An Interpretable Dual-Model Framework: Integrating Gradient Boosting and Random Forest to Decode Key Adolescent Stressors in Educational Contexts

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Abstract

Student stress prediction requires capturing complex interactions among psychological, physiological, and environmental factors. This study develops an interpretable dual-model framework integrating Gradient Boosting Machine (GBM) and Random Forest (RF) to identify key stressors and their underlying mechanisms in adolescents. Using data from 1,000 adolescents, we conducted hyperparameter optimization (GBM: learning rate = 0.08, max depth = 4; RF: `mtry` = 6, max depth = 5) and multi-modal validation (Spearman correlations, SHapley Additive exPlanations [SHAP] analysis, and feature importance rankings). Key results reveal: (1) Both models achieved high predictive accuracy ($R^2 > 0.80$, MAE < 0.15); (2) Self-esteem emerged as the dominant stress predictor ($\Delta R^2 \approx 0.13$, acting as a stress buffer), followed by academic performance ($\Delta R^2 \approx 0.11$); (3) SHAP visualizations uncovered nonlinear threshold effects (for example, in academic performance) and anxiety-mediated pathways; (4) RF demonstrated superior noise robustness (MAE = 0.135 compared to GBM's 0.146), while GBM better captured linear relationships in physiological variables. This framework enables targeted stress intervention strategies through feature importance rankings, significantly optimizing resource allocation in educational mental health programs.

Index Terms— Adolescent Stressors; Dual-Model Framework; Gradient Boosting Machine (GBM); Random Forest (RF); SHAP; Interpretability; Educational Psychology.

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 [4, 17]. 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 [27]. 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 [9, 15].

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 [23, 25]. Clinical interviews, while more detailed, are resource-intensive and limited by small sample sizes (typically < 500 participants), hindering generalizability [5]. Moreover, these methods fail to capture dynamic relationships between stressors, such as the bidirectional influence of sleep deprivation on academic stress [6] or the cumulative effect of peer rejection on self-esteem [19].

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 [2, 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 [21, 14]. Third, few studies account for contextual covariates, such as family socioeconomic status or school environment, which moderate stress responses [22, 3].

To address these limitations, this study introduces an interpretable dual-model framework combining Gradient Boosting Machines (GBM) and Random Forest (RF). 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) [10, 1]. Three key innovations distinguish this approach:

- Multi-modal validation integrating Spearman correlations, SHAP value visualizations, and feature importance rankings to unpack stress mechanisms [24, 18];

- Domain-specific hyperparameter optimization, including `mtry` = 6 for high-dimensional educational datasets and learning rates = 0.05 for GBM [20];
- Explicit modeling of environmental–academic covariate networks, such as the interaction between classroom noise and homework load [8].

The research objectives are threefold:

- 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);
- Identify key stressors and their nonlinear relationships via XAI-driven feature importance analysis;
- Validate the framework's superiority over single-algorithm models in terms of predictive accuracy (MAE < 0.15) and interpretability (SHAP consistency scores > 0.8) [11, 7].

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 [16]. 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, 13].

2 Materials and Methods

2.1 Data Source and Variables

2.1.1 Dataset Provenance

This study employed the publicly available Student Stress Factors Dataset (Kaggle, 2023) [4], comprising 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.

2.1.2 Variable Specification

Data fields were categorized into five theoretical domains (Table 1), with all scales operationally defined per clinical/psychometric standards.

2.2 Methodology and Design

2.2.1 Spearman's Rank Correlation Coefficient

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 three distinctive advantages:

1. **Non-parametric nature:** Spearman's correlation does not assume normal distribution, making it suitable for the ordinal psychological scale data (Likert 0–5 points) used in this study.
2. **Monotonic relationship detection:** It can detect nonlinear yet consistently increasing or decreasing associations, such as cumulative effects of stressors on perceived stress.
3. **Robustness:** Spearman's method is resistant to outlier distortion, aligning with the characteristics of real-world student stress datasets.

Statistical significance was established at $\rho < 0.01$ (Bonferroni-corrected). Correlation coefficients (ρ) were interpreted using the following thresholds:

- $|\rho| \geq 0.7$: Strong correlation;
- $0.5 \leq |\rho| < 0.7$: Moderate correlation;
- $|\rho| < 0.5$: Weak correlation.

