



Classification and predictors of online risk exposure among adolescents: A latent profile analysis and machine learning approach

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Received: 06 June 2026; Accepted: 24 September 2026; Published: 30 October 2026

Abstract: Online risk exposure poses a serious threat to adolescents' mental health. This study aimed to identify key sociodemographic characteristics, individual factors, and environmental factors associated with online risk exposure using machine learning methods. A total of 5700 secondary school students from six schools were surveyed (females = 49.53%). Latent profile analysis was used to identify latent classes of online risk exposure. Least Absolute Shrinkage and Selection Operator (LASSO) regression was then used to screen key predictors, and several machine learning models were constructed and compared. Shapley Additive Explanations (SHAP) analysis was applied to determine the importance of predictors and their direction of association. Among seven machine learning models, the Light Gradient Boosting Machine (LightGBM) model showed the best performance (AUC = 0.83) and performed well on the test set. SHAP analysis indicated that, at the individual level, online game addiction and anxiety were the strongest risk factors. At the environmental level, interparental conflict and parental psychological control were the most important predictors. Gender and grade also made substantial contributions to the prediction of online risk exposure. A machine-learning-based prediction model can be used to preliminarily screen adolescents at high risk of online risk exposure.

Keywords: online risk exposure; latent profile analysis; machine learning; adolescents

Introduction

Adolescents have become a major population of Internet users. Recent data indicate that the global prevalence of Internet use among adolescents has reached 82% (International Telecommunication Union, 2025). Because adolescents' psychological development is not yet mature and their self-control and risk-prevention awareness remain limited, they are more likely to encounter risks during Internet use. Previous studies have shown that the prevalence of online risk exposure among adolescents is approximately 80.63% (Zhang et al., 2024b) and that online risk exposure is closely associated with emotional distress (Zhang et al., 2024a), substance use (Richardson et al., 2026), and self-harm (Liu et al., 2026). Screening and early warning for adolescent online risk exposure are therefore particularly important. However, evidence concerning the predictors of online risk exposure among adolescents remains insufficient, and many studies still focus only on single factors. Accordingly, the present study used latent profile analysis and machine learning strategies to examine important predictors and optimal prediction models for adolescent online risk exposure, with the broader goal of improving adolescent mental health.

Screening for online risk exposure

At present, there is no clinical standard for screening online risk exposure. Previous studies have usually relied on theoretical or empirical criteria. For example, in the context of cyberbullying victimization, some studies have considered an affirmative response to any item in a measurement instrument as meeting the screening criterion (Tsegaye et al., 2025), whereas others have required scores

above the theoretical midpoint of the scale (Real-Fernández et al., 2025). As a result, reported prevalence rates vary widely across studies (Panteli et al., 2026; Tsegaye et al., 2025; Wang et al., 2025). Variable-centered screening standards therefore require refinement.

In the absence of clinical diagnostic results, combining latent profile analysis (LPA) with receiver operating characteristic (ROC) curve analysis provides an alternative approach to determining cutoff values (Luo et al., 2024). LPA is a person-centered statistical method that can reveal population heterogeneity. On the basis of LPA results, ROC analysis can be used to identify cutoff values for different risk groups, thereby facilitating precise identification of adolescents at high risk of online risk exposure and supporting targeted intervention.

Predictors of online risk exposure

Sociodemographic factors may influence online risk exposure. Previous research has shown that boys are more likely to experience online sexual solicitation, whereas girls are more likely to be exposed to harmful content (Zhang et al., 2024b). Poor family economic conditions and poorer academic performance have also been identified as risk factors for online risk exposure (Jin et al., 2026). Parental behavior is part of the family system and its interaction patterns, and that it influences adolescents' emotion regulation and online behavior, thereby affecting online risk exposure (Bowen, 1966). Studies have found that interparental conflict, parental psychological control, and parental phubbing are all associated with online risk exposure (Bu & Zhang, 2025; Chu et al., 2025). Regarding school and peer environments, social support theory suggests that teacher support and peer attachment can optimize individuals'



cognitive appraisals and behavioral choices, strengthening their resistance to online temptations and reducing the likelihood of risk (Cassel, 1976; Razzaque et al., 2026).

Machine learning

Although previous studies have identified many individual- and environmental-level predictors, most have examined the association between a single variable and online risk exposure in isolation. Such studies can verify the role of specific factors but cannot reveal the relative importance of variables. Machine learning (ML) offers a new approach to addressing these limitations. Ensemble learning algorithms, such as random forest and gradient boosting machines, can handle complex nonlinear relations among high-dimensional features and more accurately identify key predictors and their importance (Li et al., 2026). In addition, interpretable techniques such as SHAP can visualize the direction and magnitude of each risk factor's contribution to individual predictions, thereby providing a foundation for interpretable risk-warning systems (Chen et al., 2026). Accordingly, the present study first used latent profile analysis and ROC analysis to determine a screening criterion for online risk groups and then incorporated a series of individual and environmental factors on the basis of this criterion. Seven algorithms were then used to construct prediction models of online risk exposure and determine the optimal model: logistic regression (LR), random forest (RF), extreme gradient boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), support vector machine (SVM), artificial neural network (ANN), and K-nearest neighbors (KNN). Finally, SHAP analysis was used to identify key factors influencing online risk exposure in the optimal model and to further verify the relations between each variable and online risk exposure.

Theoretical basis

With respect to negative psychological states, the theory of compensatory Internet use suggests that individuals tend to use the Internet to regulate emotions when they experience negative affect (Kardefelt-Winther, 2014). Such use may increase time spent online and weaken risk-monitoring capacity, thereby increasing the likelihood of online risk exposure (Boruah et al., 2025). Previous research has found that anxiety, depression, and leisure boredom are positively associated with online risk exposure (Lepp et al., 2025; Zhang et al., 2024b). With respect to positive psychological characteristics, the broaden-and-build theory posits that positive psychological resources enhance individuals' capacity to cope with negative information in online environments and thereby reduce their tendency toward online risk exposure (Fredrickson, 2001). Studies have shown that self-esteem and subjective well-being are negatively associated with online risk exposure (Zhang et al., 2024a). With respect to character strengths, resilience theory suggests that strengths function as protective factors in online contexts, buffering the influence of negative information and reducing the probability of online risk exposure (Rutter, 1985). Previous work has found that lower neuroticism and higher psychological resilience are associated with lower online risk exposure

(Wisniewski et al., 2015). With respect to maladaptive behaviors, cyber-routine activities theory argues that high-risk online lifestyles substantially increase the likelihood of victimization in online environments (Choi, 2008). Studies have shown that online game addiction significantly increases the probability of online risk exposure (Zhang et al., 2024b).

Empirical evidence indicates that peer attachment and teacher support provide adolescents with a favorable offline environment, thereby reducing the probability of online risk exposure (Bu & Zhang, 2025). Regarding the online environment, ecological techno-subsystem theory views online social support as an important component of the online environment that can influence individual behavior (Johnson & Puplampu, 2008). Research has shown that online social support can be a risk factor for online risk exposure; higher levels of online social support may be associated with more problems during Internet use, thereby increasing online risk exposure (Chao et al., 2025).

The China Context

China's Internet user population has reached 1.125 billion, with adolescents accounting for nearly one-third of this population (China Internet Network Information Center, 2026). Internet use enriches adolescents' development, learning, and daily life, but it also introduces multiple threats to healthy development, one of which is online risk exposure. Online risk exposure refers to contact with or experiences of negative risks in online environments, including cyberbullying victimization, personal information disclosure, online sexual solicitation, and exposure to harmful content (Zhang et al., 2024a). Online risk exposure among Chinese adolescents is influenced by specific sociocultural and developmental contexts. Family, school, and individual factors may shape adolescents' patterns of Internet use and the manifestation of different online risks. Therefore, it is necessary to examine the heterogeneity of online risk exposure and its key correlates within the Chinese context to support the identification of high-risk groups and the development of targeted prevention strategies.

Goals of the Study

This study aimed to identify key sociodemographic characteristics, individual factors, and environmental factors associated with online risk exposure using machine learning methods. We hypothesized that:

H1: Online risk exposure is heterogeneous.

H2: Individual factors (positive psychological characteristics, negative psychological states, character strengths, and maladaptive behaviors), environmental factors (family, school, peer, and online environments), and sociodemographic factors (gender, family socioeconomic status, and academic performance) are all associated with online risk exposure.

Methods

Participants and setting

A convenience sample of 2690 girls (49.53%), 2732 boys (50.30%) junior high school and vocational education students from Hebei Province, China were participants. A

total of 2966 participants resided in urban areas (54.61%), 2425 in rural areas (44.65%), and 40 had missing residence information (0.74%). There were 850 only children (15.65%), 4562 non-only children (84.00%), and 19 participants with missing only-child status (0.35%). Regarding family socioeconomic status, 2871 participants reported relatively high status (52.86%), 2385 reported relatively low status (43.91%), 50% were top of their class. In terms of grade, 2148 students were in Grade 7 (39.55%), 1060 were in Grade 8 (19.52%), 1306 were in Grade 10 (24.05%), and 917 were in Grade 11 (16.88%).

