Machine learning–based prediction of suicidal thinking in adolescents: Derivation and validation in three independent worldwide cohorts in South Korea, Norway, and the USA

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Abstract

Background: Suicide is the second leading cause of death among adolescents and is associated with clusters of suicides. Despite numerous researches on this preventable cause of death, the focus has primarily been on single nations and traditional statistical methods.

Objective: This study aims to develop a predictive model for adolescent suicidal thinking using multinational datasets and machine learning (ML).

Methods: This study utilized data from the Korea Youth Risk Behavior Web–based Survey (KYRBS) with 566,875 adolescents aged 13 to 18 and conducted external validation using the Youth Risk Behavior Survey (YRBS) with 103,874 adolescents and Norway's University National General Survey (Ungdata) with 19,574 adolescents. Several tree–based ML models were developed and feature importance and SHapley Additive exPlanations (SHAP) values were analyzed to identify risk factors for adolescent suicidal thinking.

Results: When trained on the KYRBS data from South Korea with a 95% confidence interval, the XGBoost model reported an area under the receiver operating characteristic curve (AUROC) of 90.06% (95% CI, 89.97–90.16), displaying superior performance compared to other models. For external validation using the YRBS data from the USA and the Ungdata from Norway, the XGBoost model achieved an AUROC of 83.09% and 81.27%, respectively. Across all datasets, XGBoost consistently outperformed the other models with the highest AUROC score, selected as the most optimal model. In terms of predictors of suicidal thinking, feelings of sadness and despair were the most influential, accounting for 57.4% of the impact, followed by stress status at 19.8%. This was followed by age (5.7%), household income (4.0%), academic achievement (3.4%), sex (2.1%), and others contributing less than 2% each.

Conclusions: To address adolescent suicide, this study utilized ML by integrating diverse datasets from three countries. The findings highlight the important role of emotional health indicators in predicting suicidal thinking among adolescents.

Specifically, sadness and despair were identified as the most significant predictors, followed by stressful conditions and age. These findings emphasize the critical need for early diagnosis and prevention for mental health issues during adolescence.

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Machine learning–based prediction of suicidal thinking in adolescents: Derivation and validation in three independent worldwide cohorts in South Korea, Norway, and the USA

Running Title: **Suicidal thinking prediction machine learning model.**

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Key words: adolescent; machine learning; SHAP value; suicidal thinking; XGBoost;

Introduction

Adolescent suicide stands out as a prominent global public health concern, with its rank as the second leading cause of death among young populations underscoring its severity.[1, 2] Notably, adolescence is a phase characterized by an amplified suicide risk.[3] Concerningly, some geographic regions are experiencing a surge in suicide clusters, where the instances of suicides surpass the typical levels.[4] Research into these clusters indicates that individuals under the age of 25 are up to four times more likely to be affected by suicide.[5] Since suicide is preventable in the early stage, there is a pressing need for action through rigorous mental health strategies and proactive educational interventions.[6]

While various methodologies have been proposed to prevent suicidal thinking in adolescents, many lack empirical outcomes and often fail to identify key determinants.[7-9] A significant gap remains in accurately assessing the risk of suicidal thinking for individual adolescents.[2, 10, 11] Recent advances in machine learning (ML) methodologies have shown promise in addressing the challenges of adolescent suicidal tendencies. Studies leveraging boosted machine learning[12], daily data analysis through classification and regression trees [13], and risk and protective factor frameworks[14] have begun to unpack the complex interplay of factors contributing to suicidal thinking among adolescents. However, these studies have also highlighted limitations, including a focus on specific socioeconomic or short-term predictors and a lack of comprehensive risk profiles integrating emotional, social, and psychological variables.[12-14]

Therefore, in this study, we developed a predictive model for suicidal thinking among adolescents, utilizing advanced ML algorithms. Addressing the gaps identified in earlier research, our model incorporates a broader array of factors including family dynamics, emotional well-being, academic performance, and general health indicators. Across distinct adolescent cohorts from South Korea, Norway, and the USA, we aimed for a comprehensive multinational approach. By refining our approach based on previous studies' insights, our research aims to highlight the preventability of suicide and influence mental health clinicians and policymakers in developing more effective preventive measures and supportive programs.

Methods

Study design and participants

Our study aimed to develop an ML model to predict suicidal thinking among Korean adolescents. Our approach utilized multiple variables extracted from three distinct, large–scale international data sources: the Korea Youth Risk Behavior Web–based Survey (KYRBS)[15, 16], the Youth Risk Behavior Survey (YRBS), and Norway's nationwide University National General Survey (Ungdata).

