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Identifying Key Psychological, Academic, and Environmental Determinants of Student Stress Using Regression-Based Machine Learning

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Abstract

Student stress in higher education is a multifaceted phenomenon influenced by psychological, academic, and environmental factors, with significant implications for students' mental health and academic performance. While previous studies have examined stress determinants using traditional statistical approaches, such methods often fail to capture complex, non-linear interactions among multiple stressors and provide limited insight into their relative importance. This study aims to identify and rank the key determinants of student stress using regression-based machine learning models. A structured dataset comprising 1,100 student observations and 21 predictor variables was analyzed. Four regression models Linear Regression, Ridge Regression, Gradient Boosting Regressor, and Random Forest Regressor were evaluated using 5-fold cross-validation and a holdout test set. Model performance was assessed using R^2, RMSE, and MAE metrics. The Random Forest Regressor demonstrated the best performance, achieving a test R^2 of 0.812, indicating strong predictive accuracy and generalization capability. Feature importance analysis using permutation importance and model-specific measures revealed that bullying was the most influential determinant of student stress, followed by extracurricular activities, self-esteem, and sleep quality. Environmental factors such as safety and basic needs also showed notable contributions. The consistency between feature importance methods confirms the robustness of the findings. This study contributes to the literature by providing an integrated and interpretable machine learning framework for identifying dominant stress determinants, offering valuable insights to support data-driven mental health interventions and policy development in higher education.

Keywords: Student Stress, Machine Learning, Regression Analysis, Feature Importance, Higher Education

1. Introduction

Student stress has become a significant concern in higher education due to its profound impact on students' mental health, academic performance, and overall well-being. Numerous studies have shown that university students are exposed to intense academic pressures that often lead to elevated levels of anxiety, depression, and psychological distress, which in turn impair concentration, learning engagement, and academic achievement [1]. Empirical evidence consistently indicates that students experiencing high academic stress tend to demonstrate reduced academic performance and lower grades, highlighting the close relationship between mental health and educational outcomes [2].

The transition to university life further intensifies these challenges, particularly for first-year students and those studying in unfamiliar or foreign environments. Such transitions are frequently associated with increased anxiety, emotional instability, and difficulties in academic adaptation [3]. Without adequate coping mechanisms and institutional support, these stressors may accumulate and negatively affect students' academic trajectories. Consequently, several studies emphasize the importance of structured mental health support systems and effective coping strategies to mitigate the adverse effects of stress and enhance students' academic experiences [4].

Beyond academic demands, student stress is shaped by a broader set of psychological and environmental factors. Psychological variables such as anxiety, depression, self-esteem, and emotional regulation have been shown to significantly influence students' ability to cope with academic pressure, often mediating the relationship between stress and academic performance [5]. At the same time, environmental conditions including competitive learning climates,

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campus safety, availability of resources, and social support play a crucial role in determining students' mental well-being. Studies suggest that unsupportive or highly competitive environments can exacerbate psychological distress, whereas supportive social and institutional settings help buffer the negative effects of stress on academic engagement and performance [6].

Despite the extensive body of research on student stress, much of the existing literature relies on traditional statistical approaches, such as correlation analysis and linear regression, which often assume linear relationships and analyze stress determinants in isolation. These methods may be insufficient to capture the complex, interrelated, and potentially non-linear interactions among psychological, academic, and environmental factors that jointly influence student stress [7]. Moreover, prior studies frequently provide limited insight into the relative importance of different stress determinants, making it difficult to identify which factors should be prioritized for intervention [8].

Recent advances in regression-based machine learning offer promising alternatives for addressing these limitations. Machine learning models, particularly ensemble and regression-based approaches, are capable of modeling complex relationships, handling multidimensional predictors, and capturing interactions that conventional statistical techniques may overlook [9]. In addition, interpretability techniques such as feature importance and Shapley-based analyses enable researchers to quantify the contribution of individual factors to model predictions, thereby providing actionable insights into the most influential determinants of student stress [10].

