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The dual effects of individual and contextual factors on adolescent problematic internet use: Machine learning approaches and SHAP explanations

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FULL-LENGTH REPORT

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ABSTRACT

Purpose: This study applied the Interaction of Person-Affect-Cognition-Execution (I-PACE) model and the Relational Development System Theory (RDS) to identify key individual and contextual correlates of adolescents' problematic Internet use (PIU) with machine learning approaches. *Methods:* Data from 68,425 adolescents were analyzed using five ensemble models (AdaBoost, Random Forest, LightGBM, Bagging, CatBoost) within a nested cross-validation framework. Key factors were identified through SHapley Additive exPlanations (SHAP), while bivariate partial dependence analyses were used to identify interactions. *Results:* The prevalence of PIU risk was 23.2%. Five algorithms achieved comparable performance. CatBoost achieved the best performance and was selected as the final predictive model. SHAP values showed that the top 17 features explained nearly 80% of the model. At the individual level, intolerance of uncertainty was the strongest risk factor, whereas mindfulness was the main protective factor. Additionally, weekend video game time was a major behavioral risk contributor. At the contextual level, home-leaving intentions and bullying perpetration were identified as key family- and peer-related risk factors, respectively. Bivariate partial dependence analyses found both within–individual (e.g., mindfulness * intolerance of uncertainty) and individual–contextual (e.g., mindfulness * home-leaving intentions) interaction effects. *Conclusions:* This study applied five machine learning algorithms to identify key individual and contextual factors associated with adolescent PIU risk and their interactions. The results suggest that risk factors accumulate across systems and impair adolescents' adaptive capacity, whereas mindfulness exerts cross-system effects that buffer these risks, offering implications for targeted interventions.

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KEYWORDS

adolescent problematic Internet use, machine learning, I-PACE model, RDS theory, prediction model

INTRODUCTION

Problematic Internet use (PIU) is characterized by excessive Internet use that leads to psychological, social, school, or work difficulties in a person's life (Beard & Wolf, 2001). A core

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characteristic of PIU is impaired control over Internet use (Supplee, Shaw, Hailstones, & Hartman, 2004). PIU encompasses all potentially problematic Internet-related behaviours, including gaming, gambling, buying, pornography viewing, social networking, cyber-bullying, cyberchondria (Fineberg et al., 2022). Growing evidence suggests that these diverse online behaviours may share transdiagnostic vulnerabilities, including heightened impulsivity and poor emotion regulation (Brand et al., 2019; Müller et al., 2025). This vulnerability is especially pronounced in adolescents, who are developmentally more susceptible to PIU (Chambers, Taylor, & Potenza, 2003; Tereshchenko & Kasparov, 2019).

Questionnaire-based studies estimate that the prevalence of PIU ranges from 20.0 to 44.6% (Cai et al., 2023). In China, over 20% of adolescents report "somewhat dependent" or "very dependent" on the Internet according to a large-scale national survey (CNNIC, 2023). Importantly, longitudinal research using the Internet Addiction Test (IAT)—a widely used instrument for assessing PIU (Carvalho et al., 2023; Moretta, Buodo, Demetrovics, & Potenza, 2022; Çelikkol Sadiç, Kara, Gerçek, & Özkan, 2024)—has shown that such problematic use is not merely transient. Among adolescents who met the cutoff for PIU at baseline (mean IAT score ≥4), 40.64% remained above the threshold two years later (Bu, Chi, & Qu, 2021). Together, these findings underscore the persistence of PIU during adolescence and its potential for broad psychosocial impact.

The Interaction of Person-Affect-Cognition-Execution (I-PACE) model has been widely used to examine individual susceptibility to PIU (Brand et al., 2019; Gao et al., 2022). I-PACE provides a micro-level framework for understanding internal predispositions but places limited emphasis on how these vulnerabilities are embedded within broader contextual environments. In contrast, the Relational Development System (RDS) theory emphasizes dynamic relations between individuals and their environments, offering a complementary macro-level perspective on PIU development (Cabrera & Leyendecker, 2017). Empirical research indicates that both individual traits and contextual factors contribute to PIU (Chemnad et al., 2023; Chi, Lin, & Zhang, 2016; Hsieh et al., 2021; Zhang et al., 2022). Integrating the micro-level mechanisms of I-PACE with the macro-level framework of RDS, the present study investigates PIU by examining the dynamic interplay between individual and contextual influences.

Individual and contextual correlates of PIU

Individual correlates of PIU. Individual correlates of PIU encompass psychological, behavioral, and demographic factors that contribute to individual differences in risk. *Psychological factors* such as emotional problems — including anxiety and depression — increase susceptibility to PIU by promoting maladaptive coping behaviors, particularly when the Internet is used to alleviate negative emotions (Cao, Su, Liu, & Gao, 2007; Emadi Chashmi et al., 2023; Young & Rogers, 1998). Emerging evidence also suggests that intolerance of uncertainty, which has been linked to smartphone addiction, may similarly contribute to PIU vulnerability (Vujić et al., 2024). In contrast, positive resources like resilience serve as protective factors (Cui & Chi, 2021). As highlighted by the I-PACE model and RDS theory, these psychological factors interact recursively with behavioral patterns, contributing to a cyclical process of PIU (Cabrera & Leyendecker, 2017; Liang, Zhu, Dai, Li, & Zheng, 2021).

Observable *behavioral habits* —including screen time, sedentary lifestyle, and physical activity —are also relate to PIU risk. Sedentary behaviour can exacerbate emotional distress, thereby increasing the likelihood of compensatory Internet use (Han et al., 2021; Li et al., 2024). Conversely, regular physical activity is associated with improved emotional regulation and self-control, reducing PIU vulnerability (Liu et al., 2023; Sheng, Liang, Li, Chi, & Fan, 2024). Finally, *demographic characteristics* — such as age, sex, and grade - represent another key category of individual correlates. These variables have been consistently shown to relate to differences in PIU levels among adolescents (Ko, Yen, Chen, Yeh, & Yen, 2009; Liu et al., 2023; şmaz et al., 2014) and constitute essential features for characterizing the study population.

Contextual correlates of PIU. Contextual correlates, particularly family and school environments, play a vital role in adolescent PIU (Chemnad et al., 2023; Dou, Feng, Wang, & Li, 2022; Li, Yu, Zhen, & Zhang, 2021). These environments comprise both objective and subjective aspects, which dynamically interact with psychological factors and behaviours to influence PIU risk (Hsieh et al., 2021; Lozano-Blasco, Latorre-Martínez, & Cortés-Pascual, 2022; Nwufo & Ike, 2024). *Objective factors* — such as parents' education level, socioeconomic status, and school resources — offer relatively stable developmental conditions that shape adolescents' opportunities and daily contexts (Bu et al., 2021; Nwufo & Ike, 2024; Zou, Deng, Wang, Yu, & Zhang, 2022). For instance, families with higher educational attainment may better guide technology use, and well-equipped schools can provide structured activities that help reduce excessive Internet use (Davis-Kean, Tighe, & Waters, 2021; Supplee et al., 2004; Zhang et al., 2022).

