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Understanding the Psychological Impacts of School Bullying on Adolescents via Machine Learning

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Abstract. School bullying poses a significant threat to adolescent mental health, a critical factor in youth development. This paper examines the link between bullying and psychological well-being, highlighting its detrimental effects supported by empirical evidence. It explores three prevalent bullying types—verbal, cyber and physical—and their distinct impacts on adolescents. Using survey data, the study analyzes the prevalence of bullying types and their combinations, identifying key psychological factors associated with distress. The statisical analysis suggests that each form contributes uniquely to emotional harm, with combined exposures intensifying effects. Furthermore, the key psychological factors,top 10 features selected by selectKB eststrongly associates with Internet Addiction,Major Depressive Disorder,Clinical High Risk for Psychosis. Thus, these findings emphasize the need for targeted interventions with these mental disorders.

Keywords: School bullying; adolescent mental health; machine learning

1. Introduction

School bullying, a widespread issue in educational settings, significantly undermines the mental health of adolescents, a developmental period crucial for emotional and social growth. Defined as intentional, repeated aggression, bullying disrupts the well-being of its victims, with long-lasting repercussions. The importance of adolescent mental health lies in its role as a cornerstone for identity formation, academic success, and future societal contributions. Research consistently demonstrates that bullying precipitates severe psychological outcomes, necessitating urgent action from educators and policymakers [1].

The harms of bullying on mental health are profound and well-documented. Smith et al. [2] find that bullied adolescents exhibit a 2.1-fold increased risk of depression, with effects persisting into later life. Similarly, Holt et al. [3] report that chronic bullying victims face a 2.3-fold higher likelihood of anxiety disorders, underscoring the depth of emotional damage. Longitudinal research by Masten et al. [4] further reveals that bullied students display reduced prefrontal cortex connectivity, impairing their ability to regulate emotions and exacerbating distress. These findings align with evidence that bullying-related mental health issues correlate with diminished academic performance, amplifying its broader impact [5].

Bullying manifests in distinct forms—verbal, cyber and physical—each exerting unique pressures on adolescent psyche. Verbal bullying targets self-esteem through insults, cyberbullying leverages digital platforms to perpetuate harassment, and physical bullying involves bodily harm. The specific bullying type impacts the damage degree of adolescent mental health. Craig et al. [6] observe a 1.8-fold increase in depressive symptoms among verbally bullied students, with public humiliation amplifying harm. Jones et al. [6] report a 40% higher incidence of anxiety among cyberbullied teens, with sleep disturbances and suicidal ideation as frequent outcomes. Smokowski and Kopasz [7] find that victims of physical bullying report elevated post-traumatic stress symptoms.

Nevertheless, the understanding the psychological impacts of school bullying on adolescents is still confusing and uncertain restricted by the size of the data sample. This paper investigates these categories, using a large number of survey data to examine their prevalence and psychological

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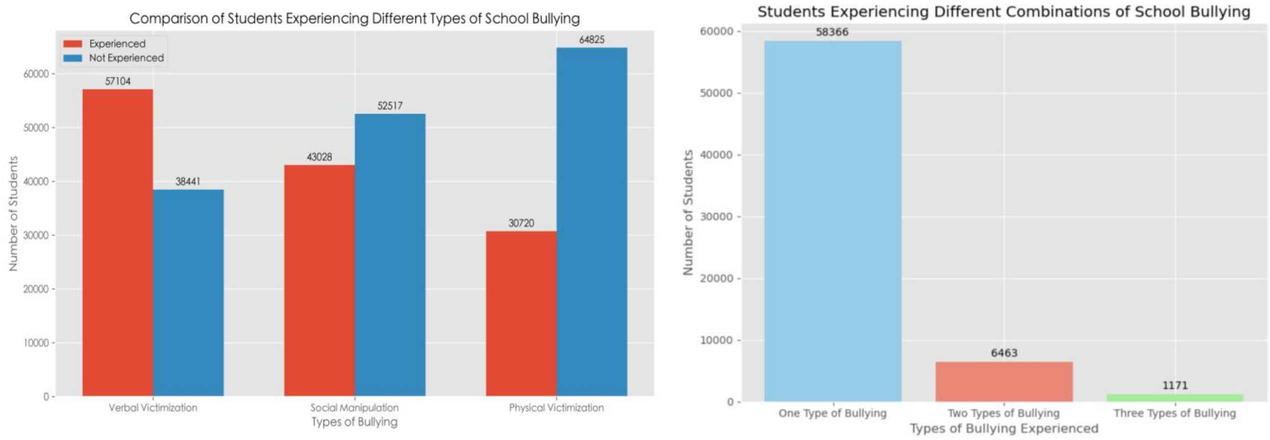
impacts, drawing on global scholarly insights. The statistical analysis of school bullying suggests that each form contributes uniquely to emotional harm, with combined exposures intensifying effects. The key psychological factors identified via machine learning method strongly associate with bullying-related distress.