While several studies have applied machine learning methods to educational and mental health data, comparative analyses focusing on regression-based machine learning models for identifying dominant psychological, academic, and environmental determinants of student stress remain limited. Existing findings suggest that academic workload, emotional well-being, social support, and resilience are key contributors to stress, yet their relative influence often varies across contexts and analytical approaches [11]. Therefore, a comprehensive and interpretable modeling framework is needed to simultaneously assess multiple stress determinants and clarify their relative importance.

In response to these gaps, this study employs regression-based machine learning models to identify and evaluate the key psychological, academic, and environmental determinants of student stress. By integrating robust model evaluation and feature importance analysis, this research aims to provide a clearer understanding of the factors that most strongly influence student stress levels and to support data-driven mental health interventions in higher education.

2. Literature Review

2.1. Student Stress in Higher Education

Student stress in higher education is widely recognized as a multidimensional construct influenced by academic, psychological, and environmental factors. Recent research emphasizes the importance of using validated and context-sensitive measurement instruments to accurately capture the complexity of stress experienced by university students. Studies have demonstrated that academic stress is closely associated with mental well-being, with variations observed across cultural and demographic groups. For example, Barbayannis et al. [12] reported differences in stress responses among students from diverse cultural backgrounds, highlighting the need for measurement tools that account for contextual and population-specific characteristics. Similarly, Jabin [13] underlined the necessity of construct validity in psychological assessments to ensure that stress scales reliably measure their intended dimensions.

In addition to general stress scales, recent studies have expanded measurement approaches to incorporate psychosocial and contextual factors. Silva and Vettore [14] emphasized the role of academic environment and social support in shaping students' mental health, particularly in demanding academic disciplines such as medicine. Moreover, Topală et al. [15] developed a specialized instrument to assess stress sources in online learning environments, reflecting the evolving nature of higher education and the need for adaptive stress measurement tools. Collectively, these studies underscore the importance of comprehensive instruments that capture both traditional and emerging stressors in contemporary academic settings.

The consequences of student stress extend beyond emotional discomfort and significantly affect learning outcomes and mental health. Elevated stress levels have been shown to reduce academic engagement, persistence, and performance, thereby creating a negative feedback loop that further exacerbates psychological distress [16]. At the same time, coping strategies play a critical mediating role in this relationship. Zhao et al. [17] demonstrated that effective coping mechanisms can buffer the adverse effects of stress on academic adjustment, while Feng et al. [18] highlighted how learning behavior patterns influenced by stress are predictive of academic outcomes. These findings suggest that understanding both stress determinants and their consequences is essential for designing interventions aimed at improving student mental health and academic success in higher education.

2.2. Psychological Determinants of Student Stress

Psychological factors play a central role in shaping student stress in higher education, with self-esteem, anxiety, depression, and bullying consistently identified as key determinants. Self-esteem, in particular, has been shown to function as a protective psychological resource. Higher levels of self-esteem are associated with better mental health outcomes and lower vulnerability to stress, anxiety, and depression [19], [20]. In contrast, students with low self-esteem tend to experience higher stress levels and are more susceptible to psychological distress, underscoring the importance of self-perception in students' mental well-being.

Anxiety and depression are highly prevalent among university students and are often intensified by academic demands and external stressors. Empirical studies indicate that preexisting psychological conditions significantly increase the likelihood of experiencing heightened anxiety and depressive symptoms during periods of elevated stress, such as during public health crises or intense academic workloads [21]. Additionally, Umar et al. [22] demonstrated a cyclical relationship between academic procrastination and psychological distress, where increased stress contributes to procrastination behaviors that further exacerbate anxiety and depression. These findings highlight the interconnected nature of psychological stressors in academic contexts.

Bullying and social stressors further compound psychological distress among students. Experiences of bullying in academic environments have been strongly linked to increased anxiety, depression, and overall psychological strain [23]. However, the presence of protective factors can moderate these negative effects. Research suggests that resilience, adaptive coping strategies, and strong social support networks play a critical role in reducing psychological vulnerability, particularly among female and minority students who may face additional stressors related to stigma and discrimination [6]. Moreover, psychological capital encompassing hope, self-efficacy, resilience, and optimism has been identified as an important moderator that enhances students' ability to cope with stress and maintain mental health [24]. Strengthening these protective mechanisms is therefore essential for fostering student well-being and academic success.