Measures

The dependent variable in this study was online risk exposure. Predictor variables included sociodemographic variables (seven variables: gender, grade, residence, only-child status, family socioeconomic status, academic performance, and parenting style), individual factors (nine variables: anxiety, depression, and leisure boredom as negative psychological states; self-esteem and subjective well-being as positive psychological characteristics; neuroticism and psychological resilience as character-related variables; and procrastination and online game addiction as maladaptive behaviors), and environmental factors (six variables: interparental conflict, parental psychological control, and parental phubbing as family environment variables; peer attachment as the peer environment variable; teacher support as the school environment variable; and online social support as the online environment variable). The measures are described below.

The Online Risk Exposure Scale contains 16 items rated from 0 (none) to 4 (many) and comprises four dimensions: cyberbullying victimization, personal information disclosure, online sexual solicitation, and exposure to harmful content (Zhang et al., 2024b). In the present study, the scale's McDonald's ω coefficient was 0.91, and the McDonald's ω coefficients for the four dimensions ranged from 0.70 to 0.88. The model showed an acceptable fit ($\chi^2/df = 38.58$, NFI = 0.92, IFI = 0.92, CFI = 0.92, RMSEA = 0.08).

Negative psychological states. The Anxiety Scale (AS) contains five items, such as 'feeling nervous, anxious, or on edge,' rated from 0 (less than 1 day) to 3 (5 to 7 days), with higher scores indicating greater anxiety (Zhang et al., 2024a). The McDonald's ω coefficient was 0.90. The model showed an acceptable fit ($\chi^2/df = 34.67$, NFI = 0.99, IFI = 0.99, CFI = 0.99, RMSEA = 0.08). The Depression Scale (DS) contains six items, such as 'feeling sad or empty,' rated from 0 (less than 1 day) to 3 (5 to 7 days), with higher scores indicating greater depression (Zhang et al., 2024a). The McDonald's ω coefficient was 0.90. The model showed an acceptable fit ($\chi^2/df = 16.22$, NFI = 0.99, IFI = 0.99, CFI = 0.99, RMSEA = 0.05). The Leisure Boredom Scale (LBS) contains three items, such as 'I do not know what to do in my free time,' rated from 1 (strongly disagree) to 5 (strongly agree), with higher scores indicating greater leisure boredom (Jin et al., 2026). The McDonald's ω coefficient was 0.86.

Positive psychological characteristics. The Self-Esteem Scale (SES) contains five items, such as 'I feel

that I am a person of worth,' rated from 1 (strongly disagree) to 4 (strongly agree), with higher scores indicating higher self-esteem (Chang et al., 2018). The McDonald's ω coefficient was 0.87. The model showed an acceptable fit ($\chi^2/df = 11.22$, NFI = 0.99, IFI = 0.99, CFI = 0.99, RMSEA = 0.04). The Subjective Well-Being Scale (SWBS) contains three items, such as 'I live happily,' rated from 1 (strongly disagree) to 4 (strongly agree), with higher scores indicating higher well-being (Bae, 2019). The McDonald's ω coefficient was 0.80.

Character-related variables. The Neuroticism Scale (NS) contains three items, such as 'I often worry about trivial things,' rated from 1 (strongly disagree) to 5 (strongly agree), with higher scores indicating greater emotional instability (Zhang et al., 2019). The McDonald's ω coefficient was 0.84. The Psychological Resilience Scale (PRS) was developed with reference to previous scales (Wang et al., 2010) and contains five items, such as 'When I encounter setbacks, it takes me a long time to recover,' rated from 1 (strongly disagree) to 5 (strongly agree). Higher scores indicate poorer psychological resilience. The McDonald's ω coefficient was 0.87. The model showed an acceptable fit ($\chi^2/df = 23.09$, NFI = 0.99, IFI = 0.99, CFI = 0.99, RMSEA = 0.06).

Maladaptive behaviors. The Online Game Addiction Scale (OGAS) was developed with reference to previous scales (Lemmens et al., 2009) and contains six items, such as 'Playing online games has become part of my daily routine,' rated from 1 (strongly disagree) to 5 (strongly agree), with higher scores indicating more severe online game addiction. The McDonald's ω coefficient was 0.90. The model showed an acceptable fit ($\chi^2/df = 30.07$, NFI = 0.99, IFI = 0.99, CFI = 0.99, RMSEA = 0.07). The Procrastination Scale (PS) was developed with reference to previous scales (Zhang et al., 2020) and contains three items, such as 'When completing a task that is due soon, I still waste time doing other things,' rated from 1 (strongly disagree) to 5 (strongly agree), with higher scores indicating more severe procrastination. The McDonald's ω coefficient was 0.81.

Family environment. The Interparental Conflict Scale (ICS) contains five items, such as 'My parents often argue and quarrel,' rated from 0 (never) to 3 (often), with higher scores indicating more intense interparental conflict (Dong & Lin, 2011). The McDonald's ω coefficient was 0.83. The model showed an acceptable fit ($\chi^2/df = 21.39$, NFI = 0.99, IFI = 0.99, CFI = 0.99, RMSEA = 0.06). The Parental Psychological Control Scale (PPCS) contains six items, such as 'My parents often ask me to comply with their views,' rated from 1 (never) to 5 (always), with higher scores indicating stronger parental control (Jin et al., 2026). The McDonald's ω coefficient was 0.89. The model showed an acceptable fit ($\chi^2/df = 43.63$, NFI = 0.98, IFI = 0.98, CFI = 0.98, RMSEA = 0.09). The Parental Phubbing Scale (PPS) was developed with reference to previous scales (Ding et al., 2020) and contains four items, such as 'When I eat with my parents, they use their mobile phones,' rated from 1 (never) to 5 (always), with higher scores indicating more frequent parental phubbing. The McDonald's ω coefficient was 0.75. The model showed an

acceptable fit ($\chi^2/df = 30.69$, NFI = 0.99, IFI = 0.99, CFI = 0.99, RMSEA = 0.07).

Peer environment. The Peer Attachment Scale (PAS) contains three items, such as 'I enjoy being with my classmates in class,' rated from 1 (never) to 5 (always), with higher scores indicating better peer attachment (Cho & Lee, 2018). The McDonald's ω coefficient was 0.78.

School environment. The Teacher Support Scale (TSS) contains five items, such as 'My teachers care about me,' rated from 1 (never) to 5 (always), with higher scores indicating higher levels of teacher support (Chang et al., 2018). The McDonald's ω coefficient was 0.90. The model showed an acceptable fit ($\chi^2/df = 41.40$, NFI = 0.99, IFI = 0.99, CFI = 0.99, RMSEA = 0.09).

Online environment. The Online Social Support Scale (OSSS) contains four items, such as 'I can seek help online,' rated from 1 (strongly disagree) to 5 (strongly agree), with higher scores indicating higher levels of online social support (Frison & Eggermont, 2016). The McDonald's ω coefficient was 0.86. The model showed an acceptable fit ($\chi^2/df = 3.78$, NFI = 0.99, IFI = 0.99, CFI = 0.99, RMSEA = 0.02).

Procedure

This study was approved by the Ethics Committee of Hebei Normal University (2022LLSC051), in accordance with the principles of the Declaration of Helsinki. All participants were minors. Therefore, informed consent was obtained from their parents or legal guardians, and all participants retained the right to withdraw from the study at any time. Prior to administration, the researcher explained the purpose of the study, the principle of anonymity, and the scope of data use to the participants, and informed them that their responses would be used solely for academic research purposes and would not affect any personal evaluation. After being fully informed of the relevant information, all participants voluntarily agreed to take part in the study. These procedures were intended to minimize defensive responding and social desirability bias.

Data analysis

Mplus 8.3 was used to conduct latent profile analysis, and the optimal number of classes was selected on the basis of model fit indices. Lower values of the Akaike information criterion (AIC), Bayesian information criterion (BIC), and sample-size-adjusted BIC (aBIC) indicate better fit. Nonsignificant results for the Lo-Mendell-Rubin (LMR) likelihood-ratio test and the bootstrap likelihood-ratio test (BLRT) indicate that the model with $k-1$ classes is preferable to the model with k classes. Higher entropy values indicate better classification accuracy, and each class should preferably include more than 5% of the sample (Zhang et al., 2024a). After the optimal latent class model was identified, the BCH method was further applied to examine differences across latent classes in external continuous variables.

Using stratified sampling, the data were split into a training set (80%) and a test set (20%), and multiple imputation was conducted separately for the two datasets,

with the random seed set to 123. LASSO regression was used to screen predictor variables. Ten-fold cross-validation was used to evaluate model performance, and the largest lambda within one standard error was selected as the final parameter. Variables with nonzero coefficients were retained as efficient predictors. Prediction models for online risk exposure were then constructed in Python 3.10.4 using seven algorithms: logistic regression (LR), random forest (RF), extreme gradient boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), support vector machine (SVM), artificial neural network (ANN), and K-nearest neighbors (KNN).

During model training, grid search combined with five-fold cross-validation was used to optimize hyperparameters. Model performance was comprehensively evaluated on the test set using accuracy, precision, recall, F1 score, negative predictive value, and area under the ROC curve (AUC) (Deng et al., 2026). Higher values of accuracy, precision, recall, F1 score, and negative predictive value indicate better predictive performance. An AUC closer to 1 indicates stronger discriminative performance. Finally, the best-performing model was selected for SHAP analysis.