Subjective factors, such as perceived social support, potentially influence adolescents' coping strategies by buffering or amplifying the effects of negative experiences (Cui & Chi, 2021; Guo et al., 2021; Li et al., 2021; Lo et al., 2021). During adolescence, support mainly comes from family and peers. Frequent parent-child conflicts and poor family functioning increase the likelihood of using the Internet as a coping mechanism, raising addiction risk (Bao, Whitbeck, & Hoyt, 2000; Chi, Hong, & Chen, 2020). In contrast, strong peer networks reduce PIU risk, while peer conflict significantly heightens it (Wang et al., 2020; Zhao, Qu, Chen, & Chi, 2023).

The current research

This study addressed the following research questions: (1) Which individual and contextual factors are most strongly associated with adolescent PIU? (2) What SHAP-based threshold values of key predictors are associated with increased or decreased PIU risk? (3) How are interactions among these predictors associated with PIU?

METHODS

Procedure and participants

With support from the Shenzhen Education Commission, this survey employed stratified sampling across public primary/middle schools. After consulting school administrators and psychologists, students in grades 5–6, 7–8, and 10–11 were included for their cognitive ability to complete self-reports. Students in grades 9 and 12 were excluded because they were preparing for high school and college entrance exams and might not have been able to allocate time for such a large-scale survey. The survey conducted March 1–25, 2021 via online questionnaires during 40-min sessions.

From 79,664 recruited participants, 78,428 completed surveys (98.4% response rate), yielding 68,425 valid cases (51.9% male, 48.1% female) across 135 schools. Participants averaged 13.04 years (SD = 1.78; range = 10–17), with grade distribution: 20.8% (Grade 5), 20.7% (Grade 6), 22.2% (Grade 7), 18.8% (Grade 8), 17.5% (Grade 10–11).

Measurements

The outcome variable was adolescent PIU risk, measured by the 10-item Internet Addiction Scale (IAT-10; Shek, Tang, & Lo, 2008). Participants answered "Yes" (1) or "No" (0) to 10 items assessing PIU symptoms, with scores ≥4 indicating PIU. In this study, the PIU risk prevalence rate was 23.2% (15,903 cases). Guided by the RDS and I-PACE frameworks, predictors covering individual (psychological, behavioral habits, demographic characteristics) and contextual (family, peer, school) factors were collected. Detailed descriptions of the measurement instruments are provided in Appendix.

Statistical analysis

Machine learning approaches. Given the large cross-sectional sample and the inclusion of multiple individual-contextual factors, many of which may interact in nonlinear ways, PIU was modeled as a supervised binary classification task (at risk vs. not at risk). While regression-based methods remain valuable for hypothesis-driven analyses, they often rely on predefined theoretical models and functional forms, assume primarily linear relationships, and allow only limited interactions among variables (Bu et al., 2021; Chi et al., 2023; Yao, Liang, Zhang, & Chi, 2023). Accordingly, flexible machine learning models were adopted as a primary analytic approach to accommodate nonlinear associations and higher-order interactions among predictors without requiring strong parametric assumptions (Jordan & Mitchell, 2015; Ren, Wang, Mao, & Cheung, 2022). In this study, both boosting-based (AdaBoost, LightGBM, CatBoost) and bagging-based (Random Forest, Bagging) algorithms were implemented, representing distinct ensemble learning strategies emphasizing bias and variance reduction, respectively (Dietterich, 2000). To enhance interpretability, SHapley Additive exPlanations (SHAP) were applied to quantify feature-level contributions to model predictions, providing both global and local insights into the associations between predictors and PIU risk (Lundberg & Lee, 2017).

Data preprocessing. Given the substantial class imbalance between adolescents at risk and not at risk of PIU, this study employed a cluster-based random under-sampling strategy (Rayhan et al., 2017). Specifically, the majority-class samples were subjected to under-sampling, the samples were partitioned into k clusters using the k-means algorithm. The number of clusters (k) was determined automatically as the square root of the number of majority-class samples (i.e., $k \approx \sqrt{N}$). After clustering, random sampling without replacement was performed independently within each cluster. From each cluster, randomly select a number of samples such that the total number of retained majority-class samples is roughly equivalent to the size of the minority class.

Compared with stratified random undersampling, the clustering-based strategy better captures the heterogeneity of the majority class by preserving examples from multiple subspaces. This is achieved by k-means clustering, which assigns each instance to a specific cluster, whereas many alternative methods may fail to retain representative majority-class samples. Furthermore, unlike oversampling techniques such as SMOTE, the current method does not introduce synthetic data, thereby minimizing the risk of overfitting and artificial data bias.

Machine learning modeling. Five machine learning algorithms (AdaBoost, Random Forest, LightGBM, Bagging, and CatBoost) were systematically evaluated. To ensure robust and unbiased evaluation, this study adopted a nested cross-validation framework (5 outer folds × 3 inner folds). The inner folds were used for model training and hyperparameter optimization, where Optuna Bayesian optimization (Tree-structured Parzen Estimator sampler) with up to 30 trials per fold was applied to identify the best hyperparameters for each classifier (Akiba, Sano, Yanase, Ohta, & Koyama, 2019). The outer folds served as independent test sets to estimate generalization performance on unseen data. Stratified sampling was applied across all folds to maintain a consistent ratio of positive and negative cases, ensuring that both training and testing sets reflected the true distribution of adolescent PIU.

Model evaluation. Model performance was evaluated across multiple indicators, including AUC, Accuracy, Recall, and F1-score. All performance metrics were obtained from the outer folds of the nested cross-validation and reported as mean values across folds. Comparative evaluation across algorithms was conducted using summary tables and combined ROC/PR curves, providing a comprehensive overview of predictive performance. Based on these results, relatively better-performing algorithms were selected for constructing the final predictive model.

Model explanation. The final predictive model was further interpreted using SHAP. Model interpretation was conducted using a final model trained on the full dataset. SHAP values were first computed to assess the contribution of each predictor. Based on these results, cumulative feature contributions were analyzed, and the predictors accounting for 80% of the explanatory power was identified. SHAP swarm plots were generated to visualize the distribution of feature effects across individuals, and boxplots were employed to examine how feature values were distributed above and below the SHAP decision boundary (0). Furthermore, to investigate potential interactions between key predictors, bivariate partial dependence plots (PDPs) were constructed for selected individual-contextual features. The complete data processing pre-analysis workflow is shown in Fig. 1.

Ethics

This survey study was approved by Shenzhen University Research Board (No. 2020005), and permission to conduct the study was obtained from the teachers and principals at the participating schools.

