart for the participant selection process.

Table 1
Characteristics of the first-onset and the never-onset groups.

Characteristics	First-onset group (n = 163)	Never-onset group (n = 4075)	*p*-Value
Sex, n (%)			<0.001
Male	41 (25.2)	2188 (53.7)	
Female	122 (74.8)	1887 (46.3)	
Race/ethnicity, n (%)			0.037
White	89 (54.6)	2345 (57.5)	
Black	9 (5.5)	421 (10.3)	
Hispanic	36 (22.1)	819 (20.1)	
Asian	3 (1.8)	97 (2.4)	
Other	26 (16.0)	393 (9.6)	
Grade, mean (SD)[a]	6.4 (0.7)	6.3 (0.8)	0.012
Pubertal development, mean (SD)[b]	3.1 (0.8)	2.6 (1.0)	<0.001
Sexual orientation (gay or bisexual), n (%)			<0.001
No	113 (69.3)	3673 (90.1)	
Maybe	21 (12.9)	124 (3.0)	
Yes	25 (15.3)	94 (2.3)	
Unknown	4 (2.5)	184 (4.5)	
Lifetime suicidal ideation, n (%)	59 (36.2)	555 (13.6)	<0.001
Lifetime non-suicidal self-injury, n (%)	36 (22.1)	396 (9.7)	<0.001

[a] Youth's grade in the fall: 0 = kindergarten; 1 = 1st grade; 2 = 2nd grade; 3 = 3rd grade; 4 = 4th grade; 5 = 5th grade; 6 = 6th grade; 7 = 7th grade; 8 = 8th grade; 9 = 9th grade; 10 = 10th grade; 11 = 11th grade; 12 = 12th grade.
[b] Assessed with Pubertal Developmental Scale, youth report: 1 = prepuberty; 2 = early puberty; 3 = mid puberty; 4 = late puberty; 5 = post puberty.

derived from baseline assessments. This approach was justified by two reasons. First, these variables were not reassessed at the 2-year follow-up. Second, they represent inherently stable characteristics that remain constant over time. Lastly, lifetime suicidal ideation and non-suicidal self-injury at the 2-year follow-up were determined synthesizing K-SADS-5 diagnostic information at baseline, 1-year and 2-year follow-ups.

2.3. *Statistical analysis*

2.3.1. *Extremely randomized trees approach*

We used an Extremely Randomized Trees (Extra-Trees) algorithm (Geurts et al., 2006), a tree-based ensemble method for supervised classification and regression problems, for building the prediction model of suicide attempts. By incorporating a heightened level of randomness during the training phase, this method notably reduces its susceptibility to overfitting—a common limitation observed in other tree-based models (Geurts et al., 2006; Goetz et al., 2014; Pagliaro, 2023). The Extra-Trees also has the advantages of high accuracy, computational efficiency, and robustness, and has demonstrated exceptional diagnostic performance in the prediction of psychiatric disorders (Gibbons et al., 2022; Gopalakrishnan et al., 2022), as well as other medical conditions (Goetz et al., 2014; Haak et al., 2022; Mathew, 2022).

We implemented the Extra-Trees model using the "ExtraTreesClassifier" from the scikit-learn package in Python (version 3.8.16) (Pedregosa et al., 2011). To tackle the issue of class imbalance, we utilized the class weight parameter in the model. The "balanced" mode automatically adjusts the importance of classes based on their frequency in the data. By doing so, we were able to weigh the minority class and reduce prediction bias toward the majority class.

2.3.2. *Model development*

To develop and validate our model, we employed a nested cross-validation approach (Stone, 1974; Varma and Simon, 2006)—an established and robust method for assessing machine learning performance while minimizing the risk of overfitting from hyperparameter tuning. This approach involves two levels of cross-validation: an outer loop for evaluating model performance and an inner loop for tuning hyperparameters (see Fig. 2).

In the outer loop, the dataset was divided into five stratified folds to maintain consistent incidence rates across all subsets. Each fold served once as the test set, while the remaining four were used for training. Stratification ensured that class distributions remained similar between training and test sets.

After splitting the data, we addressed missing values using single imputation methods (Ruiz-Rizzo et al., 2022). Specifically, for numeric predictors, we imputed missing values in both the training and test datasets using the mean calculated only from the training dataset. Similarly, in the case of categorical predictors, the most frequent values of the training data were utilized for imputation. This method was selected for two primary reasons (Lavelle-Hill et al., 2023). First, by splitting the data before imputation, it effectively prevents any potential data leakage, ensuring that the model trained does not accidentally learn from the test data. Second, the imputation method employed resembles the real-world clinical practices more closely, where missing values are typically handled based on prior knowledge rather than estimated using descriptive statistics of new data. In sum, this method of imputation after splitting the data, as opposed to before, safeguards the integrity and generalizability of the model.

Within each iteration of the outer loop, an inner cross-validation loop was conducted on the training set. The training data were further split into three stratified folds, with two used for training and one for validation. A grid search was performed to explore combinations of two hyperparameters: the number of trees in the forest and the maximum depth of each tree. The optimal hyperparameter set was defined as the one achieving the highest average out-of-fold area under the receiver operating characteristic curve (AUC).

Finally, using the optimal hyperparameters from the inner loop, we trained the model on the full training set and evaluated it on the corresponding outer test set. This process was repeated five times, ensuring each fold in the outer loop served once as the test set.

2.3.3. *Model evaluation*

The model's generalizability was assessed by evaluating its performance on the test dataset using various performance metrics (Burke et al., 2019; Navarro et al., 2021), including AUC, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV). The AUC, ranging from 0.5 (indicating random prediction) to 1 (indicating perfect prediction), measures the model's discrimination capacity. Given the significant class imbalance in our dataset, we also computed sensitivity, specificity, PPV, and NPV to better understand the proportion of correctly classified cases within each actual and predicted class. Additionally, we calculated 95% confidence intervals for the AUC score using Delong's method (DeLong et al., 1988), implemented in R (version 4.3.1) with the pROC package. This further strengthens the reliability of our evaluation of the model's discriminative power.

2.3.4. *Predictor importance*

Predictor importance was calculated through permutation importance (Altmann et al., 2010), a method where each feature's values in the test dataset are randomly permuted to observe the resulting decline in the model's performance. The choice of permutation importance over impurity-based feature importance is justified for two key reasons. Firstly, impurity-based measures tend to display a bias toward features with a larger number of distinct values (high cardinality). Such bias can inflate the estimated importance of certain features while diminishing that of others, leading to inaccurate conclusions about their contributions to the prediction model. Secondly, because impurity-based importance is derived from training data, there's a risk that the estimation could be skewed by model overfitting. Permutation importance, on the other hand, is calculable using the test dataset. This approach provides a reliable estimate of feature importance, particularly in enhancing model generalization.

