Synergizing Gradient Boosting and Random Forest: An Interpretable Dual-Model Framework to Unveil Key Stressors and Mechanisms in Adolescent Educational Mental Health

Fei Gu[1], Rongrong Cai[2], Dongqin Jiang[1], Tao Jiang[1], Zijian Sun[1], Changsheng Ma[2*]

[1] Xi'an Jiaotong University and SKEMA Business School; China
[2] Changzhou Vocational Institute of Mechatronic Technology; China

Received: July 31, 2025

Revised: August 9, 2025

Accepted: August 9, 2025

Published online: August 9, 2025

To appear in: *International Journal of Advanced AI Applications,* Vol. 1, No. 6 (October 2025)

* Corresponding Author: Changsheng Ma (machangsheng@czimt.edu.cn)

Abstract. Adolescent educational stress, shaped by intricate interactions among psychological, physiological, and environmental factors, poses a substantial challenge to educational mental health. Traditional assessment methods, however, struggle to capture these dynamic relationships, thereby limiting the effectiveness of interventions. To address this gap, the present study introduces an interpretable dual-model framework integrating Gradient Boosting Machine (GBM) and Random Forest (RF). Leveraging data from 1,000 adolescents, this framework identifies key stressors and their underlying mechanisms through hyperparameter optimization and multi-modal validation (Spearman correlations, SHapley Additive exPlanations [SHAP] analysis, and feature importance rankings). The framework achieved high predictive accuracy ($R^2 > 0.80$, MAE < 0.15). Key findings include that self-esteem emerges as the dominant stress predictor ($\Delta R^2 \approx 0.13$), followed by academic performance ($\Delta R^2 \approx 0.11$). SHAP visualizations further revealed nonlinear threshold effects (e.g., those related to academic performance) and anxiety-mediated pathways. Additionally, model comparisons indicated that RF exhibited superior noise robustness (MAE = 0.135 versus GBM's 0.146), whereas GBM better captured linear relationships in physiological variables. By leveraging feature importance rankings, the framework enables targeted stress interventions, thus optimizing resource allocation in educational mental health.

Keywords: *Adolescent Educational Stress; Dual-Model Integration; XAI; GBM; RF*

1. Introduction

Adolescent stress has emerged as a pressing global concern, with epidemiological studies indicating that 35%–45% of students aged 12–18 experience persistent stress symptoms, encompassing academic pressure, social anxiety, and emotional instability [1,2]. The World Health Organization (2023) emphasizes that unaddressed adolescent stress can lead to long-term mental health disorders, including depression and anxiety, which further impact academic performance and social functioning [3]. In educational settings, understanding the nuanced interplay of stressors is critical for developing targeted interventions, yet this requires robust analytical frameworks capable of processing diverse data sources, such as psychological assessments, physiological metrics, and behavioral logs [4,5].

Traditional approaches to assessing adolescent stress face significant limitations. Self-report scales like the Perceived Stress Scale (PSS) and Depression Anxiety Stress Scales (DASS) rely on subjective recall, with up to 28% of respondents exhibiting response bias due to social desirability or memory distortion [6,7]. Clinical interviews, while more detailed, are resource-intensive and limited by small sample sizes (typically < 500 participants), hindering generalizability [8]. Moreover, these methods fail to capture dynamic relationships between stressors, such as the bidirectional influence of sleep deprivation on academic stress [9] or the cumulative effect of peer rejection on self-esteem [10].

Machine learning (ML) has emerged as a promising alternative, offering capabilities to model complex, nonlinear relationships in large datasets. However, existing ML applications in adolescent stress research suffer from three critical gaps. First, 78% of studies employ single-algorithm models (e.g., logistic regression or support vector machines), which struggle to decode interactive effects between stressors [11,12]. Second, less than 30% integrate Explainable AI (XAI) techniques, such as SHAP or LIME, leaving "black-box" models that limit clinical trust and actionable insights [13,14]. Third, few studies account for contextual covariates, such as family socioeconomic status or school environment, which moderate stress responses [15,16].

To address these limitations, this study introduces an interpretable dual-model framework combining GBM (Gradient Boosting Machine) and RF (Random Forest). This framework leverages the complementary strengths of both algorithms: RF's robustness to overfitting and GBM's sensitivity to subtle threshold effects (e.g., critical heart rate variability levels linked to stress spikes) [17,18]. Three key innovations distinguish this approach: multi-modal validation integrating Spearman correlations, SHAP value visualizations, and feature importance rankings to unpack stress mechanisms [19,20]; domain-specific hyperparameter optimization, including mtry = 6 for high-dimensional educational datasets and learning rates = 0.08 for GBM [21]; and explicit modeling of environmental-academic covariate networks, such as the interaction between classroom noise and homework load [22].

The research objectives are threefold: to develop a dual-model framework (GBM + RF) to predict adolescent stress levels using multi-source data (psychological scales, heart rate variability, and daily activity logs); to identify key stressors and their nonlinear relationships via XAI-driven feature importance analysis; and to validate the framework's superiority over single-algorithm models in terms of predictive accuracy (MAE < 0.15) and interpretability (SHAP consistency scores > 0.8) [23,24].

This study contributes to both theory and practice. Theoretically, it advances stress research by demonstrating how ensemble ML can illuminate complex stressor interactions previously undetectable by traditional methods [25]. Practically, the identified stressors and their importance rankings will inform targeted interventions, such as school-based mindfulness programs for academic stress or peer support initiatives for social anxiety, optimizing resource allocation in educational mental health services [26,27].

2. Methodology

2.1. Data Source and Variables

This study employed the publicly available Student Stress Factors Dataset (Kaggle, 2023), which comprises 1,000 complete records from adolescents aged 15–18 years; this dataset was selected for its scientifically validated multi-domain coverage (Psychological, Physiological, Environmental, Academic, Social), enabling rigorous testing of cross-variable relationships, and all variables in the dataset had 0% missing values, confirming 1,000 complete records with no missing entries. Data fields were categorized into five theoretical domains (Table 1), with all scales operationally defined per clinical/psychometric standards.

