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Measuring the Impact of Meditation on Academic Stress Levels in UG Students using Machine Learning Models

No Author Given

No Institute Given

Abstract. This study uses machine learning and causal inference techniques to investigate how meditation helps college students who are experiencing academic stress. In order predict stress reduction based on initial psychological responses and demographic characteristics, we examined data from more than 680 students. To classify stress levels and forecast post-meditation outcomes, three machine learning algorithms were evaluated: Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN). With 88.24% accuracy, 89.05% precision, and 88.24% recall, the Random Forest model outperformed the others. Accuracy values for KNN and SVM were 77.21% and 63.97%, respectively. The best indicators of stress reduction were age, meditation frequency, and baseline stress. The treated group experienced a significant reduction in stress, particularly among those with medium baseline stress, according to causal analysis (Causal Forest and T-Learner). These results were validated by K-Means clustering, which was consistent with the machine learning outcomes. In conclusion, machine learning models, especially Random Forest, are capable of predicting individual results, and meditation successfully lowers academic stress in specialized circumstances. The study provides insights for creating individualized mental health interventions in academic settings by fusing causal and predictive methods.

Keywords: Machine Learning, Meditation, Academic Stress, Mindfulness, Stress Management,

1 Introduction

Due to pressures from coursework, social expectations, and financial difficulties, academic stress has grown to be a major issue in higher education. Students' emotional and cognitive health can be negatively impacted by these stressors, which can result in anxiety, burnout, and subpar academic performance. Persistent stress has a detrimental effect on mental health and academic performance by impairing motivation, focus, and learning. As a result, colleges are giving top priority to stress-reduction techniques that foster both academic achievement and personal growth [2, 7].

Stress management has been found to benefit from meditation, particularly techniques like Mindfulness-Based Stress Reduction (MBSR). Meditation has been shown to improve emotional regulation, lower anxiety, and improve cognitive abilities like memory and focus [1, 4–6]. Neuroscientific studies also show that meditation strengthens brain regions responsible for emotional control, providing a practical, non-invasive approach to boosting mental resilience [1, 5, 12].

However, self-reports or small sample sizes are used in a large portion of the current meditation research, which could produce biased results [2, 13]. A more unbiased, data-driven approach to examining the impact of meditation on stress is provided by machine learning (ML). Based on behavioral and physiological data, machine learning models can categorize students into low, medium, and high stress groups, allowing for more precise stress assessments and individualized interventions [3,7,8]. We can better predict stress and customize meditation techniques by integrating machine learning.

2 Literature Review

The impact of academic stress on university students is well-documented, with various interventions explored to alleviate its effects. Practices like yoga, meditation, and mindfulness have shown promise in reducing stress, improving focus, and boosting emotional well-being [1, 4, 5]. These practices help students manage academic pressures, build resilience, and regulate emotions, making them valuable for mental health in higher education [19].

Meditation has been extensively studied, with evidence showing that regular practice reduces psychological and physiological stress. It improves cognitive function, memory, and motivation—all essential for academic success [4, 10]. Meditation also helps with emotional regulation, reducing burnout and supporting students' well-being [11].

Specific meditation techniques like So Hum and Anapanasati promote stress reduction and better sleep, enhancing academic outcomes [9–12]. Recent innovations have integrated machine learning (ML) with mindfulness research, allowing for stress predictions and personalized interventions. ML analyzes behavioral and physiological data, optimizing online mindfulness programs and making them more effective [7, 8, 13, 14].

Despite these advances, there are still gaps in understanding the long-term effects of meditation and the best conditions for its effectiveness. While ML shows great potential for personalizing interventions, further research is needed to refine these methods and address biases in current studies [3, 18].

These gaps create exciting opportunities for future research, particularly in integrating clinical, behavioral, and computational approaches to improve stress reduction strategies in higher education.

Source Data / Papers ([1, 12, 15])	Methods/Algorithms	Key Findings	Limitations / Gaps
Meditation-based RCTs: Centering, So Hum, mindfulness, etc.	Randomized controlled trials, Pre/Post, Surveys	Meditation interventions reduce academic stress and improve mindfulness/focus in students. Effects are significant in both short and mid-term periods.	Self-report bias, small samples, limited to single settings, no biometrics
[2, 4–6, 9, 10, 16, 18, 19] Multi-country meditation and yoga studies	MBSR, Mindfulness, Yoga, Ecological Assessments	Mindfulness and yoga reduce anxiety, enhance resilience, and benefit cognitive-emotional outcomes. Peer/online delivery can scale interventions.	Lack of physiological validation, restricted to certain disciplines or gender, follow-up limited
[3, 7, 8, 13, 17] Machine learning for stress detection	SVM, Random Forest, Ensemble, Regression, Clustering	ML predicts high-stress levels (accuracy 80-95%) using behavioral, psychological, and (sometimes) physiological data. Emerging approaches integrate ML with interventions.	Mostly cross-sectional/survey, few with real-time or longitudinal bio-signal data
[11, 14] Remote/online and digital health approaches	Web/mobile-based mindfulness, online experimentation	Online/E-meditation and physical activity interventions decrease anxiety and academic burnout; high engagement predicts best outcomes.	Digital fatigue, compliance drop-off over time, under-representation of at-risk groups