Data preparation and harmonization

Initial data preprocessing involved adjusting the sample sizes after the removal of missing values: KYRBS from 1,145,178 to 566,875, YRBS from 438,566 to 103,874, and Ungdata from 89,077 to 19,574. We analyzed data from adolescents aged 13 to 18 who participated in the KYRBS from 2009 to 2021, the YRBS in 2021, and Ungdata from 2017 to 2019. The primary outcome, termed 'current suicidal thinking', was derived from participants' affirmative responses to the question, "During the past 12 months, did you ever seriously consider attempting suicide?" This outcome indicated that participants had contemplated serious suicidal thinking at least once in the preceding year. The analysis considered several covariates: region, age, sex, body mass index (BMI; kg/m^2), academic achievement, household income, smoking status, alcoholic consumption, stress status, feelings of sadness and despair, exercise habits, and screen time.[17]

We harmonized the datasets for XGBoost model compatibility. addressing the challenge posed by different variable configurations within the same questions. Our preprocessing aligned each variable across the KYRBS, YRBS, and Ungdata datasets, ensuring they matched in terms of content and format. Recognizing the potential disparities in variable configurations across these datasets, we standardized the variable names, formats, and scales, focusing on key features such as demographic information, behavioral factors, psychosocial aspects, and environmental influences that could serve as predictors for suicidal thinking. To ensure consistency, we adopted the following strategic approach to cases where YRBS and Ungdata were missing certain features: By calculating the median of the missing variables in the KYRBS dataset, we were able to effectively impute the missing values to maintain the integrity and comparability of the dataset compilations. Through variable alignment and addressing missing data, we successfully harnessed the diverse strengths of each dataset, facilitating the development of a comprehensive model designed to address adolescent suicidal thinking effectively.

Machine learning model development

Our ML model underwent training and validation to ensure its predictive accuracy in identifying suicidal thinking. We utilized the KYRBS dataset to build a model tailored to predict suicidal thinking among Korean adolescents aged 13 to 18. Recognizing the intricate characteristics of the data, we employed a variety of tree–based ML techniques, including extreme gradient boosting (XGBoost), Adaptive Boosting (AdaBoost), Light Gradient–Boosting Machine (LightGBM), and Random Forest to train dataset, for data training in our modeling process.[18] Prior to this, data preprocessing measures, such as addressing missing values and encoding categorical variables, were executed to maintain data integrity and optimize the data for the modeling phase.

To rigorously assess the performance efficacy of the ML model, we adopted the 10–fold cross–validation method, dividing the initial dataset into ten equal–sized subsets. Of these, nine are designated for model training, while the remaining subset serves as validation.[19] The process iterates ten times, ensuring each subset undergoes validation at least once. During each cycle, we computed various performance metrics such as AUROC, sensitivity, specificity, accuracy, and balanced accuracy, along with their respective 95% confidence intervals (CIs).[20-25] The 95% CIs provide a range of possible values for the model's performance metrics, allowing us to assess the stability and generalizability of the model. For a visual representation of the model efficacy, we employed visualization methods, primarily the receiver operating characteristic (ROC) curve. After ten iterations, the metrics from each were averaged to determine the final performance evaluation.

We trained our model on the KYRBS dataset using 10-fold cross-validation. The model trained on the KYRBS dataset was then externally validated with YRBS and Ungdata datasets preprocessed with the same column structure as KYRBS. This rigorous process reinforced the reliability of our model's performance trained on the KYRBS dataset.[26] Among the four models tested, XGBoost consistently yielded the highest AUROC scores across all datasets, leading to its selection as the primary model.

To optimize the performance of the XGBoost model, we performed hyperparameter tuning using GridSearchCV, prioritizing the maximization of the AUROC score to determine the optimal hyperparameter combination. Hyperparameters were carefully selected for improved performance: the gbtree booster was utilized for its effectiveness in classification tasks, and the logloss evaluation metric was chosen to ensure accurate probability estimations. We set the learning rate at 0.08 to balance training speed with model accuracy, and the max depth was capped at 5 to prevent overfitting while allowing the model to capture complex patterns. Additionally, 350 trees (n_estimators) were employed to construct a robust model, with further adjustments made to parameters like "scale_pos_weight" and subsample to address class imbalance and enhance model stability. These adjustments were important in refining our model's predictive capabilities and are detailed in **Table S1**. In order to interpret and gain insights into the model predictions, we utilized SHapley Additive exPlanations (SHAP) values, a unified measure derived from cooperative game theory. Data set variables were analyzed with SAS software, version 9.3 (SAS Institute Inc, Cary, NC, USA), and ML analysis was performed utilizing Python version 3.11.4 (Python Software Foundation, Wilmington, DE, USA). The main Python libraries utilized are as follows: NumPy 1.26.0 for data arrays and operations, Pandas 2.1.0 for data manipulation and analysis. All three – scikit–learn 1.2.2, TensorFlow–gpu 2.6.0, and Keras 2.6.0 – were employed for constructing and training ML models.[27] Additionally, the SHAP package, version 0.42.1, was utilized to interpret the ML models and for its explanation capabilities.[28]

Software and libraries

All computations, model training, and evaluations were executed using Python 3.11.4. Key libraries from our toolbox included Scikit–learn 1.2.2, NumPy 1.24.0, and Pandas 2.1.0 for ML tasks and data wrangling. Visualization was facilitated using Matplotlib 3.7.2 and Seaborn 0.12.2.

Ethical statement

The study protocol was approved by the Institutional Review Board of the Korean Disease Control and Prevention Agency (KDCA), U.S. Centers for Disease Control and Prevention (CDC), Norwegian Social Research institute (NOVA), and Kyung Hee University (KHUH 2022–06–042), and all participants provided written informed consent. This research followed the guidelines outlined in the transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD) statement (**Table S2**).