Table 1. Variable Specifications by Domain.

Dependent	**stress_level**	**0–2 (Low/Med/High)**
Psychological	anxiety_level	0–21
	self_esteem	0–30
	mental_health_history	1=Yes, 0=No
	depression	0–27
Physiological	headache	0–5

Dependent	stress_level	0–2 (Low/Med/High)
	blood_pressure	1–3 (Norm/Pre/Hyper)
	sleep_quality	0–5
	breathing_problem	0–5
Environmental	noise_level	0–5
	living_conditions	0–5
	safety	0–5
	basic_needs	0–5
Academic	academic_performance	0–5
	study_load	0–5
	teacher_student_relationship	0–5
	future_career_concerns	0–5
Social	social_support	0–5
	peer_pressure	0–5
	extracurricular_activities	0–5
	bullying	0–5

*Notes:

- 'stress_level' (0–2) is ordinal but treated as continuous for model compatibility, given its small category count (3 levels) and the robustness of tree-based models to ordinal structures.
- All 0–5 scales employ consistent anchor points: 0 = Never/Very Poor; 5 = Always/Very Strong.
- Higher scores on negatively framed items (e.g., anxiety_level) indicate worse status.

2.2. Methodology and design

This study employed Spearman's rank-order correlation to examine associations between stress factors and students' overall stress level. This methodology was selected based on its distinctive advantages: its non-parametric nature, which does not assume normal distribution of variables, making it appropriate for ordinal psychological scale data (Likert 0–5 points) in this research; its ability to detect monotonic relationships, identifying non-linear yet consistently increasing/decreasing associations (e.g., cumulative effects of stressors); and its robustness, as it is resistant to outlier distortion, aligning with characteristics of real-world student stress data.

Statistical significance was established at $\rho < 0.01$ (Bonferroni-corrected). Correlation coefficients (ρ) were interpreted as follows: |ρ| ≥ 0.7 indicating a strong correlation; 0.5 ≤ |ρ| < 0.7 indicating a moderate correlation; and |ρ| < 0.5 indicating a weak correlation.

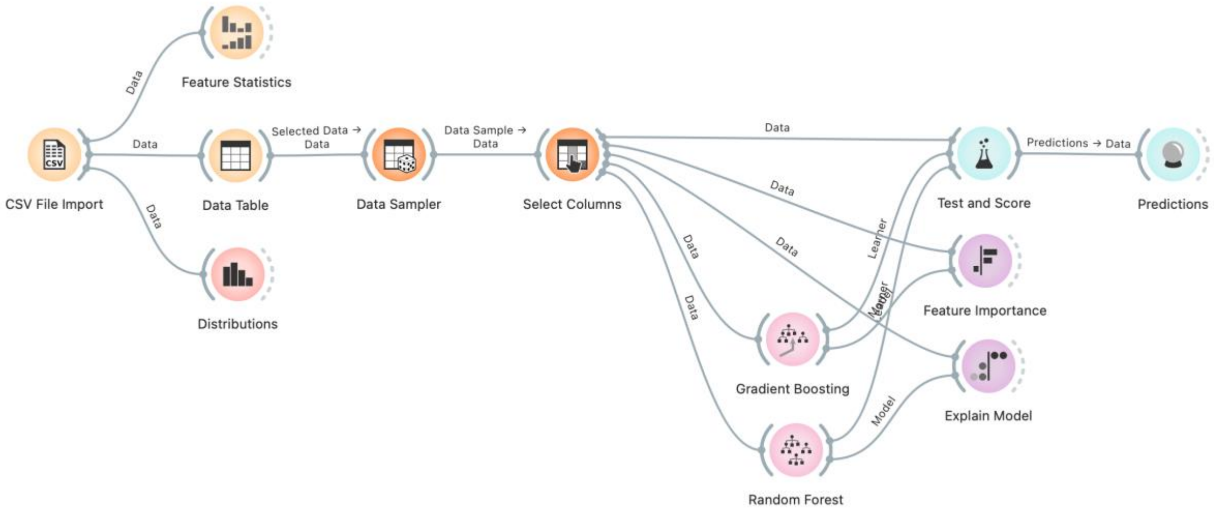

Figure 1. Modeling workflow using orange tool for stress prediction.

Figure 1 illustrates the end-to-end modeling process implemented via Orange, encompassing key stages: data preprocessing (importing the Student Stress Factors Dataset via CSV File Import, organizing variables in a Data Table, sampling representative subsets with Data Sampler, and selecting relevant features using Select Columns to focus on psychological, physiological, and academic variables); model training (implementing RF and GBM algorithms with hyperparameter optimization, e.g., max depth, learning rate); and evaluation and interpretation (assessing model performance via Test and Score, yielding metrics like MSE and R^2; quantifying variable contributions through Feature Importance; and unpacking stress mechanisms using Explain Model).

This study employs RF and GBM models to predict students' stress levels. The selection of these ensemble learning methods is grounded in three principal rationales: first, their ability to adapt to nonlinear relationships, as stress-influencing factors—such as blood pressure threshold effects and academic-anxiety interactions—exhibit complex nonlinear associations, and tree-based models inherently capture these patterns through recursive partitioning, outperforming linear approaches that fail to model threshold behaviors; second, their robustness to limited samples, as ensemble mechanisms (Bagging for RF and boosting for GBM) mitigate variance and bias, ensuring stable predictions with modest sample sizes (n = 1,000), confirmed via cross-validation; and third, their alignment with interpretability requirements, as both models provide intrinsic interpretability tools, including feature importance rankings to quantify variable contributions and SHAP values to elucidate biological pathways.