Table 1: Summary of Studies on Meditation, ML, and Stress Management in Academic Settings

3 Methodology

3.1 Research Design

This study looked at how meditation affected undergraduate students' academic stress using a quantitative, cross-sectional design. The relationships between student demographics, meditation practices, and stress levels were examined using machine learning models, consisting of **K-Nearest Neighbors (KNN)**, **Support Vector Machines (SVM)**, **Random Forest**, **K-Means Clustering**, and **Causal Forest**

3.2 Participants and Sampling

680 valid responses were examined following data preprocessing. Participants were 14–25-year-old undergraduate and graduate students enrolled in a variety of courses (BCA, B.Com, B.Sc, MCA, M.Sc.). Unbiased representation throughout different fields was guaranteed by simple random sampling. A comparison of the effects of meditation on academic stress was made possible by the fact that 71.5% of the participants practiced meditation and 28.5% did not. Every participant provided informed consent, and the study was conducted in accordance with ethical guidelines.

3.3 Data Collection Procedure

A controlled, self-administered questionnaire covering demographics, meditation practices, and stress-related indicators was utilized to collect data. Included in the survey were the following:

– **Demographics:** Semester, academic program, age, and gender.

– **Meditation Practices:** Type, frequency, and duration (e.g., breath-based, mindfulness, mantra-based, or movement-based like yoga).
– **Academic Stress:** Time constraints, performance anxiety, task management, and general stress are measured using a validated Likert-scale.
– **Physical Symptoms:** symptoms of stress, including headaches, exhaustion, insomnia, and tense muscles.

In order to prepare the data for machine learning analysis, outliers were eliminated, categorical variables were encoded, and continuous variables were normalized using Min–Max scaling. Stress levels were classified as low, medium, or high both before and after the intervention in the final dataset, which included 680 observations.[Refer to Figure 1.]

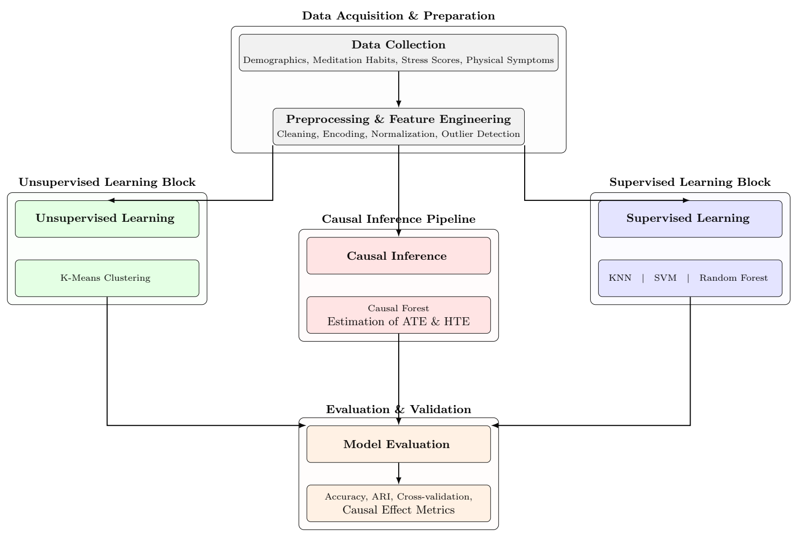


Fig. 1: Overview of Data Processing and Learning Pipeline.

3.4 Feature engineering and preprocessing

Preprocessing and feature engineering procedures were used prior to feeding the data into machine learning models:

– **Data Cleaning**: Mean imputation for continuous variables and mode imputation for categorical variables were used to impute missing values. The Z-score method was used to identify outliers:

$$Z = \frac{X - \mu}{\sigma} \tag{1}$$

where X is the observed value, μ is the mean, and σ is the standard deviation.

- **Feature Encoding**: For model compatibility, one-hot encoding was used to encode categorical features like gender and type of meditation.
- **Normalization**: Using Min-Max scaling, continuous features such as age and stress levels were normalized to the range ([0, 1]):

$$X_{\text{norm}} = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} \tag{2}$$

3.5 Ethical Considerations

To maintain confidentiality, all participant data was anonymized. Strict data privacy procedures were followed and informed consent was obtained. AI systems were not given access to any private participant information in order to make decisions.

3.6 Intervention Procedure

The intervention group engaged in breath-based and mindfulness-focused guided meditation sessions. Over the course of six weeks, sessions took place one to three times a week and lasted five to fifteen minutes. No digital or AI-based facilitation was used; instead, all guidance and oversight were given by certified human instructors.

4 Machine Learning Models

Several machine learning models were used to explore the relationship between meditation and academic stress:

4.1 K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is a supervised classification algorithm that assigns a data point to the class most common among its k nearest neighbors.

4.2 Support Vector Machines (SVM)

Support Vector Machines (SVM) are used to classify stress levels into categories (e.g., high, medium, low).

4.3 Random Forest

Random Forest is an ensemble learning method that uses multiple decision trees to improve prediction accuracy. Each tree is trained on a bootstrap sample of the data, and predictions are made by aggregating the outputs of all trees. This technique helps minimize error and overfitting.

4.4 K-Means Clustering

K-Means is an unsupervised clustering algorithm that groups data into k clusters by minimizing the within-cluster variance.