RESULTS

Machine learning modeling performances

Table 1 summarizes the predictive performance of the five machine learning algorithms. Considering the class imbalance and the clinical importance of identifying at-risk

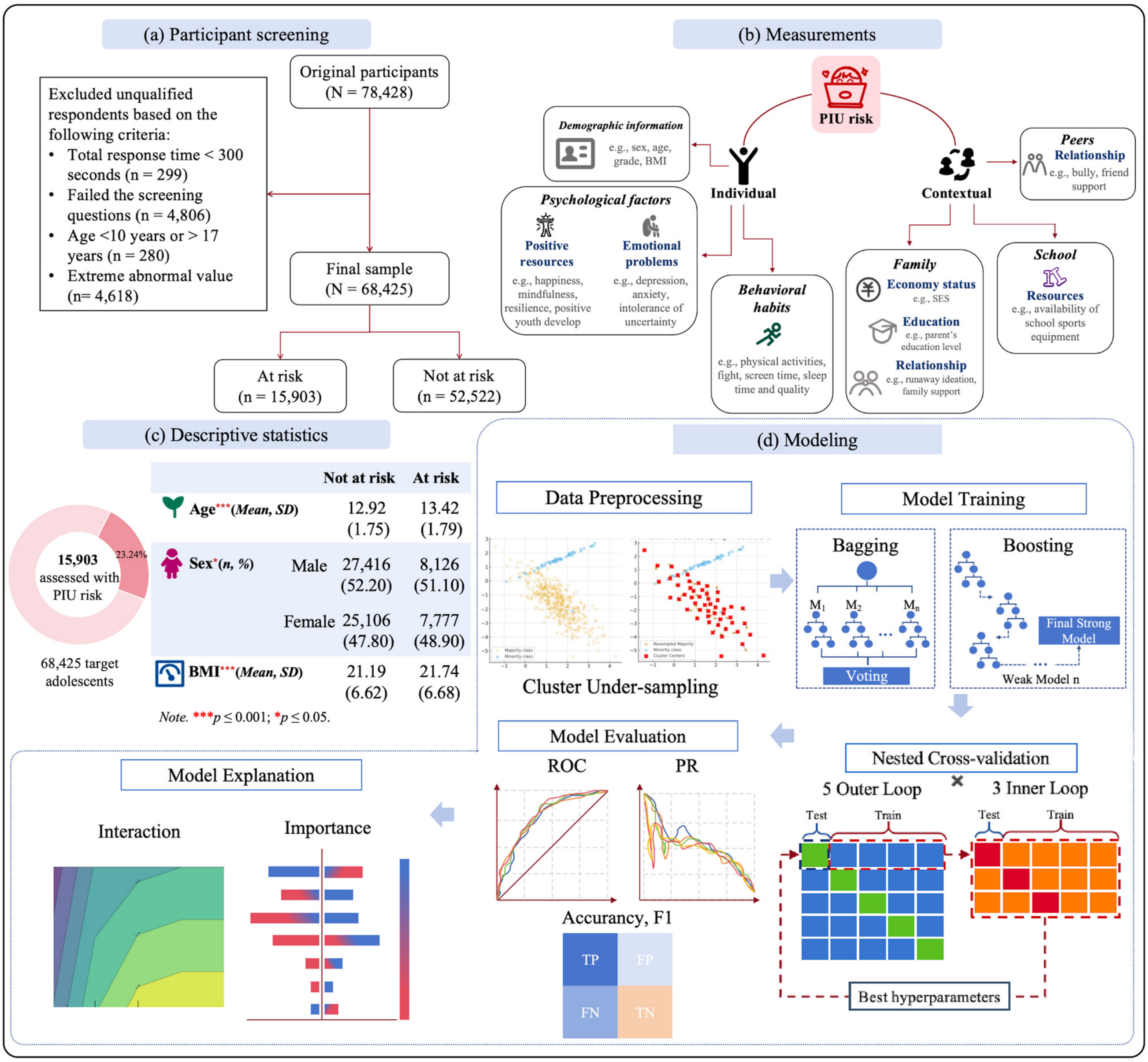

Fig. 1. Data processing pre-analysis workflow

Table 1. Machine learning algorithm performances for adolescent PIU risk

Model	AUC score	Accuracy	Recall	F1 score
	M (*SD*)			
AdaBoost	0.803 (.005)	0.746 (.006)	0.685 (.022)	0.556 (.006)
Random Forest	0.808 (.005)	0.738 (.012)	0.715 (.036)	0.559 (.006)
LightGBM	0.811 (.003)	0.756 (.008)	0.681 (.027)	0.565 (.003)
Bagging	0.799 (.005)	0.711 (.003)	0.758 (.013)	0.549 (.005)
Catboost	0.814 (.003)	0.754 (.004)	0.691 (.010)	0.567 (.007)

adolescents, we evaluated AUC, Accuracy, Recall, F1-score. All models showed good discriminatory ability, with mean AUC values ranging from 0.799 to 0.814 and mean accuracy between 0.711 and 0.756 (see Fig. 2). Recall ranged from 0.681 to 0.758, indicating that the models successfully identified over half of the high-risk individuals. PR-AUC (0.546–0.568) was substantially higher than the random baseline (0.16), confirming their effectiveness in detecting positive cases (see Fig. 3). Among them, CatBoost achieved the highest AUC (0.814 ± 0.003), PR-AUC (0.568 ± 0.007), and F1-score (0.567 ± 0.007), while maintaining competitive Recall (0.691 ± 0.010), highlighting its overall superior performance.

Feature importance to predict adolescent PIU

Based on the overall performance, the CatBoost model was selected for an in-depth explanation analysis. The global feature importance was assessed using SHAP to interpret the model's predictions. To enhance model parsimony and identify the most efficient subset of features, a cumulative SHAP analysis was conducted (see Fig. 4). The results indicated that approximately 80% of the model's explanatory power was achieved by the top 17 features (see Fig. 5). These key features were, in order of importance: intolerance of uncertainty-expected behaviours (unc2), mindfulness-awareness and non-judgment (mind1), home-leaving intentions (leave1), depression (dep), weekend video game time (game2), resilience (res), bullying perpetration, days of muscle-strength training per week (muscle), anxiety (anx), weekend online chat time (chat2), weekday video game time (game1), intolerance of uncertainty-inhibitory activity (unc3), bedtime (bed1), weekly days of ≥ 60-min MVPA (pa_days).