Results

Demographic characteristics

This study was conducted to develop a ML–based predictive model for suicidal thinking among adolescents aged 13 to 18. After collecting independent data from three countries, covariates were standardized for the ML prediction modeling process (**Figure 1 and 2**).

The distribution of age in the initial training cohort for KYRBS from South Korea, which was utilized to build the prediction model, shows: 13 years old (16.74%), 14 years old (17.40%), 15 years old (17.73%), 16 years old (15.89%), 17 years old (16.24%), and 18 years old (16.00%). For the external validation cohort utilizing YRBS from the USA, the age distribution exhibited: 13 years old (0.34%), 14 years old (20.31%), 15 years old (26.97%), 16 years old (24.96%), 17 years old (21.57%), and 18 years old (5.85%). Another external validation stage using Ungdata from Norway had the following age distribution: 13 years old (25.74%), 14 years old (24.90%), 15 years old (25.72%), 16 years old (16.25%), 17 years old (4.32%), and 18 years old (3.07%) (**Table 1**).

Both the initial training cohort and the external validation cohorts took into account socio–economic backgrounds, such as household income and academic achievement, as well as risk behaviors such as alcohol consumption, smoking, and screen time. Additionally, factors that could potentially influence mental health, such as feelings of sadness and despair, were also considered. Inconsistencies or missing values in validation sets were addressed by implementing median imputation from the primary training data. Such thorough demographic incorporation bolsters our model performance, offering a nuanced understanding of suicidal thinking in adolescents.

Machine learning model results

Table S1 and **Figure 3** present the process of hyperparameter tuning XGBoost model and evaluation of our models conducted on datasets from three distinct countries using five performance metrics. Notably, XGBoost emerged as the frontrunner among the four tested models by getting hyperparameters of booster: gbtree, eval_metric: logloss, learning_rate: 0.08, max_depth: 5, n_estimators: 350, scale_pos_weight: 2, subsample: 0.09 (Table S1). When put to the training on the KYRBS dataset from South Korea, with a 95% confidence interval, the XGBoost model reported an AUROC of 90.06 (95% CI, 89.97–90.16), sensitivity was 82.11 (95% CI, 81.67–82.55), specificity was 82.16 (95% CI, 81.68–82.63), accuracy was 82.13 (95% CI, 82.01–82.26), and balanced accuracy was 82.13 (95% CI, 82.01–82.26), consistently displaying superior results compared to the other three models. During the external validation assessment, the model evaluation was conducted without considering the 95% CI. For the external model validation, using the YRBS from the USA, the XGBoost model achieved an AUROC of 83.09%, sensitivity of 80.26%, specificity of 75.52%, accuracy of 76.58%, and balanced accuracy of 77.89%. For the external validation using the Ungdata from Norway, the XGBoost model achieved an AUROC of 81.27%, sensitivity of 79.19%, specificity of 80.00%, accuracy of 79.92%, and balanced accuracy of 79.60%. Across all datasets, XGBoost consistently outperformed all other models with the highest AUROC score, which was selected as the most optimal model.

Feature importance

Table 2 shows the feature importance derived from the XGBoost model, illustrating the relative contributions of each feature to predicting suicidal thinking. Notably, feelings of sadness and despair emerge as the most dominant predictor, accounting for 57.4% of the influence, followed by stress status at 19.8%. Subsequent factors include age (5.7%), household income (4.0%), academic achievement (3.4%), sex (2.1%), and others contributing less than 2% each.

SHAP value

We addressed a deeper visual interpretation of the Shapley Additive Explanations (SHAP) values within our ML model.[29] (**Figure S2**) **Figure S3** provides a waterfall plot, distinctively showcasing the cumulative contribution of each feature to a single prediction. We interpreted individual predictions by starting from the initial estimate and sequentially incorporating the influence of each feature to reach the final prediction. E[f(x)] refers to the average predicted output of model across the entire dataset, providing insights into the model's overall prediction tendency. The starting point of the illustration, denoted as E[f(X)] = 0.83, represents the model's average prediction for the given dataset. Among the variables, sadness and despair stood out, boosting the prediction by 1.17 and ranking as the most influential factor. Conversely, stress status and sex reduced the prediction by 0.86 and 0.22 respectively. This visualization offers a clear insight into the profound influence each feature wields in predicting adolescent suicidal thinking. Our ML model notably underscores a substantial reliance on the sadness and despair and stress status features. (**Figure S3**)

Code availability

Based on the results of ML model, we established a web–based application for policy implementation or health system management to support in their decision–making process for cases involving suicidal thinking prediction use in adolescents (website: https:// https://suicidalthinkingpredict3validation.streamlit.app/). An example of a web interface and the results are shown in **Figure S4**. Custom code for the website is available online at https:// github.com/CenterForDH/suicidalthinking_predict_3validation.

Discussion

Key finding

Our research represents a pioneering machine–learning initiative in predicting suicidal thinking among adolescents. We sourced distinct datasets from South Korea (KYRBS), the USA (YRBS), and Norway (Ungdata). This provided comprehensive analysis related to socioeconomic indicators and key mental health influencers such as alcohol consumption, smoking status, and feelings of sadness and despair. Importantly, our findings highlight XGBoost as the optimal predictive model, achieving an AUROC of 88.6% with the KYRBS dataset. External validation with the data from the US and Norway yielded AUROCs of 82.9% and 83.6%, respectively. The most significant predictor of suicidal thinking was sadness and despair with a feature influence of 61.0%, followed by stress status at 19.6%. Using SHAP values, we further emphasized the pivotal roles of sadness and despair and stress in predicting suicidal thinking in adolescents. To enhance the practical application of our research, we have developed an online platform to visualize the prediction model, accompanied by a mobile interface, enhancing its accessibility and user experience. This dual–platform system provides a more methodical and analytical approach for the public to comprehend and manage potential suicidal concerns.