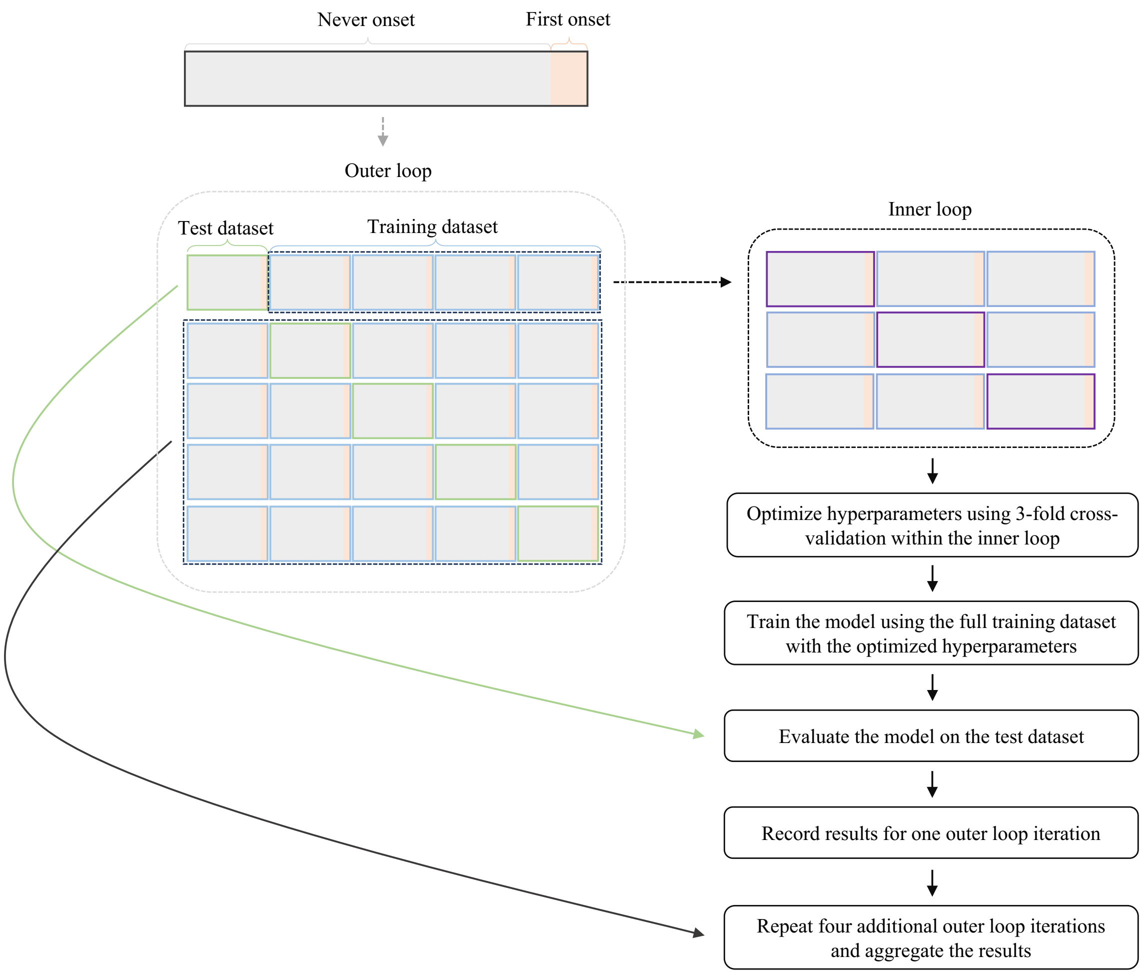

Fig. 2. The nested cross-validation procedure for model development and validation.

3. Results

3.1. Prevalence of first suicide attempt and lifetime suicidal ideation/non-suicidal self-injury

In the current study, we identified a cohort of 4,238 early adolescents who reported no prior suicide attempts at the 2-year follow-up. Within this group, 415 participants (9.8%) reported a history of suicidal ideation in the absence of non-suicidal self-injury, while 233 participants (5.5%) reported a history of non-suicidal self-injury without experiencing suicidal ideation. Additionally, 199 participants (4.7%) had a history of both suicidal ideation and non-suicidal self-injury. Between the 2-year and 4-year follow-ups, 163 participants (3.8%) reported their first suicide attempt.

3.2. Model discrimination

The prediction model demonstrated good discriminative ability for the first onset of suicide attempts between the 2-year and 4-year follow-ups. The AUC on the test dataset was 0.82, with a 95% confidence interval (CI) ranging from 0.79 to 0.85, as illustrated by the receiver operating characteristic (ROC) curve in Fig. 3.

When using a default risk threshold of 0.5, the model exhibited a sensitivity of 0.63 and a specificity of 0.83. This configuration yielded a PPV of 0.13 and an NPV of 0.98. After employing Youden index to identify the optimal threshold of 0.46 (Youden, 1950), sensitivity improved to 0.82 and specificity went down to 0.69, accompanied by a PPV of 0.10 and an NPV of 0.99. These outcomes align with previous research findings that utilize machine learning approaches to detect suicide attempts among adolescents (McHugh et al., 2023; Su et al., 2020; Su et al., 2023).

3.3. Predictor importance

The importance of each predictor was first estimated using the permutation method on the test dataset within the outer loop, and the final importance scores were obtained by averaging across iterations. Fig. 4 shows the top 20 variables critical to the performance of the prediction model. Notably, sex assigned at birth emerged as the most significant predictor, followed by sexual orientation, negative affect as measured by the Early Adolescent Temperament Questionnaire (EATQ), internalizing problems as measured by the Brief Problem Monitor (BPM) Scale, lifetime suicidal ideation, attention problems as measured by the BPM Scale, bully victimization, school disengagement as measured by the PhenX School Risk & Protective Factors, pubertal development, and the number of psychotic symptoms as measured by the Prodromal Psychosis Scale. Additionally, these top 20 predictors span a diverse range of domains, highlighting the complex and multifaceted nature of the first onset of suicide attempts.