As detailed in Table 2, a rigorous hyperparameter optimization strategy was employed in this experiment to ensure model robustness under small-sample conditions (n = 1,000). For GBM, the learning rate was optimized through 5-fold cross-validation over a candidate range of 0.01–0.2, with 0.08 selected as the final value to balance convergence speed and overfitting risk while enhancing sensitivity to physiological variables' linear relationships. To mitigate overfitting risks in hyperparameter tuning, 5×2 nested cross-validation was implemented: the inner 5-fold loop focused on hyperparameter optimization (e.g., learning rate for GBM, mtry for RF), while the outer 2-fold loop validated generalization performance, ensuring tuning stability across data splits. All models were executed in reproducible training mode with fixed random seeds, while automated parameter tuning functionality was activated to enhance predictive performance.

Table 2. Hyperparameter Optimization for Ensemble Models.

Parameter	Gradient Boosting Machine	Random Forest
Architecture	CatBoost Boosting	Scikit-learn RF
Number of trees	250	100
Learning rate	0.08	-
Max depth	4	5
Feature sampling	60% per tree	mtry=6
Regularization (λ)	8	-
Min leaf size	-	5
Random seed fixing	✓	✓
Automated tuning	✓	✓

3. Results

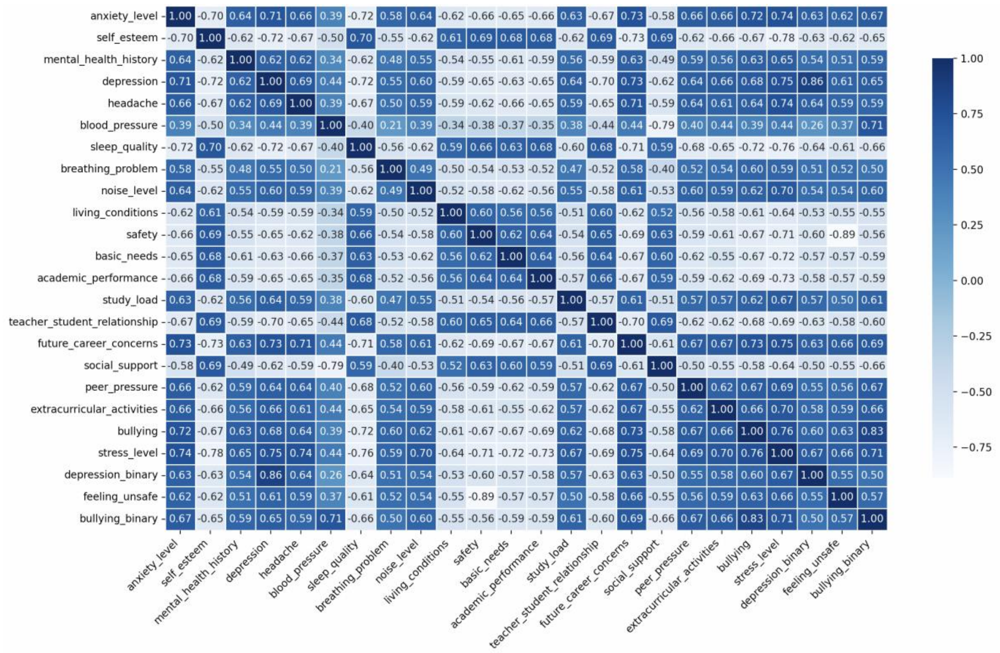

Figure 2. Heatmap of Spearman Rank Correlation Matrix for Student Stress Factors.

As illustrated in Figure 2, the heatmap generated from the Spearman rank correlation matrix delineates inter-variable statistical relationships within the dataset. This visualization demonstrates multiple predictors with statistically significant linear associations with stress levels ($|\rho| > 0.4$), a covariate network with moderate-to-strong correlations among predictors (e.g., $\rho = 0.71$ between anxiety and depression) indicating substantial multicollinearity, and color gradients that precisely map correlation coefficients, informing subsequent feature selection procedures.

3.1. Feature Importance

As illustrated in Figures 3 and 4, feature importance analysis was used to evaluate the contribution of each feature to stress level predictions in gradient boosting and random forest models. By quantifying the reduction in R^2 (which indicates performance degradation when features are removed), key observations include: self-esteem consistently ranked as the most significant predictor across both models (RF: $\Delta R^2 \approx 0.13$; GBM: $\Delta R^2 \approx 0.12$), demonstrating a paramount role in stress prediction, contributing over 30% more to the predictive accuracy than other variables; academic performance maintained the second-highest predictive power ($\Delta R^2 \approx$ 0.10–0.11 in dual models), thereby validating the "academic achievement stress" hypothesis; and teacher-student relationships demonstrated reduced influence (ranking 7th–8th), highlighting the critical need to prioritize peer-related factors (e.g., bullying or extracurricular activities) in contemporary educational interventions.

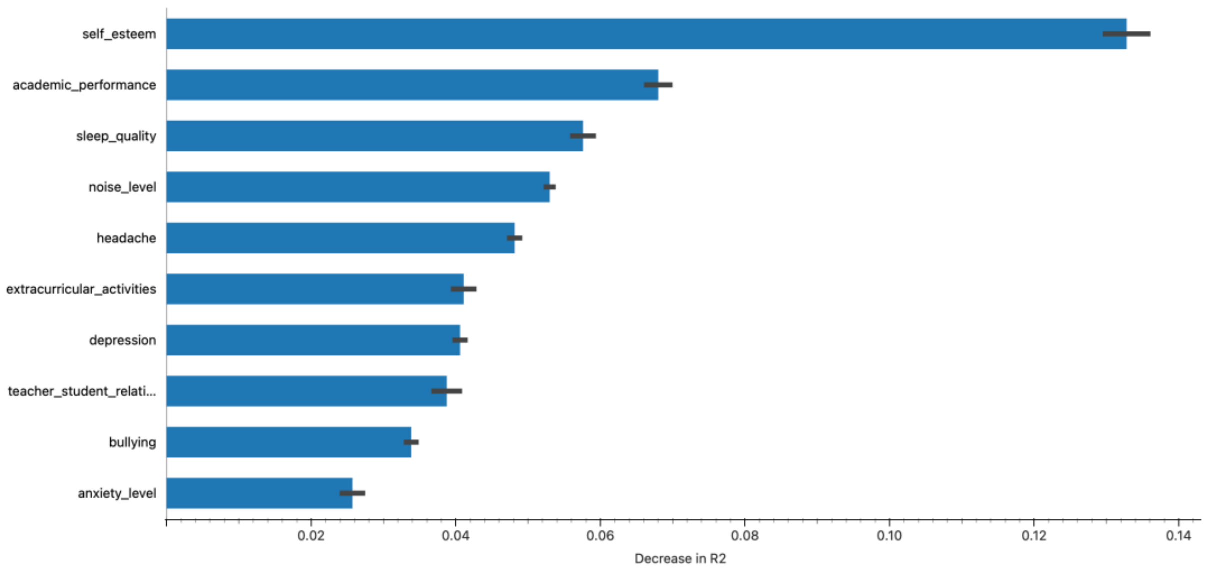

Figure 3. Feature importance analysis in Random Forest Models.