Plausible mechanism

The close relationship between feelings of sadness and despair and suicidal thinking in adolescents can be understood from various perspectives, encompassing biological and environmental factors.[30] During adolescence, the brain undergoes significant development, especially in the prefrontal cortex which controls impulses and emotions.[31] Persistent sadness can interfere with adolescent brain development, resulting in a perpetual state of negative emotions. This increases their risk of suicidal thinking due to feelings of despair and impulsive actions.[32]

The influence of external portrayals, be it from peers or the media, cannot be underestimated.

When adolescents confront with additional adversities such as bullying, social isolation, or academic failures, these inherent stressors are amplified. Adolescents exposed to narratives that associating despair with suicidal behaviors might inadvertently absorb these sentiments. This phenomenon, known as "suicide contagion", postulates that exposure to others' suicidal actions can reshape an individual's perspective.[33] The confluence of these environmental stressors and limited emotional regulation capacities heightens their vulnerability, potentially leading them to view suicide as a viable solution to their emotional turmoil.[34]

Furthermore, due to their developmental stage, many adolescents have not yet acquired the necessary emotional coping strategies.[35] When faced with intense stressors without these tools, some may come to view suicide as their only way to escape from increasingly desperate circumstances.

This emotional vulnerability is further compounded by physiological changes. The stress response, regulated by the hypothalamic–pituitary–adrenal (HPA) axis, is intensified during adolescence.[36] Heightened sensitivity of the HPA axis results in increased cortisol production in response to stress.[37] Chronic exposure to these elevated cortisol levels not only exacerbates feelings of sadness and despair but also directly contributes to an increased vulnerability to suicidal thoughts.[38] Understanding these relationships makes it evident that both the emotional responses induced by stress and the physiological effects of stress significantly influence the increased propensity for suicidal thinking during this critical phase of life.

Strengths and limitations

Limitations of our study should be stated. One primary concern pertains to the usage of self–reported data, which exposes our results to potential biases, such as recall and social desirability. While this approach offers insights directly from the participants, such susceptibilities might skew the data and ultimately affect the model’s performance. It is also worth noting that the foundational training data was sourced predominantly from adolescents in South Korea.[39, 40] This could amplify specific cultural or racial attributes distinctive to Korean adolescents. Equally important to note, establishing a direct cause–and–effect relationship between significant risk factors and adolescent suicidal thinking remains elusive. Our study, while expansive, does not determine if suicidal thinking is a cause or an effect of other risk factors. Further research is needed to unravel these complex interconnections. The potential for overfitting is another critical limitation to consider. Our comprehensive model, regardless of its use of 10–fold cross–validation, might inadvertently capture anomalies rather than genuine patterns.[41] Furthermore, our method for managing missing data, especially through median imputation, poses the risk of introducing unintended biases, which could impact the model's performance.[42] Lastly, while predicting suicide attempts rather than suicide ideation may be crucial in suicide-related research, the low prevalence of suicide attempts presents limitations in constructing ML models: thus, we have developed predictive models for suicide ideation. With our predictive model, policy researchers, physicians, and community neighbors can develop individualized prevention strategies for these adolescents.

Despite these limitations, the strengths of our study are manifold. Notably, the SHAP value analysis highlights the importance of diverse demographic and behavioral indicators in understanding suicidal thinking among adolescents. This study provides nuanced insight into each feature's unique influence and the model's decision–making process.[43] The robustness of the model is also noteworthy, evidenced by its uniform effectiveness across datasets spanning South Korea, the USA, and Norway. Such wide–reaching efficacy suggests the adaptability of the model in different cultural and demographic landscapes. Another strength lies in the real–world applicability of our research. The development of our advanced online platform and mobile interface marks a notable advancement in practical application. By offering a user–friendly interface tailored for both desktop and mobile users, we enhance accessibility and promote greater self–awareness about suicidal risk. This can encourage individuals to seek timely professional assistance or supportive resources, serving as a preventive measure against severe mental health crises.[44]

Clinical and policy implications

In light of the findings, several crucial policy implications emerge. Foremost, the significant role of sadness and despair as a predictor underscores the necessity to prioritize mental health support for the adolescents.[45] This prominence not only necessitates immediate interventions but also stresses the vital role of education and awareness initiatives, targeting both risk behaviors and associated mental health ramifications. Early identification of suicidal thinking is paramount.[46] Recognizing these indications enables healthcare professionals to initiate early intervention strategies. This preemptive approach should include tailored counseling, support group engagements, or intensive therapeutic interventions. This can prevent the progression towards actual suicide attempts, which might be driven by mixed emotions or even an intent just to signal distress.[47] Moreover, there is a pressing need to bolster educational and awareness campaigns concerning suicide. Such campaigns serve to equip adolescents with the tools and knowledge necessary, encouraging them to navigate challenges related to risk behaviors and maintain positive mental health perspectives.[48]