To better understand the direction of associations, we conducted post hoc analyses using univariate logistic regression for the top 20 predictors. The corresponding results are provided in Supplementary Table S2. To further substantiate our findings, we computed impurity-based feature importance—first estimated on the training data within the outer loop and then averaged across iterations—and employed an L2-regularized logistic regression model as a comparative reference. The

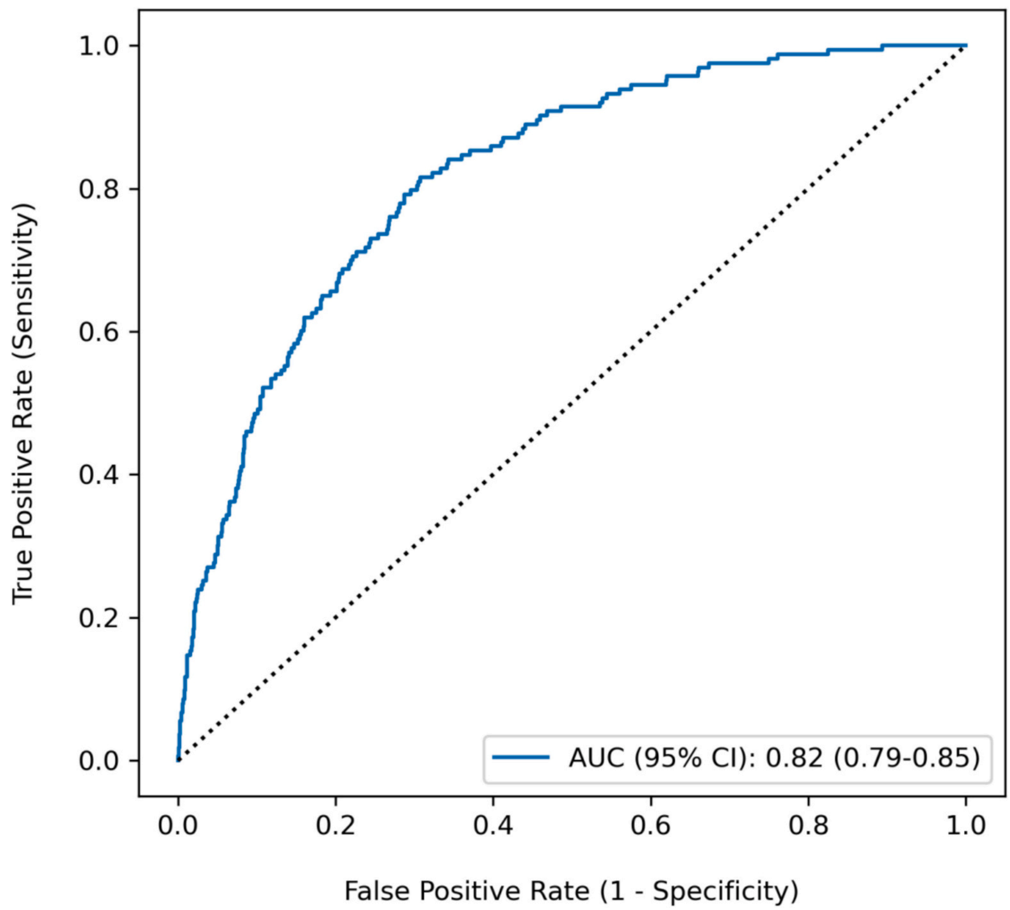

Fig. 3. ROC curve for predicting the first suicide attempt in the test dataset.

top predictors identified through permutation importance demonstrated strong concordance with those prioritized by impurity-based importance and by the absolute magnitudes of standardized coefficients from the regularized model, indicating a high degree of agreement across modeling approaches (see Supplementary Figs. S2–S3).

4. Discussion

To the best of our knowledge, this study is the first to investigate factors prospectively associated with the first onset of suicide attempts in early adolescence. We observed a two-year incidence rate of 3.8% for the first suicide attempt. By employing a machine learning algorithm, our analysis demonstrated good discriminative ability in predicting the individual risk of developing a first suicide attempt. The algorithm highlighted sex assigned at birth as the most influential factor, followed by sexual orientation, trait negative affect, internalizing problems, and lifetime suicidal ideation. Additionally, the top 20 predictors for the first onset of suicide attempts encompassed variables across various domains, including demographics, psychopathology, disposition, physical health, gender identity and sexual development, social environments, and cognitive functioning. This diversity of predictors underscores the complexity of the factors predisposing individuals to suicide attempts. When evaluating multiple risk factors together, developmental history played a limited role compared to other risk domains.

Our model demonstrated strong predictive performance, achieving a test AUC of 0.82 (95% CI [0.79, 0.85]), consistent with expectations. This result aligns closely with findings from a systematic review by Bernert et al. (2020), which reported an average highest AUC of 0.81 (SD = 0.09; 95% CI [0.76, 0.87]) across machine learning studies predicting suicide attempts. Despite this favorable performance, the model exhibited relatively low PPV and specificity, indicating a high rate of false positives—an issue commonly observed in predictive models applied to low-incidence populations (Belsher et al., 2019). Additionally, the task of prospectively predicting first-onset suicide attempts further reduced model precision. Prior research has shown that when predictive models are developed for both general suicide attempts and first-onset subgroups, the latter consistently yields a significantly lower AUC (Macalli et al., 2021). These findings highlight the need for a more nuanced understanding of the underlying mechanisms driving suicidal behaviors to improve preventive measures.

Among all predictors, sex assigned at birth emerged as the most important factor in our prediction model. Previous studies utilizing baseline data from the ABCD cohort have indicated a heightened risk of lifetime suicidal behaviors among male children aged 9–10 years (Harman et al., 2021; Janiri et al., 2020; Wen et al., 2023). In contrast, our results showed that early adolescent girls (aged 11–14 years) faced a threefold higher risk of initiating suicide attempts compared to boys. This observation is consistent with Ortin et al. (2019), who found a higher 12-month prevalence of suicide attempts among girls starting from age 11, but not at age 10. The increased risk of suicide attempts in early adolescent girls suggests that developmental changes render them more vulnerable during this period. Girls in this age group often experience greater emotional and interpersonal distress than boys, along with unstable self-concept and a potential decline in self-esteem (Galambos, 2004; Hill and Lynch, 1983; Simmons et al., 1979). These factors may contribute to their heightened vulnerability, necessitating further research to elucidate the specific underlying mechanisms.