Results

Latent classes and screening criterion for adolescent online risk exposure

On the basis of the 16 items of the Online Risk Exposure Scale, LPA models with one to four latent classes were constructed sequentially. The results showed that AIC, BIC, and aBIC decreased as the number of latent classes increased, and all entropy values were higher than 0.80 (Table 1). The LMR test was not significant for the four-class model, indicating that the three-class model was preferable to the four-class model. Compared with the two-class model, the three-class model had lower information criterion values, and both the LMR and BLRT tests were significant. However, the smallest class in the three-class model accounted for 4.95% of the sample, which was slightly below the prespecified 5% criterion. In addition, although the information criterion values continued to decrease in the three-class model, the magnitude of the decrease was markedly reduced. The two-class model also had the highest entropy value, suggesting better classification certainty. Therefore, the two-class model was selected as the primary analytical solution, and the results of the three-class model were further reported as a sensitivity analysis. One class showed higher standardized scores across all items, whereas the other showed lower standardized scores across all items; these classes were labeled the low-risk group and the high-risk group, respectively (Figure 1).

The BCH analysis showed that the differences between the low-risk group and the high-risk group were significant across all continuous variables (Table 2). Compared with the low-risk group, the high-risk group had higher scores on parental phubbing, neuroticism, psychological resilience, leisure boredom, online social support, procrastination, online game addiction, depression, anxiety,

Table 1. Fit indices from latent profile analyses of adolescent online risk exposure

Classes	AIC	BIC	aBIC	Entropy	LMR	BLRT	Class probability (%)
1	205,338.38	205,549.58	205,447.89				100.00
2	179,459.47	179,782.87	179,627.16	0.98	0.003	0.000	88.88/11.12
3	169,414.07	169,849.66	169,639.94	0.94	0.005	0.000	72.44/22.61/4.95
4	165,035.35	165,583.14	165,319.39	0.94	0.110	0.000	69.75/18.71/7.97/3.57

Note. **Abbreviations:** AIC = Akaike information criterion, BIC = Bayesian information criterion, aBIC = sample-size-adjusted Bayesian information criterion, LMR = Lo-Mendell-Rubin, BLRT = bootstrap likelihood-ratio test. Bold indicates the two-class solution selected for subsequent analyses.

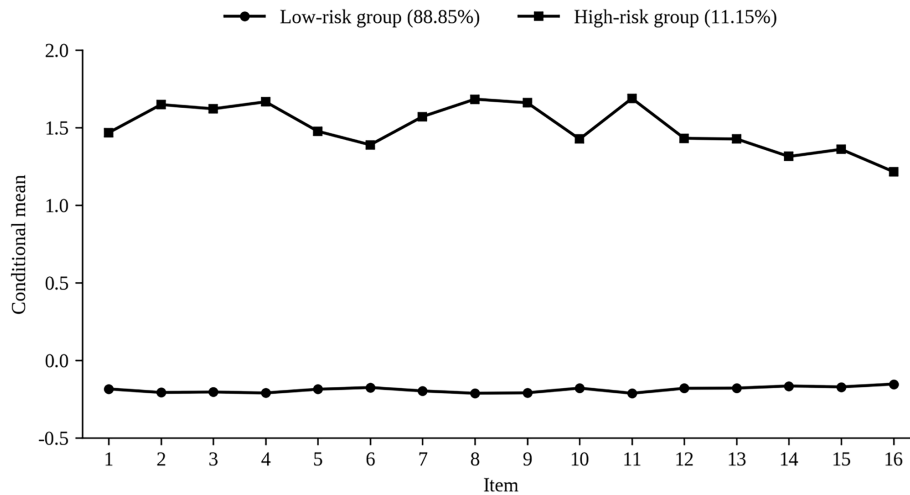


Figure 1. Latent profile analysis of online risk exposure. *Note.* Items 1–4 = cyberbullying victimization; items 5–7 = personal information disclosure; items 8–11 = online sexual solicitation; items 12–16 = harmful content exposure.

Table 2. Results of the BCH analysis

Variable	Low-risk group M	High-risk group M	χ^2	<i>p</i>
PPS	8.47	10.39	148.66	<0.001
PAS	11.33	9.623	172.84	<0.001
SES	14.40	13.18	63.06	<0.001
SWBS	8.99	7.68	188.08	<0.001
NS	8.70	10.08	103.48	<0.001
PRS	13.50	16.69	226.70	<0.001
LBS	7.99	9.89	164.38	<0.001
OSSS	9.13	10.58	64.67	<0.001
PS	7.59	9.05	119.52	<0.001
OGAS	12.14	16.97	323.21	<0.001
DS	4.55	8.74	364.56	<0.001
AS	3.60	7.24	340.63	<0.001
ICS	4.44	6.63	178.86	<0.001
TSS	18.68	16.08	132.52	<0.001
PPCS	12.15	16.47	223.23	<0.001

Note. **Abbreviations:** PPS = Parental Phubbing Scale; PAS = Peer Attachment Scale; SES = Self-Esteem Scale; SWBS = Subjective Well-Being Scale; NS = Neuroticism Scale; PRS = Psychological Resilience Scale; LBS = Leisure Boredom Scale; OSSS = Online Social Support Scale; PS = Procrastination Scale; OGAS = Online Game Addiction Scale; DS = Depression Scale; AS = Anxiety Scale; ICS = Interparental Conflict Scale; TSS = Teacher Support Scale; PPCS = Parental Psychological Control Scale. All abbreviations used hereafter have the meanings defined in this table.

interparental conflict, and parental psychological control, but lower scores on peer attachment, self-esteem, subjective well-being, and teacher support.

Based on the LPA results, ROC analysis was used to determine the preliminary reference cutoff for the high-risk group. The results showed that the cutoff value

Table 3. Cutoff values from ROC analysis

Cutoff value	Sensitivity	Specificity	Youden index
12.5	1	0.91	0.91
13.5	1	0.93	0.93
14.5	0.99	0.95	0.94
15.5	0.972	0.97	0.94
16.5	0.937	0.98	0.92

Note. **Abbreviations:** ROC = Receiver Operating Characteristic. Bold indicates the cutoff value with the largest Youden index.

with the largest Youden index was 14.5 (Table 3), corresponding to a sensitivity of 0.99, a specificity of 0.95, and an AUC of 0.997. Therefore, a score of 15 or higher was used as the reference cutoff for online risk exposure. Among the 5431 participants, 830 (15.28%) were assigned to the high-risk group and 4601 (84.72%) to the low-risk group.

Variable selection

LASSO regression selected 14 variables as feature variables (Figure 2). These included sociodemographic characteristics (two variables: gender and grade), individual factors (six variables: anxiety and depression as negative psychological states; subjective well-being as a positive psychological characteristic; psychological resilience as a character-related variable; and procrastination and online game addiction as maladaptive behaviors), and environmental factors (six variables: interparental conflict, parental psychological control, and parental phubbing as family environment variables; peer attachment as the peer environment variable; teacher support as the school environment variable; and online social support as the online environment variable).

Machine learning results

Correlation analysis was conducted on the 14 variables selected by LASSO regression (Figure 3). All correlation coefficients among the variables were below 0.80, indicating that there was no multicollinearity among the variables (Shrestha, 2020).

Seven machine learning algorithms were used to train the prediction models, and grid search with five-fold cross-validation was applied to determine the optimal parameters for each model (Table 4). Logistic regression used the default parameters. The LightGBM model had a relatively high F1 score and also performed well on AUC, accuracy, and other indices; it therefore showed the best overall performance (Table 5). For this model, the classification threshold was set at 0.22, and the corresponding confusion matrix is presented in Figure 4c.

Figure 4a presents the ROC curves for different models on the test set. The figure further evaluates the performance of the LightGBM model on the test set, showing an AUC of 0.83 and indicating favorable discriminative ability on the internal test set. Figure 4b presents the calibration curves for different models on the test set. The Brier score of the LightGBM model was 0.10, indicating good calibration performance.

SHAP analysis

SHAP is based on Shapley values from game theory. It can quantify the contribution of each feature to an individual prediction and provide interpretability at both global and local levels. As shown in Figure 5, the global feature-importance analysis based on the LightGBM model indicated that online game addiction was the strongest risk factor at the individual level, followed by anxiety. At the environmental level, interparental conflict and parental psychological control were the most important predictors. Gender and grade also played prominent roles in predicting online risk exposure. Further evidence from the LightGBM beeswarm plot (Figure 6) and dependence plots (Figure 7) showed that individual factors (online game addiction and anxiety) and environmental factors (interparental conflict and parental psychological control) were positively associated with online risk exposure. Boys and students in higher grades were also more susceptible to online risk exposure.

To examine whether the prediction results depended on the two-class profile solution, we further conducted a machine learning sensitivity analysis using a three-class solution. The SHAP analysis showed that the key predictors were largely consistent with those identified in the main two-class model (Figure 8). Online gaming addiction, anxiety, depression, parental conflict, parental psychological control, gender, and grade remained important variables for distinguishing different risk classes, whereas teacher support, peer attachment, and subjective well-being showed relatively protective effects. These findings suggest that the three-class solution did not alter the main conclusions regarding the key predictors, indicating that the two-class model demonstrated a certain degree of stability.

Discussion

This study found that adolescent online risk exposure could be divided into two classes: a low-risk group (88.88%) and a high-risk group (11.12%). This finding suggests that exposure to different types of online risks tends to co-occur during Internet use. In the low-risk group, scores on all dimensions were low. This pattern may be explained by a favorable family environment and social relationships, which allow adolescents to obtain offline support when facing negative emotions, reduce maladaptive online motives and behaviors, and thereby lower the risk of online risk exposure (Boruah et al., 2025; Shao et al., 2024). In the high-risk group, scores on all dimensions were high. This may be because adolescents in this group are affected by negative family environments and poorer social skills, leading them to shift more time and emotional needs to the Internet (Luo et al., 2026). At the same time, adolescents may have insufficient awareness of potential risks in online contexts and weak self-protection awareness. When confronted with risky situations, they may have difficulty identifying and coping with them effectively, which increases the risk of online risk exposure (Sun et al., 2026). Further analysis indicated that the screening cutoff for the high-risk group was 15, providing a practical reference criterion for screening adolescent online risk exposure.