Conclusion

In addressing the pressing global concern of adolescent suicide, our study employed ML to offer novel insights into preemptive detection. By integrating diverse datasets across three nations, the study spotlighted the superiority of the XGBoost model in predicting suicidal thinking, achieving remarkable AUROCs of 90.06% (95% CI, 89.97–90.16), (KYRBS from South Korea [discovery]), 83.09% (YRBS from the United States [extra–validation]), and 81.27% (Ungdata from Norway [extra–validation]). Our findings emphasize the significant role of emotional health indicators in predicting suicidal thinking among adolescents. Specifically, sadness and despair proved to be the most influential predictor, followed by stress status and age. Through our robust, cross–cultural validated model and its accessibility via online platforms, we underscore the potential for timely interventions and offer a promising blueprint for future mental health strategies and preventive measures for at–risk adolescents.

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Conflicts of interests

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Contributors

Dr DKY had full access to all of the data in the study and took responsibility for the integrity of the data and the accuracy of the data analysis. All authors approved the final version before submission. *Study concept and design*: HK, YS, Hojae L, RK, SW, and DKY; *Acquisition, analysis, or interpretation of data*: HK, YS, Hojae L, RK, SW, and DKY; *Drafting of the manuscript*: HK, YS, Hojae L, RK, SW, and DKY; *Critical revision of the manuscript for important intellectual content*: all authors; *Statistical analysis*: HK, YS, Hojae L, RK, SW, and DKY; *Study supervision*: RK, SW, and DKY. DKY supervised the study and is guarantor for this study. HK, YS, and Hojae Lee contributed equally as first authors. RK, SW, and DKY contributed equally as corresponding authors. The corresponding author attests that all listed authors meet authorship criteria and that no others meeting the criteria have been omitted.

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None

Data sharing statement

Data are available on reasonable request. Study protocol, statistical code: available from DKY (email: yonkkang@gmail.com). Data set: available from the Korean Disease Control and Prevention Agency (KDCA), U.S. Centers for Disease Control and Prevention (CDC), and Norwegian Social Research institute (NOVA) through a data use agreement.

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Table 1. Demographic characteristics of KYRBS data from South Korea (2009–2021), YRBS data from the USA (2021), and Ungdata from Norway (2017–2019)

aracteristics	KYRBS	YRBS	Ungdata
mber, n	566,875	103,874	19,574
gion, n (%)			
Urban	259,453 (45.77)	N/A	N/A
Rural	307,422 (54.23)	N/A	N/A
e, years, n (%)			
3	94,923 (16.74)	351 (0.34)	5,039 (25.74)
4	98,624 (17.40)	21,095 (20.31)	4,874 (24.90)
5	100,490 (17.73)	28,016 (26.97)	5,034 (25.72)
6	90,057 (15.89)	25,929 (24.96)	3,181 (16.25)
7	92,071 (16.24)	22,405 (21.57)	845 (4.32)
8	90,710 (16.00)	6,078 (5.85)	601 (3.07)
, n (%)			
Male	289,311 (51.04)	51,842 (49.91)	9,812 (50.13)
Female	277,564 (48.96)	52,032 (50.09)	9,762 (49.87)
I [a], n (%)			
Underweight	44,539 (7.86)	12,541 (12.07)	N/A
Normal	423,384 (74.69)	47,592 (45.82)	N/A
Overweight	48,951 (8.64)	14,439 (13.90)	N/A
Obese	50,001 (8.82)	29,302 (28.21)	N/A
ademic achievement, n (%)			
Low (0–19 percentile)	56,799 (10.02)	N/A	N/A

ower–middle (20–39 percentile)	132,774 (23.42)	N/A	N/A
Iiddle (40–59 percentile)	162,447 (28.66)	N/A	N/A
Jpper–middle (60–79 percentile)	146,401 (25.83)	N/A	N/A
Iigh (80–100 percentile)	68,454 (12.08)	N/A	N/A
usehold income, n (%)			
ow (0–19 percentile)	19,200 (3.39)	N/A	8,466 (43.25)
ower–middle (20–39 percentile)	82,314 (14.52)	N/A	6,557 (33.50)
Iiddle (40–59 percentile)	274,093 (48.35)	N/A	3,523 (18.00)
Jpper–middle (60–79 percentile)	148,848 (26.26)	N/A	818 (4.18)
Iigh (80–100 percentile)	42,420 (7.48)	N/A	210 (1.07)
oking status, n (%)			
Ion–smoker	467,707 (82.51)	84,984 (81.81)	16,594 (84.78)
moker	99,168 (17.49)	18,890 (18.19)	2,980 (15.22)
oholic consumption, n (%)			
Ion–drinker	478,305 (84.38)	76,571 (73.72)	9,673 (49.42)
Drinker	88,570 (15.62)	27,303 (26.28)	9,901 (50.58)
ss status[b], n (%)			
ow to moderate	337,938 (59.61)	70,817 (68.18)	N/A
Iigh to severe	228,937 (40.39)	33,057 (31.82)	N/A
ness and despair, n (%)			
ow to moderate	401,253 (70.78)	64,190 (61.80)	14,522 (74.19)
Iigh to severe	165,622 (29.22)	39,684 (38.20)	5,052 (25.81)
rcise status, n (%)			
Iot enough	496,475 (87.58)	87,510 (84.25)	N/A
nough	70,400 (12.42)	16,364 (15.75)	N/A
cide thinking in the past year, n (%)			
Io	482,613 (85.14)	80,561 (77.56)	17,652 (90.18)
es	84,262 (14.86)	23,313 (22.44)	1,922 (9.82)
eentime status, n (%)			
ow to moderate	165,382 (29.17)	27,569 (26.54)	994 (5.08)
Iigh to severe	401,493 (70.83)	76,305 (73.46)	18,580 (94.92)