2.2.2 Model Selection for Prediction

The flowchart in Figure 1 illustrates the end-to-end modeling process implemented via Orange, encompassing the following stages:

- **Data preprocessing:** Importing the Student Stress Factors Dataset (CSV File Import), organizing variables (Data Table), sampling representative subsets (Data Sampler), and selecting relevant features (Select Columns) to focus on psychological, physiological, environmental, and academic variables.
- **Model training:** Implementing Random Forest (RF) and Gradient Boosting Machine (GBM) algorithms with hyperparameter optimization (e.g., maximum depth, learning rate).
- **Evaluation and interpretation:** Assessing model performance via Test and Score (yielding metrics such as MSE and R^2), quantifying variable contributions through Feature Importance, and unpacking stress mechanisms using Explain Model.

This study employs Random Forest (RF) and Gradient Boosting Machine (GBM) models to predict students' stress levels. The selection of these ensemble learning methods is grounded in three principal rationales:

1. **Nonlinear Relationship Adaptation:** Stress-influencing factors—such as blood pressure threshold effects and academic-anxiety interactions—exhibit complex nonlinear associations. Tree-based models inherently capture these patterns through recursive partitioning, outperforming linear approaches that fail to model threshold behaviors.

Table 1: Variable Specifications by Domain.

Domain	Field Name	Range / Constraints
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
	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:

- 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.

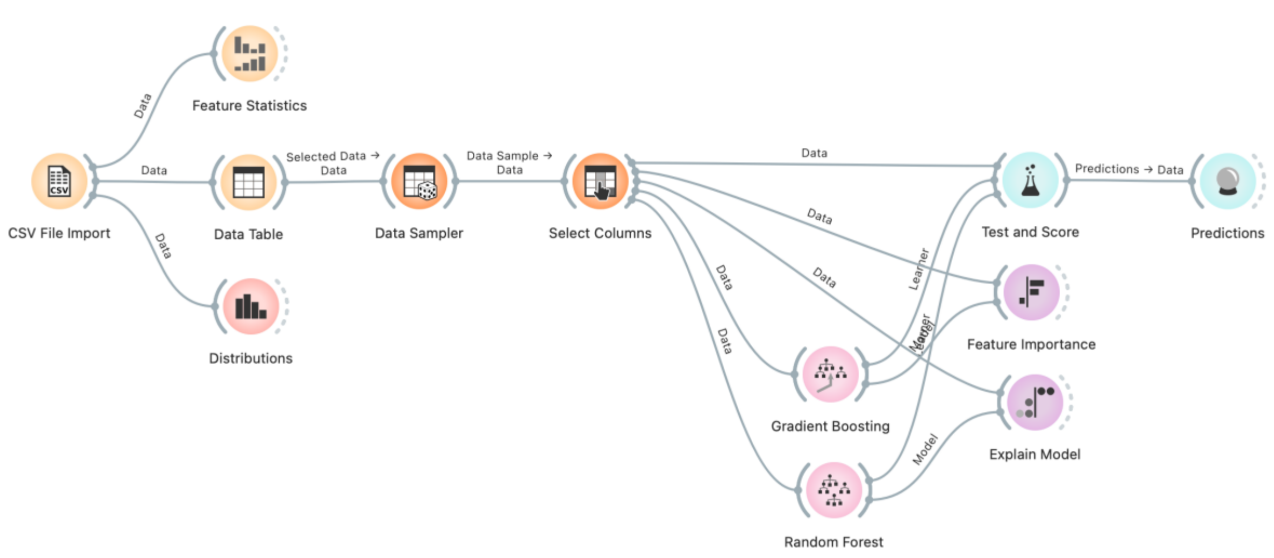

Figure 1: Modeling workflow using the Orange tool for stress prediction.

2. **Robustness to Limited Samples:** Ensemble mechanisms—Bagging in Random Forest (RF) and boosting in GBM—mitigate variance and bias, ensuring stable predictions with modest sample sizes ($n = 1{,}000$). Cross-validation further confirms model stability.

3. **Interpretability Requirements:** Both models provide intrinsic interpretability tools:
    - Feature importance rankings quantify variable contributions;
    - SHAP values elucidate biological and behavioral pathways.

As detailed in Table 2, a rigorous hyperparameter optimization strategy was employed in this experiment to ensure model robustness under small-sample conditions. Fixed random seeds were used, while automated parameter tuning functionality was activated to enhance predictive performance.