2.3. Academic Determinants of Student Stress

Academic workload is a major contributor to student stress in higher education, as increasing academic demands are closely associated with heightened anxiety and reduced mental well-being. Empirical evidence shows that rigorous coursework, high performance expectations, and changes in learning modes such as the shift to online education during the COVID-19 pandemic have significantly intensified perceived academic stress among students. Ahuja et al. [25] reported that a large proportion of students experienced moderate academic stress, largely driven by extensive coursework and examination pressure. Similarly, Timsinha and Parajuli [26] found that students with lower academic performance were more likely to experience anxiety and depression, indicating a reciprocal relationship in which academic difficulties and psychological distress reinforce one another.

Extracurricular activities represent another important academic-related stressor, as they may function both as a source of engagement and as an additional burden. While participation in extracurricular activities can promote social interaction and personal development, excessive involvement may intensify stress when students struggle to balance academic responsibilities with non-academic commitments. Seyedi et al. [27] demonstrated that simultaneous demands from academic and clinical activities could lead to compounded stress, emphasizing the importance of effective time management and workload regulation in reducing stress among students.

In addition to workload-related factors, the quality of teacher–student relationships play a critical role in shaping academic stress and performance. Supportive and approachable instructors contribute to a positive learning environment, fostering students' sense of belonging and reducing stress levels. Raza et al. [28] showed that positive teacher–student interactions are associated with lower stress and improved academic outcomes, whereas poor communication and lack of support exacerbate psychological distress. This relationship becomes particularly salient during periods of academic transition or crisis, such as the COVID-19 pandemic, where strong teacher–student relationships have been shown to buffer stress and enhance academic satisfaction [29]. Collectively, these findings highlight academic workload, extracurricular demands, and teacher–student relationships as key academic determinants of student stress in higher education.

2.4. Environmental and Social Determinants of Student Stress

Environmental conditions play a crucial role in shaping student stress and overall well-being in higher education. Factors such as campus safety, noise levels, and the fulfillment of basic needs have been shown to significantly influence students' mental health. Lim [30] reported that concerns related to safety and environmental stressors, including excessive noise, are strongly associated with elevated stress levels among students. These findings highlight the importance of creating safe and supportive learning environments, supported by effective communication between students and educational institutions, to reduce environmental stressors and promote psychological well-being.

Social support further interacts with environmental conditions to buffer the negative effects of stress. Empirical evidence suggests that students who perceive strong social and institutional support experience lower stress levels and better mental health outcomes. Malik et al. [31] emphasized that environments fostering social support contribute positively to students' well-being, while Berrío-Quispe et al. [32] demonstrated that campus safety and access to adequate resources are directly linked to students' emotional and psychological health. These findings underscore the importance of strengthening social support systems within educational institutions as a strategy for mitigating stress.

Beyond immediate environmental stressors, the broader campus environment also influences student well-being and academic functioning. Research indicates that physical campus characteristics, such as access to green spaces and thoughtful campus design, are associated with reduced stress and enhanced cognitive and emotional functioning [33]. Similarly, He et al. [34] showed that well-designed university landscapes facilitate relaxation and psychological restoration by enabling students to engage with natural environments. In addition, positive social interactions within the campus community, including peer networks and supportive academic relationships, contribute to resilience and academic success [35]. Collectively, these findings demonstrate that environmental and social determinants are integral to understanding and addressing student stress in higher education.

2.5. Machine Learning Approaches for Stress Analysis

Conventional statistical methods, such as traditional regression techniques, have been widely used to analyze student stress; however, they present notable limitations when applied to complex psychosocial phenomena. These methods typically assume linear relationships among variables and impose strict distributional assumptions, which may not adequately reflect the multidimensional and non-linear nature of student stress. As stress often emerges from the interaction of academic demands, social pressures, and psychological conditions, linear models may fail to capture these intricate relationships, leading to incomplete or potentially misleading interpretations of stress determinants [36]. Moreover, conventional approaches tend to generalize findings across populations, limiting their ability to account for individual variability in stress experiences and to support tailored interventions [37].