Table 4. Optimal parameters of the prediction models

Model	Optimal parameters
RF	n_estimators = 475; max_features = 2
XGBoost	learning_rate = 0.03; max_depth = 5; n_estimators = 100; subsample = 0.6
LightGBM	learning_rate = 0.03; num_leaves = 100; n_estimators = 80; subsample = 0.4; colsample_bytree = 0.4
SVM	C = 1; kernel = linear; gamma = scale; degree = 2
ANN	activation = logistic; hidden_layer_sizes = (50,)
KNN	algorithm = brute; n_neighbors = 19; p = 1; weights = distance

Note. Abbreviations: RF = Random Forest; XGBoost = eXtreme Gradient Boosting; LightGBM = Light Gradient Boosting Machine; SVM = Support Vector Machine; ANN = Artificial Neural Network; KNN = K-Nearest Neighbors. All abbreviations used hereafter have the meanings defined in this table.

The results showed that adolescent online risk exposure was associated with variables at three levels: individual factors (online game addiction, anxiety, depression,

psychological resilience, subjective well-being, and procrastination), environmental factors (interparental conflict, parental psychological control, online social support,

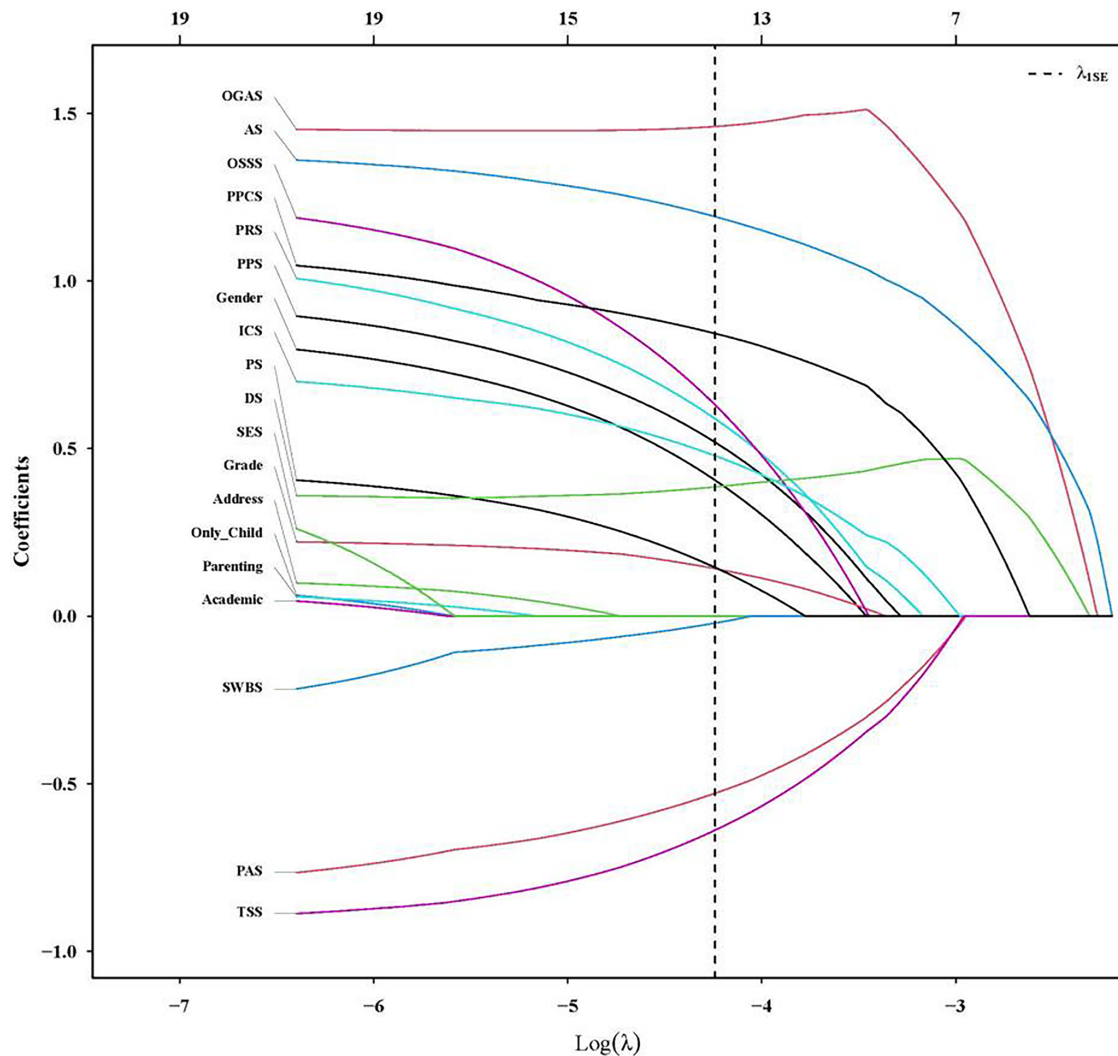


Figure 2. Predictor selection based on LASSO regression. *Note. Abbreviations:* PPS = Parental Phubbing Scale; PAS = Peer Attachment Scale; SWBS = Subjective Well-Being Scale; PRS = Psychological Resilience Scale; OSSS = Online Social Support Scale; PS = Procrastination Scale; OGAS = Online Game Addiction Scale; DS = Depression Scale; AS = Anxiety Scale; ICS = Interparental Conflict Scale; TSS = Teacher Support Scale; PPCS = Parental Psychological Control Scale. Each curve represents a candidate predictor. The x-axis represents $\log(\lambda)$, where λ is the LASSO regularization parameter, and the y-axis represents the corresponding regression coefficients. The numbers on the upper axis indicate the number of variables with non-zero coefficients at different λ values. The vertical dashed line indicates λ_1SE , which was used as the criterion for final variable selection. At λ_1SE , variables with non-zero coefficients were retained, whereas those with coefficients equal to zero were excluded. A total of 14 predictors were retained.

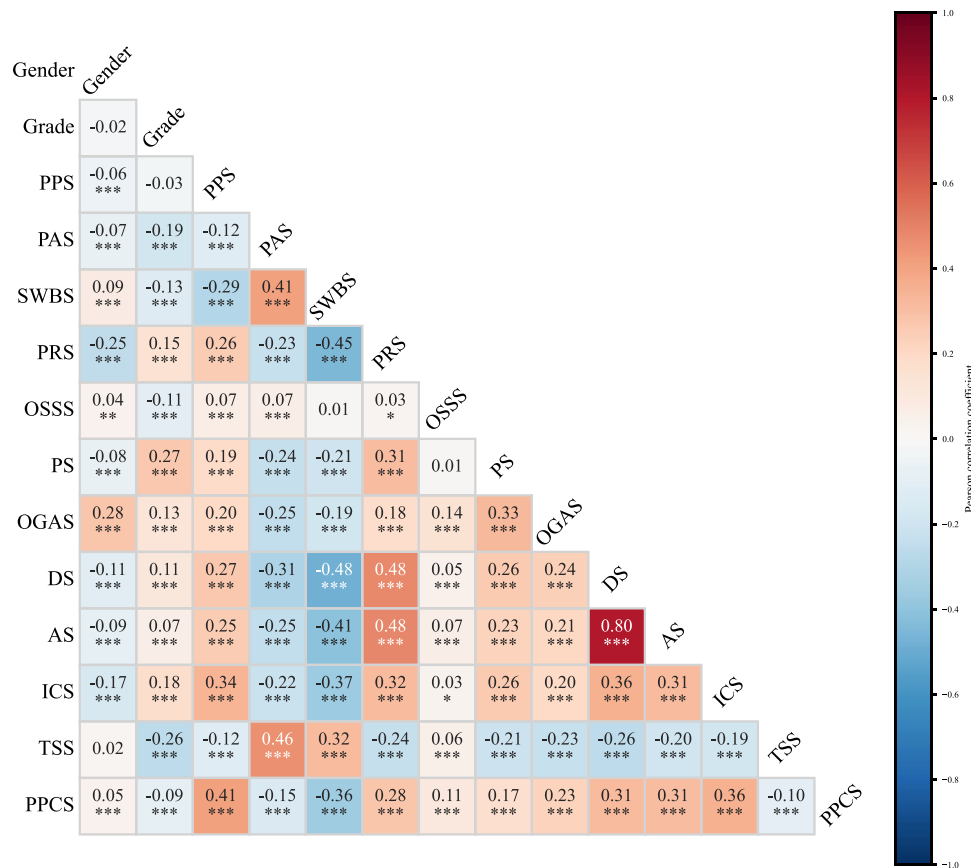


Figure 3. Correlation analysis. *Note.* * $p < .05$; ** $p < .01$; *** $p < .001$. PPS = Parental Phubbing Scale; PAS = Peer Attachment Scale; SWBS = Subjective Well-Being Scale; PRS = Psychological Resilience Scale; OSSS = Online Social Support Scale; PS = Procrastination Scale; OGAS = Online Game Addiction Scale; DS = Depression Scale; AS = Anxiety Scale; ICS = Interparental Conflict Scale; TSS = Teacher Support Scale; PPCS = Parental Psychological Control Scale.