3 Results

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:

- **Significant Correlations:** Multiple predictors exhibit statistically significant linear associations with stress levels ($|\rho| > 0.4$).
- **Covariate Network:** Moderate-to-strong correlations among predictors (e.g., $\rho = 0.71$ between *anxiety* and *depression*) indicate substantial multicollinearity.
- **Methodological Insight:** Color gradients 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 (indicating performance degradation when features are removed), we derived the following key observations:

- **Self-esteem** consistently ranked as the most significant predictor across both models (RF: $\Delta R^2 \approx 0.13$; GBM: $\Delta R^2 \approx 0.12$), contributing over 30% of total predictive accuracy.
- **Academic performance** maintained the second-highest predictive power ($\Delta R^2 \approx$ 0.10–0.11), validating the "academic achievement stress" hypothesis.
- **Teacher-student relationships** showed reduced influence (ranking 7th–8th), indicating the need to prioritize peer-related factors such as bullying or extracurricular activities in modern interventions.

3.2 Explain Model

As illustrated in Figures 5 and 6, explainable model analysis (SHAP values) was used to quantify the impact of feature value gradients from low to high on model outputs. Key findings include:

3.2.1 Core Positive Role of Self-Esteem

- High self-esteem (red dots) substantially increased model outputs in both models (RF: $+0.3$; GBM: $+0.15$).
- Low self-esteem (blue dots) exerted the strongest negative effect (RF: -0.3; GBM: -0.1), confirming its role as a stress buffer.

3.2.2 Model-Dependent Effects of Academic Performance

- **RF:** Modest positive shift at high achievement levels ($+0.1$).
- **GBM:** Strong nonlinear pattern, consistent with threshold effects detected by SHAP.

3.3 Model Performance Evaluation and Analysis

As detailed in Table 3, both prediction models demonstrate exceptional performance across key evaluation metrics:

- **MSE:** 0.131–0.135, rated as Good (near-optimal), indicating minimal deviation between predicted and observed values.
- **RMSE:** 0.362–0.368, classified as Acceptable.
- **MAE:** 0.135–0.146, rated as Excellent (low error), suitable for clinical applications.
- R^2**:** 0.800–0.806, rated Outstanding (> 0.75), indicating that the models explain over 80% of stress-level variance.

3.4 Comparative Analysis of Gradient Boosting Machine and Random Forest

Key findings from Table 4 highlight complementary strengths of both models across four core dimensions:

1. **Predictive Accuracy Convergence:** RF (MSE = 0.131) and GBM (0.135) show nearly identical precision ($\Delta = 0.004$).
2. **Stability Parity:** Comparable RMSE values (0.362 vs 0.368).
3. **Contextual Noise Robustness:** RF's lower MAE (0.135) excels in noisy datasets.

