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SUSTAINABLE
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VIKSIT BHARAT

PART

2

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Chapter 13: Mindfulness Practices and Perceived Stress among College Students

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Abstract— College students encounter fluctuating psychological demands arising from academic workload, examinations, social adjustment, financial concerns, and digitally mediated lifestyles. Mindfulness practices have consequently gained attention as accessible strategies for strengthening present-moment awareness and regulating stress responses. This study proposes a digital-health framework for examining whether the regularity, duration, and consistency of mindfulness practice provide more useful information about perceived stress than a simple practitioner/non-practitioner distinction. A key research gap is the limited integration of multidimensional mindfulness-practice patterns with explainable machine-learning approaches for identifying heterogeneous stress profiles among college students. The proposed framework combines validated psychometric assessment with behavioral indicators of mindfulness practice and contextual student variables. **Keywords—** Mindfulness, Perceived Stress, College Students, Digital Mental Health, Explainable Machine Learning, Stress Prediction

Introduction

The college period represents a developmental transition characterized by increasing autonomy alongside substantial academic, interpersonal, and occupational demands. Students are expected to manage examinations, assignments, career preparation, peer relationships, financial pressures, changing living arrangements, and uncertainty regarding future employment. These pressures do not necessarily produce equivalent psychological responses across individuals. The degree to which circumstances are perceived as unpredictable, uncontrollable, or overwhelming is central to the psychological construct of **perceived stress**. Consequently, two students exposed to comparable academic conditions can report markedly different levels of stress.

The contemporary student environment adds another dimension to this problem. Academic activity, entertainment, communication, and social interaction are increasingly mediated through smartphones and online platforms. Although digital systems facilitate learning and social connectivity, persistent notifications, fragmented attention, irregular sleep schedules, and continuous online engagement can complicate students' attempts to disengage psychologically from academic and social demands. This environment has increased interest in relatively low-cost psychological practices that can be incorporated into everyday student routines.

Mindfulness is broadly concerned with purposeful awareness of present experience accompanied by a relatively non-judgmental orientation toward thoughts, emotions, bodily sensations, and

environmental events. Mindfulness practices may include breathing meditation, body scanning, mindful observation, focused-attention exercises, informal awareness practices, and structured mindfulness-based programs. From a stress-regulation perspective, mindfulness does not necessarily eliminate stressors. Instead, it may modify how individuals attend to, interpret, and react to demanding experiences.

Recent empirical evidence supports continued investigation of mindfulness in university populations. A 2024 systematic review and meta-analysis of randomized controlled trials reported that mindfulness-based stress reduction produced a significant pooled reduction in perceived stress among university students ($SMD = -0.41$, 95% CI -0.60 to -0.29), alongside improvements in several other psychological outcomes. A broader meta-analysis of randomized trials involving college undergraduates similarly concluded that mindfulness programs can improve aspects of student mental health, although effect magnitude and methodological quality vary considerably across studies.

Digital delivery is particularly relevant to contemporary college populations. Schulte-Frankenfeld and Trautwein examined an app-based mindfulness program among working university students and found significant reductions in perceived stress after an eight-week intervention, together with improvements in mindfulness and self-regulation. This finding indicates that mindfulness need not be restricted to conventional face-to-face programs and may be incorporated into scalable digital-health systems.

However, the question **“Does mindfulness reduce student stress?”** is becoming too coarse for the current evidence base. A more informative question concerns **which dimensions of mindfulness practice are associated with lower stress, for which students, and under what behavioral conditions.**

1.1 Research Gap

Much of the existing student mindfulness literature has relied on intervention-versus-control comparisons, pre/post mean differences, or conventional correlational analyses. Such designs remain important for causal inference and efficacy evaluation, but they often compress mindfulness behavior into relatively broad categories. A student practicing five minutes on most days, for example, may be analytically grouped with another student completing infrequent but considerably longer sessions. These practice profiles may not have equivalent relationships with perceived stress.