Table 5. Comparison of predictive model performance

Model	AUC (95%)	Accuracy (95%)	Precision (95%)	Recall(95%)	F1 score (95%)	PR-AUC (95%)
LR	0.82 (0.78~0.85)	0.83 (0.81~0.85)	0.44 (0.37~0.52)	0.48 (0.40~0.56)	0.46 (0.39~0.53)	0.46 (0.38~0.54)
RF	0.83 (0.80~0.86)	0.83 (0.81~0.86)	0.46 (0.39~0.54)	0.52 (0.54~0.6)	0.49 (0.42~0.55)	0.36 (0.30~0.55)
XGBoost	0.82 (0.78~0.85)	0.84 (0.81~0.86)	0.47 (0.39~0.54)	0.51 (0.44~0.59)	0.49 (0.42~0.55)	0.47 (0.37~0.53)
LightGBM	0.83 (0.80~0.86)	0.82 (0.80~0.84)	0.44 (0.37~0.50)	0.61 (0.53~0.68)	0.51 (0.45~0.57)	0.46 (0.38~0.54)
SVM	0.79 (0.75~0.82)	0.76 (0.74~0.79)	0.36 (0.30~0.41)	0.67 (0.60~0.74)	0.47 (0.41~0.52)	0.39 (0.32~0.47)
ANN	0.82 (0.78~0.85)	0.82 (0.80~0.85)	0.44 (0.37~0.51)	0.56 (0.47~0.63)	0.49 (0.43~0.55)	0.44 (0.37~0.52)
KNN	0.80 (0.76~0.83)	0.77 (0.75~0.80)	0.36 (0.31~0.42)	0.66 (0.58~0.73)	0.47 (0.41~0.52)	0.43 (0.36~0.51)

Note. **Abbreviations:** LR = Logistic Regression; AUC = Area Under the ROC Curve; PR-AUC = Area Under the Precision-Recall Curve; SVM = Support Vector Machine; ANN = Artificial Neural Network; KNN = K-Nearest Neighbors. All abbreviations used hereafter have the meanings defined in this table.

teacher support, parental phubbing, and peer attachment), and sociodemographic characteristics (gender and grade).

Among individual factors, the most important predictors were online game addiction and anxiety. Higher online game addiction scores were associated with a greater likelihood of online risk exposure, which is consistent with the findings of Zhang et al. (2024b) and cyber-routine activities theory (Choi, 2008). First, more severe online game addiction is associated with longer Internet use, which may increase individuals' sense of belonging and presence online and thereby increase the risk of personal information disclosure (Gavriilidou & Gritzalis, 2026). Second, compared with nonaddicted groups, individuals

with online game addiction often show marked impairments in executive function (Rostami et al., 2025). This decline in cognitive control makes it more difficult for them to respond appropriately in online conflict situations, thereby increasing their risk of cyberbullying victimization (Real-Fernández et al., 2025). In addition, anxiety was second only to online game addiction in predicting online risk exposure. Higher anxiety scores were associated with a higher probability of online risk exposure. This finding is consistent with Zhang et al. (2024b) and the theory of compensatory Internet use (Kardefelt-Winther, 2014). Highly anxious individuals may use the Internet to avoid emotions or seek support. Such negatively driven online

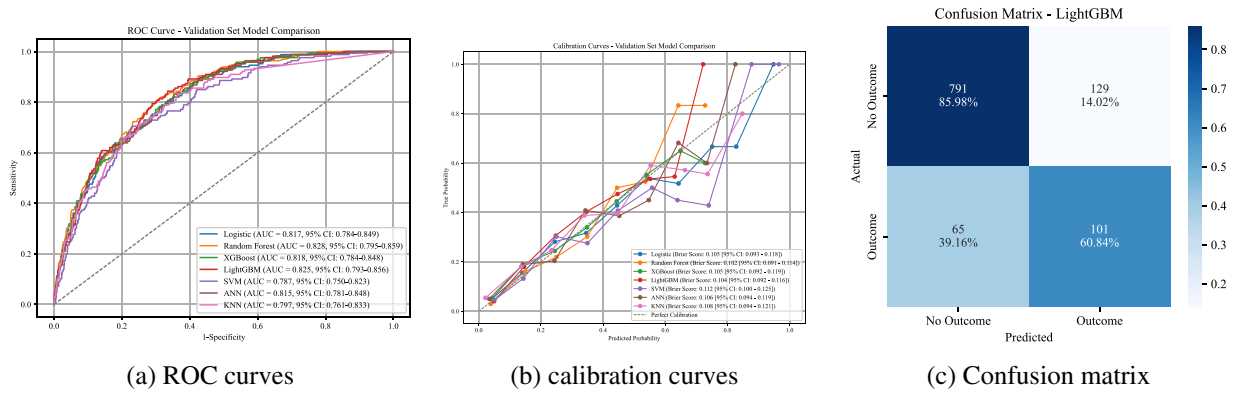


Figure 4. Model performance on the test set: (a) ROC curves, (b) Calibration curves, and (c) Confusion matrix for the LightGBM model

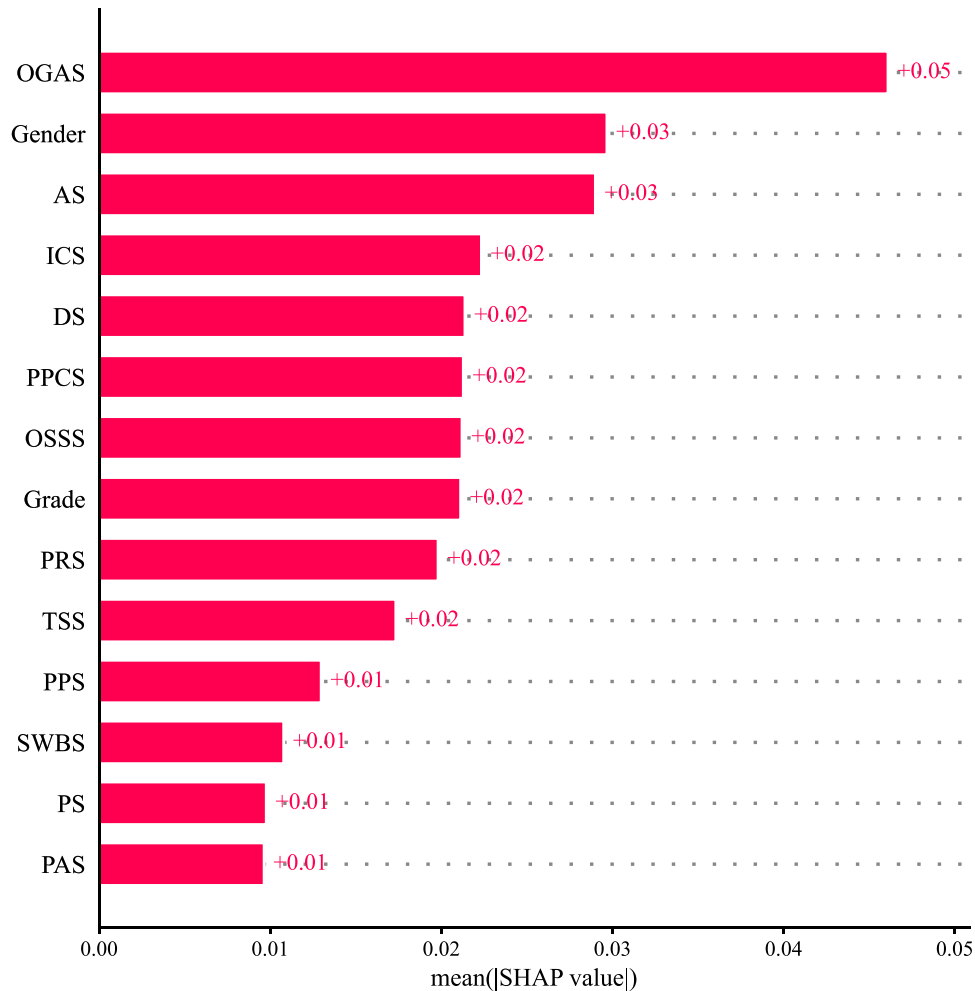


Figure 5. Feature-importance ranking in the LightGBM model

behavior may make them more likely to encounter harmful content, and exposure to such content may in turn increase anxiety, forming a vicious cycle (Biswas et al., 2025).