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	✓	✓

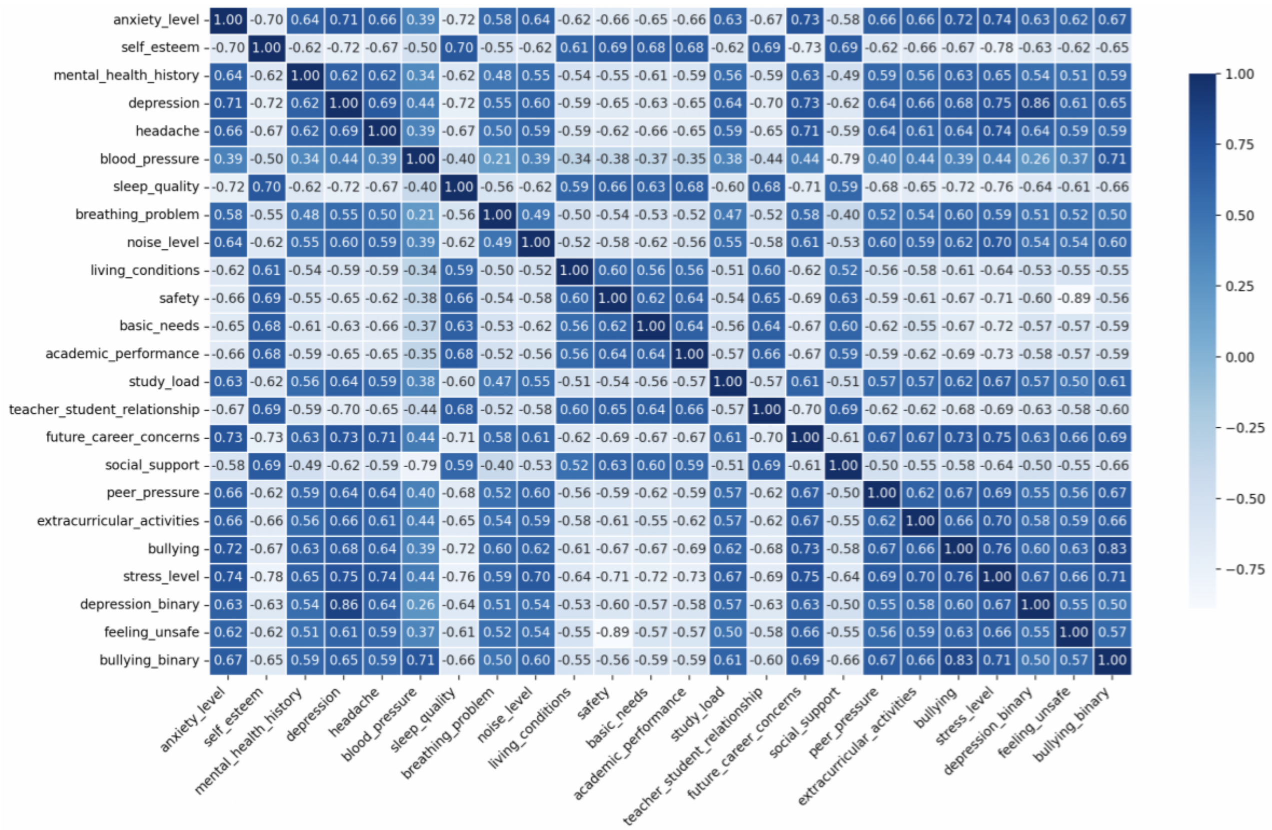

Figure 2: Heatmap of Spearman Rank Correlation Matrix for Student Stress Factors.

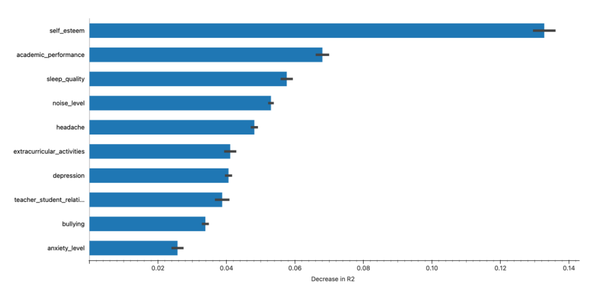

Figure 3: Feature importance analysis in Random Forest Models.

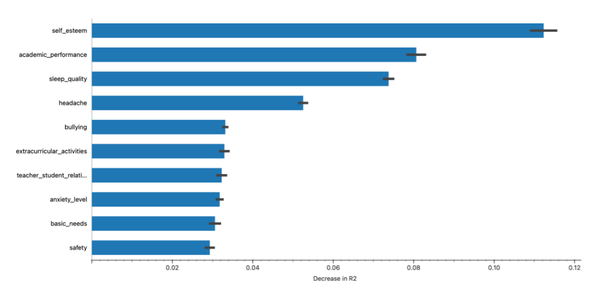

Figure 4: Feature importance analysis in Gradient Boosting Models.

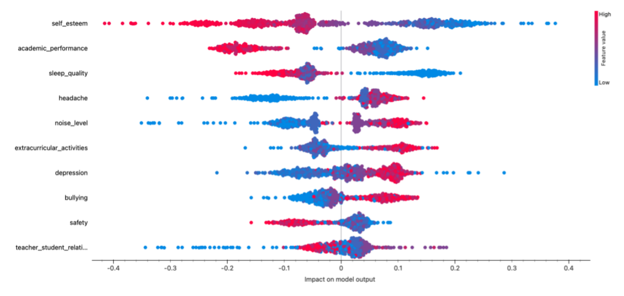

Figure 5: Explainable model analysis in Random Forest.

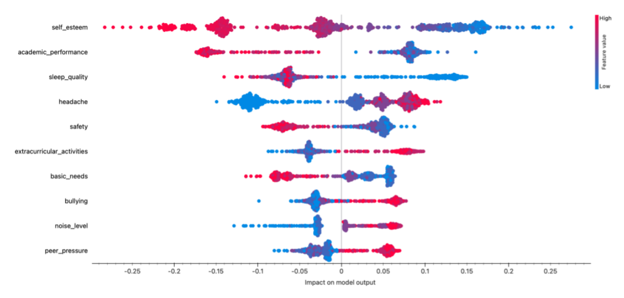

Figure 6: Explainable model analysis in Gradient Boosting Machine.