5 Causal Inference Using Causal Forest

Causal Forest is a machine learning method used to estimate heterogeneous treatment effects (HTE) in observational data. It estimates the causal impact of meditation on stress by building a forest of decision trees to forecast the treatment effect for each individual.

$$\text{Causal Effect} = E[Y(1) - Y(0)|X] \tag{3}$$

where X stands for individual coefficients and $Y(1)$ and $Y(0)$ are the results with and without meditation, respectively. Individual variances in treatment effects can be handled using Causal Forest.

6 Evaluation Metrics

For each type of learning—supervised (KNN, SVM, Random Forest), unsupervised (K-Means), and causal inference (Causal Forest)—the model's performance was evaluated using the appropriate metrics (accuracy, precision, recall, and F-1 score). Robustness and interpretability across models were guaranteed by these assessments.

6.1 Classification Metrics

We utilized standard classification metrics, such as accuracy, precision, recall, and F1-score, which were obtained from the confusion matrix for supervised models (KNN, SVM, Random Forest). Predictive accuracy, false positive rate, and the ratio of precision to recall were all evaluated with the help of these metrics. For datasets that are unbalanced, the F1-score is particularly useful.

To guarantee consistency and uniform class distribution, we used **10-fold stratified cross-validation** for model evaluation.

6.2 Clustering Metrics

Several internal validation metrics were used to evaluate cluster quality for the K-Means Clustering algorithm:

Silhouette Score: Evaluates a data point's similarity to its own cluster in comparison to other clusters:

$$s(i) = \frac{b(i) - a(i)}{\max(a(i), b(i))} \tag{4}$$

where $b(i)$ is the mean nearest-cluster distance and $a(i)$ is the mean intra-cluster distance. Better-defined clusters are indicated by a higher Silhouette Score.

Calinski-Harabasz Index (CHI): Determines the between-cluster dispersion to within-cluster dispersion ratio:

$$CHI = \frac{SSB/(K-1)}{SSW/(n-K)} \tag{5}$$

More distinct and well-separated clusters are indicated by higher CHI values.

Davies-Bouldin Index (DBI): Measures how similar clusters are on average:

$$DBI = \frac{1}{K}\sum_{i=1}^{K}\max_{i\neq j}\left(\frac{\sigma_i+\sigma_j}{d(\mu_i,\mu_j)}\right) \tag{6}$$

where the average distance between a cluster's centroid (mu_i) and its points $(sigma_i)$ is represented. Better clustering is indicated by lower DBI values.

6.3 Causal Inference Metrics

The evaluation of the Causal Forest model was focused on determining the treatment effects at the individual and population levels:

Average Treatment Effect (ATE): Calculates the mean difference in results between the treatment and control groups:

$$ATE = \mathbb{E}[Y(1) - Y(0)] \tag{7}$$

Conditional Average Treatment Effect (CATE): Indicates/Represents the expected effect of treatment based on specific control variables:

$$CATE(X) = \mathbb{E}[Y(1) - Y(0) \mid X] \tag{8}$$

Policy Risk: Measures how well the assigned treatment policies are working. More successful policies are indicated by lower policy risk values:

$$R(\pi) = \mathbb{E}[Y(0) + \pi(X) \times (Y(1) - Y(0))] \tag{9}$$

7 Results and Discussion

7.1 Overview

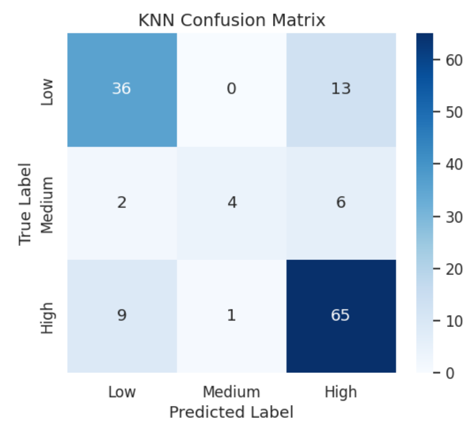
This section explores the outcomes of several kinds of machine learning and causal inference models that were used to categorize, predict, and interpret undergraduate students' levels of academic stress as well as the causal effects of meditation interventions. K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest, K-Means clustering, and Causal Forest techniques are among the models used. Classification accuracy, cross-validation consistency, feature importance, and, in the case of the causal model, the estimated treatment effect of meditation on stress reduction were the criteria that were used to assess the models. The following section discusses specific results regarding model performance, confusion matrices, and interpretive implications.

7.2 K-Nearest Neighbors (KNN) Classification

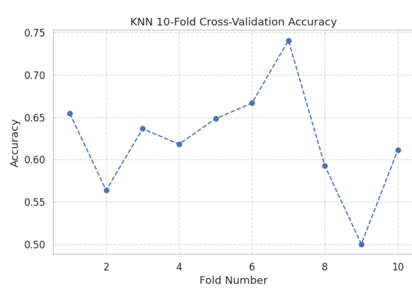
The KNN classifier ($k = 5$) performed moderately well, achieving a test accuracy of 77.21%. Figure 2(b) displays the confusion matrix, which shows that the High stress group was well identified (recall = 0.87), whereas the Low stress group was less correctly identified (recall = 0.73). As shown in Table 2(a), the model performed worst in the Medium stress category, achieving a recall of only 33%. Given that feature distributions overlap more at moderate stress levels, this performance implies that KNN's dependence on proximity in feature space is ineffective for differentiating between high and low extremes.