Figure 6 details these features' directional impacts using a zero SHAP decision boundary (values > 0 predicted PIU risk). Among the top 17 features, 16 demonstrated distinct directional impacts, as their data distributions clearly spanned across the SHAP value decision boundary of zero in the boxplot. It is evident that participants with moderate or higher intolerance of uncertainty-expected behaviours (unc2 > 11), low mindfulness-awareness and non-judgment (mind1 < 22),mild or greater depression (dep > 0), presence of home-leaving intentions (leave1 = yes), weekend video game time ≥ 2 h (game2 > 2), low resilience (res < 33), had bullied others (bully = yes), muscle-strength training per week < 2 days (muscle < 3), mild or greater anxiety (anx > 0), weekend online chat time ≥ 2h (chat2 > 2), weekday video game time ≥2 h (game1 > 2), low intolerance of uncertainty-inhibitory activity (unc3 < 7), weekly days of ≥ 60-min MVPA ≤ 2 days (pa_days < 4), male (sex = 1), frequent lack

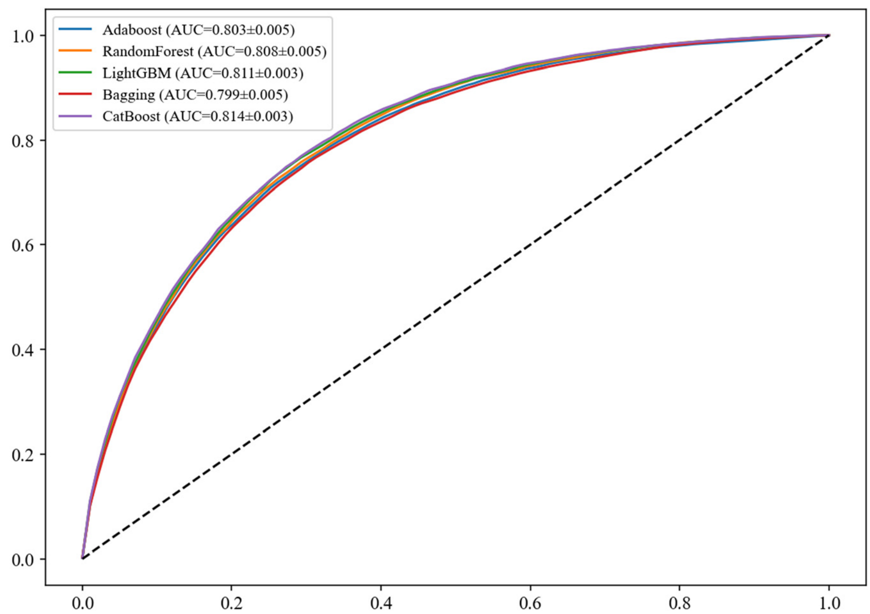

Fig. 2. Receiver operating characteristic (ROC) curves for various machine learning models

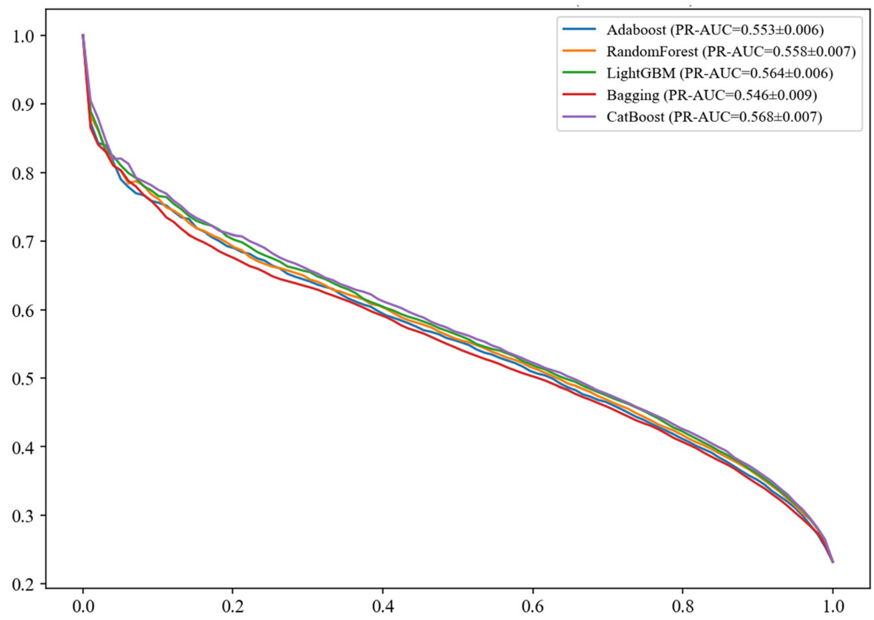

Fig. 3. Precision-recall area under the curve (PR-AUC) for various machine learning models

of energy (lack > 2), and had fought with others had a higher risk of PIU.

Interactions of important features in predicting adolescent PIU

Bivariate partial dependence plots were employed to visualize the interaction effects. The analysis examined interactions within individual-level factors and between individual-level and contextual-level factors. Specifically, five notable interactions were explored to understand the combined effects of individual and contextual factors.

For individual correlates, within psychological factors, the interaction between psychological risk (intolerance of uncertainty-expected behaviours) and protective (mindfulness-awareness and non-judgment) factors exhibited opposing effects: PIU risk increased with higher expected behaviours but decreased with greater awareness and non-judgment, and individuals with high expected behaviours paired with high awareness and non-judgment had lower estimated risk than those with high expected behaviours and low awareness and non-judgment (see Fig. 7a). Additionally, the interaction between psychological and behavioral factors showed that PIU risk rose as both expected behaviours and weekend video game time increased (see Fig. 7b).

For interactions between individual and contextual correlates, psychological (intolerance of uncertainty-expected behaviours) and family (home-leaving intentions) risk factors exhibited additive effects on PIU risk, as PIU risk increased with expected behaviours and was consistently higher among those reporting home-leaving intentions (see Fig. 7c). The psychological protective (mindfulness-awareness and non-judgment) factors and family risk factors (home-leaving intentions) indicated that high awareness and non-judgment levels conferred protection against PIU even in the presence of home-leaving intentions, whereas low awareness and non-judgment combined with home-leaving intentions resulted in the highest estimated risk (see Fig. 7d). Finally, the interaction of behavioral (weekend video game time) and contextual (home-leaving intentions) factors showed that risk increased with weekend video game time, and adolescents reporting home-leaving intentions generally exhibited higher risk across screen time levels (Fig. 7e).

DISCUSSION

Since the emergence of PIU research, key gaps remain in integrating psychological and contextual factors and capturing their nonlinear interactions. Guided by the RDS framework and the I-PACE model, this study conceptualized adolescent PIU as arising from interactions among psychological, behavioral, and contextual factors. Using interpretable machine learning, it identified core predictors and elucidated their relative importance and interaction patterns within a unified analytical framework. Specifically, this study evaluated five machine learning algorithms tailored for imbalanced data. The findings revealed that CatBoost demonstrated superior overall performance, achieving the highest AUC (0.814 ± 0.003), F1-score (0.567 ± 0.007), and PR-AUC (0.568 ± 0.007), as well as a strong Recall (0.691 ± 0.010). SHAP analysis identified multiple dimensions predictors, with the Top 17 features accounting for 80% of the model's explanatory power. Furthermore, bivariate partial dependence plots revealed complex interactions between individual and contextual correlates.