Among environmental factors, interparental conflict and parental psychological control were prominent predictors of adolescent online risk exposure. Adolescents exposed to more interparental conflict and stronger parental psychological control had higher levels of online risk exposure, which is consistent with Bu & Zhang (2025) and family systems theory (Bowen, 1966). Families

with high interparental conflict often lack a secure and stable family climate. Frequent marital conflict can lead to emotion dysregulation and reduced impulse control in adolescents, making them more likely to overreact during online interactions and become targets of cyberbullying victimization (Herbawani et al., 2026). In addition, excessive parental psychological control can deprive adolescents of autonomy and induce problems such as low self-esteem and social anxiety. When adolescents encounter online harassment, they may be more likely to respond through

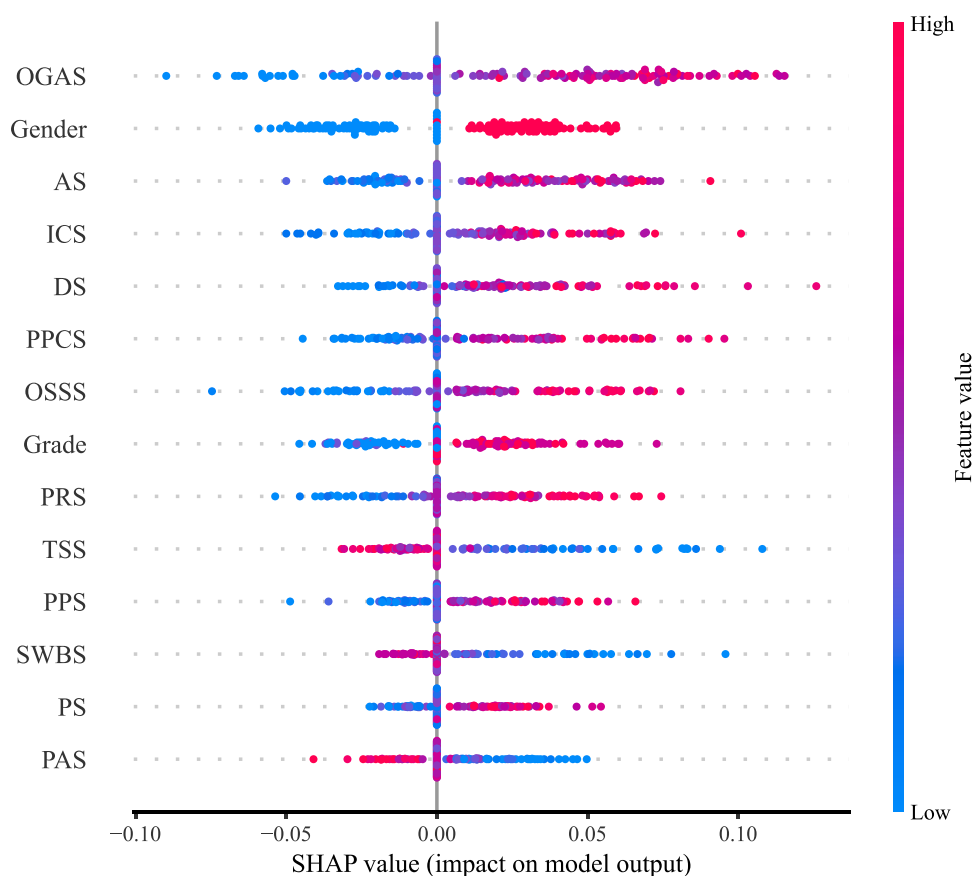


Figure 6. SHAP beeswarm plot of feature importance. *Note.* **Abbreviations:** PPS = Parental Phubbing Scale; PAS = Peer Attachment Scale; SWBS = Subjective Well-Being Scale; PRS = Psychological Resilience Scale; OSSS = Online Social Support Scale; PS = Procrastination Scale; OGAS = Online Game Addiction Scale; DS = Depression Scale; AS = Anxiety Scale; ICS = Interparental Conflict Scale; TSS = Teacher Support Scale; PPCS = Parental Psychological Control Scale.

suppression and avoidance rather than actively seeking help or blocking the source of harm. This passive response pattern ultimately increases their risk of cyberbullying victimization (Calaresi et al., 2025).

Among sociodemographic factors, gender and grade were the most important predictors of online risk exposure. The present results indicated that boys had a higher probability of online risk exposure than girls. This may be related to boys' more frequent participation in online games and anonymous social platforms, which increases opportunities to encounter potential sources of threat and therefore makes them more vulnerable to cyberbullying victimization, online sexual solicitation, personal information disclosure, and other risk behaviors (Nagata et al., 2026). Grade was another important sociodemographic predictor. Senior high school students had significantly higher levels of online risk exposure than junior high school students. As grade increases, adolescents use the Internet more autonomously, and direct supervision by parents and teachers tends to decrease. Their digital activities also become more diverse in type and scope, increasing their objective opportunities to encounter harmful information and other risky online situations (Kasturiratna et al., 2024).

Implications for Prevention and Intervention

This study has several implications. First, it identified latent classes of online risk exposure and a cutoff value for high-risk groups, which may facilitate rapid screening of online risk exposure. Second, by combining machine learning with SHAP analysis, the study provided empirical evidence for precise prevention and intervention for high-risk groups from the perspectives of individual factors, environmental factors, and sociodemographic characteristics. At the individual level, prevention should focus on online game addiction and anxiety, including interventions for addictive behaviors and emotion-regulation training. At the family level, interparental conflict and parental psychological control were the most salient environmental risk sources. Parents should therefore be made aware of the importance of their behavior for adolescents' mental health, avoid conflicts in front of children as much as possible, and create a positive family climate. Parents should also reduce excessive control and enhance adolescents' autonomy and problem-solving capacity. In addition, boys and students in higher grades were more likely to encounter online risk exposure. Differentiated strategies should therefore be developed for specific groups, and risk identification for these groups should be strengthened in prevention systems.

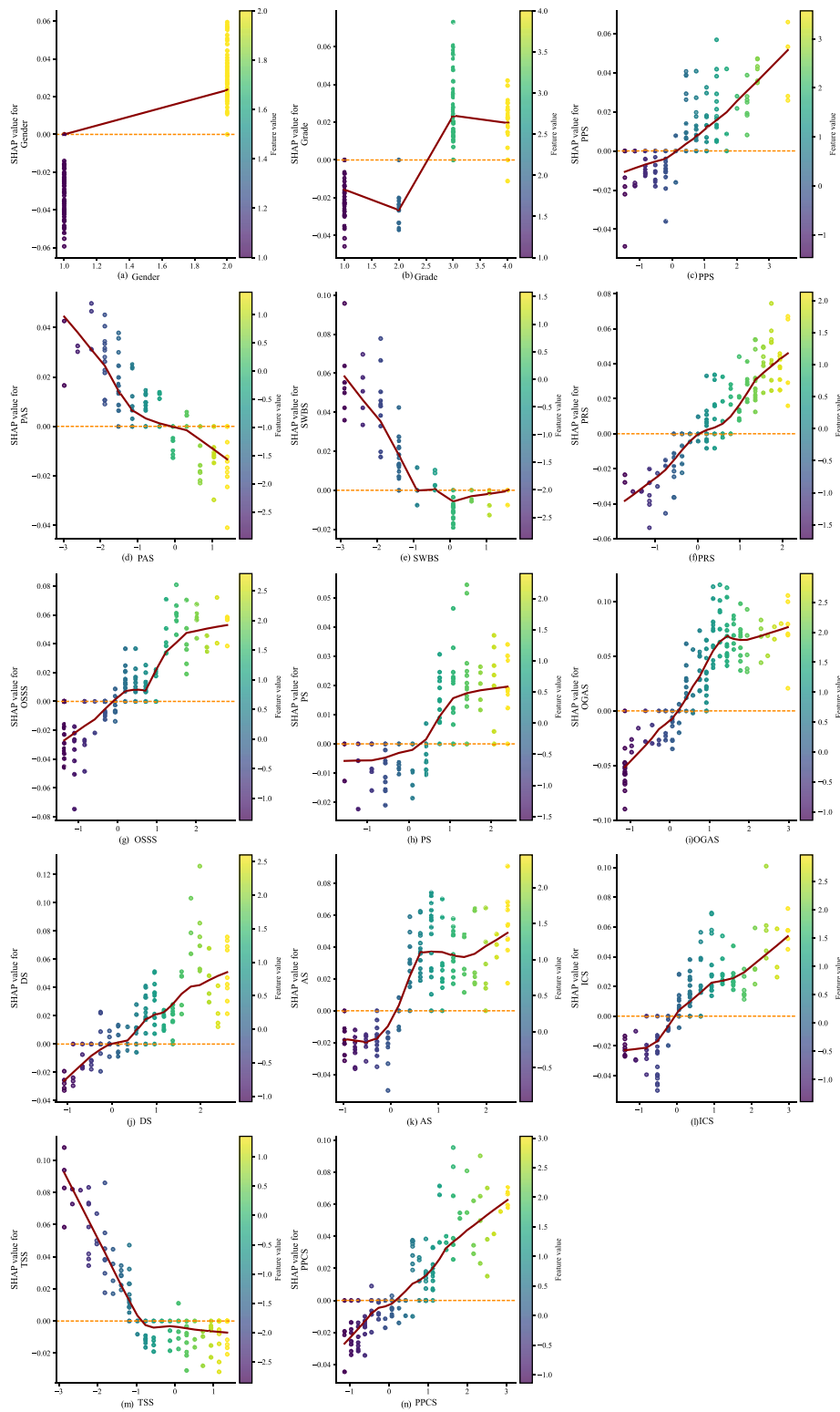


Figure 7. SHAP dependence plots: (a) Gender; (b) Grade; (c) PPS = Parental Phubbing Scale; (d) PAS = Peer Attachment Scale; (e) SWBS = Subjective Well-Being Scale; (f) PRS = Psychological Resilience Scale; (g) OSSS = Online Social Support Scale; (h) PS = Procrastination Scale; (i) OGAS = Online Game Addiction Scale; (j) DS = Depression Scale; (k) AS = Anxiety Scale; (l) ICS = Interparental Conflict Scale; (m) TSS = Teacher Support Scale and (n) PPCS = Parental Psychological Control Scale.