* Abbreviation: KYRBS, Korea Youth Risk Behavior Web–based Survey; Ungdata, Norwegian nationwide Ungdata surveys; YRBS, Youth Risk Behavior Survey.

[a] BMI, body mass index; BMI was divided into four groups according to the National Growth Charts: underweight (0–4 percentile), normal (5–84 percentile), overweight (85–94 percentile), and obese (95–100 percentile).

[b] Stress was defined by receipt of mental health counseling owing to stress.

Table2. Feature importance of the XGBoost.

Feature	**Importance, %**
Sadness and despair	57.4
Stress status	19.8
Age	5.7
Household income	4.0
Academic achievement	3.4
Sex	2.1
Smoking status	1.7
BMI (kg/m^2)	1.6
Alcohol consumption	1.3
Exercise status	1.3
Screentime status	1.0
Region	0.8

* Abbreviation: XGBoost, Extreme Gradient Boosting.

Figure 1. Study architecture. Abbreviations: KYRBS, Korea Youth Risk Behavior Web–based Survey; Ungdata, Norwegian nationwide Ungdata surveys; YRBS, Youth Risk Behavior Survey of USA adolescent

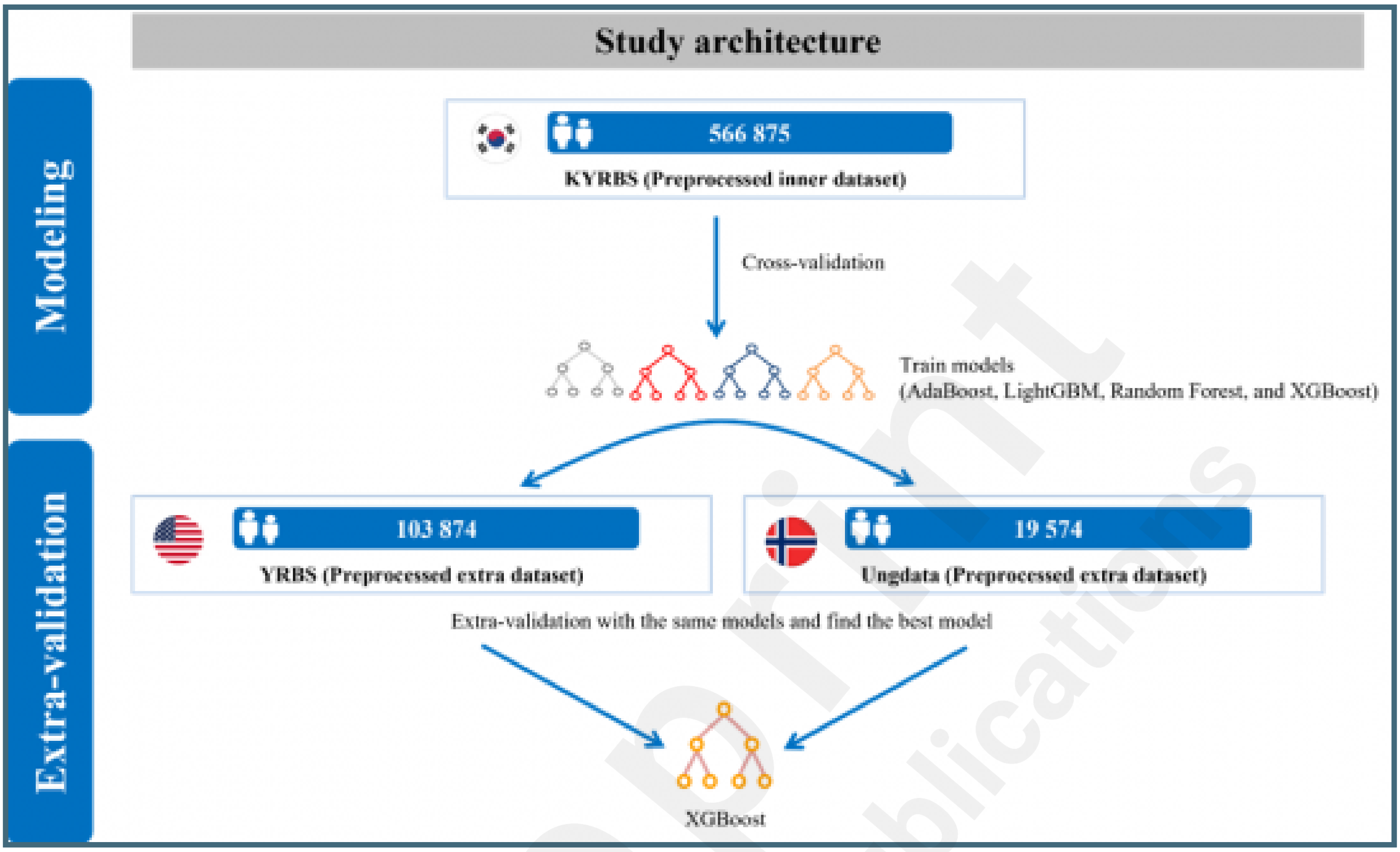
Figure 2. Model architecture. The original KYRBS dataset was partitioned into original dataset for model development, with performance assessed using AUROC scores. Selected high–performing models were further validated using an external YRBS dataset. The validation results were derived from the original dataset, external results from the additional YRBS dataset, and the Ungdata dataset. Abbreviations: AUROC, Area Under the Receiver Operating Characteristic Curve; CV, cross validation; KYRBS, Korea Youth Risk Behavior Web–based Survey; Ungdata, Norwegian nationwide Ungdata surveys; XGBoost, Extreme Gradient Boosting; YRBS, Youth Risk Behavior Survey