In contrast, regression-based machine learning models offer substantial advantages in analyzing student stress by accommodating complex data structures and capturing non-linear interactions among multiple predictors. These models are capable of handling high-dimensional datasets that include diverse psychological, academic, and environmental variables, thereby providing a more comprehensive understanding of stress dynamics [37]. Importantly, regression-based machine learning supports interpretability through feature importance analysis, enabling researchers and practitioners to identify the most influential stress determinants. Prior studies have demonstrated that machine learning approaches can effectively highlight key predictors such as mental health indicators and sleep patterns, facilitating more targeted and data-driven intervention strategies [38].

Despite these advantages, a critical research gap remains in the development of integrated and interpretable multi-factor models for student stress analysis. Much of the existing literature continues to examine stress determinants in isolation, without fully accounting for the interrelated nature of psychological, academic, and environmental factors. Furthermore, while some studies employ machine learning techniques, they often lack transparency, limiting their

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practical applicability in educational and mental health contexts. Addressing this gap requires the adoption of regression-based machine learning frameworks that not only integrate multiple stress dimensions but also prioritize interpretability, thereby enabling educators and policymakers to translate analytical insights into effective, evidence-based interventions.

3. Methodology

3.1. Dataset Description

This study utilizes a structured dataset consisting of 1,100 student observations, with each record representing an individual student's reported conditions related to stress and its potential determinants. The dataset contains 21 variables, all measured using numerical or ordinal scales derived from self-reported assessments, and does not contain missing values, ensuring data completeness for model training and evaluation.

The target variable in this study is stress level, which represents the overall level of stress experienced by students. This variable is treated as a continuous numerical outcome, making it suitable for regression-based modeling approaches. Modeling stress level as a regression task enables a more nuanced analysis of stress intensity compared to categorical or binary classification.

The predictor variables are grouped into three main categories based on theoretical and empirical considerations. Psychological factors include variables such as self-esteem, anxiety level, depression, mental health history, and experiences of bullying. Academic factors comprise study load, extracurricular activities, academic performance, teacher–student relationships, and future career concerns. Environmental and social factors include safety, noise level, living conditions, basic needs, and social support. This categorization supports an integrated analysis of multidimensional stress determinants and aligns with prior literature on student stress in higher education.

3.2. Data Preprocessing

Prior to model development, several preprocessing steps were applied to ensure data quality and suitability for regression-based machine learning. First, data cleaning and validation were conducted to verify data completeness and consistency. All variables were examined for missing values and invalid entries, and no missing data were identified. Since all features were measured using structured numerical or ordinal scales, no imputation or categorical encoding was required.

Second, feature scaling and normalization were performed to improve model stability and comparability, particularly for linear regression–based models. Numerical features were standardized using z-score normalization, transforming each variable to have zero mean and unit variance. This step prevents features with larger numerical ranges from disproportionately influencing model estimation, while maintaining compatibility with tree-based models, which are generally insensitive to feature scaling.

Finally, a train–test split strategy was employed to evaluate model generalization. The dataset was randomly divided into training and testing subsets using an 80:20 ratio. The training set was used for model fitting and cross-validation, while the test set served as a holdout dataset for final performance evaluation. This strategy ensures an unbiased assessment of model performance on unseen data.

3.3. Regression-Based Machine Learning Models

To model student stress levels and compare predictive performance, several regression-based machine learning models were employed. These models were selected to represent both traditional and ensemble-based approaches, enabling a comprehensive evaluation of linear and non-linear relationships among stress determinants.

Linear Regression was used as a baseline model to establish a reference for model performance. This model assumes a linear relationship between the predictor variables and the target stress level, providing a simple and interpretable framework for assessing the direction and magnitude of feature effects.

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Ridge Regression was applied as an extension of linear regression to address potential multicollinearity among predictor variables. By incorporating L2 regularization, Ridge Regression penalizes large coefficient values, improving model stability and generalization while retaining interpretability.

To capture non-linear interactions and complex relationships among stress determinants, ensemble-based models were also employed. The Random Forest Regressor utilizes an ensemble of decision trees trained on bootstrapped samples with random feature selection, enabling robust modeling of high-dimensional data and reducing overfitting. This model is particularly suitable for identifying influential features through built-in importance measures.