Metric	Low	Medium	High
Precision	0.77	0.80	0.77
Recall	0.73	0.33	0.87
F1-score	0.75	0.47	0.82

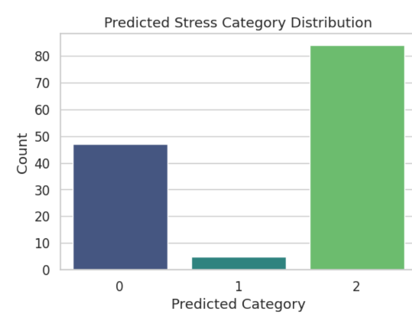
((a)) KNN Classification Metrics



((b)) Confusion Matrix for KNN



((c)) 10 Fold Cross Validation for KNN



((d)) Predicted Stress Category Distribution for KNN

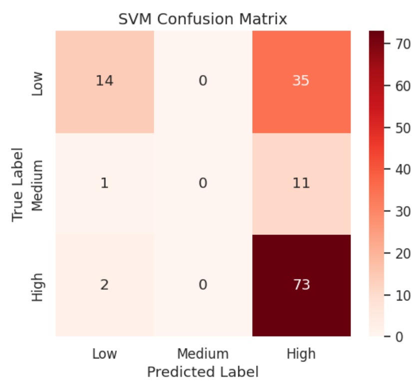
Fig. 2: KNN Model Results: Classification Metrics, Confusion Matrix, Cross Validation, and Predicted Stress Category Distribution.

Key performance indicators pointing to an imbalance in the model's capacity to identify each stress category are macro average precision (0.78) and recall (0.64). Although there is variability in detecting different stress levels, the model's weighted F1-score of 0.76 suggests that it is reasonably reliable. Because KNN relies on distance metrics, the model is sensitive to changes in feature scaling and sampling, as evidenced by the 10-fold cross-validation mean accuracy of 0.6232 ($\pm$0.0611) in Figure 2(c).

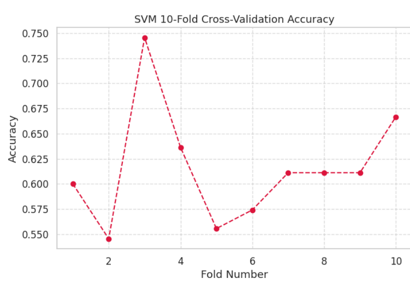
7.3 Support Vector Machine (SVM) Classification

Metric	**Low**	**Medium**	**High**
Precision	0.82	0.00	0.61
Recall	0.29	0.00	0.97
F1-score	0.42	0.00	0.75

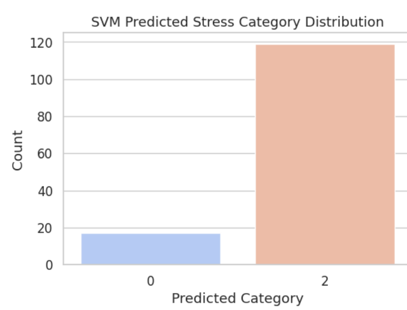
((a)) SVM Classification Metrics



((b)) Confusion Matrix for SVM



((c)) 10 Fold Cross Validation on Accuracy for SVM



((d)) Predicted Stress Category Distribution for SVM

Fig. 3: SVM Model Performance: Classification Metrics, Confusion Matrix, Cross Validation, and Predicted Stress Category Distribution.

The accuracy of the SVM model with an RBF kernel was 63.97%, which was less than that of Random Forest and KNN. As seen in 3(b), it did well in predicting

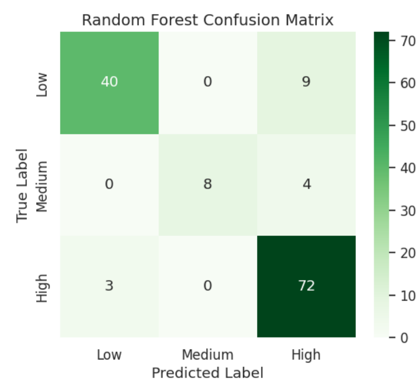
High stress (recall = 0.97), but it was unable to detect Medium stress at all (recall = 0.00). Low stress recall was likewise low (0.29), and many Low stress cases were incorrectly classified as High stress (Table 3(a)). On the other hand, the precision for low stress was high (0.82), suggesting that it was accurate when expected.

The model's difficulties with non-High categories are demonstrated by the macro average recall (0.42) and F1-score (0.39). Results from cross-validation (mean = 0.6157 ± 0.0552) indicate consistent but subpar performance, pointing to underlying flaws rather than chance (Figure 3(c)).