Our study underscores the significant role of sexual orientation in predicting suicide attempts, with sexual minority adolescents exhibiting a higher risk for the onset of such behaviors. This elevated risk is

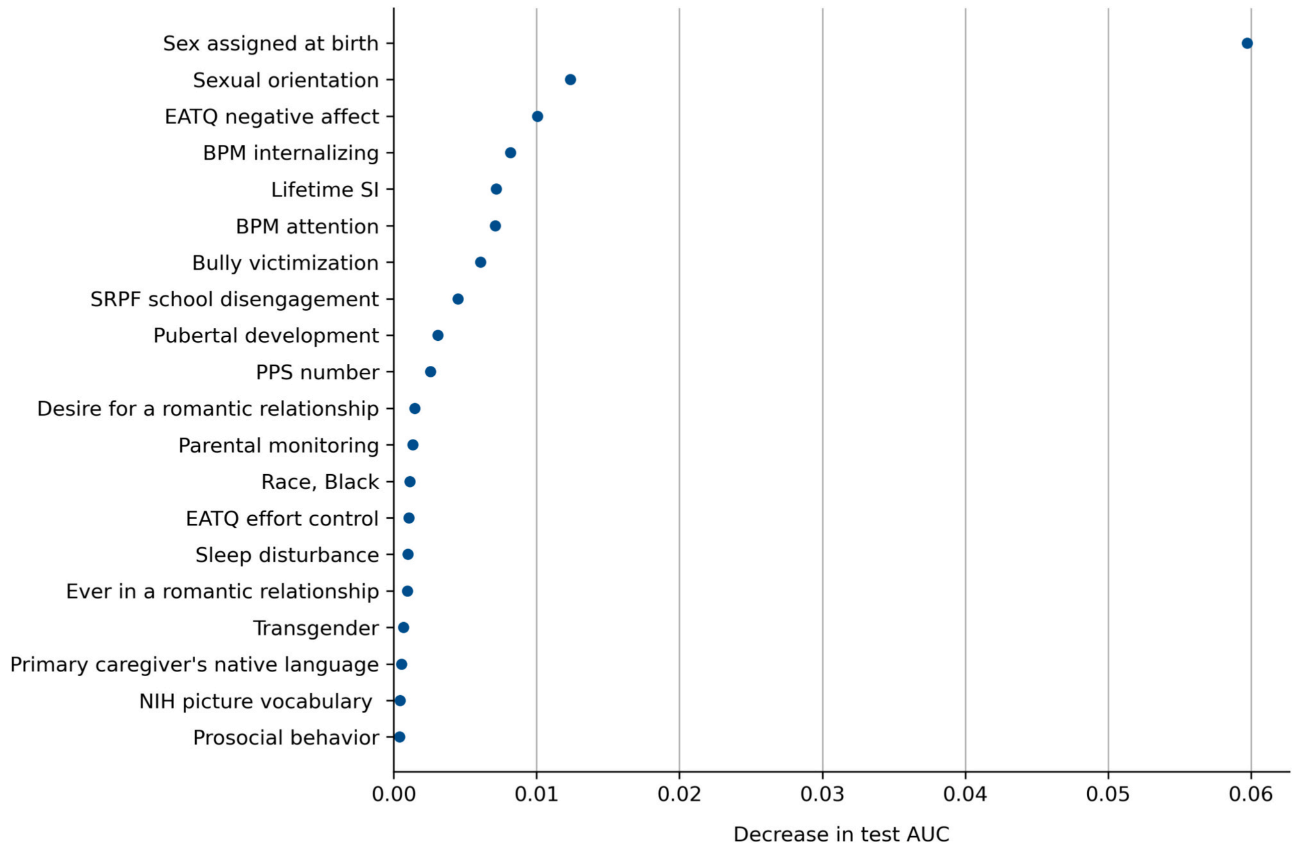

Fig. 4. Predictor importance identified by the algorithm predicting the first suicide attempt. EATQ: Early Adolescent Temperament Questionnaire; BPM: Brief Problem Monitor Scale; SRPF: PhenX School Risk & Protective Factors; PPS: Prodromal Psychosis Scale.

consistent with findings from a population-based longitudinal cohort study of 1,771 adolescents (Luk et al., 2021), which reported that sexual minority youth faced greater lifetime risks of suicide ideation, planning, and attempts. Moreover, the association between sexual minority status and the onset of suicide attempts was found to be stronger before age 15 compared to after. These results point to a critical need for targeted attention toward early adolescents who are beginning to explore and understand their sexual identity and attractions. During this developmental stage, the desire for peer acceptance is particularly strong, and minority status may lead to internal conflict and external stressors, including social exclusion and perceived deviation from normative expectations (Pachankis and Jackson, 2023). Notably, adolescents who reported uncertainty about their sexual orientation were also found to be at heightened risk, highlighting the importance of comprehensive education and the provision of inclusive, affirming support systems for all youth navigating these experiences.

Building on a broader developmental context of early adolescence, pubertal development also played a key role in this process. Youths in the first-onset group were more likely to be in later stages of pubertal maturation. This finding aligns with Larsson and Sund (2008), who found that early adolescents who attempted suicide tended to be more physically mature than their peers. Early maturation may create a mismatch between adolescents' physical development and their emotional and cognitive development, prematurely exposing them to adult social norms and expectations (Galambos, 2004; Susman and Rogol, 2004). This imbalance can increase vulnerability to psychological distress and mental health challenges.

Negative affect emerged as a critical predictor in our model. Existing theories within the ideation-to-action framework consistently posit negative emotions as pivotal in the development of suicidal ideation (Klonsky and May, 2015; O'Connor and Kirtley, 2018; Van Orden et al., 2010), yet place less emphasis on their role in the transition from ideation to actual behaviors. Intriguingly, our results revealed that trait negative affect provided incremental predictive value beyond that of lifetime suicidal ideation, internalizing symptoms, and impulsivity. Similarly, Yen et al. identified negative temperament as a robust prospective predictor of suicide attempts, even after controlling for disinhibition/impulsivity, the course of major depressive disorders, and other factors (Yen et al., 2009). These findings suggest more attention should be paid to trait negative affect, particularly regarding its impact on actual suicidal behaviors.

As expected, psychopathology—including internalizing problems, attention problems, and the number of psychotic symptoms—contributed significantly to our prediction model. Past research on early adolescents (Fotti et al., 2006; Kelleher et al., 2013; Larsson and Sund, 2008; Ortin et al., 2019) and other age groups (Barbeito et al., 2021; Franklin et al., 2017; Hoertel et al., 2015) has consistently reported strong associations between internalizing/psychotic symptoms and suicide attempts, indicating the robustness of these findings. While a meta-analysis has demonstrated a significant association between attention-deficit/hyperactivity disorder (ADHD) and a range of suicidal behaviors—including ideation, plans, attempts, and completed suicides—across various populations (Septier et al., 2019), specific investigations focused on early adolescents are limited. Ortin et al. were among the few to investigate the role of behavioral disorders, including ADHD, oppositional defiant disorder, and conduct disorder, finding significant links to suicidal ideation but not to suicide attempts in early adolescence (Ortin et al., 2019). These findings underscore the need for further research into the role of attention problems in suicidal behaviors among early adolescents, as the existing evidence is limited and somewhat mixed.