Finally, the Gradient Boosting Regressor was included to evaluate the effectiveness of sequential ensemble learning. This model builds decision trees iteratively, with each tree correcting the errors of its predecessors, allowing for fine-grained modeling of complex patterns in the data. The inclusion of this model enables comparison between bagging-based and boosting-based ensemble approaches in the context of student stress prediction.

3.4. Model Evaluation

Model performance was evaluated using a robust validation strategy to ensure reliable and unbiased results. A k-fold cross-validation approach with five folds was applied to the training dataset. In this strategy, the data were partitioned into five subsets, where each subset was used once as a validation set while the remaining subsets were used for model training. This procedure reduces variance in performance estimation and provides a more stable assessment of model generalization across different data splits.

To assess predictive accuracy and error magnitude, three standard regression evaluation metrics were employed: Coefficient of Determination (R^2), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). The R^2 metric measures the proportion of variance in the stress level explained by the model, serving as the primary indicator of explanatory power. RMSE quantifies the average magnitude of prediction errors while penalizing larger errors more heavily, whereas MAE provides a more interpretable measure of average absolute error. The combination of these metrics offers a comprehensive evaluation of model performance by capturing both goodness-of-fit and prediction accuracy.

3.5. Feature Importance Analysis

To identify the most influential determinants of student stress, feature importance analysis was conducted using both model-agnostic and model-specific approaches. This dual strategy was adopted to enhance the robustness and interpretability of the findings.

First, permutation importance was employed as a model-agnostic method to evaluate the contribution of each predictor variable. This approach measures the change in model performance after randomly permuting the values of a single feature while keeping all other features unchanged. A larger decrease in performance indicates a greater contribution of the permuted feature to the model’s predictive accuracy. Permutation importance allows for consistent comparison of feature relevance across different regression models and is particularly suitable for interpreting complex, non-linear models.

Second, for tree-based models, particularly the Random Forest Regressor, built-in feature importance measures were utilized. These importance scores are derived from the reduction in prediction error or impurity achieved by each feature across all trees in the ensemble. While model-specific, this method provides complementary insights into how frequently and effectively features are used in the decision-making process of the model. By combining permutation importance with built-in feature importance, this study ensures a more reliable identification of key psychological, academic, and environmental determinants of student stress.

4. Results and Discussion

4.1. Performance of Top Regression Pipelines

To compare the predictive performance of the evaluated regression models, a 5-fold cross-validation strategy was employed. The comparative results are summarized in Table 1, which reports the average values and standard deviations of R^2, RMSE, and MAE for each model.

Table 1. Cross-Validation Performance of Regression Models.

Model	Avg R^2	Std R^2	Avg RMSE	Std RMSE	Avg MAE	Std MAE
Random Forest	0.7873	0.0327	0.3768	0.0232	0.1409	0.0168
Ridge Regression (α = 1.0)	0.7450	0.0476	0.4118	0.0348	0.2259	0.0215
Linear Regression	0.7447	0.0478	0.4120	0.0349	0.2261	0.0215
Gradient Boosting	0.7162	0.0941	0.4298	0.0635	0.1661	0.0304

As shown in Table 1, the Random Forest Regressor achieved the highest average R^2 value (0.7873), indicating the strongest explanatory power among the evaluated models. In addition, it produced the lowest average RMSE (0.3768) and MAE (0.1409), demonstrating superior prediction accuracy and lower error magnitude. The relatively small standard deviations across all metrics indicate stable performance across cross-validation folds.

Linear Regression and Ridge Regression exhibited comparable performance, with similar average R^2 values (approximately 0.745) and error metrics. This suggests that linear models are capable of capturing a substantial portion of variance in student stress levels; however, their higher RMSE and MAE values compared to Random Forest indicate limitations in modeling more complex relationships. In contrast, the Gradient Boosting Regressor showed the lowest average R^2 and the highest variability across folds, suggesting less consistent performance for this dataset.

The numerical results presented in Table 1 are further illustrated in Figure 1, which provides a visual comparison of the average R^2, RMSE, and MAE values across models. Figure 1 clearly shows that the Random Forest model consistently outperforms the other approaches across all evaluation metrics. The alignment between the numerical values in Table 1 and the visual trends in Figure 1 confirms the robustness of the comparative evaluation.