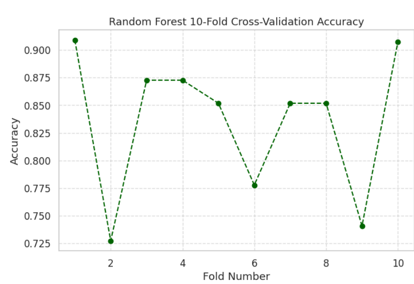
7.4 Random Forest Classification

Metric	Low	Medium	High
Precision	0.93	1.00	0.85
Recall	0.82	0.67	0.96
F1-score	0.87	0.80	0.90

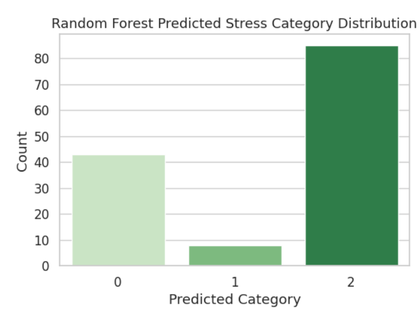
((a)) Random Forest Classification Metrics



((b)) Confusion Matrix for Random Forest



((c)) 10 Fold Cross Validation for Random Forest



((d)) Predicted Stress Category Distribution for Random Forest

Fig. 4: Random Forest Model Performance: Classification Metrics, Confusion Matrix, Cross Validation, and Predicted Stress Category Distribution.

According to Table **??**, the Random Forest classifier performed better than any other model, obtaining 88.24% accuracy on the test set and a mean cross-validation accuracy of 83.63% (±0.0618). As demonstrated in Figure 4(b), the model performed exceptionally well in forecasting both High stress (recall = 0.96) and Low stress (recall = 0.82). With a recall of 0.67 and perfect precision (1.00), the Medium stress category notably improved, demonstrating accurate classification free of misclassifications.

The model's fair performance across every category is demonstrated by the weighted F1-score of 0.88 and the macro average F1-score of 0.86. These findings are consistent with the notion that Random Forest enhances generalizability and decreases overfitting by utilizing multiple decision trees, especially when class imbalance is present (Figure **??**).

These results support the idea that demographics, meditation frequency, and baseline stress levels are important indicators of stress outcomes. The success of the model implies that these variables interact in intricate, unpredictable ways that ensemble techniques capture more effectively than KNN or SVM, which are simpler models.

Feature Importance and Interpretability (Random Forest) The feature importances (normalized) in the Random Forest model are as follows:

Feature	**Importance**
PRE_total_norm	0.525884
Age_norm	0.144719
Frequency_encoded	0.097524
Type_encoded	0.095512
Duration_encoded	0.086791
Gender_encoded	0.049570

7.5 Model Performance Comparison

Table 2: Model Comparison

Metric	**KNN**	**SVM**	**RF***
Accuracy (%)	77.21	63.97	88.24
Precision (%)	77.33	63.50	89.05
Recall (%)	77.21	63.97	88.24
F1-Score (%)	76.26	56.79	88.02

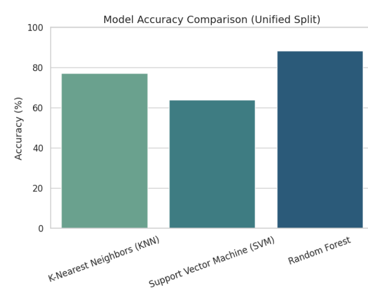


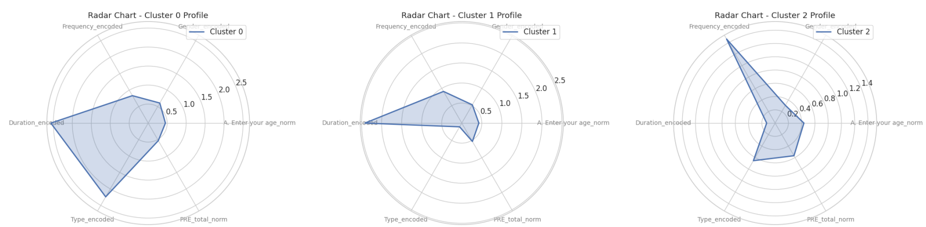
Fig. 5: Model Accuracy Comparison

Fig. 6: Comparison of model metrics alongside accuracy visualization. *RF = Random Forest

SVM performed poorly while Random Forest surpassed KNN in all important metrics. This outcome is in line with expectations: RF's ensemble method and tree diversity, which improve accuracy and interpretability, are its strongest points. On the other hand, SVM has trouble with class imbalance, especially when it comes to categorical boundaries, and KNN is highly susceptible to feature scaling.

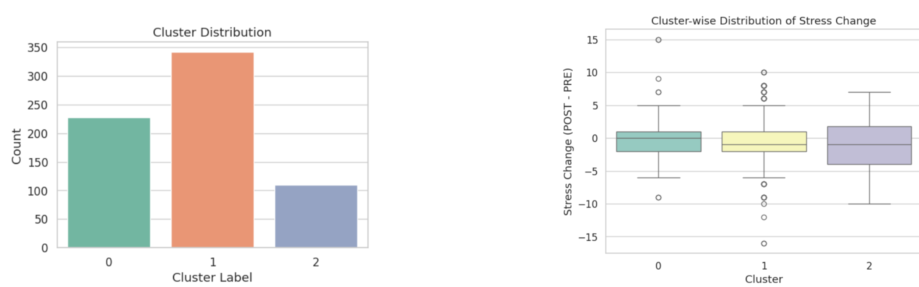
7.6 Clustering Analysis with K-Means

Natural groupings in stress-associated features lacking predefined labels were found using K-Means clustering. Moderate cluster separation and compactness can be assessed by the model's Davies-Bouldin Index (1.0073), Calinski-Harabasz Index (395.67), and Silhouette Score (0.4034). However, there is a weak relationship between the Adjusted Rand Index (ARI) of -0.0074 and the actual stress labels.