Significant factors of adolescent PIU encompassed psychological factors (i.e., intolerance of uncertainty-expected behaviours and inhibitory activity, mindfulness-awareness and non-judgment, depression, resilience, anxiety), behavioral factors (i.e., weekly video game time, bedtime, days of muscle-

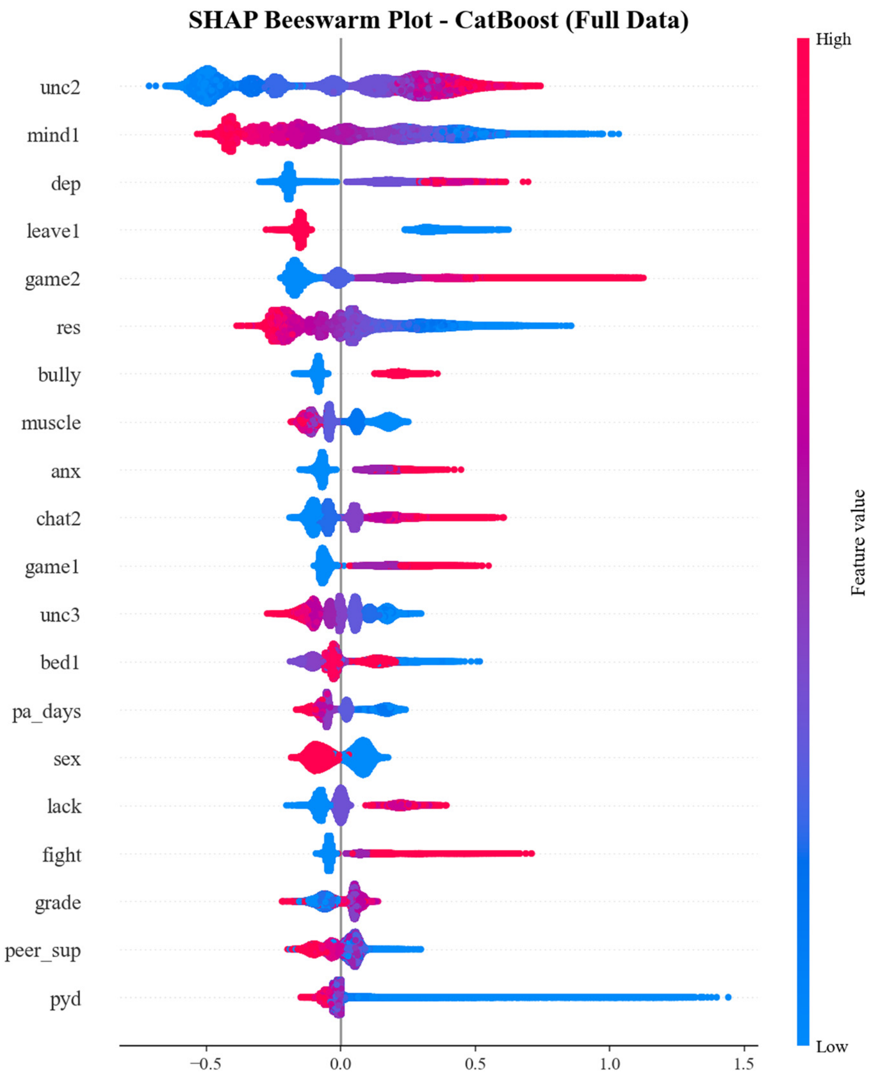

Fig. 4. SHapley Additive exPlanations (SHAP) values for adolescent PIU risk from CatBoost
Notes. unc2 = intolerance of uncertainty (expected behaviours); mind1 = mindfulness (awareness and non-judgment); dep = depression; leave1 = home-leaving intentions; game2 = weekend video game time; res = resilience; bully = bullying experience; muscle = number of days of weekly participation in muscle training; anx = anxiety; chat2 = weekend online chat time (chat2); game1 = weekday video game time; unc3 = intolerance of uncertainty-inhibitory activity; bed1 = bedtime; pa_days = weekly days of ≥ 60-min MVPA; lack = lack of energy; peer_sup = perceiving peer support; pyd = positive youth development. The *X*-axis represents the features, with higher positions indicating a greater influence on the model's predictions. The *Y*-axis represents the SHAP values, which measures the impact of features on the model's predictions. Positive values indicate that the feature increases the predicted value (i.e., increases the likelihood of PIU), while negative values suggest that the feature decreases the predicted value (i.e., reduces the likelihood of PIU). The color represents the magnitude of the feature values.

strength training per week, weekend online chat time, weekly days of ≥ 60-min MVPA, lack of energy), family-related factors (i.e., home-leaving intentions), peer-related factors (i.e., bullying perpetration). Consistent with prior evidence, intolerance of uncertainty remained the most critical risk factor (Gregorini et al., 2025; Wang, Zhang, Zhang, & Sun, 2024; Zhang et al., 2022). Our study extends this established knowledge by differentiating the core subdimensions of intolerance of uncertainty, a construct that is empirically supported in the Chinese adolescent sample (Wu, Wang, & Qi, 2016). Collectively, these findings point to the notion that adolescent development is a complex systemic process, which is highly consistent with the core proposition of the RDS framework (Lerner, Lerner, P. Bowers, & John Geldhof, 2015; Lerner & Schmid Callina, 2015). The RDS framework posits that developmental outcomes emerge from continuous and dynamic interactions between the individual and multiple layers of contextual environments. Our results exemplify these systemic interactions: adolescent PIU risk is shaped not only by their intrinsic self-regulatory capacities but also by family and peer contextual influences.

At the individual level, intolerance of uncertainty (expected behaviours) remained the most critical risk factor. When individuals struggle to mobilize positive regulatory resources to cope with uncertainty about the future, they may exhibit maladaptive behaviours (Lerner et al., 2015).