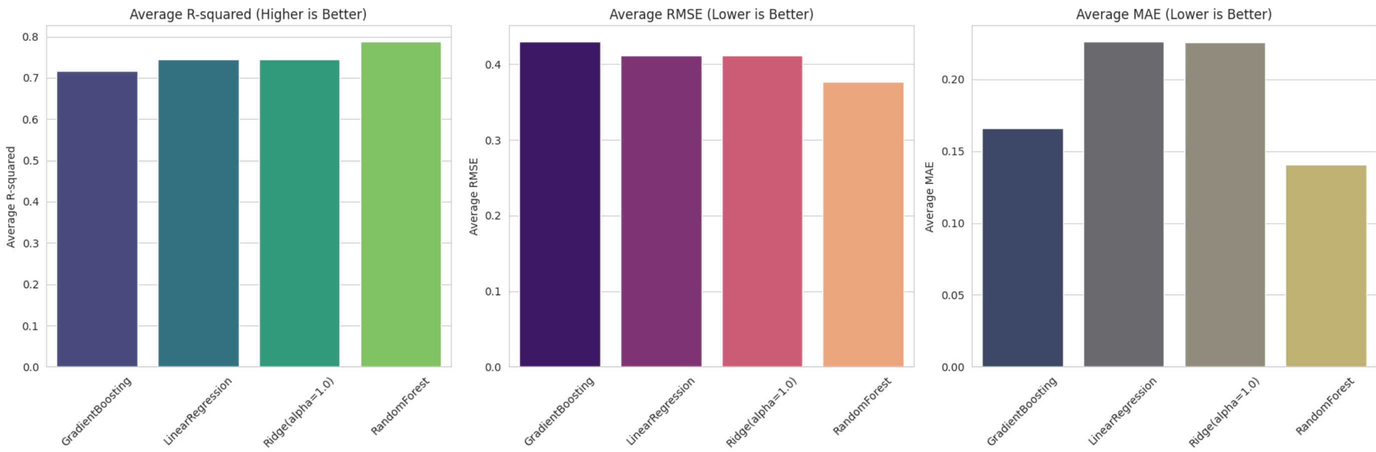

Figure 1. Comparison of Regression Model Performance Using R^2, RMSE, and MAE

Based on the combined evidence from Table 1 and Figure 1, the Random Forest Regressor was selected as the best-performing model and was therefore used for subsequent analysis of student stress determinants.

4.2. Performance of the Best Model

The selected Random Forest Regressor was further evaluated on a held-out test set comprising 20% of the dataset to assess its generalization capability. The model achieved a test R^2 of 0.812, indicating that more than 81% of the variance in student stress levels was explained by the model. Additionally, the test RMSE (0.355) and MAE (0.131) values demonstrate low prediction error, confirming strong predictive performance on unseen data.

The consistency between cross-validation and test set results suggests that the model does not suffer from overfitting and generalizes well beyond the training data. This indicates that the relationships learned by the model are stable and representative of underlying stress dynamics among students, supporting the reliability of subsequent feature importance analysis.

4.3. Key Determinants of Student Stress

To identify the most influential determinants of student stress, feature importance analysis was conducted using permutation importance on the Random Forest model. The results are presented in Figure 2, which displays the top 15 features ranked by their mean permutation importance scores.