Bully victimization and school disengagement were also significant predictors of first-onset suicide attempts in early adolescents, consistent with previous findings (Marraccini and Brier, 2017; Van Geel et al., 2014). According to the interpersonal theory of suicide (Van Orden et al., 2010), these factors may contribute to perceived burdensomeness and thwarted belongingness—psychological states that increase the likelihood of developing suicidal ideation. Moreover, the erosion of protective social connections and support, typically provided by the school environment, may further exacerbate vulnerability to suicidal behaviors. These findings highlight the importance of school-based interventions aimed at preventing bullying and fostering school engagement, both of which may serve as key strategies in reducing suicide risk among early adolescents.

This study had several limitations. First, the dataset analyzed represents only a subset of the full ABCD Study cohort. This constraint was due to the incomplete status of the four-year follow-up assessments, which limited the availability of corresponding data. Future data releases may enable the validation and extension of the present findings. Second, our prediction model focused on detecting the first suicide attempt within a 2-year period, which may not fully capture the temporal dynamics of suicidal behaviors. This limitation stems from the low incidence rate of suicide, necessitating a longer interval between waves to accumulate a sufficient number of onset cases. We made this compromise to ensure the robustness of the algorithm. Third, our analysis maintained a static perspective, overlooking the temporal fluctuations of risk and protective factors that may influence suicidal behaviors over time. However, adopting a dynamic approach would require multiple waves of survey data or intensive measurement over shorter periods, such as real-time or daily assessments. Future research may consider employing specific designs to address this issue. Fourth, to our knowledge, no suicide deaths have been documented within the ABCD cohort to date. Consequently, our sample is limited to individuals who survived their first suicide attempt. This restricts our ability to examine potential differences between those who survive a first attempt and those who die. Future research should aim to distinguish between these groups to develop a more nuanced understanding of suicide risk and identify individuals at ultra-high risk. Fifth, because the ABCD study was not specifically designed for suicide research, certain important risk factors, such as access to lethal means, were unavailable for analysis. Nevertheless, we chose this population-based cohort to leverage its longitudinal design, comprehensive assessments, and large sample size. Future research focusing specifically on early adolescents could build on the risk factors identified in the current study and incorporate additional candidate factors that were not captured in our dataset. This approach may enhance predictive accuracy for this demographic. Lastly, our sample predominantly comprised White and Hispanic populations, leading to the under-representation of early adolescents from other racial and ethnic backgrounds. Therefore, the generalizability of our findings to more diverse populations and other cultural contexts also warrants further exploration.

Notwithstanding these limitations, our study makes several significant contributions to the field of suicide prediction. First, we addressed a critical gap in the literature by identifying predictors of first-onset suicide attempts specifically during early adolescence—a developmental period marked by heightened vulnerability. Prior research has often combined various adolescent age groups and failed to distinguish between first and subsequent attempts, limiting the precision of prevention efforts. Second, we expanded the scope of risk factor evaluation by examining 87 candidate variables across eight domains, offering a more comprehensive assessment of the diverse factors contributing to first-onset suicide attempts. Third, we leveraged advanced machine learning techniques to rigorously identify the most informative predictors while accounting for complex, non-linear relationships that traditional methods may overlook. By focusing on first-onset suicide attempts in early adolescents, our findings provide novel insights that can guide the development of more targeted and effective prevention strategies for this vulnerable population.

5. Conclusions

This study demonstrates the capability of machine learning algorithms to examine a wide range of factors in predicting individual risk for first suicide attempt among early adolescents. We validated and highlighted several domains of risk factors, including those related to sex assigned at birth, pubertal and sexual development, trait negative affect, psychopathology, and adverse social experiences. These findings contribute to a deeper empirical understanding of suicide risk in early adolescents, emphasizing the importance of focusing research efforts on this critical developmental stage. We hope our findings will illuminate the risk factors associated with initial suicide attempts in early adolescents, offering insights that could inform the development of effective screening and targeted preventive strategies to promote youth mental health.

CRediT authorship contribution statement

Chen Huang: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yanling Yue:** Data curation. **Zimao Wang:** Data curation. **Yong-Jin Liu:** Writing – review & editing, Supervision, Funding acquisition. **Nisha Yao:** Writing – review & editing, Supervision, Conceptualization. **Wenting Mu:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used OpenAI's ChatGPT 4 in order to improve the readability and linguistic presentation of our manuscript. After using this tool/service, the authors carefully reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Declaration of competing interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jad.2025.03.201.

References

Abascal-Peiró, S., Alacreu-Crespo, A., Peñuelas-Calvo, I., López-Castromán, J., Porras-Segovia, A., 2023. Characteristics of single vs. multiple suicide attempters among adult population: a systematic review and meta-analysis. Curr. Psychiatry Rep. 25, 769–791. https://doi.org/10.1007/s11920-023-01461-5.

Altmann, A., Toloşi, L., Sander, O., Lengauer, T., 2010. Permutation importance: a corrected feature importance measure. Bioinformatics 26, 1340–1347. https://doi.org/10.1093/bioinformatics/btq134.

Ati, N.A.L., Paraswati, M.D., Windarwati, H.D., 2021. What are the risk factors and protective factors of suicidal behavior in adolescents? A systematic review. J. Child Adolesc. Psychiatr. Nurs. 34, 7–18. https://doi.org/10.1111/jcap.12295.

Barbeito, S., Vega, P., Sánchez-Gutiérrez, T., Becerra, J.A., Gonzalez-Pinto, A., Calvo, A., 2021. A systematic review of suicide and suicide attempts in adolescents with psychotic disorders. Schizophr. Res. 235, 80–90.

Belsher, B.E., Smolenski, D.J., Pruitt, L.D., Bush, N.E., Beech, E.H., Workman, D.E., Morgan, R.L., Evatt, D.P., Tucker, J., Skopp, N.A., 2019. Prediction models for suicide attempts and deaths: a systematic review and simulation. JAMA Psychiatry 76, 642–651.