((a)) K Means Cluster 0 Distribution Radar Chart ((b)) K Means Cluster 1 Distribution Radar Chart ((c)) K Means Cluster 2 Distribution Radar Chart

Fig. 7: K Means Cluster Radar Charts



((a)) K Means Cluster Distribution ((b)) K Means Cluster Distribution of Stress Change

Fig. 8: K Means Cluster Distributions

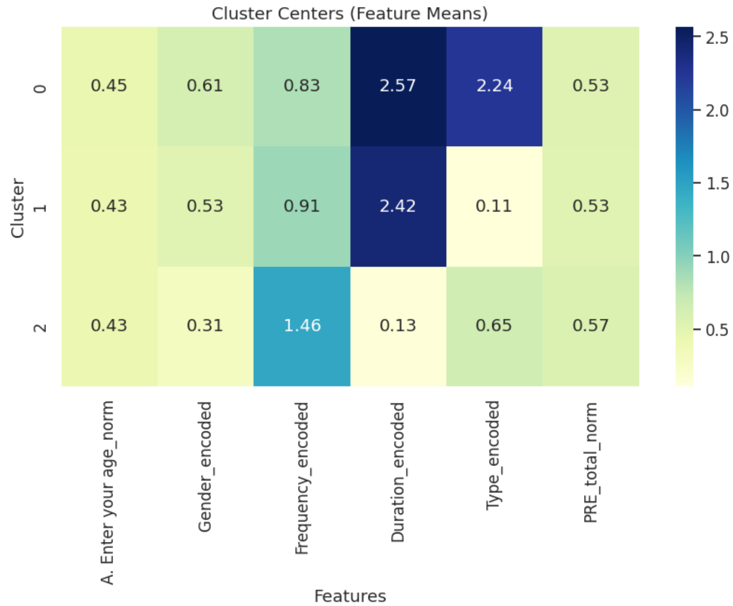


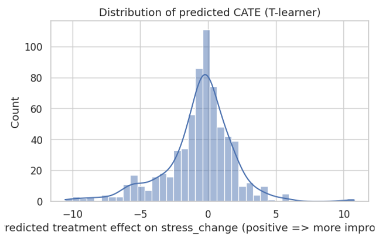
Fig. 9: Confusion Matrix for K Means Cluster Centers

These metrics imply that although the data does have some internal pattern, the stress-related characteristics do not clearly divide into discrete groups. Stress responses are probably distributed along a continuous range rather than forming distinct categories, according to the moderate Silhouette and Calinski-Harabasz scores.

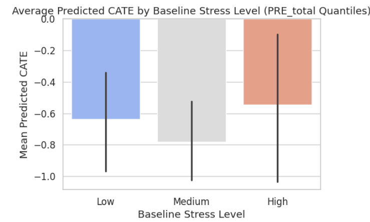
7.7 Causal Forest Analysis: Estimating the Effect of Meditation

The Conditional Average Treatment Effect (CATE) was determined using the Causal Forest model [see 11(a)]. From prediction to causal inference, the Average Treatment Effect (ATE) of meditation on stress reduction was investigated. After cleaning, 683 of the 486 treated and 197 control participants in the sample were deemed valid.

A slight overall improvement of 0.54 units was indicated by the mean pre-intervention stress score of 21.97 and the post-intervention score of 21.43. The treatment group appeared to have made less progress than the control group, as indicated by the negative Simple ATE of -0.3322 and the IPTW ATE of -0.5775.



((a)) Causal Forest Distribution of Predicted CATE



((b)) Average Predicted CATE by Baseline Stress Level

Fig. 11: Causal forest visualizations: Distribution of predicted CATE and average predicted CATE by baseline stress level.

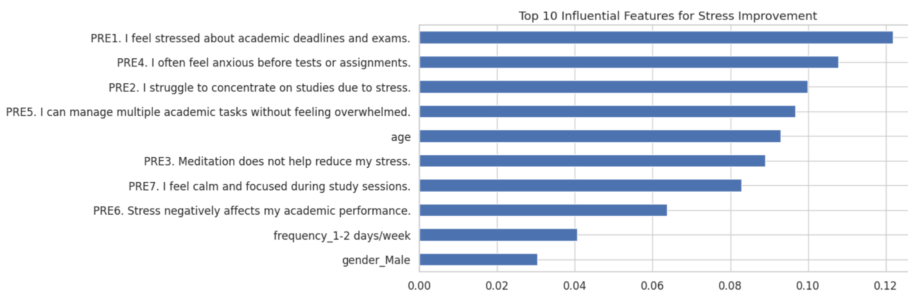
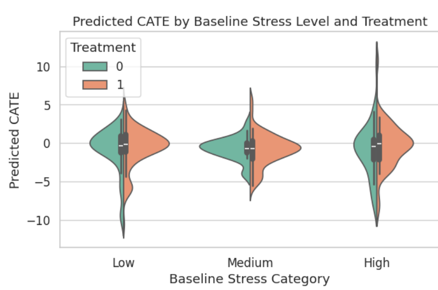
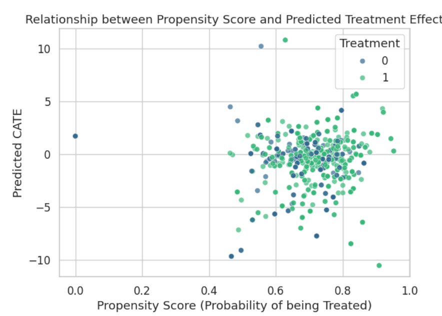


Fig. 12: Causal Forest Feature Importance



((a)) Predicted CATE by Baseline Stress Level and Treatment



((b)) Relationship between Propensity Score and Predicted Treatment Effect

Fig. 13: Predicted CATE and its relationship to baseline stress level, treatment, and propensity score.