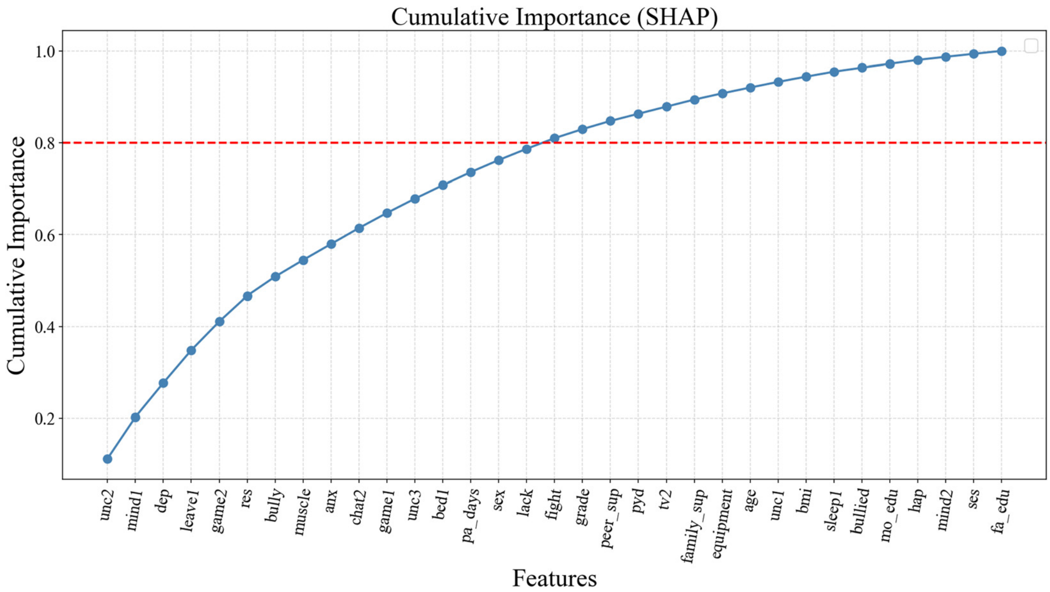

Fig. 5. Cumulative probability of the Top-N feature SHAP importance values

Notes. The horizontal axis represents the number of features, from 1 to 33, and it can be seen how the cumulative probability changes as the number of features increases, and the vertical axis represents the cumulative probability, which is the cumulative sum of the contribution of each feature to the overall model's significance. As the number of features increases, the cumulative probability should approach 1, indicating that more features are incorporated into the model.

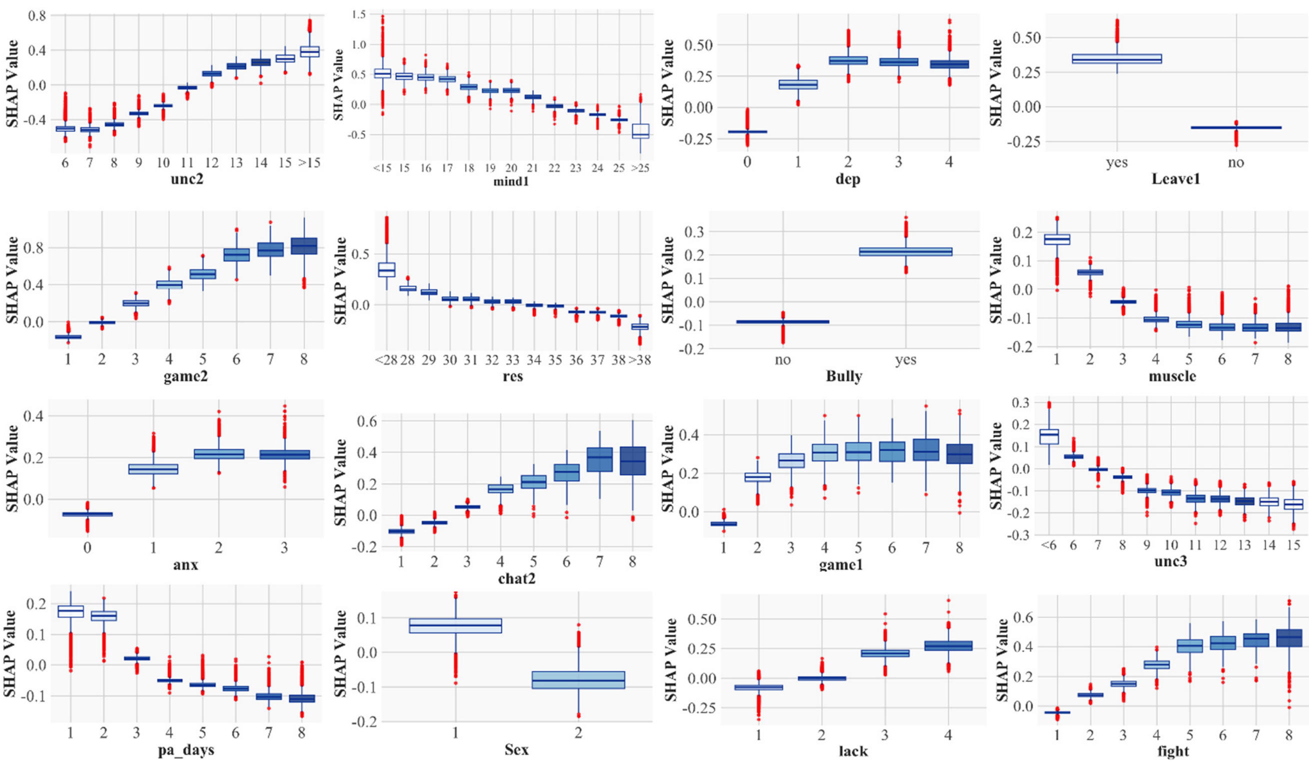

Fig. 6. SHAP value for features in adolescent PIU risk from Catboost

Notes. The figure demonstrates the impact of different features on the model's prediction results, with the feature values on the horizontal axis and the SHAP values on the vertical axis. The higher the SHAP value, the greater the positive impact of the feature on the prediction outcome; conversely, lower SHAP values indicate a stronger negative impact.

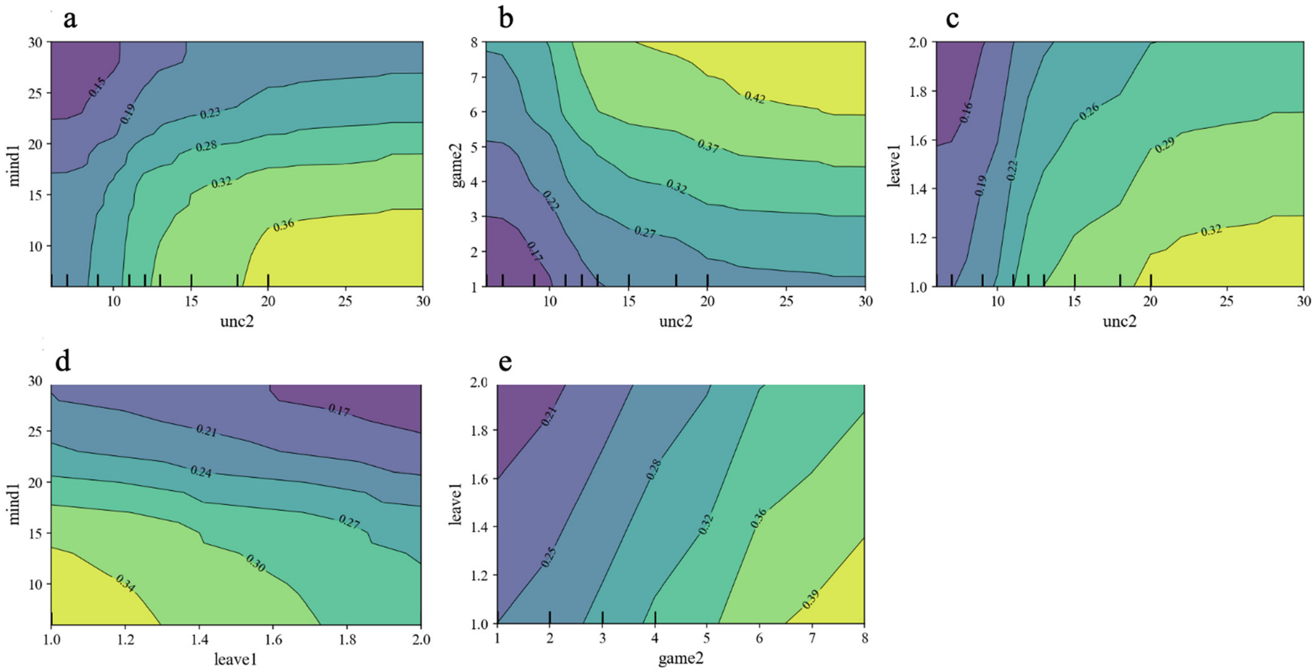

Fig. 7. Bivariate partial dependence plots
Notes. The figure illustrates the marginal effect of two features on the predicted outcome of a machine learning model, conditional on the values of all other features being fixed.