Bernert, R.A., Hilberg, A.M., Melia, R., Kim, J.P., Shah, N.H., Abnousi, F., 2020. Artificial intelligence and suicide prevention: a systematic review of machine learning investigations. Int. J. Environ. Res. Public Health 17, 5929.

Bostwick, J.M., Pabbati, C., Geske, J.R., McKean, A.J., 2016. Suicide attempt as a risk factor for completed suicide: even more lethal than we knew. Am. J. Psychiatry 173, 1094–1100. https://doi.org/10.1176/appi.ajp.2016.15070854.

Burke, T.A., Ammerman, B.A., Jacobucci, R., 2019. The use of machine learning in the study of suicidal and non-suicidal self-injurious thoughts and behaviors: a systematic review. J. Affect. Disord. 245, 869–884. https://doi.org/10.1016/j.jad.2018.11.073.

Carballo, J.J., Llorente, C., Kehrmann, L., Flamarique, I., Zuddas, A., Purper-Ouakil, D., Hoekstra, P.J., Coghill, D., Schulze, U.M.E., Dittmann, R.W., Buitelaar, J.K., Castro-Fornieles, J., Lievesley, K., Santosh, P., Arango, C., 2020. Psychosocial risk factors for suicidality in children and adolescents. Eur. Child Adolesc. Psychiatry 29, 759–776. https://doi.org/10.1007/s00787-018-01270-9.

Caskey, M.M., Anfara Jr., V.A., 2007. Research Summary: Young Adolescents' Developmental Characteristics. National Middle School Association.

Centers for Disease Control and Prevention, 2022. Leading causes of death. https://wisqars.cdc.gov/lcd/?o=LCD&y1=2022&y2=2022&ct=10&cc=ALL&g=00&s=0&r=0&ry=2&e=0&ar=lcd1age&at=groups&ag=lcd1age&a1=0&a2=199 (accessed May 13).

Cha, C.B., Franz, P.J., E, M.G., Glenn, C.R., Kleiman, E.M., Nock, M.K., 2018. Annual research review: suicide among youth — epidemiology, (potential) etiology, and treatment. J. Child Psychol. Psychiatry 59, 460–482. https://doi.org/10.1111/jcpp.12831.

Christie, D., Viner, R., 2005. Adolescent development. Bmj 330, 301–304. https://doi.org/10.1136/bmj.330.7486.301.

DeLong, E.R., DeLong, D.M., Clarke-Pearson, D.L., 1988. Comparing the areas under two or more correlated receiver operating characteristic curves: a nonparametric approach. Biometrics 44, 837–845.

Ezquerra, B., Alacreu-Crespo, A., Peñuelas-Calvo, I., Abascal-Peiró, S., Jiménez-Muñoz, L., Nicholls, D., Baca-García, E., Porras-Segovia, A., 2023. Characteristics of single vs. multiple suicide attempters among adolescents: a systematic review and meta-analysis. Eur. Child Adolesc. Psychiatry. https://doi.org/10.1007/s00787-023-02260-2.

Fotti, S.A., Katz, L.Y., Afifi, T.O., Cox, B.J., 2006. The associations between peer and parental relationships and suicidal behaviours in early adolescents. Can. J. Psychiatry 51, 698–703. https://doi.org/10.1177/070674370605101106.

Franklin, J.C., Ribeiro, J.D., Fox, K.R., Bentley, K.H., Kleiman, E.M., Huang, X., Musacchio, K.M., Jaroszewski, A.C., Chang, B.P., Nock, M.K., 2017. Risk factors for suicidal thoughts and behaviors: a meta-analysis of 50 years of research. Psychol. Bull. 143, 187–232. https://doi.org/10.1037/bul0000084.

Galambos, N.L., 2004. Gender and gender role development in adolescence. In: Handbook of Adolescent Psychology, pp. 233–262.

Geoffroy, M.C., Boivin, M., Arseneault, L., Turecki, G., Vitaro, F., Brendgen, M., Renaud, J., Séguin, J.R., Tremblay, R.E., Côté, S.M., 2016. Associations between peer victimization and suicidal ideation and suicide attempt during adolescence: results from a prospective population-based birth cohort. J. Am. Acad. Child Adolesc. Psychiatry 55, 99–105. https://doi.org/10.1016/j.jaac.2015.11.010.

Geurts, P., Ernst, D., Wehenkel, L., 2006. Extremely randomized trees. Mach. Learn. 63, 3–42. https://doi.org/10.1007/s10994-006-6226-1.

Gibbons, R.D., Chattopadhyay, I., Meltzer, H.Y., Kane, J.M., Guinart, D., 2022. Development of a computerized adaptive diagnostic screening tool for psychosis. Schizophr. Res. 245, 116–121. https://doi.org/10.1016/j.schres.2021.03.020.

Goetz, M., Weber, C., Bloecher, J., Stieltjes, B., Meinzer, H.-P., Maier-Hein, K., 2014. Extremely randomized trees based brain tumor segmentation. In: Proceeding of BRATS Challenge-MICCAI, vol. 14, p. 24.

Goldman-Mellor, S.J., Caspi, A., Harrington, H., Hogan, S., Nada-Raja, S., Poulton, R., Moffitt, T.E., 2014. Suicide attempt in young people: a signal for long-term health care and social needs. JAMA Psychiatry 71, 119–127. https://doi.org/10.1001/jamapsychiatry.2013.2803.

Gopalakrishnan, A., Venkataraman, R., Gururajan, R., Zhou, X., Zhu, G., 2022. Predicting women with postpartum depression symptoms using machine learning techniques. Mathematics 10, 4570. https://doi.org/10.3390/math10234570.

Haak, B.W., Brands, X., Davids, M., Peters-Sengers, H., Kullberg, R.F.J., van Houdt, R., Hugenholtz, F., Faber, D.R., Zaaijer, H.L., Scicluna, B.P., van der Poll, T., Joost Wiersinga, W., 2022. Bacterial and viral respiratory tract microbiota and host characteristics in adults with lower respiratory tract infections: a case-control study. Clin. Infect. Dis. 74, 776–784. https://doi.org/10.1093/cid/ciab568.

Hamburg, B.A., 1985. Early adolescence. A time of transition and stress. Postgrad. Med. 78, 158–161, 164–157. https://doi.org/10.1080/00325481.1985.11699062.

Harman, G., Kliamovich, D., Morales, A.M., Gilbert, S., Barch, D.M., Mooney, M.A., Feldstein Ewing, S.W., Fair, D.A., Nagel, B.J., 2021. Prediction of suicidal ideation and attempt in 9 and 10 year-old children using transdiagnostic risk features. PloS One 16, e0252114. https://doi.org/10.1371/journal.pone.0252114.