Figure 3. The AUROC of four different machine learning algorithms in the KYRBS dataset for validation, YRBS dataset for extra validation, and another external validation at Ungdata dataset. Abbreviations: AdaBoost, Adaptive Boosting; AUROC, Area Under the Receiver Operating Characteristic Curve; CI, confidence interval; KYRBS, Korea Youth Risk Behavior Web–based Survey; LightGBM, Light Gradient–Boosting Machine; ROC, receiver operating characteristic; Ungdata, Norwegian nationwide Ungdata surveys; XGBoost, Extreme Gradient Boosting; YRBS, Youth Risk Behavior Survey

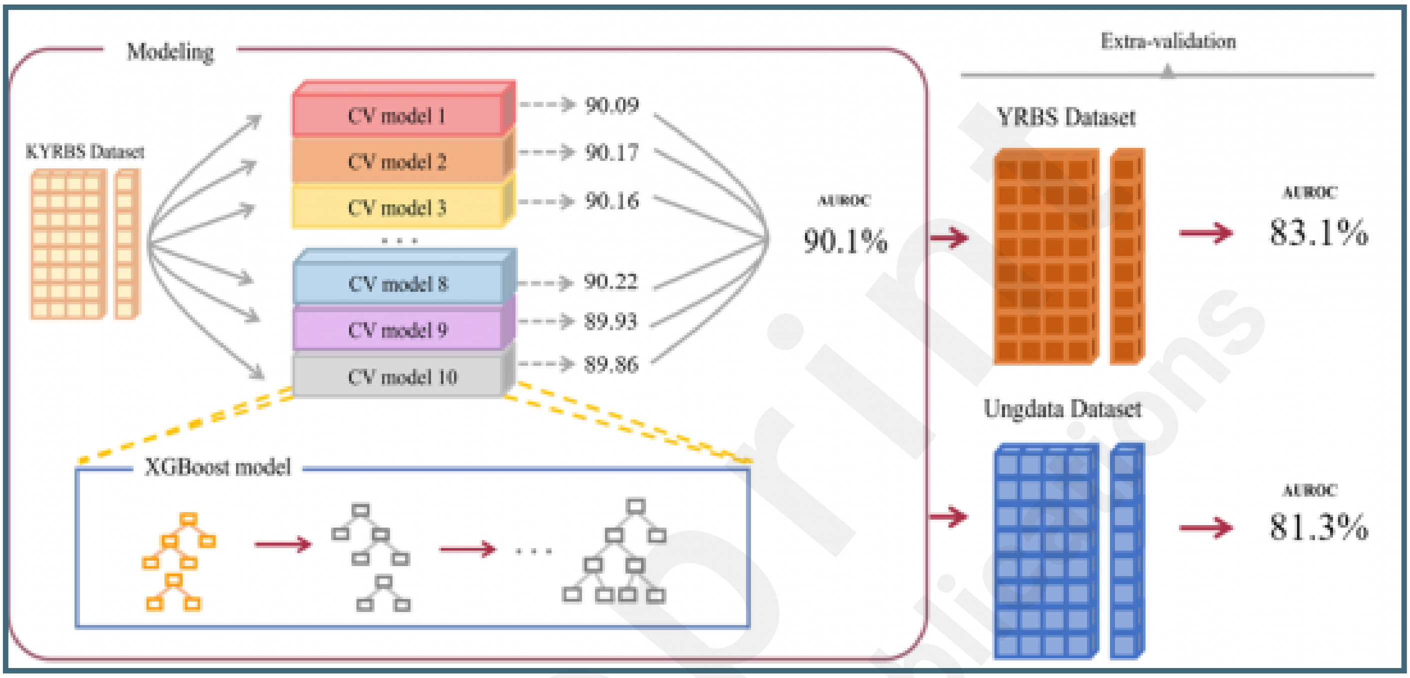
Supplementary Files

Figures

Study architecture. Abbreviations: KYRBS, Korea Youth Risk Behavior Web–based Survey; Ungdata, Norwegian nationwide Ungdata surveys; YRBS, Youth Risk Behavior Survey of USA adolescent.