Such maladaptation disrupts positive developmental processes and may drive individuals to seek compensatory experiences in the online environment to regain a sense of control or escape from distress (Brand, Young, Laier, Wölfling, & Potenza, 2016; Carleton, 2016; Kardefelt-Winther, 2014). Mindfulness emerged as a paramount protective factor, second only to intolerance of uncertainty in overall importance. Mindfulness represents a positive form of self-regulatory capacity that fosters awareness and non-judgmental acceptance, enabling adolescents to maintain emotional balance when facing uncertainty rather than resorting to rigid avoidance behaviors (Song & Park, 2019; Tang & Lee, 2021). Notably, findings indicate that adolescents who play video games for more than two hours on weekends may be more likely to develop PIU. Weekdays video game play is constrained by school schedules and subject to stricter external supervision (Brook et al., 2001). In contrast, weekends video game play requires individuals to rely on self-regulation to manage their Internet use behaviour. Excessive weekend gaming time may indicate weaker emotional regulation and self-control, making adolescents more susceptible to compensatory and immersive gaming patterns, leading to potential functional impairments such as disrupted sleep and reduced offline social engagement (Kowert, Domahidi, Festl, & Quandt, 2014; Reardon, Lushington, & Agostini, 2023).

At the contextual level, home-leaving intentions surfaced as a salient family-related risk factor. The family, as the primary microsystem in adolescent development, exerts a profound influence on adaptive outcomes (Bronfenbrenner, 2000). Such intentions may signal dysfunction within the family system and a lack of supportive microsystemic resources (Plass & Hotaling, 1995; Tucker, Edelen, Ellickson, & Klein, 2011). When the family fails to provide a secure and supportive environment, adolescents' self-regulatory development may be hindered, prompting them to seek compensation within the virtual microsystem, thereby elevating PIU risk (Kardefelt-Winther, 2014). Similarly, bullying perpetration within the peer system represents another form of microsystemic stressor that may lead adolescents to replicate maladaptive social patterns in online settings.

More importantly, this study revealed the interactive effects of multiple risk and protective factors across individual and contextual domains. According to the cumulative risk model, the co-occurrence of multiple risk factors amplifies the likelihood of maladaptive outcomes, especially when protective factors are insufficient (Appleyard, Egeland, van Dulmen, & Alan Sroufe, 2005; Evans, Li, & Whipple, 2013). Consistent with this framework, our findings demonstrated that adolescents simultaneously exposed to high psychological risk (e.g., elevated intolerance of uncertainty-expected behaviours) and high behavioral risk (e.g., prolonged weekend video game time) exhibited substantially greater PIU risk than those exposed to either factor alone. Similarly, cross-domain interactions revealed that the combination of high psychological risk (intolerance of uncertainty-expected behaviours) and adverse contextual risk (home-leaving intentions) further exacerbated vulnerability to PIU.

Fortunately, protective mechanisms operated across domains and mitigated the impact of risk exposures. High levels of mindfulness (awareness and non-judgment) consistently buffered against PIU risk, even in the presence of psychological vulnerabilities or contextual stressors (Calvete, Gámez-Guadix, & Cortazar, 2017). PIU thus reflects dynamic interactions between risks and protections within and across systems, consistent with the RDS framework, which views adolescent development as a reciprocal, adaptive process. While risk factors accumulate across different systems and undermine adolescents' adaptive capacity, protective factors such as mindfulness can exert cross-systemic effects to buffer these risks (Lerner et al., 2015; Lerner & Schmid Callina, 2015).

Implications

This study holds significant theoretical and practical value for the prevention and intervention of adolescent PIU. First, this study integrates RDS framework with the I-PACE model, offering a multidimensional theoretical framework for adolescent PIU research from a dynamic systems perspective of individual-contextual interactions, thereby revealing the complex mechanisms underlying adolescent PIU. Second, study identifies key predictors of PIU, enabling schools and families to detect critical characteristics, pinpointing at-risk students and providing a theoretical basis for the design of interventions. Moreover, the findings reveals that high level of mindfulness-awareness and non-judgment (mind1 $\geq$ 22, total 30), exerts a protective effect against PIU among adolescents. This finding highlights the potential of mindfulness as a protective factor within prevention frameworks for PIU (Fendel, Vogt, Brandtner, & Schmidt, 2024; Lan et al., 2018; Song & Park, 2019).

Limitations

This study has the following limitations. Firstly, the data was collected from schools in Shenzhen. As a high-tech city, Shenzhen may exhibit higher detection rate and distinct features of PIU (Cheng & Li, 2014; Xu et al., 2020). Future studies should take random sampling across more regions (e.g., rural and less developed areas) and groups (e.g., left-behind children) into consideration to enhance the representativeness of samples. Second, although the constructed model accounts for contextual factors to some extent, it may overlook several critical aspects, such as school climate or digital environment. These limitations arise because the study aimed to explore numerous factors, which required reducing the number of variables due to time constraints and participant fatigue. Future research may incorporate key factors and newly identified characteristics related to PIU to further explore the potential mechanisms underlying adolescent PIU. Thirdly, the data was self-reported by participants. While individuals' perceptions and attitudes towards their environment can directly influence their behavioral choices and mental states (Ajzen, 1991), and self-reports are considered flexible and reliable by researchers (Corneille & Gawronski, 2024), future studies could incorporate other-informant assessments and objective measures. Finally, although SHAP was employed to enhance the interpretability of the machine learning model, SHAP values reflect model-based associations rather than causal effects. Future studies integrating causal inference approaches may help further clarify the causal mechanisms underlying adolescent PIU.

Conclusions

This study contributes to deepening our understanding of PIU among adolescents by examining it within the dynamic interaction. Findings indicate that PIU is not a direct reflection of isolated individual risk factors, but rather the result of multiple vulnerabilities and protective mechanisms intertwining and interacting within contexts. The findings suggest that cumulative risks heighten susceptibility to PIU, while accessible self-regulatory resources (e.g. mindfulness) exert a counterbalancing effect on PIU across different risk factors. Overall, this study underscores the necessity of moving beyond a single explanatory framework to understand PIU as a relational and interactive process embedded within developmental contexts. This approach enables a more accurate grasp of its formation mechanisms and individual variations.