Hill, J.P., Lynch, M.E., 1983. The intensification of gender-related role expectations during early adolescence. In: Brooks-Gunn, J., Petersen, A.C. (Eds.), Girls at Puberty: Biological and Psychosocial Perspectives. Springer US, Boston, MA, pp. 201–228.

Hoertel, N., Franco, S., Wall, M.M., Oquendo, M.A., Kerridge, B.T., Limosin, F., Blanco, C., 2015. Mental disorders and risk of suicide attempt: a national prospective study. Mol. Psychiatry 20, 718–726. https://doi.org/10.1038/mp.2015.19.

Janiri, D., Doucet, G.E., Pompili, M., Sani, G., Luna, B., Brent, D.A., Frangou, S., 2020. Risk and protective factors for childhood suicidality: a US population-based study. Lancet Psychiatry 7, 317–326. https://doi.org/10.1016/s2215-0366(20)30049-3.

Kelleher, I., Corcoran, P., Keeley, H., Wigman, J.T., Devlin, N., Ramsay, H., Wasserman, C., Carli, V., Sarchiapone, M., Hoven, C., Wasserman, D., Cannon, M., 2013. Psychotic symptoms and population risk for suicide attempt: a prospective cohort study. JAMA Psychiatry 70, 940–948. https://doi.org/10.1001/jamapsychiatry.2013.140.

Klonsky, E.D., May, A.M., 2015. The three-step theory (3ST): a new theory of suicide rooted in the "ideation-to-action" framework. Int. J. Cogn. Ther. 8, 114–129. https://doi.org/10.1521/ijct.2015.8.2.114.

Kranzler, A., Fehling, K.B., Anestis, M.D., Selby, E.A., 2016. Emotional dysregulation, internalizing symptoms, and self-injurious and suicidal behavior: structural equation modeling analysis. Death Stud. 40, 358–366. https://doi.org/10.1080/07481187.2016.1145156.

Larsson, B., Sund, A.M., 2008. Prevalence, course, incidence, and 1-year prediction of deliberate self-harm and suicide attempts in early Norwegian school adolescents. Suicide Life Threat. Behav. 38, 152–165. https://doi.org/10.1521/suli.2008.38.2.152.

Lavelle-Hill, R.E., Smith, G., Murayama, K., 2023. Machine Learning Meets Traditional Statistical Methods in Psychology: Challenges and Future Directions. OSF Preprints. https://doi.org/10.31219/osf.io/6xt82. October, 30.

Lawson, K.M., Kellerman, J.K., Kleiman, E.M., Bleidorn, W., Hopwood, C.J., Robins, R. W., 2022. The role of temperament in the onset of suicidal ideation and behaviors across adolescence: findings from a 10-year longitudinal study of Mexican-origin youth. J. Pers. Soc. Psychol. 122, 171–186. https://doi.org/10.1037/pspp0000382.

Linthicum, K.P., Schafer, K.M., Ribeiro, J.D., 2019. Machine learning in suicide science: applications and ethics. Behav. Sci. Law 37, 214–222. https://doi.org/10.1002/bsl.2392.

Luk, J.W., Goldstein, R.B., Yu, J., Haynie, D.L., Gilman, S.E., 2021. Sexual minority status and age of onset of adolescent suicide ideation and behavior. Pediatrics 148.

Macalli, M., Navarro, M., Orri, M., Tournier, M., Thiébaut, R., Côté, S.M., Tzourio, C., 2021. A machine learning approach for predicting suicidal thoughts and behaviours among college students. Sci. Rep. 11, 11363.

Marraccini, M.E., Brier, Z.M., 2017. School connectedness and suicidal thoughts and behaviors: a systematic meta-analysis. Sch. Psychol. Q. 32, 5.

Martin, G., Richardson, A.S., Bergen, H.A., Roeger, L., Allison, S., 2005. Perceived academic performance, self-esteem and locus of control as indicators of need for assessment of adolescent suicide risk: implications for teachers. J. Adolesc. 28, 75–87. https://doi.org/10.1016/j.adolescence.2004.04.005.

Mathew, T.E., 2022. An optimized extremely randomized tree model for breast cancer classification. J. Theor. Appl. Inf. Technol. 31, 5234–5246.

McHugh, C.M., Ho, N., Iorfino, F., Crouse, J.J., Nichles, A., Zmicerevska, N., Scott, E., Glozier, N., Hickie, I.B., 2023. Predictive modelling of deliberate self-harm and suicide attempts in young people accessing primary care: a machine learning analysis of a longitudinal study. Soc. Psychiatry Psychiatr. Epidemiol. 58, 893–905. https://doi.org/10.1007/s00127-022-02415-7.

McKeown, R.E., Garrison, C.Z., Cuffe, S.P., Waller, J.L., Jackson, K.L., Addy, C.L., 1998. Incidence and predictors of suicidal behaviors in a longitudinal sample of young adolescents. J. Am. Acad. Child Adolesc. Psychiatry 37, 612–619. https://doi.org/10.1097/00004583-199806000-00011.

Mendez-Bustos, P., de Leon-Martinez, V., Miret, M., Baca-Garcia, E., Lopez-Castroman, J., 2013. Suicide reattempters: a systematic review. Harv. Rev. Psychiatry 21, 281–295. https://doi.org/10.1097/hrp.0000000000000001.

Miller, A.B., Prinstein, M.J., 2019. Adolescent suicide as a failure of acute stress-response systems. Annu. Rev. Clin. Psychol. 15, 425–450. https://doi.org/10.1146/annurev-clinpsy-050718-095625.

Navarro, M.C., Ouellet-Morin, I., Geoffroy, M.-C., Boivin, M., Tremblay, R.E., Côté, S.M., Orri, M., 2021. Machine learning assessment of early life factors predicting suicide attempt in adolescence or young adulthood. JAMA Netw. Open 4, e211450. https://doi.org/10.1001/jamanetworkopen.2021.1450.

Nock, M.K., Borges, G., Bromet, E.J., Cha, C.B., Kessler, R.C., Lee, S., 2008. Suicide and suicidal behavior. Epidemiol. Rev. 30, 133–154. https://doi.org/10.1093/epirev/mxn002.