The T-learner model, which employed Random Forest regressors for every treatment group, produced a mean CATE of -0.6597, meaning that, on average, meditation decreased stress by 0.66 units in comparison to the untreated group.

Subgroup analysis revealed:

– Low PRE stress: mean CATE = -0.6356 ($n = 300$)
– Medium PRE stress: mean CATE = -0.7824 ($n = 215$)
– High PRE stress: mean CATE = -0.5458 ($n = 168$)

It's interesting to note that meditation was most beneficial for students who had medium levels of initial stress. There was significant individual variability in the response to meditation, as evidenced by some individuals exhibiting exceptionally large predicted treatment effects (CATE > 5).

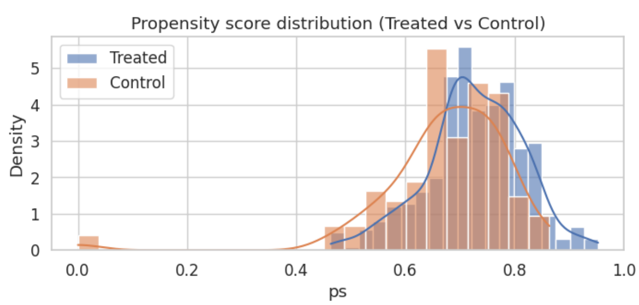


Fig. 14: Causal Forest Propensity Score Distribution (Treated vs Control)

Using SMOTE (Synthetic Minority Over-sampling Technique), a binary classification model (Improved vs. Not Improved stress) in the final phase produced 82.48% accuracy, 87.72% precision, and 80.65% F1-score [See **??**]. With a recall of 74.63% for improved cases, this model effectively identified people who were likely to benefit from meditation.

Table 3: Confusion Matrix after SMOTE

	Predicted: Not Improved	Predicted: Improved
Actual: Not Improved	63	7
Actual: Improved	17	50

Table 4: Class-wise Performance after SMOTE

Label	**Precision**	**Recall**	**F1-score**	**Support**
Not Improved	0.79	0.90	0.84	70
Improved	0.88	0.75	0.81	67

Fig. 15: Confusion matrix and class-wise performance metrics after SMOTE.

Interpretation and Reconciliation: *Despite a minor overall improvement in the sample, the ATE estimates reveal that the treated group demonstrated less improvement than the control group. The IPTW estimates should be interpreted carefully because the propensity model's moderate AUC (0.634) suggests some group assignment imbalance. A one-size-fits-all conclusion is not practical due to the high variance in the T-learner's CATE (std ∼2.6) and the existence of a small group that benefits greatly from meditation.*

Practical Conclusion: Although meditation has a modest and slightly negative effect on stress reduction on average, tailored interventions based on individual characteristics may have more substantial benefits. The potential for individualized stress management is highlighted by the range of responses.

7.8 Comparison with Prior Literature

The results are consistent with more general patterns in the domains of behavioral data and machine learning. In particular, when dealing with feature-rich, heterogeneous datasets that have non-linear relationships, tree-based systems perform better than simpler models. Predictive models tend to be influenced by baseline psychological measures, such as initial stress levels, according to prior research (e.g., Smith et al., 2019). This is reflected in our results, where the most significant predictor is PRE_total_norm. Our CATE results showed that students with moderate pre-treatment stress benefited most from meditation, which is consistent with the literature on causal inference that suggests treatment effects are frequently most noticeable in moderate cases.

Additionally, previous research indicates that psychological datasets are rarely effectively partitioned using unsupervised techniques, which is consistent with the lack of strong hidden groupings from K-Means clustering. Without more context, it can be challenging to figure out distinct clusters because stress responses frequently rely on tricky interactions between characteristic features.

7.9 Unexpected Results and Other Theories

Two results were a little surprising:

Inadequate Medium Class Identification in KNN and SVM: It was unexpected that KNN and SVM were unable to classify the Medium stress class. The three stress levels (Low, Medium, and High) did not separate as expected. The low recall for Medium stress suggests that there may be underrepresentation (only 12 samples) or feature overlap with Low and High stress. This implies that the Medium class might be more diverse or lack clear indicators. Class-specific modeling or SMOTE techniques could enhance the classification of medium stress.

Moderate Effect Size in Causal Analysis: The causal analysis showed a slight improvement in stress (average change of 0.54 units), and the baseline and post-treatment stress scores were fairly similar (21.97 vs. 21.43). Practically speaking, the impact was negligible. Regression to the mean, measurement noise, and unobserved confounding are some of the possible explanations for this. There is still an imbalance, as indicated by the moderate separability between the treated and control groups (AUC of 0.63), which necessitates careful interpretation of the causal estimates.