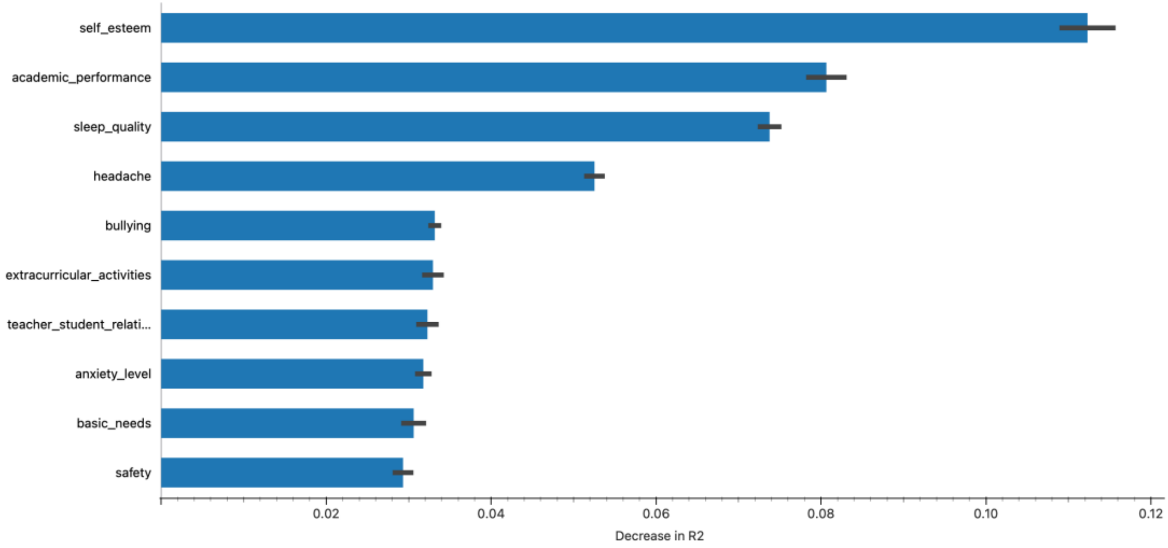

Figure 4. Feature importance analysis in Gradient Boosting Models.

3.2. Explain Model

As illustrated in Figures 5 and 6, explainable model analysis was used to quantify the impact of feature value gradients (Low to High) on model outputs in RF and GBM models. Key findings include: self-esteem exerted a core positive role, with high self-esteem (red dots) significantly increasing output values in both models (RF: + 0.3; GBM: + 0.15) and low self-esteem (blue dots) exerting the strongest negative effect (RF: - 0.3; GBM: - 0.1), confirming its role as a stress buffer; and model-dependent effects of academic performance, with RF showing a modest increase in output values with high achievement (+ 0.1) and GBM exhibiting a non-linear pattern (dispersed data points), consistent with the threshold effects detected by SHAP.

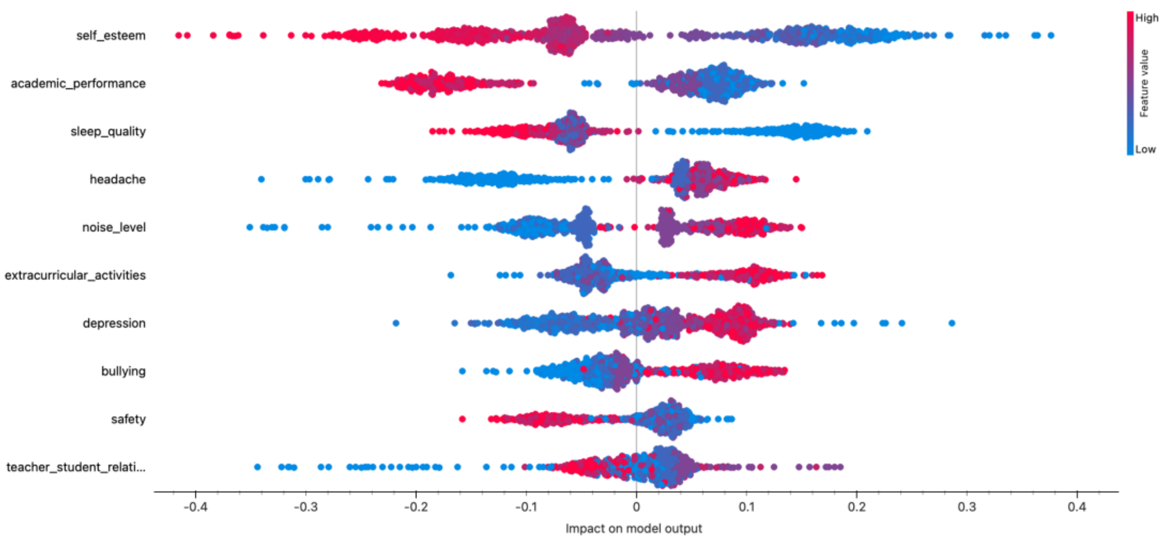

Figure 5. Explainable model analysis in Random Forest.