Nock, M.K., Green, J.G., Hwang, I., McLaughlin, K.A., Sampson, N.A., Zaslavsky, A.M., Kessler, R.C., 2013. Prevalence, correlates, and treatment of lifetime suicidal behavior among adolescents: results from the National Comorbidity Survey Replication Adolescent Supplement. JAMA Psychiatry 70, 300–310. https://doi.org/10.1001/2013.jamapsychiatry.55.

O'Connor, R.C., Kirtley, O.J., 2018. The integrated motivational-volitional model of suicidal behaviour. Philos. Trans. R. Soc. Lond. B Biol. Sci. 373. https://doi.org/10.1098/rstb.2017.0268.

O'Connor, R.C., Nock, M.K., 2014. The psychology of suicidal behaviour. Lancet Psychiatry 1, 73–85. https://doi.org/10.1016/s2215-0366(14)70222-6.

Orri, M., Vergunst, F., Turecki, G., Galera, C., Latimer, E., Bouchard, S., Domond, P., Vitaro, F., Algan, Y., Tremblay, R.E., Geoffroy, M.-C., Côté, S.M., 2022. Long-term economic and social outcomes of youth suicide attempts. Br. J. Psychiatry 220, 79–85. https://doi.org/10.1192/bjp.2021.133.

Ortin, A., Elkington, K.S., Eisenberg, R., Miranda, R., Canino, G., Bird, H.R., Duarte, C.S., 2019. Suicide attempts and course of suicidal ideation among Puerto Rican early

adolescents. J. Abnorm. Child Psychol. 47, 1723–1734. https://doi.org/10.1007/s10802-019-00554-1.
Pachankis, J.E., Jackson, S.D., 2023. A developmental model of the sexual minority closet: structural sensitization, psychological adaptations, and post-closet growth. Arch. Sex. Behav. 52, 1869–1895.
Pagliaro, A., 2023. Forecasting significant stock market price changes using machine learning: extra trees classifier leads. Electronics 12, 4551. https://doi.org/10.3390/electronics12214551.
Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., 2011. Scikit-learn: machine learning in Python. J. Mach. Learn. Res. 12, 2825–2830.
Ruiz-Rizzo, A.L., Archila-Meléndez, M.E., González Veloza, J.J.F., 2022. Predicting the probability of finding missing older adults based on machine learning. J. Comput. Soc. Sci. 5, 1303–1321. https://doi.org/10.1007/s42001-022-00171-x.
Septier, M., Stordeur, C., Zhang, J., Delorme, R., Cortese, S., 2019. Association between suicidal spectrum behaviors and attention-deficit/hyperactivity disorder: a systematic review and meta-analysis. Neurosci. Biobehav. Rev. 103, 109–118. https://doi.org/10.1016/j.neubiorev.2019.05.022.
Simmons, R.G., Blyth, D.A., Van Cleave, E.F., Bush, D.M., 1979. Entry into early adolescence: the impact of school structure, puberty, and early dating on self-esteem. Am. Sociol. Rev. 44, 948–967. https://doi.org/10.2307/2094719.
Spirito, A., Boergers, J., Donaldson, D., 2000. Adolescent suicide attempters: post-attempt course and implications for treatment. Clin. Psychol. Psychother. 7, 161–173. https://doi.org/10.1002/1099-0879(200007)7:3<161::AID-CPP233>3.0.CO;2-C.
Stein, D., Apter, A., Ratzoni, G., Har-Even, D., Avidan, G., 1998. Association between multiple suicide attempts and negative affects in adolescents. J. Am. Acad. Child Adolesc. Psychiatry 37, 488–494. https://doi.org/10.1097/00004583-199805000-00011.
Stone, M., 1974. Cross-validatory choice and assessment of statistical predictions. J. R. Stat. Soc. B. Methodol. 36, 111–133.
Su, C., Aseltine, R., Doshi, R., Chen, K., Rogers, S.C., Wang, F., 2020. Machine learning for suicide risk prediction in children and adolescents with electronic health records. Transl. Psychiatry 10, 413. https://doi.org/10.1038/s41398-020-01100-0.
Su, R., John, J.R., Lin, P.I., 2023. Machine learning-based prediction for self-harm and suicide attempts in adolescents. Psychiatry Res. 328, 115446. https://doi.org/10.1016/j.psychres.2023.115446.
Susman, E.J., Rogol, A., 2004. Puberty and psychological development, In: Handbook of Adolescent Psychology. pp. 15–44.
Van Geel, M., Vedder, P., Tanilon, J., 2014. Relationship between peer victimization, cyberbullying, and suicide in children and adolescents: a meta-analysis. JAMA Pediatr. 168, 435–442.
Van Orden, K.A., Witte, T.K., Cukrowicz, K.C., Braithwaite, S.R., Selby, E.A., Joiner Jr., T.E., 2010. The interpersonal theory of suicide. Psychol. Rev. 117, 575–600. https://doi.org/10.1037/a0018697.
Vander Stoep, A., Adrian, M., McCauley, E., Crowell, S.E., Stone, A., Flynn, C., 2011. Risk for suicidal ideation and suicide attempts associated with co-occurring depression and conduct problems in early adolescence. Suicide Life Threat. Behav. 41, 316–329. https://doi.org/10.1111/j.1943-278X.2011.00031.x.
Varma, S., Simon, R., 2006. Bias in error estimation when using cross-validation for model selection. BMC Bioinformatics 7, 1–8.
Voss, C., Ollmann, T.M., Miché, M., Venz, J., Hoyer, J., Pieper, L., Höfler, M., Beesdo-Baum, K., 2019. Prevalence, onset, and course of suicidal behavior among adolescents and young adults in Germany. JAMA Netw. Open 2, e1914386. https://doi.org/10.1001/jamanetworkopen.2019.14386.
Wen, X., Qu, D., Zhang, X., Wang, Y., Cui, Z., Zhang, X., Chen, R., 2023. The transition trajectories of self-injurious thoughts and behaviours among children from a biopsychosocial perspective. Nat. Ment. Health 1, 782–791. https://doi.org/10.1038/s44220-023-00130-z.
Yen, S., Shea, M.T., Sanislow, C.A., Skodol, A.E., Grilo, C.M., Edelen, M.O., Stout, R.L., Morey, L.C., Zanarini, M.C., Markowitz, J.C., McGlashan, T.H., Daversa, M.T., Gunderson, J.G., 2009. Personality traits as prospective predictors of suicide attempts. Acta Psychiatr. Scand. 120, 222–229. https://doi.org/10.1111/j.1600-0447.2009.01366.x.
Youden, W.J., 1950. Index for rating diagnostic tests. Cancer 3, 32–35.