Limitations and Future Research Directions

This study also has limitations. First, the design does not allow causal relations among variables to be established. Future studies should use longitudinal designs to further verify the causal relations between the identified factors and online risk exposure. Second, because both the LPA

classification and ROC analysis were derived from the same online risk exposure scale and sample, there may be a tendency toward circular reasoning. Therefore, the cutoff should not be directly interpreted as evidence of independent screening validity. Future studies should use independent samples or longitudinal follow-up data to

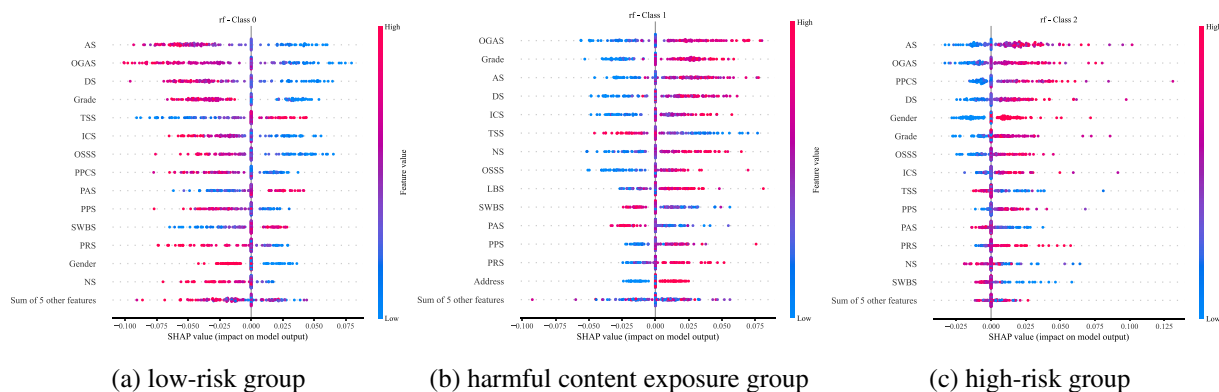


Figure 8. SHAP beeswarm plots for the three-class model: (a) low-risk group; (b) harmful content exposure group; and (c) high-risk group. *Note.* **Abbreviations:** PPS = Parental Phubbing Scale; PAS = Peer Attachment Scale; SWBS = Subjective Well-Being Scale; PRS = Psychological Resilience Scale; OSSS = Online Social Support Scale; PS = Procrastination Scale; OGAS = Online Game Addiction Scale; DS = Depression Scale; AS = Anxiety Scale; ICS = Interparental Conflict Scale; TSS = Teacher Support Scale; PPCS = Parental Psychological Control Scale.

further examine the stability and predictive validity of this cutoff. Finally, the sample in this study was drawn from six schools within the same province, which may have introduced school-level clustering effects. Accordingly, the current model cannot fully demonstrate external generalizability across schools or regions. Future research should incorporate independent external samples to further evaluate the robustness and practical generalizability of the model.

Conclusion

This study classified adolescent online risk exposure using latent profile analysis and divided participants into a low-risk group and a high-risk group, with a cutoff score of 15 used as the screening criterion. LASSO analysis identified 14 key predictors, and seven machine learning models were used to predict online risk exposure. Light-GBM was identified as the optimal model. SHAP analysis showed that the variables contributing to the prediction of online risk exposure, in descending order of importance, were online game addiction, gender, anxiety, interparental conflict, depression, parental psychological control, online social support, grade, psychological resilience, teacher support, parental phubbing, subjective well-being, procrastination, and peer attachment.

Acknowledgement: None.

Funding Statement: This work was supported by the Science Research Project of Hebei Education Department (BJ2025238), the 2026 Hebei Provincial Youth Development Research Project (2026HBQN94), and the 2026 Provincial Foreign Intellectual Introduction Project entitled “Research on the Mechanism, Challenges and Countermeasures of Digital Education Transformation Empowered by Artificial Intelligence” (25305023).

Author Contributions: Xinru Zhou was responsible for drafting the manuscript, designing the study, and analyzing the data; Yali Zhang was responsible for data collection and for revising and polishing the manuscript; Yuhong Ren conducted a systematic academic review of the entire

manuscript. All authors participated in the review of the final manuscript and take responsibility for the integrity and reliability of the research content. All authors reviewed and approved the final version of the manuscript.

Availability of Data and Materials: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Ethics Approval: This study was approved by the Ethics Committee of Hebei Normal University (2022LLSC051), in accordance with the principles of the Declaration of Helsinki. All participants were minors. Therefore, informed consent was obtained from their parents or legal guardians, and all participants retained the right to withdraw from the study at any time.

Conflicts of Interest: The authors declare no conflicts of interest.

References

- Bae, S. M. (2019). The relationship between smartphone use for communication, social capital, and subjective well-being in Korean adolescents: Verification using multiple latent growth modeling. *Children and Youth Services Review*, 96(5), 93–99. <https://doi.org/10.1016/j.childyouth.2018.11.032>
- Biswas, T., Edmed, S. L., Tran, N., Huda, M. M., Pattinson, C., et al. (2025). Access to potentially harmful online content and psychological distress in Australian older adolescents: A population-based study. *Child Indicators Research*, 18(2), 867–883. <https://doi.org/10.1007/s12187-025-10217-x>
- Boruah, A., Cormier, M., Murray, N. E., Marin-Dragu, S., Saad Hossne, J., et al. (2025). The moderating role of social media motives in the relationship between screen usage and cybervictimization. *Child Abuse & Neglect*, 160(2), 107239. <https://doi.org/10.1016/j.chiabu.2024.107239>
- Bowen, M. (1966). The use of family theory in clinical practice. *Comprehensive Psychiatry*, 7(5), 345–374. [https://doi.org/10.1016/S0010-440X\(66\)80065-2](https://doi.org/10.1016/S0010-440X(66)80065-2)
- Bu, R., & Zhang, Y. (2025). Latent classes and its influencing factors of online risk exposure among Chinese high