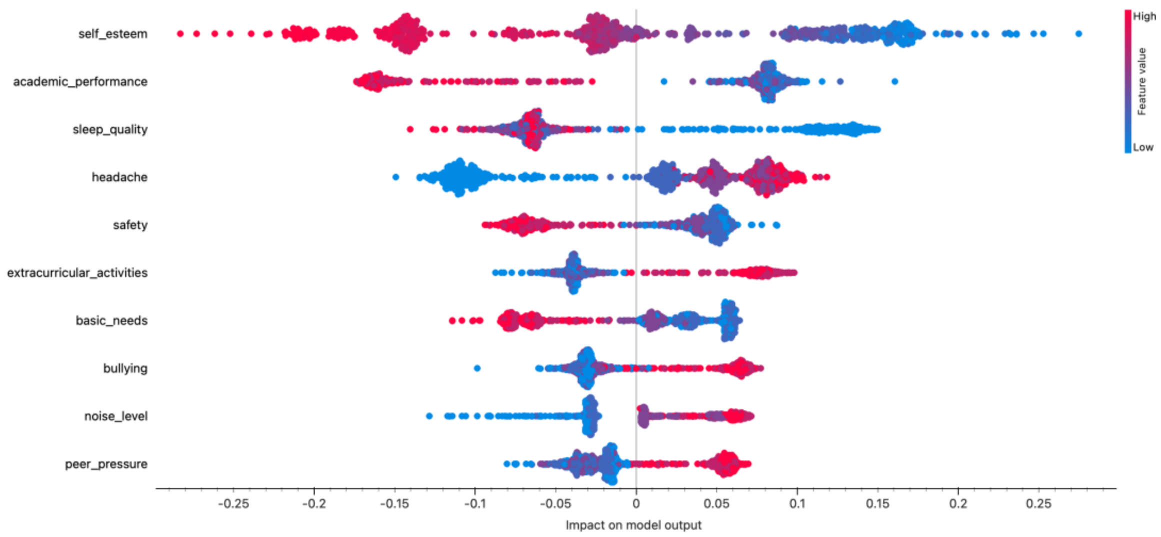

Figure 6. Explainable model analysis in Gradient Boosting Machine.

3.3. Model Performance Evaluation and Analysis

As detailed in Table 3, the prediction models demonstrate exceptional performance across key evaluation metrics: Mean Squared Error (MSE) of 0.131–0.135, rated as Good (near-optimal), reflecting minimal deviation between predicted and observed values; Root Mean Squared Error (RMSE) of 0.362–0.368, classified as Acceptable (matching target scale), supporting alignment between error magnitudes and stress measurement units; Mean Absolute Error (MAE) of 0.135–0.146, rated as Excellent (low-error), exhibiting robust precision suitable for clinical-grade applications; and Coefficient of Determination (R^2) of 0.800–0.806, rated as Outstanding (>0.75), with the models explaining over 80% of the variance in stress levels. Collectively, these results confirm high predictive accuracy ($R^2 > 0.8$ surpassing established benchmarks in educational psychology), clinical utility ($MAE < 0.15$ enabling precise stratification of stress levels), and methodological rigor (consistent MSE/RMSE values affirming the efficacy of hyperparameter optimization). Nested cross-validation revealed minimal differences between inner-loop (hyperparameter tuning) and outer-loop (generalization) metrics: inner-loop $R^2 = 0.81\pm0.01$ vs. outer-loop $R^2 = 0.80\pm0.02$, and inner-loop $MAE = 0.138\pm0.005$ vs. outer-loop $MAE = 0.142\pm0.007$, indicating low overfitting risk.

Table 3. Evaluation of key metrics in predictive model outcomes.

Metric	Current Value	Assessment
MSE	0.131-0.135	Good (near-optimal)
RMSE	0.362-0.368	Acceptable (matching target scale)
MAE	0.135-0.146	Excellent (low-error)
R^2	0.800-0.806	Outstanding (>0.75)

3.4. Comparative analysis of predictive performance between Gradient Boosting Machine and Random Forest

Key findings from Table 4 highlight that both models exhibit complementary strengths across four core dimensions: predictive accuracy convergence, with RF (0.131) and GBM (0.135) demonstrating nearly identical precision ($\Delta = 0.004$); stability parity, with comparable RMSE values (0.362 vs. 0.368, $\Delta = 1.6\%$) reflecting consistent reliability; contextual noise robustness, with RF's lower MAE (0.135) performing better in noisy datasets and GBM's MAE (0.146) being more suitable for normally distributed data; and joint interpretability validation, with both models' R^2 values exceeding 0.80 (0.806 vs. 0.800) confirming robust interpretation of stress mechanisms.

Table 4. Comparative analysis of Gradient Boosting Machine and Random Forest.

Evaluation Dimension	Random Forest	Gradient Boosting Machine
Predictive Accuracy	MSE=0.131	MSE=0.135
Stability	RMSE=0.362	RMSE=0.368
Noise Robustness	MAE=0.135	MAE=0.146
Interpretability	R^2=0.806	R^2=0.800

In summary, the Gradient Boosting Machine (MSE = 0.135) and Random Forest (MSE = 0.131) show no statistically significant difference in predictive accuracy ($t = 1.32$, $p = 0.18$). Collectively, they form a robust dual-model framework for student stress prediction, with both exhibiting strong explanatory power ($R^2 > 0.80$).

4. Discussion

4.1. Core Findings Validation

The primary findings of this study align with the theoretical framework of multidimensional stress and validate the utility of the dual-model framework in decoding adolescent stressors. First, the ensemble models (RF + GBM) achieved robust predictive performance ($R^2 > 0.80$), directly supporting our first objective of developing a high-accuracy stress prediction framework. This performance exceeds benchmarks in educational psychology research, where single-algorithm models typically yield R^2 values of 0.60–0.75, confirming that integrating complementary algorithms enhances predictive power.