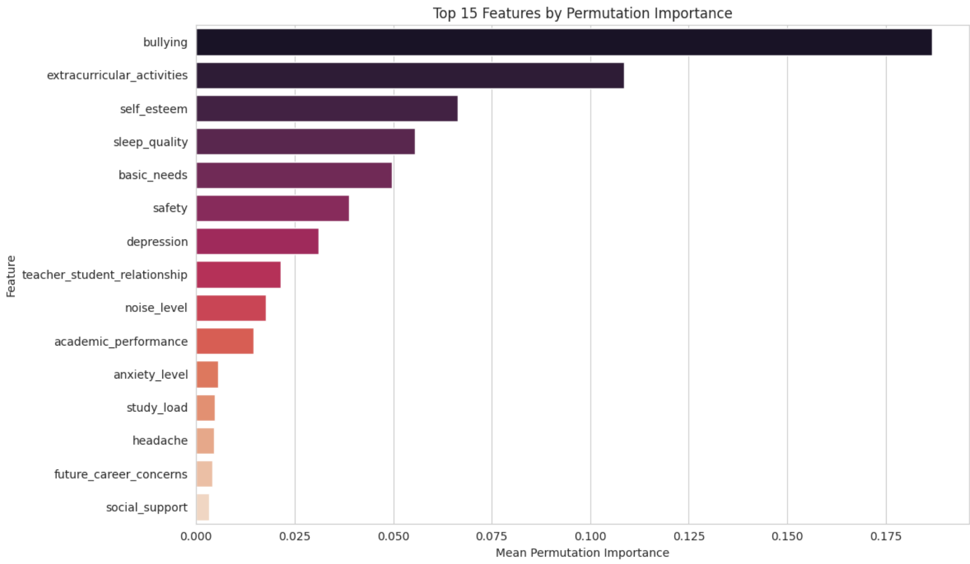

Figure 2. Top 15 Determinants of Student Stress Based on Permutation Importance

The results indicate that bullying is the most influential predictor of student stress by a considerable margin. This is followed by extracurricular activities, self-esteem, and sleep quality, all of which exhibit substantially higher importance scores than other variables. Environmental and basic well-being factors, including basic needs, safety, and noise level, also show notable contributions to stress levels.

Academic-related variables such as teacher–student relationship and academic performance demonstrate moderate influence, whereas factors including study load, future career concerns, and social support have relatively smaller contributions within the overall model. Nevertheless, these variables still contribute to the prediction of stress levels, highlighting the multifactorial nature of student stress.

To validate the robustness of these findings, the permutation importance results were compared with the built-in feature importance derived from the Random Forest model. Both methods consistently ranked bullying, extracurricular activities, self-esteem, sleep quality, safety, and basic needs among the most influential features. This consistency confirms the stability of the identified determinants across different feature importance estimation approaches.

5. Discussion

5.1. Interpretation of Key Findings

The findings of this study indicate that psychological stressors are the dominant contributors to student stress, with bullying emerging as the most influential determinant. This result reinforces the conceptualization of student stress as a multidimensional psychological construct shaped by social and interpersonal experiences, as highlighted in prior studies on higher education stress dynamics [12], [13]. The prominence of bullying is consistent with empirical evidence demonstrating its strong association with heightened anxiety, depression, and psychological distress among university students [23]. This suggests that adverse social interactions within academic environments can exert a more substantial impact on stress levels than purely academic pressures.

Conversely, self-esteem and sleep quality function as important protective factors, indicating that students with higher self-worth and healthier sleep patterns exhibit greater resilience to stress. This finding aligns closely with prior research identifying self-esteem as a key psychological resource that buffers stress and reduces vulnerability to anxiety and depression [19], [20]. Similarly, the role of sleep quality supports earlier evidence showing that poor sleep exacerbates

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psychological distress and impairs emotional regulation among students [21]. Together, these results underscore the importance of psychological capital and well-being-related behaviors in mitigating student stress.

Academic factors also play a significant role, particularly extracurricular activities, which were identified as a major contributor to stress. While extracurricular involvement is often associated with engagement and personal development, the findings suggest that excessive or poorly balanced participation may intensify stress levels. This observation is consistent with studies indicating that compounded academic and non-academic demands can overwhelm students' coping capacities, especially when time management skills are insufficient [27]. Environmental determinants, including safety and basic needs, further contribute to stress outcomes, reinforcing the notion that student stress is not solely an academic or psychological phenomenon but is also deeply shaped by broader living and learning conditions [30].

5.2. Comparison with Previous Studies

Overall, the results of this study are largely consistent with previous research emphasizing the combined influence of psychological, academic, and environmental factors on student stress. Prior studies have documented the detrimental effects of bullying, low self-esteem, and sleep disturbances on students' mental health and academic functioning [23], [19]. The present findings corroborate these results by quantitatively demonstrating the dominant role of these psychological factors within an integrated predictive framework.