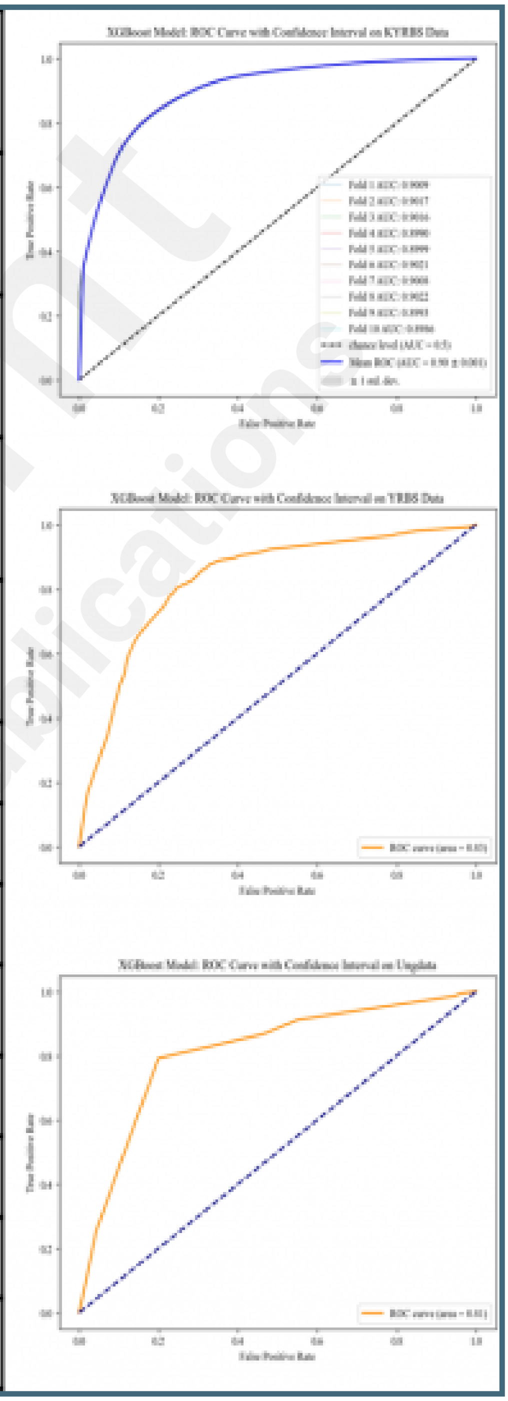


Model architecture. The original KYRBS dataset was partitioned into original dataset for model development, with performance assessed using AUROC scores. Selected high–performing models were further validated using an external YRBS dataset. The validation results were derived from the original dataset, external results from the additional YRBS dataset, and the Ungdata dataset. Abbreviations: AUROC, Area Under the Receiver Operating Characteristic Curve; CV, cross validation; KYRBS, Korea Youth Risk Behavior Web–based Survey; Ungdata, Norwegian nationwide Ungdata surveys; XGBoost, Extreme Gradient Boosting; YRBS, Youth Risk Behavior Survey.



The AUROC of four different machine learning algorithms in the KYRBS dataset for validation, YRBS dataset for extra validation, and another external validation at Ungdata dataset. Abbreviations: AdaBoost, Adaptive Boosting; AUROC, Area Under the Receiver Operating Characteristic Curve; CI, confidence interval; KYRBS, Korea Youth Risk Behavior Web–based Survey; LightGBM, Light Gradient–Boosting Machine; ROC, receiver operating characteristic; Ungdata, Norwegian nationwide Ungdata surveys; XGBoost, Extreme Gradient Boosting; YRBS, Youth Risk Behavior Survey.

Dataset	Model	AUROC	Sensitivity	Specificity	Accuracy	Balanced Accuracy
South Korea	**XGBoost**	**90.06 (89.97, 90.16)**	**82.11 (81.67, 82.55)**	**82.16 (81.68, 82.63)**	**82.13 (82.01, 82.26)**	**82.13 (82.01, 82.26)**
	AdaBoost	85.26 (85.14, 85.38)	78.08 (77.94, 78.21)	78.09 (77.96, 78.22)	78.08 (77.95, 78.21)	78.08 (77.95, 78.21)
	LightGBM	84.64 (84.53, 84.75)	78.96 (78.88, 79.04)	78.96 (78.88, 79.04)	78.96 (78.88, 79.04)	78.96 (78.88, 79.04)
	Random forest	84.10 (83.99, 84.21)	76.91 (76.73, 77.10)	77.06(76.98, 77.15)	76.99 (76.86, 77.11)	76.99 (76.86, 77.11)
United States	**XGBoost**	**83.09**	**80.26**	**75.52**	**76.58**	**77.89**
	AdaBoost	82.13	76.75	77.06	76.99	76.91
	LightGBM	83.93	79.85	75.87	76.76	77.86
	Random forest	83.20	78.28	77.43	77.62	77.86
Norway	**XGBoost**	**81.27**	**79.19**	**80.00**	**79.92**	**79.60**
	AdaBoost	79.14	79.19	80.00	79.92	79.60
	LightGBM	84.14	77.98	81.95	81.87	79.97
	Random forest	79.23	79.50	79.50	79.55	79.97



Multimedia Appendixes

Supplement Material.
URL: http://asset.jmir.pub/assets/634d31a0abd5a7da34d8d4655a8b030b.docx