- school students. *Psychological: Techniques and Applications*, 13(3), 147–156. <https://doi.org/10.16842/j.cnki.issn2095-5588.2025.03.002>
- Calaresi, D., Verrastro, V., Giordano, F., & Saladino, V. (2025). Cyberbullying and cybervictimization: The role of parental psychological control and Dark Triad. *Social Sciences*, 14(6), 370. <https://doi.org/10.3390/socsci14060370>
- Cassel, J. (1976). The contribution of the social environment to host resistance. *American Journal of Epidemiology*, 104(2), 107–123. <https://doi.org/10.1093/oxfordjournals.aje.a112281>
- Chang, C. W., Yuan, R., & Chen, J. K. (2018). Social support and depression among Chinese adolescents: The mediating roles of self-esteem and self-efficacy. *Children and Youth Services Review*, 88(6), 128–134. <https://doi.org/10.1016/j.childyouth.2018.03.001>
- Chao, M., Wang, Y., Liu, J., & Gu, L. (2025). Relationship between online social support and problematic internet use: A three-level meta-analysis. *BMC Psychology*, 13(1), 745. <https://doi.org/10.1186/s40359-025-03076-2>
- Chen, H., Fan, Y., Zhou, L., Lin, J., Liu, D., et al. (2026). Key factors of depression in middle-aged and older adults based on social-ecological systems theory: An interpretable machine learning approach. *Journal of Affective Disorders*, 392(1), 120167. <https://doi.org/10.1016/j.jad.2025.120167>
- China Internet Network Information Center. (2026). The 57th statistical report on China's Internet development. <https://cnnic.cn/6/86/88/index.html>
- Cho, S., & Lee, J. M. (2018). Explaining physical, verbal, and social bullying among bullies, victims of bullying, and bully-victims: Assessing the integrated approach between social control and lifestyles-routine activities theories. *Children and Youth Services Review*, 91(5), 372–382. <https://doi.org/10.1016/j.childyouth.2018.06.018>
- Choi, K. S. (2008). Computer crime victimization and integrated theory: An empirical assessment. *International Journal of Cyber Criminology*, 2(1), 308–333.
- Chu, X., Yang, Y., Li, Q., Jia, Y., & Chen, H. (2025). Testing for indirect pathways between parental phubbing and cyberbullying in Chinese adolescents. *Journal of Applied Developmental Psychology*, 98(2), 101768. <https://doi.org/10.1016/j.appdev.2025.101768>
- Deng, Y., Shen, H., Zhang, C., Han, J., Ye, Z., et al. (2026). Construction and validation of a predictive model for suicidal attempts in patients with mood disorders after discharge based on machine learning methods: A two-year follow-up study. *Journal of Affective Disorders*, 405(2), 121607. <https://doi.org/10.1016/j.jad.2026.121607>
- Ding, Q., Wang, Z., & Zhang, Y. (2020). Revision of the Chinese version of parents phubbing scale in adolescents. *Chinese Journal of Clinical Psychology*, 28(5), 942–945. <https://doi.org/10.16128/j.cnki.1005-3611.2020.05.017>
- Dong, Q., & Lin, C. (2011). *Manual of the Psychological Development Database for Chinese Children and Adolescents Aged 6~15 (in Chinese)*. Beijing: Science Press. Retrieved September 23, 2026. https://www.amazon.com/dp/7030301447?lv=shuf&language=en_US&channelId=425&plpRedirect=mhFallback&cy=HKD
- Fredrickson, B. L. (2001). The role of positive emotions in positive psychology: The broaden-and-build theory of positive emotions. *American Psychologist*, 56(3), 218–226. <https://doi.org/10.1037/0003-066X.56.3.218>
- Frison, & Eggermont (2016). Exploring the relationships between different types of facebook use, perceived online social support, and adolescents' depressed mood. *Social Science Computer Review*, 34(2), 153–171. <https://doi.org/10.1177/0894439314567449>
- Gavriilidou, O., & Gritzalis, S. (2026). I disclose, therefore I exist: Time, control, and true self expression in social networking sites. *Psychology International*, 8(2), 29. <https://doi.org/10.3390/psycholint8020029>
- Herbawani, C. K., Karima, U. Q., Agustanti, R. D., Ramadhanti, I., Fitri, A. E. R., et al. (2026). Family conflict and digital risk as determinants of adolescent violence victimization: A cross-sectional study in Depok. *Indonesia Diversity: Disease Preventive of Research Integrity*, 6(2), 105–116. <https://doi.org/10.24252/diversity.v6i2.61845>
- International Telecommunication Union. (2025). Measuring digital development: Facts and figs. 2025. ITU. Retrieved September 23, 2026. <https://www.itu.int/en/ITU-D/Statistics/Pages/facts/default.aspx>
- Jin, K., Shang, S., & Zhang, Y. (2026). Analysis of internet risk exposure and its influencing factors among junior high school students. *Journal of Bio-Education*, 14(1), 10–16. <https://doi.org/10.3969/j.issn.2095-4301.2026.01.003>
- Johnson, G., & Ptoplampu, K. (2008). A conceptual framework for understanding the effect of the Internet on child development: The ecological techno-subsystem. *Canadian Journal of Learning and Technology*, 34(4), 19–28. https://doi.org/10.1007/978-3-031-61333-3_2
- Kardefelt-Winther, D. (2014). A conceptual and methodological critique of internet addiction research: Towards a model of compensatory internet use. *Computers in Human Behavior*, 31(1), 351–354. <https://doi.org/10.1016/j.chb.2013.10.059>
- Kasturiratna, K. T. A. S., Hartanto, A., Chen, C. H. Y., Tong, E. M. W., & Majeed, N. M. (2024). Umbrella review of meta-analyses on the risk factors, protective factors, consequences and interventions of cyberbullying victimization. *Nature Human Behaviour*, 9(1), 101–132. <https://doi.org/10.1038/s41562-024-02011-6>
- Lemmens, J. S., Valkenburg, P. M., & Peter, J. (2009). Development and validation of a game addiction scale for adolescents. *Media Psychology*, 12(1), 77–95. <https://doi.org/10.1080/15213260802669458>
- Lepp, A., Yim, B., & Barkley, J. E. (2025). Smartphone hookup app use (e.g., Tinder) and college student's risky sexual behavior: A model including leisure boredom, sensation seeking, and the moderating role of gender. *Computers in Human Behavior*, 166(2), 108581. <https://doi.org/10.1016/j.chb.2025.108581>
- Li, Z., Long, Q., Hao, M., Liu, L., Weng, Y., et al. (2026). Discovery of factors associated with smartphone addiction among high school adolescents: Using machine learning and network analysis. *Journal of Affective Disorders*, 392(6), 120096. <https://doi.org/10.1016/j.jad.2025.120096>
- Liu, Y., Zeng, S., Luo, X., Cheng, W., Chen, Y., et al. (2026). Cyberbullying victimization on non-suicidal self-injury among college students: A moderated mediation model. *Psychology Research and Behavior Management*, 19, 466487. <https://doi.org/10.2147/PRBM.S466487>
- Luo, J., Bei, D.-L., Gong, J., & Wang, M.-C. (2024). Classification of nomophobia among Chinese college students: Evidence from latent profile and ROC analysis. *Journal of Behavioral Addictions*, 13(2), 482–494. <https://doi.org/10.1556/2006.2024.00013>
- Luo, F., Du, Y., Sun, Q., Peng, N., & Li, Y. (2026). Family functioning and mobile phone dependency among adolescents: The mediating role of positive youth development and the moderating effect of physical activity. *BMC Psychology*, 14(1), 476. <https://doi.org/10.1186/s40359-026-04248-4>

- Nagata, J. M., Low, P., Lee, E. D., Yu, S., Leong, A. W., et al. (2026). Digital media use and psychosocial health among adolescent boys and young men. *Current Psychiatry Reports*, 28(1), 31. <https://doi.org/10.1007/s11920-026-01681-5>
- Panteli, S., Friberg, P., Beckman, L., & Chen, Y. (2026). Longitudinal associations of traditional and cyberbullying victimization with perceived stress in adolescents: Findings from the STARS cohort. *BMC Public Health*, 26(1), 698. <https://doi.org/10.1186/s12889-026-26395-4>
- Razzaque, S., Munir, F., Atta, K., & Niazi, N. A. K. (2026). Cyberbullying exposure and adolescent mental health: The mediating role of perceived social support in university students. *Review of Education, Administration and Law*, 9(1), 13–24. <https://doi.org/10.47067/real.v9i1.467>
- Real-Fernández, M., Navarro-Soria, I., Rosales-Gómez, M., Delgado, B. (2025). Problematic Internet use and its relationship with cyberbullying, anxiety, and executive functions in adolescence. *Children*, 12(4), 503. <https://doi.org/10.3390/children12040503>
- Richardson, M. K., Agbonlahor, O., Hart, J. L., Diaby, M., & Mattingly, D. T. (2026). Adolescent cyberbullying and polysubstance use: Unpacking sex differences. *Scientific Reports*, 16(1), 2204. <https://doi.org/10.1038/s41598-025-24108-2>
- Rostami, F., Esteki, A., Khoniveh, S., Ghamari, R., & Sarabi-Jamab, A. (2025). Impaired interference control in individuals with internet addiction: Evidence from event-related potentials and brain oscillations. *Addiction Biology*, 30(7), e70062. <https://doi.org/10.1111/adb.70062>
- Rutter, M. (1985). Resilience in the face of adversity: Protective factors and resistance to psychiatric disorder. *British Journal of Psychiatry*, 147(6), 598–611. <https://doi.org/10.1192/bjp.147.6.598>
- Shao, I. Y., Al-shoaibi, A. A. A., Testa, A., Ganson, K. T., Baker, F. C., & et al. (2024). The association between family environment and subsequent risk of cyberbullying victimization in adolescents. *Academic Pediatrics*, 24(6), 957–962. <https://doi.org/10.1016/j.acap.2023.11.019>
- Shrestha, N. (2020). Detecting multicollinearity in regression analysis. *American Journal of Applied Mathematics and Statistics*, 8(2), 39–42. <https://doi.org/10.12691/ajams-8-2-1>
- Sun, J., Ghazali, A. H. A., & Abdul, R. S. N. (2026). Risky online self-disclosure in adolescents: A meta-analytic review of predictors and outcomes. *Frontiers in Psychology*, 16, 1734301. <https://doi.org/10.3389/fpsyg.2025.1734301>
- Tsegaye, T. G., Kena, S. S., Debela, D. E., & Azeze, G. A. (2025). Cyberbullying, its associated factors, and coping mechanisms among female health science students in Hawassa City. 2025 *BMC Public Health*, 25(1), 4362. <https://doi.org/10.1186/s12889-025-25630-8>
- Wang, L., Shi, Z., Zhang, Y., & Zhang, Z. (2010). Psychometric properties of the 10-item Connor–Davidson resilience scale in Chinese earthquake victims. *Psychiatry and Clinical Neurosciences*, 64(5), 499–504. <https://doi.org/10.1111/j.1440-1819.2010.02130.x>
- Wang, Y., Cai, J., Wang, C., Mu, Y.-F., Deng, Z.-Y., et al. (2025). The prevalence and association of traditional bullying and cyber bullying with mental health among adolescent and youth students in China: A study after the lifting of COVID-19 restrictions. *BMC Public Health*, 25(1), 618. <https://doi.org/10.1186/s12889-024-20940-9>
- Wisniewski, P., Jia, H., Wang, N., Zheng, S., Xu, H., Rosson, M. B., Carroll, J. M. (2015). Resilience mitigates the negative effects of adolescent Internet addiction and online risk exposure. In: *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems* (pp. 4029–4038). ACM Press. <https://doi.org/10.1145/2702123.2702240>
- Zhang, X., Wang, M. C., He, L., Jie, L., & Deng, J. (2019). The development and psychometric evaluation of the Chinese big five personality inventory-15. *PLoS One*, 14(8), e0221621. <https://doi.org/10.1371/journal.pone.0221621>
- Zhang, Y., Jin, K., An, L., & Zhang, Y. (2024b). Preliminary application of online risk exposure scale in Chinese adolescents. *Chinese Journal of Clinical Psychology*, 32(6), 1383–1387. <https://doi.org/10.16128/j.cnki.1005-3611.2024.06.035>
- Zhang, Y., Jin, K., Huang, Y., & Jiang, Y. (2024a). Online risk exposure and mental health in Chinese junior high school students: A latent profile analysis. *Journal of Psychology in Africa*, 34(6), 637–643. <https://doi.org/10.1080/14330237.2024.2425274>
- Zhang, Y., Li, S., & Yu, G. (2020). Reliability and validity test of the short general procrastination scale in Chinese college students. *Chinese Journal of Clinical Psychology*, 28(3), 483–486. <https://doi.org/10.16128/j.cnki.1005-3611.2020.03.010>