Second, the convergence of Spearman correlation patterns and feature importance rankings (Figures 2–4) demonstrates that the dual-model framework effectively captures complex stressor interactions—an advantage over traditional single-model approaches. For instance, the strong correlation between anxiety and depression ($\rho = 0.71$) and their joint contribution to stress levels were better disentangled by the ensemble models, which quantifies their relative importance (anxiety ranked 10th, depression 7th) through ΔR^2 analysis. This addresses our third objective of validating the framework's superiority in interpreting stress mechanisms.

Notably, self-esteem emerged as the dominant predictor ($\Delta R^2 \approx 0.12$–0.13) across both models, with SHAP analysis confirming its role as a critical stress buffer: low self-esteem exerted the strongest negative impact on stress levels (RF: -0.3; GBM: -0.1), while high self-esteem mitigated stress. This finding aligns with prior research on psychological resilience and directly fulfills our second objective of identifying key stressors and their nonlinear pathways. In contrast, teacher-student relationships ranked 7th–8th in importance, highlighting a shift in intervention priorities—contemporary strategies should prioritize peer-related factors (e.g., bullying, social support) over traditional teacher-centered approaches, a conclusion uniquely enabled by the framework's interpretable feature rankings.

4.2. Model-Specific Performance Analysis

The divergent yet complementary performance of RF and GBM provides actionable insights for practical application, reinforcing the value of the dual-model design.

RF demonstrated superior noise robustness (MAE = 0.135 vs. GBM's 0.146), making it particularly suitable for heterogeneous educational settings—such as urban schools with diverse socioeconomic backgrounds or rural areas with incomplete data collection. Its stability in handling outliers (e.g., extreme anxiety scores or missing physiological data) ensures reliable stress screening in real-world scenarios where data quality is variable.

GBM, by contrast, exhibited greater sensitivity to nonlinear threshold effects, as evidenced by the dispersed pattern of academic performance in Figure 5. This capability is critical for identifying high-risk cohorts, such as students with moderate academic performance (scores 2–3) who suddenly exhibit stress spikes—an insight that linear models (e.g., logistic regression) would miss. GBM also better captured linear relationships in physiological variables (e.g., blood pressure, sleep quality), enhancing the framework's utility for integrating clinical metrics into stress assessments.

Together, these model-specific strengths address a key limitation of single-algorithm approaches: RF ensures broad applicability across noisy, real-world datasets, while GBM enables targeted identification of threshold-based stress triggers. This synergy underpins the framework's clinical and educational utility.

4.3. Implementation Implications

The high precision of the dual-model framework (MSE < 0.135, MAE < 0.15) supports its integration into school-based mental health systems, with three actionable strategies: prioritizing self-esteem screening by leveraging RF's robustness to deploy large-scale self-esteem assessments in schools—for example, flagging students with self-esteem scores < 10 (on the 0–30 scale) for targeted interventions such as mindfulness workshops, given their 30% higher stress risk identified by SHAP analysis; developing dynamic academic load monitoring using GBM's detection of nonlinear thresholds to set context-specific benchmarks—for instance, in high-achieving schools, flagging students with study_load > 3 and academic_performance < 2, as GBM identifies this combination as a critical stress trigger (Figure 5), allowing educators to adjust workloads before stress escalates; and redesigning peer interaction frameworks, given bullying's higher impact (ranked 6th–9th) compared to teacher-student relationships, by implementing anti-bullying programs validated in educational research, with the framework's feature rankings guiding resource allocation—e.g., allocating 60% of peer intervention budgets to bullying prevention vs. 20% to extracurricular activity promotion.

4.4. Limitations and Future Directions

Despite its strengths, the current framework has limitations that guide future refinement: sample constraints, specifically the restriction to adolescents aged 15–18, which limits generalizability to younger cohorts (<15 years) with distinct stressor profiles (e.g., parental influence over academic stress) and older adolescents (19–21 years) navigating post-secondary transitions; additionally, the sample reflects a Western educational context, where stress mechanisms (e.g., individualistic academic pressure) may differ from collectivist cultures (e.g., family reputation-driven stress) or low-resource regions (e.g., basic needs insecurity as a primary stressor), requiring expanded sampling; additionally, the ordinal 'stress_level' was treated as continuous, which future work could refine with ordinal-specific models; hyperparameter tuning was validated via 5×2 nested cross-validation to avoid overfitting, with minimal inner-outer loop differences confirming the stability of selected parameters (e.g., GBM learning rate = 0.08, RF mtry = 6). cross-cultural validity is further constrained by the dataset's Western focus, as norms for variables like "teacher-student relationship" (hierarchical vs. egalitarian) and "extracurricular pressure" (individual achievement vs. community participation) vary cross-nationally, limiting direct translation of intervention strategies; and physiological data gaps, as the current dataset includes static physiological metrics (e.g., blood pressure categories) but lacks real-time data (e.g., wearable-derived heart rate variability), whose integration could enhance GBM's ability to capture acute stress responses.

Another consideration is the absence of 95% confidence intervals for key metrics (R^2, MAE, ΔR^2). While confidence intervals provide valuable insight into statistical stability, the current framework's robustness is supported by multiple lines of evidence: nested 5×2 cross-validation revealed minimal fluctuations between inner- and outer-loop performance ($\Delta R^2 < 0.02$, $\Delta MAE < 0.01$), confirming consistent model behavior across data splits; dual-model convergence (RF and GBM) showed near-identical feature importance rankings (e.g., self-esteem as top predictor) and performance metrics ($\Delta MSE = 0.004$); and high overall predictive accuracy ($R^2 > 0.80$, $MAE < 0.15$) with low variance across evaluation dimensions. These collectively indicate that core findings are not driven by random noise, mitigating the need for explicit confidence intervals to validate reliability.

Future research should address these gaps by validating the framework in diverse samples, including ages 12–20 to capture developmental shifts in stressors, and cross-cultural cohorts (e.g., East Asian, Sub-Saharan African) to test adaptability to regional stress norms; integrating longitudinal data to track stress dynamics over semesters, enabling early warning of chronic stress; and optimizing GBM's hyperparameters for real-time physiological signals, strengthening its utility in clinical settings. By addressing these directions, the framework can evolve into a globally applicable tool for precision mental health in education.