2. Statistical Analysis of School Bullying

We analyzes the survey data from 68,327 junior and senior high school students in a mid-sized city in western mainland China, comprising 25,203 junior high students (36.9%) and 43,124 senior high students (63.1%). The dataset documents various features related to bullying experiences and mental health. Descriptive statistics are used to assess the prevalence of different bullying types—verbal victimization, social manipulation (a proxy for cyberbullying in this context), and physical victimization—and their combinations. Specifically, the number of students experiencing each type of bullying, as well as those facing one, two, or three types, is calculated to understand the distribution and overlap of bullying experiences. Figure 1 shows the empirical results on the statistical analysis of school bullying.



(a) (b)

Fig. 1 The distribution of (a) three-type school bullying and (b) their combinations.

First, we comprehensively discuss the comparison of students experiencing different types of school bullying, as shown in Fig1 (a). Verbal bullying, encompassing taunts and derogatory remarks, erodes an adolescent's self-worth. Its insidious nature lies in its invisibility, yet its effects are enduring. 57,104 students experienced verbal victimization, while 38,441 did not, making it the most prevalent form among the types studied. Cyberbullying, often manifested as social manipulation in digital contexts, extends harassment beyond physical boundaries, making it uniquely pervasive. 43,028 students experienced social manipulation, with 52,517 not affected. The pervasive nature of digital harassment heightens its psychological toll, as victims struggle to escape online attacks. Physical bullying, such as hitting or shoving, directly threatens an adolescent's sense of security. 30,720 students experienced physical victimization, while 64,825 did not, indicating it as the least common among the three types studied. This form of aggression fosters hypervigilance and social withdrawal, disrupting peer interactions and classroom participation.

Then, we then briefly discuss the combined effects of bullying types. As shown in Fig.1(b), their psychological impact escalates when bullying types converge. Furthermore, it reveals that 58,366 students experienced one type of bullying, 6,463 faced two types, and 1,171 encountered all three types. This result demonstrates that most students face single-type bullying, but combined exposures are significant. It also suggests that the polyvictimization doubles the odds of severe distress, consistent with cumulative trauma frameworks [6]. Thus, this compounding effect necessitates comprehensive intervention strategies.

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3. Key Psychological Factors Associated with School Bullying

To identify key psychological factors associated with bullying-related distress, the feature importance analysis is conducted. This involved ranking features such as depression (PHQ-9), anxiety (GAD-7), and smartphone addiction (SABAS) based on their association with mental health outcomes, using machine learning methods of Random Forest (RF) ranking [9] and SelectKBest [10]. Principal Component Analysis (PCA) [11] is also applied to explore the variance explained by these features, providing insight into the most influential factors.

First, to understand the psychological factors most associated with bullying-related distress, feature importance analysis was conducted via RF ranking. Specific, total 31 psychological factors and 1 are correlated with the bullying-related distress through RF classification task. For a given feature j, the permutation importance is calculated as follows:

$$\mathrm{Importance(j)} = \frac{1}{T}\sum_{t=1}^{T} (\mathrm{Accuracy(t)} - \mathrm{Accuracy}(\mathrm{t}, \pi_j \quad)) \tag{1}$$

where T is the total number of trees in the forest, $\mathrm{Accuracy(t)}$ is the accuracy of tree t on the original data, and $\mathrm{Accuracy}(\mathrm{t}, \pi_\mathrm{j})$ is the accuracy of tree t on the data where feature j has been permuted. By using these formulas, we can quantify the importance of each feature and rank them accordingly for feature selection. Figure 2 ranks 31 psychological factors by their importance. We identify smartphone and Internet addiction (SABAS and IGDS9-SF), mental well-being (WEMWBS), and resilience (CD-RISC-10) as top contributors to mental health outcomes.

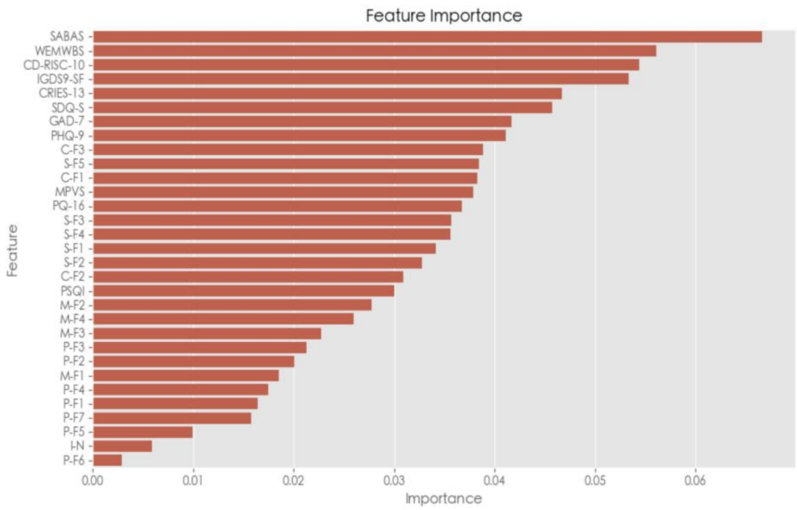

Fig.2 Feature important analysis via RF ranking.