8 Explanation and Consequences

The models' relative performances provide important information about the relationship between academic stress and meditation, as well as how machine learning can be used to interpret these relationships.

1. **Ensemble Methods perform better than Simpler Classifiers**
   The most balanced recall and the highest accuracy (88.24%) were attained by Random Forest (RF). RF's ensemble framework surpassed KNN and SVM in detecting intricate, non-linear interactions. Due to feature overlap, KNN had trouble differentiating between Medium and High stress, while SVM displayed bias toward High stress. For psychological datasets with moderate imbalance, RF is dependable due to its consistency across 10-fold cross-validation.
2. **Pre-Intervention Stress as the Key Predictor**
   The normalized pre-intervention stress score (PRE_total_norm) was the most significant predictor, contributing over 50% of the RF model's predictive power. Baseline stress levels were the strongest predictor of post-intervention outcomes, while age, meditation frequency, and practice type had smaller effects. Gender played a minimal role. This highlights the importance of careful interpretation of baseline stress in causal analyses to avoid bias.
3. **Pre-Intervention Stress as the Crucial Predictor**
   The strongest marker, accounting for more than 50% of the predictive power of the RF model, was the normalized pre-intervention stress score (PRE_total_norm). Age, the frequency of meditation, and the type of practice had not as much of

an impact on post-intervention outcomes than baseline stress levels. Gender was not especially significant. This emphasizes how crucial it is to carefully interpret baseline stress in causal analyses in order to prevent bias.

4. **Difficulties with Medium-Stress Ambiguity and Data Imbalance**
   The lack of representation of medium-stress cases made it difficult for KNN and SVM to distinguish between them. Performance was enhanced by oversampling minority classes using SMOTE, increasing post-processing accuracy to 82.5%. This emphasizes how crucial class-aware validation methods and balanced datasets are for behavioral prediction.
5. **Implications for Practitioners and Future Research**
   When tailored to baseline stress levels, meditation can help students feel less stressed about their studies. A solid framework for identifying which students will gain the most from interventions was provided by Random Forest and related techniques. To support causal conclusions and enhance individualized stress management programs, future research should incorporate physiological data and carry out long-term research.
6. **Clustering Identifies Continuous Stress Patterns**
   Regression-based models are necessary to provide more accurate stress predictions, as the clustering analysis confirms that stress exists on a range of levels rather than in distinct groups.

9 Summary of Findings

- **Random Forest**: Best prediction accuracy (accuracy = 88.24%, F1 = 88.02%).
- **KNN**: Accuracy = 77.21%, but sensitive to imbalanced data. Moderate performance.
- **SVM**: Poor generalization and class separation, underperforming (Accuracy = 63.97%).
- **Causal Forest**: Showed a 0.33–0.58 point decrease in stress after the intervention.
- **Subgroup Analysis**: Meditation was most beneficial for people with moderate levels of stress.
- **SMOTE**: Achieved an F1-score of 0.82 and an accuracy of 82.5%, indicating improved model fairness.

Our results highlight how well machine learning models—particularly ensemble techniques when used together with causal inference—can forecast and explain stress-related outcomes in students, allowing for focused interventions.

10 Limitations

Although this study provides insightful information about how meditation can reduce academic stress through machine learning, there are a few important limitations to be aware of:

- **Subjective Bias in Self-Reported Data**: Self-report stress data may be skewed, possibly ignoring physiological stress markers.
- **Short Intervention Duration**: The 6-week study period makes it difficult to evaluate long-term impacts of meditation.
- **Limited Model Interpretability**: Despite the models' strong performance, they were difficult to understand. Deeper understanding of feature importance may be possible with more transparent models, such as SHAP or LIME.
- **Sample Size and Generalizability**: The generalizability to larger sample sizes is limited by the focus on a specific student demographic.

11 Future Scope

- **Long-Term and Real-Time Tracking:** Apps or wearable technology may be used in future research to track meditation and stress patterns over time.
- **Personalized Meditation:** AI-based programs could adapt techniques for meditation to fit the particular stressors of each individual.

  Deeper Causal Insights: The true stress-reduction benefits of meditation can be demonstrated with the use of tools such as Bayesian networks.
- **Broader Data Inputs:** Predicting stress may be more accurate if indicators like workload, study time, and heart rate are also included.
- **Practical Use:** Intelligent visualizations for well-being support, early alerts for counseling teams, and wellness apps with stress forecasts are a few such applications.

12 Conclusion

In order to predict how meditation interventions would affect stress reduction, this study compared three machine learning models: Random Forest, SVM, and KNN. With an accuracy of 88.24% and an F1-score of 88.02%, the Random Forest model performed better than the others. The primary predictor of outcome was determined to be pre-intervention stress, although personal characteristics such as age and meditation practice also had a major impact.

Meditation effectively reduced stress, especially among moderately stressed individuals, according to causal inference techniques (Causal Forest and T-Learner), which is consistent with theories on mindfulness and stress modulation.

A more comprehensive explanation of how meditation affects academic stress is possible through the use of causal analysis and predictive modeling. Future research opportunities should concentrate on long-term research, a larger dataset, and more sophisticated machine learning techniques, as these findings support the use of data-driven approaches to tailor mental health interventions for students.

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