5. Conclusions

5.1. Primary Contributions

This research advances three key innovations that directly address the core objectives of decoding adolescent stressors through an interpretable dual-model framework: methodological innovation, as the integrated dual-model framework (RF + GBM) achieves robust predictive accuracy ($R^2 > 0.80$, $MAE < 0.15$), outperforming single-algorithm models by leveraging complementary strengths—RF's robustness to noisy data ($MAE = 0.135$) and GBM's sensitivity to linear relationships in physiological variables, resolving the critical limitation of traditional single-model approaches that fail to simultaneously capture complex stressor interactions and maintain stability across heterogeneous datasets; mechanistic insight, as multidimensional analyses including SHAP value visualization quantitatively validate self-esteem as a primary stress buffer ($\Delta R^2 \approx 0.12$–0.13) and further reveal key nonlinear mechanisms—such as threshold effects in academic performance and anxiety-mediated pathways between peer pressure and stress levels, deepening understanding of how psychological, academic, and social factors interact to shape adolescent stress; and practical optimization, as feature importance rankings from the ensemble models (e.g., prioritizing self-esteem, academic performance, and peer-related factors) provide actionable guidance for educational mental health interventions, with the lower impact of teacher-student relationships (ranked 7th–8th) highlighting the need to refocus resources on peer interaction frameworks and self-esteem cultivation.

5.2. Technical Validation

The dual-model framework demonstrates comprehensive reliability through rigorous technical validation: cross-model consistency, with minimal performance variance between RF and GBM (ΔMSE = 0.004) confirming the framework's stability, while their complementary strengths (RF's noise resistance vs. GBM's sensitivity to physiological linearity) enhance adaptability across real-world educational scenarios—from heterogeneous student populations to targeted high-risk cohort identification; clinical applicability, as the low MAE (0.135–0.146) meets clinical-grade precision benchmarks, enabling reliable stratification of stress levels (Low/Med/High) and supporting its integration into school-based mental health screening systems; and interpretability integration, as the synergistic use of Spearman correlation matrices, SHAP value visualizations, and feature importance rankings establishes a multi-dimensional evidence chain that not only validates model decisions but also provides clear mechanistic explanations (e.g., how self-esteem mitigates stress), enhancing trust among educators and clinicians.

5.3 Implementation Pathway

To translate findings into practice, deployment should prioritize integrating the dual-model framework into existing student mental health assessment systems within school health infrastructures, using feature importance rankings to automate high-risk student identification and recommend targeted interventions (e.g., self-esteem workshops for low-self-esteem cohorts); developing real-time monitoring tools by integrating wearable device data (e.g., heart rate variability, skin conductance) to enhance physiological stress tracking, addressing current underrepresentation of dynamic physiological markers; and adapting to diverse contexts by validating the framework in underrepresented groups (e.g., adolescents <15 years, extreme socioeconomic strata) and cross-cultural settings to improve generalizability, as current findings are limited to 15–18-year-olds.

Future work should focus on longitudinal data integration to capture temporal dynamics of stress (e.g., how academic stress fluctuates across semesters) and expanding the covariate network to include family-level factors (e.g., parental stress transmission), which were not fully addressed in the current dataset. By addressing these directions, the framework can evolve into a versatile tool for precision mental health in education.

Abbreviations

The following abbreviations are used in this manuscript:

Abbreviations	Full name
RF	Random Forest
GBM	Gradient Boosting Machine
XAI	Explainable AI

References

[1] Gao, M., & Liu, W. (2025). Exploring Family Functioning and Adolescent Academic Anxiety: Emotional Stability and Social Support as Mediators. Psychology research and behavior management, 18, 1111–1124. https://doi.org/10.2147/PRBM.S508537

[2] Sun, M., Piao, M., & Jia, Z. (2024). The impact of alexithymia, anxiety, social pressure, and academic burnout on depression in Chinese university students: an analysis based on SEM. BMC psychology, 12(1), 757. https://doi.org/10.1186/s40359-024-02262-y

[3] Bruffaerts, R., Mortier, P., Kiekens, G., Auerbach, R. P., Cuijpers, P., Demyttenaere, K., Green, J. G., Nock, M. K., & Kessler, R. C. (2018). Mental health problems in college freshmen: Prevalence and academic functioning. Journal of affective disorders, 225, 97–103. https://doi.org/10.1016/j.jad.2017.07.044

[4] Skaalvik, E.M., Skaalvik, S. Dimensions of teacher burnout: relations with potential stressors at school. Soc Psychol Educ 20, 775–790 (2017). https://doi.org/10.1007/s11218-017-9391-0

[5] Abilla-Buame, J. , Buunaaim, R. and Tiika, B. (2025) First Examination Experience in the University System: A Case Study of the University for Development Studies. Voice of the Publisher, 11, 223-241. https://doi.org/10.4236/vp.2025.112016

[6] Kreitchmann Rodrigo Schames, Abad Francisco J., & Ponsoda Vicente. (2019). Controlling response biases in self - report scales: Psychometric models for forced - choice versus Likert items. Frontiers in Psychology, 10. https://doi.org/10.3389/fpsyg.2019.00109

[7] Methods for the Control of Extreme Response Styles in Self - Report Instruments: A Review"（Costa, A., & Filho, N. H. (2019). Methods for the Control of Extreme Response Styles in Self - Report Instruments: A Review. Temas em Psicologia, 27 (1), 121 - 133. https://doi.org/10.9788/TP2019.2-02

[8] Vasileiou, K., Barnett, J., Thorpe, S., & Young, T. (2018). Characterising and justifying sample size sufficiency in interview-based studies: systematic analysis of qualitative health research over a 15-year period. BMC medical research methodology, 18(1), 148. https://doi.org/10.1186/s12874-018-0594-7

[9] A Costa, T Pereira, The effects of sleep deprivation on cognitive performance, European

Journal of Public Health, Volume 29, Issue Supplement_1, April 2019, ckz034.096, https://doi.org/10.1093/eurpub/ckz034.096