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Appendix

Table A1. Domains and factors for detecting adolescents PIU

Factors	Variables in the dataset	Description/Sample item (Scale)
Grade	grade	What's your grade?
Sex	sex	What's your sex?
Age	age	How old are you?
Father education	fa_edu	What is your father's level of education?
Mother education	mo_edu	What is your mother's level of education?
The sports equipment of school	equipment	Are the school's sports grounds and equipment (e.g., playground, dugout, football, basketball, etc.) able to meet your physical activity needs?
Weekly days of ≥ 60-min MVPA	pa_days	Moderate-to-high-intensity physical activity refers to a variety of exercises that make your heart beat faster and leave you out of breath for a period. This includes a variety of physical activities (e.g., running, playing ball games) performed in physical education classes, sports, and in daily life. In the past week, the number of days on which you participated in moderate-to-high-intensity physical activity for a cumulative total of at least 60 min per day was (0–7 days)?
Days of muscle-strength training per week	muscle	In the past week, the number of days you participated in muscular strength training such as push-ups, sit-ups, pull-ups, etc. was (0–7 days)?
Weekday video game time	game1	During the past week, approximately how much time did you spend daily playing video games (on devices like computers, phones, or tablets) in your leisure time on weekdays?
Weekend video game time	game2	During the past week, approximately how much time did you spend daily playing video games (on devices like computers, phones, or tablets) in your leisure time on weekend?
Weekly TV time	tv	During the past week, approximately how much time did you spend daily watching TV in your leisure time?
Weekend online chat time	chat2	During the past week, approximately how much time did you spend daily using a computer for activities such as chatting, browsing the web, checking email, or doing homework in your leisure time on weekend?
Bedtime	bed1	In the past month, you usually went to bed at ____ o'clock at night
Actual sleep time	sleep1	In the past month, you usually got hours of actual sleep per night (not equal to time in bed)
Lack of energy	lack	In the past month, have you often felt a lack of energy to do things?
Perceived Social Support	family_sup peer_sup	The Perceived Social Support Scale comprises three dimensions: Significant Other Support, Family Support, and Friend Support, with a total of 12 items - four for each dimension. This study measured the Family Support subscale (e.g., "My family gives me practical help.") and the Friend Support subscale (e.g., "My friends can truly help me."). Responses were recorded on a 7-point Likert scale. The scores for each subscale were summed, with higher total scores indicating a greater perceived level of social support
Mindfulness	mind1 mind2	Mindfulness was measured using the Chinese version of the Child and Adolescent Mindfulness Measure (CAMM). This scale consists of two dimensions: Awareness and Non-judgment (coded as *mind1*; e.g., "I get upset with myself for having certain feelings.") and Acceptance (coded as *mind2*; e.g., "I tell myself that I shouldn't be feeling the way I'm feeling.")
Resilience	res	Resilience was assessed using a short version of the Connor–Davidson Resilience Scale (CD-RISC, e.g., "Able to adapt to change."; "Close and secure relationships."). It reflects the ability to tolerate experiences, such as change, personal problems, illness, pressure, failure, and painful feeling. Participants responded to 10 items on a 5-point Likert scale (0 = not true at all to 4 = true nearly all the time), with total scores ranging from 0 to 40 (higher points indicate greater resilience capacity)
Subjective Well-Being	hap	WHO-5 is a short self-reporting tool developed by the World Health Organization for assessing SWB (e.g., "I have felt cheerful and in good spirits."). In 2007, WHO-5 was translated into simplified Chinese and is available on the official WHO-5 website. The five items of the scale cover

(continued)

Table A1. Continued

Factors	Variables in the dataset	Description/Sample item (Scale)
Depression	dep	The Chinese version of the 9-item Patient Health Questionnaire (PHQ-9, e.g., “Little interest or pleasure in doing things.”; “Feeling down, depressed, or hopeless.”) was used to measure level of depressive symptoms. Each item that can earn 0 to 3 points (0 = “not at all” to 3 = “nearly every day”), and a total score ranged from 0 to 27 (higher points indicating more severe depressive symptoms)
Anxiety	anx	Anxiety symptoms were measured using the Chinese version of the Generalized Anxiety Disorder scale (GAD-7, e.g., “Feeling nervous, anxious or on edge.”; “Not being able to stop or control worrying.”), which is an appropriate measure of anxiety symptoms in general. ach item has four response options (0 = “Not at all” to 3 = “Nearly every day”). Each participant can obtain a total score that ranged from 0 to 21, with higher score indicating more severe anxiety
Positive youth development	pyd	The Five Cs of Positive Youth Development-Very Short Form (PYD-VSF, e.g., “Some teenagers do very well at their class work, BUT Other teenagers don’t do very well at their class work.”) was used in this study to measure positive youth development problems. The adapted Chinese version of the 17-item PYD-VSF has been shown to have acceptable reliability and validity among Chinese adolescents. Each item is rated on a 5-point Likert scale ranging from 1 (not at all) to 5 (very much), with higher total scores indicating better positive development
Intolerance of Uncertainty	unc1 unc2 unc3	Intolerance of Uncertainty was measured using the Chinese version of the Short Intolerance of Uncertainty Scale. This instrument comprises three distinct dimensions: prospective beliefs and emotions (3 items, coded unc1; e.g., “Unforeseen events upset me greatly”), expected behaviours (6 items, coded unc2; e.g., “Uncertainty makes it difficult for me to have a fulfilling life”), and inhibitory activity (3 items, coded unc3; e.g., “I always prepare in advance to avoid being caught off guard”). All items were rated on a 5-point Likert scale. A total score was computed for each dimension, with a higher score indicating a greater level of intolerance of uncertainty in that specific domain
Home-leaving intentions	leave1	In the past year, have you home-leaving intentions (for 24 h or more without parental permission)?
Body Mass Index	bmi	“What is your height (cm)?”; “What is your weight (kg)?” (BMI = weight/[(height/100) × (height/100)])?
Have been bullied in school	bullied	In the last year, have you experienced any of the following types of bullying in school (yes/no): 1) physical violence, being kicked or punched; 2) verbal violence, being maliciously nicknamed or ridiculed or verbally abused; 3) being rumored or slandered by others; 4) being isolated by others; 5) being forced or threatened to do something; 6) having something intentionally broken by others
Bullying experience	bully	In the last year, have you bullied anyone at school (yes/no): 1) Physical violence, kicking or punching; 2) verbal violence, maliciously nicknaming or ridiculing or abusing others; 3) rumor mongering or slandering; 4) isolation or ostracism; 5) forced or threatened someone to do something; 6) intentionally breaking someone’s things
Fight	fight	In the past year, have you ever gotten into a physical fight with another person (1 or more)?