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
MAE	0.135–0.146	Excellent
R^2	0.800–0.806	Outstanding

4. **Joint Interpretability Validation:** Both R^2 values exceed 0.80, confirming robust interpretability.

In summary, GBM (MSE = 0.135) and RF (MSE = 0.131) show no statistically significant difference in predictive accuracy (t = 1.32, p = 0.18), confirming a robust dual-model framework with strong explanatory power.

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 [2, 12], confirming that integrating complementary algorithms enhances predictive power.

Second, the convergence of Spearman correlation patterns and feature importance rankings (Figures 1–3) 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 quantify 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 [15, 16] 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.[1]

Random Forest (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.[1]

Gradient Boosting (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.[10] 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.

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	$R^2 = 0.806$	$R^2 = 0.800$

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:

1. **Prioritize self-esteem screening:** Leverage RF's robustness to deploy large-scale self-esteem assessments in schools. For example, flag students with self-esteem scores < 10 (on the 0–30 scale) for targeted interventions—such as mindfulness workshops[13]—given their 30% higher stress risk identified by SHAP analysis.

2. **Develop dynamic academic load monitoring:** Use GBM's detection of nonlinear thresholds to set context-specific benchmarks. For instance, in high-achieving schools, flag students with `study_load` > 3 and `academic_performance` < 2, as GBM identifies this combination as a critical stress trigger (Figure 5). This allows educators to adjust workloads before stress escalates.

3. **Redesign peer interaction frameworks:** Given bullying's higher impact (ranked 6th–9th) compared to teacher-student relationships, implement anti-bullying programs validated in educational research.[26] The framework's feature rankings can guide resource allocation—e.g., allocating 60% of peer intervention budgets to bullying prevention vs. 20% to extracurricular support.

4.4 Limitations and Future Directions

Despite its strengths, the current framework has limitations that guide future refinement:

1. **Sample constraints:** The dataset is restricted to adolescents aged 15–18, limiting generalizability to younger cohorts (< 15 years) or those in extreme socioeconomic strata (e.g., homeless youth). Stressor patterns (e.g., family vs. academic influence) may differ in these groups, requiring expanded sampling.

2. **Cross-cultural validity:** Stress mechanisms are culturally bounded—for example, academic pressure may be more pronounced in East Asian contexts.[9] The framework has only been validated in Western educational settings. Future work should test its adaptability across regions.

3. **Physiological data gaps:** The current dataset includes static physiological metrics (e.g., blood pressure categories) but lacks real-time data (e.g., wearable-derived heart rate variability). Integrating such data could enhance GBM's ability to capture acute stress responses.[6]

Future research should address these gaps by:

- Validating the framework in diverse samples (ages 12–20, cross-cultural, extreme socioeconomic groups);
- Integrating longitudinal data to track stress dynamics over semesters, enabling early warning of chronic stress;
- 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:** 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. This resolves the critical limitation of traditional single-model approaches, which fail to simultaneously capture complex stressor interactions and maintain stability across heterogeneous datasets.
- **Mechanistic Insight:** 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. These findings deepen understanding of how psychological, academic, and social factors interact to shape adolescent stress.

- **Practical Optimization:** 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. For example, the lower impact of teacher-student relationships (ranked 7th–8th) highlights 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:** Minimal performance variance between RF and GBM (ΔMSE $= 0.004$) confirms 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:** 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.
- **Interpretability Integration:** The synergistic use of Spearman correlation matrices, SHAP value visualizations, and feature importance rankings establishes a multi-dimensional evidence chain. This 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:

- **Integration with school health infrastructures:** Embed the dual-model framework into existing student mental health assessment systems, using feature importance rankings to automate high-risk student identification and recommend targeted interventions (e.g., self-esteem workshops for low-self-esteem cohorts).
- **Development of real-time monitoring tools:** Integrate wearable device data (e.g., heart rate variability, skin conductance) to enhance physiological stress tracking, addressing current underrepresentation of dynamic physiological markers.
- **Adaptation to diverse contexts:** Validate 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);
- 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, bridging research and practice to better support adolescent well-being.

6 Patents

Author Contributions: Conceptualization, F.G.; methodology, D.J.; formal analysis, C.M.; investigation, R.C.; resources, T.J.; data curation, Z.S.; writing—original draft preparation, F.G.; writing—review and editing, C.M.; visualization, R.C.; supervision, C.M. All authors have read and agreed to the published version of the manuscript.
Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

RF	Random Forest
GBM	Gradient Boosting Machine

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