Similarly, the significant contribution of extracurricular workload aligns with earlier research showing that academic overload and competing commitments can exacerbate stress when students struggle to maintain balance between academic and non-academic responsibilities [25], [27]. The observed influence of environmental factors, such as safety and fulfillment of basic needs, also supports existing evidence highlighting the role of supportive campus environments in promoting student well-being [31], [32].

However, this study extends prior literature by providing a quantitative ranking of stress determinants using regression-based machine learning. Unlike traditional statistical approaches that often examine stress factors in isolation, the present analysis captures non-linear interactions and relative importance across psychological, academic, and environmental domains. This integrated perspective addresses limitations identified in earlier studies that relied on linear assumptions and fragmented analyses [36], [37], thereby offering a more comprehensive understanding of student stress dynamics.

5.3. Practical Implications

The findings have important practical implications for higher education institutions and policymakers. Given the strong influence of bullying and psychological factors, institutions should prioritize bullying prevention programs, accessible mental health services, and initiatives aimed at strengthening students' psychological capital, including self-esteem and resilience. These recommendations align with prior evidence emphasizing the role of protective psychological resources in reducing stress and enhancing academic success [24].

Additionally, universities should critically evaluate the structure and expectations of extracurricular activities to ensure that they foster engagement without imposing excessive burdens on students. Effective workload regulation and time management support may help mitigate the stress associated with competing academic and non-academic demands, as suggested by previous research [27]. Improving campus safety, ensuring the fulfillment of basic needs, and strengthening teacher–student relationships can further contribute to a supportive learning environment, consistent with findings highlighting the buffering role of social and environmental support [28], [30].

Importantly, the interpretability of the regression-based machine learning framework employed in this study enables institutions to translate data-driven insights into targeted interventions. By identifying and prioritizing the most influential stress determinants, decision-makers can design evidence-based strategies that more effectively address student mental health needs.

5.4. Limitations and Future Research

Despite its contributions, this study has several limitations. First, the dataset relies on self-reported measures, which may be subject to response bias and social desirability effects. Second, the cross-sectional design limits the ability to infer causal relationships between stress determinants and outcomes, consistent with limitations noted in prior stress

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research. From a methodological perspective, although the Random Forest model demonstrated strong predictive performance, it does not explicitly model temporal dynamics or causal pathways.

Future research should consider longitudinal designs to examine how stress determinants evolve over time and to better understand causal mechanisms. The integration of advanced explainable AI techniques, such as SHAP-based temporal or interaction analysis, could further enhance model transparency and address concerns regarding interpretability in machine learning applications. Additionally, incorporating physiological or behavioral data alongside self-reported measures may provide deeper insights into the complex mechanisms underlying student stress in higher education.

6. Conclusion

This study investigated the key psychological, academic, and environmental determinants of student stress using regression-based machine learning models. The results demonstrated that the Random Forest Regressor outperformed other regression approaches in predicting stress levels, indicating that non-linear ensemble models are more effective in capturing the complex relationships underlying student stress. Feature importance analysis consistently identified bullying as the most influential determinant, followed by extracurricular activities, self-esteem, and sleep quality, highlighting the dominant role of psychological and social stressors.

The findings confirm that student stress is a multidimensional construct shaped not only by academic demands but also by interpersonal experiences and environmental conditions. Psychological protective factors, particularly self-esteem and healthy sleep patterns, emerged as important buffers against stress, while environmental factors such as safety and fulfillment of basic needs further contributed to stress outcomes. These results underscore the necessity of addressing student stress through holistic and integrated intervention strategies.

From a practical perspective, this study provides evidence-based insights that can inform institutional policies and mental health programs in higher education. By leveraging interpretable machine learning models, universities can prioritize interventions targeting the most influential stress determinants, such as bullying prevention, workload regulation, and campus well-being initiatives. Future research should extend this approach using longitudinal data and advanced explainable AI techniques to better understand causal mechanisms and temporal dynamics of student stress.

7. Declarations

6.1. Author Contributions

Author Contributions: Conceptualization A.S. and E.P.; Methodology, A.S. and E.P.; Software, A.S.; Validation, A.S.; Formal Analysis, A.S.; Investigation, E.P.; Resources, A.S.; Data Curation, E.P.; Writing Original Draft Preparation, A.S.; Writing Review and Editing, A.S. and E.P.; Visualization, E.P. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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