Then, we use PCA method to obtain explained variance by principal components. As shown in Fig.3(a), it indicates that the first component explains over 35% of the variance, with subsequent components contributing less, suggesting a few key factors drive most of the variability in mental health outcomes. Meanwhile, we further choose the 10 psychological factors and highlights them by SelectKBest. It shows that SABAS (smartphone addiction), IDGS9-SF (Internet addiction), PHQ-9 (depression), and GAD-7 (anxiety) scoring highest, indicating their strong association with bullying-related distress. These findings align with research by Masten et al. [3], who noted that resilience (CD-RISC-10) can mitigate bullying's emotional impact, while depression and anxiety exacerbate it.

4. Summary

School bullying, whether verbal, cyber (social manipulation), or physical, exacts a heavy toll on adolescent mental health. Verbal bullying is the most prevalent, affecting 57,104 students, followed by social manipulation (43,028) and physical bullying (30,720), as shown in Fig 1(a). Combined exposures, with 6,463 students facing two types and 1,171 facing all three-type bullying, magnify

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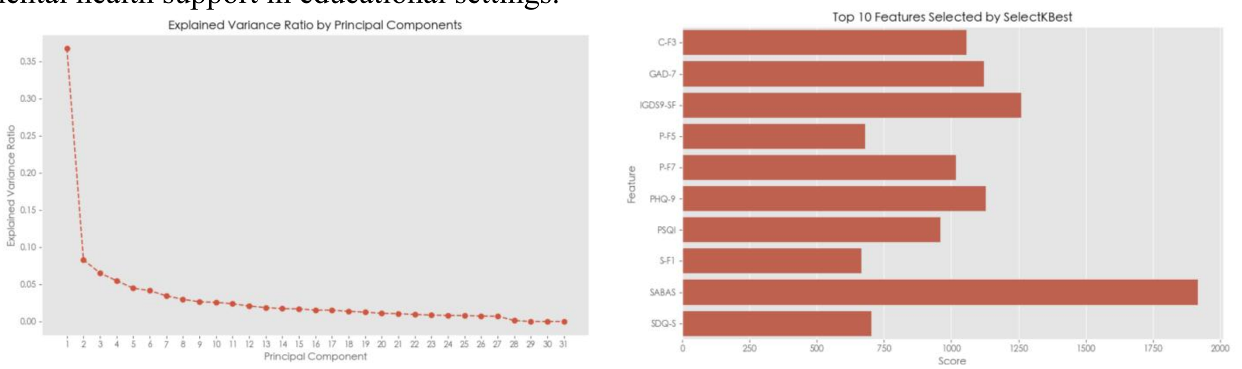
these harms, as shown in Fig. 1(b). Feature importance analysis identifies depression, anxiety, and smartphone addiction as key factors linked to distress, while resilience offers a protective buffer. Addressing this crisis requires recognizing these distinct yet interconnected effects and prioritizing mental health support in educational settings.



(a) PCA analysis (b) SelectKBest analysis

Fig.3 The explained results of key psychological factors

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References

[1] Zhao N., Yang S., Zhang Q., et al. School bullying results in poor psychological conditions: evidence from a survey of 95,545 subjects. Frontiers in psychology, 2024, 15: 1279872.

[2] Smith P. K., Mahdavi J., Carvalho M., et al. Cyberbullying: Its nature and impact in secondary school pupils. Journal of Child Psychology and Psychiatry, 2008, 49(4): 376–385.

[3] Holt M. K., Vivolo-Kantor A. M., Polanin J. R., et al. Polyvictimization and mental health in adolescents: A meta-analysis. Journal of Youth and Adolescence, 2022, 51(4): 678–694.

[4] Masten A. S., Lucke C. M., Nelson K. M., et al. Resilience in development: Progress and transformation. Developmental Psychology, 2021, 57(7): 1022–1042.

[5] Barnett P., Arundell L. L., Saunders R., et al. The efficacy of psychological interventions for the prevention and treatment of mental health disorders in university students: A systematic review and meta-analysis. Journal of Affective Disorders, 2021, 280: 381–406.

[6] Craig W., Harel-Fisch Y., Fogel-Grinvald H., et al. A cross-national profile of bullying and victimization among adolescents in 40 countries. International Journal of Public Health, 2009, 54(Suppl 2): 216–224.

[7] Jones S. M., Barnes S. P., Bailey R., et al. A tiered approach to reducing bullying-related mental health disparities. Harvard Educational Review, 2023, 93(1): 45–68.

[8] Smokowski P. R., Kopasz K. H. Bullying in school: An overview of types, effects, family characteristics, and intervention strategies. Children & Schools, 2005, 27(2): 101–110.

[9] Devendran K., et al. Feature selection for disease prediction in medical diagnosis using machine learning. 2024 International Conference on IoT, Communication and Automation Technology (ICICAT). IEEE, 2024.

[10] Iranzad R., Liu X. A review of random forest-based feature selection methods for data science education and applications. International Journal of Data Science and Analytics (2024).

[11] Dorabiala O., Aravkin A. Y., Kutz J. N. Ensemble principal component analysis. IEEE Access, 2024 12: 6663-6671.