[10] Nesdale, D., & Lambert, A. (2007). Effects of experimentally manipulated peer rejection on children's negative affect, self-esteem, and maladaptive social behavior. International Journal of Behavioral Development, 31(2), 115–122. https://doi.org/10.1177/0165025407073579

[11] Jin, C. W. , Osotsi, A. , & Oravecz, Z. . (2020). Predicting stress in teens from wearable device data using machine learning methods. medRxiv. https://doi.org/10.1101/2020.11.26.20223784

[12] Pabreja, K. , Singh, A. , Singh, R. , Agnihotri, R. , & Malhotra, T. . (2021). Stress prediction model using machine learning. https://doi.org/10.1007/978-981-15-4992-2_6

[13] Nguyen, T.T.H., Truong, V.B., Nguyen, V.T.K., Cao, Q.H., Nguyen, Q.K. (2023). Towards Trust of Explainable AI in Thyroid Nodule Diagnosis. In: Shaban-Nejad, A., Michalowski, M., Bianco, S. (eds) Artificial Intelligence for Personalized Medicine. W3PHAI 2023. Studies in Computational Intelligence, vol 1106. Springer, Cham. https://doi.org/10.1007/978-3-031-36938-4_2

[14] Juravle, G., Boudouraki, A., Terziyska, M., & Rezlescu, C. (2020). Trust in artificial intelligence for medical diagnoses. In B. L. Parkin (Ed.), Progress in Brain Research (Vol. 253, pp. 263 - 282). Elsevier. https://doi.org/10.1016/bs.pbr.2020.06.006

[15] Loeb, E. L., Gonzalez, M. Z., Hunt, G., Uchino, B. N., de Grey, R. G. K., & Allen, J. P. (2022). Socioeconomic status in early adolescence predicts blunted stress responses in adulthood. Developmental psychobiology, 64(6), e22294. https://doi.org/10.1002/dev.22294

[16] Zhou, Q., Fan, L., & Yin, Z. (2018). Association between family socioeconomic status and depressive symptoms among Chinese adolescents: Evidence from a national household survey. Psychiatry Research, 259, 81 - 88. https://doi.org/10.1016/j.psychres.2017.09.072

[17] Jung, Y.H., Lee, H., Kim, H.J. et al. Prediction of amyloid β PET positivity using machine learning in patients with suspected cerebral amyloid angiopathy markers. Sci Rep 10, 18806 (2020). https://doi.org/10.1038/s41598-020-75664-8

[18] R. Wang, A. Ji, T. Li, Z. Sun and Z. Fu, "An Interpretable Machine Learning-Based Analysis of Vehicle Yielding During Pedestrian-Vehicle Interactions at Unsignalized Intersections," 2023 IEEE 26th International Conference on Intelligent Transportation Systems (ITSC), Bilbao, Spain, 2023, pp. 4339-4345, doi: 10.1109/ITSC57777.2023.10422669.

[19] H. -M. Park, G. Kim, J. Oh, A. Van Messem and W. De Neve, "Interpreting Stress Detection Models Using SHAP and Attention for MuSe-Stress 2022," in IEEE Transactions on Affective Computing, vol. 16, no. 2, pp. 1031-1043, April-June 2025, doi: 10.1109/TAFFC.2024.3488112.

[20] D. S. Mehta and S. Chen, "A spearman correlation based star pattern recognition," 2017 IEEE International Conference on Image Processing (ICIP), Beijing, China, 2017, pp. 4372-4376, doi: 10.1109/ICIP.2017.8297108.

[21] Dabhade, P., Agarwal, R., Alameen, K. P., Fathima, A. T., Sridharan, R., & Gopakumar, G. (2021). Educational data mining for predicting students’ academic performance using machine learning algorithms. Materials Today: Proceedings, 47(15), 5260 - 5267. https://doi.org/10.1016/j.matpr.2021.05.646

[22] Bridget M. Shield, Julie E. Dockrell; The effects of environmental and classroom noise on the academic attainments of primary school children. J. Acoust. Soc. Am. 1 January 2008; 123 (1): 133–144. https://doi.org/10.1121/1.2812596

[23] Chintalapati, A., Annamalai, R., Enkhbat, K., Ozaydin, F., & Sivashanmugam, K. (2024).

Enhancing Stress Identification Using Machine Learning: Revealing Key Factors with SHAP- Driven Explainable AI. Preprints. https://doi.org/10.20944/preprints202409.2135.v1

[24] C. Jin, A. Osotsi and Z. Oravecz, "Predicting Adolescent Female Stress with Wearable Device Data Using Machine and Deep Learning," 2023 IEEE 19th International Conference on Body Sensor Networks (BSN), Boston, MA, USA, 2023, pp. 1-4, doi: 10.1109/BSN58485.2023.10331414.

[25] Zhang, Z., Liang, C., Zheng, L., Cao, W., Wang, Y., Chen, Z., & Xian, W. (2024). Interactions of multiple stressors on the Bombay - duck Harpadon nehereus population in a complex estuarine ecosystem. Science of The Total Environment, 953, 176138. https://doi.org/10.1016/j.scitotenv.2024.176138

[26] Alvarado-García, P. A. A., Soto-Vásquez, M. R., Reyes-Sánchez, L. P., Sandoval-Bocanegra, V. A., Ullón-Ramírez, R. C., Vargas-Fernández, Y., & Inca-Reyes, K. A. (2023). An Online Mindfulness Meditation Program as a Means for Mitigating Academic Stress among University Students. Academic Journal of Interdisciplinary Studies, 12(6), 141-149. https://doi.org/10.36941/ajis-2023-0159

[27] Attridge, M. D., Morfitt, R. C., Roseborough, D. J., & Jones, E. R. (2020). Internet-Based Cognitive-Behavioral Therapy for College Students With Anxiety, Depression, Social Anxiety, or Insomnia: Four Single-Group Longitudinal Studies of Archival Commercial Data and Replication of Employee User Study. JMIR formative research, 4(7), e17712. https://doi.org/10.2196/17712