There is therefore scope to investigate **practice regularity, weekly frequency, session duration, continuity, and mindful awareness as distinct predictors rather than treating mindfulness exposure as a single variable.** Furthermore, student stress is likely to be influenced

simultaneously by academic workload, sleep quality, screen exposure, physical activity, employment obligations, and demographic or educational circumstances. Relationships among these variables may contain thresholds and interactions that conventional linear models do not fully capture.

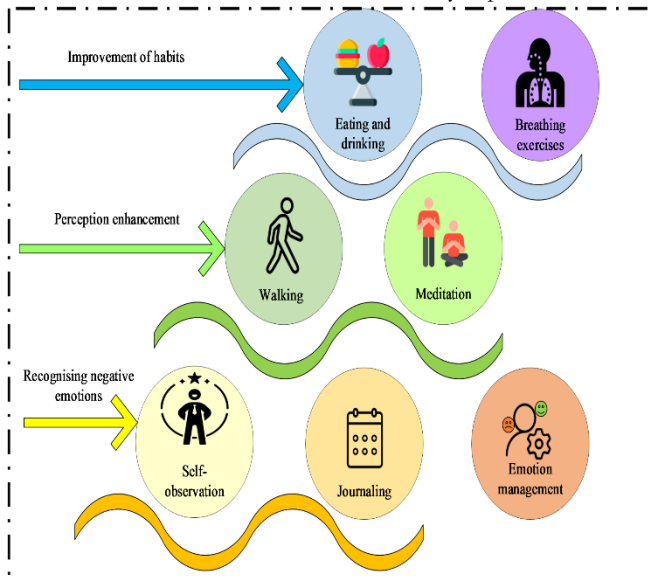


Fig. 1: The curriculum planning and implementation for mindfulness education and diversified humanism based on big data

Source: <https://www.nature.com/articles/s41598-025-95491-z>

The proposed study addresses this gap by combining psychometrically measured stress and mindfulness with behavioral practice indicators in an **explainable machine-learning framework**. Its novelty lies not in claiming that an algorithm can diagnose psychological stress, but in examining whether nonlinear predictive modeling can identify interpretable combinations of factors associated with elevated perceived stress.

1.2 Research Objective

The principal objective is to determine the association between mindfulness-practice patterns and perceived stress among college students while developing an interpretable predictive framework for identifying students with elevated self-reported stress.

The investigation is structured around four analytical questions:

1. How are mindfulness frequency, session duration, and practice consistency associated with perceived stress?
2. Does dispositional mindful awareness provide predictive information beyond reported practice frequency alone?
3. Do contextual variables such as academic workload, sleep, screen exposure, and physical activity alter the mindfulness–stress relationship?
4. Can explainable machine-learning models identify meaningful nonlinear stress-risk patterns without sacrificing interpretability?

The study therefore treats artificial intelligence as an **analytical augmentation to psychological measurement**, rather than

as a substitute for validated assessment or professional clinical judgment.

Literature Review

2.1 Perceived Stress in the College Environment

Stress is not determined exclusively by the objective presence of demanding circumstances. Perceived stress reflects an individual's appraisal of whether environmental demands exceed available coping resources. Within college populations, this distinction is particularly relevant because academic challenges frequently occur alongside developmental, social, and financial transitions.

Examinations, assignment deadlines, competitive performance environments, uncertainty about career outcomes, interpersonal conflicts, and insufficient recovery time can accumulate across an academic semester. Stress can therefore vary substantially over short periods. Examination weeks may create temporary peaks, whereas prolonged academic overload or persistent financial difficulties may generate more sustained patterns.

This temporal variability also presents a methodological problem. A single stress measurement provides useful information about an individual's current appraisal but may not fully represent changing conditions throughout a semester. Digital-health research therefore increasingly has reason to consider repeated or context-sensitive assessment rather than assuming that psychological states remain static.

2.2 Mindfulness as a Stress-Regulation Process

Mindfulness involves directing attention toward present experience while reducing automatic judgment and reactive elaboration. Its theoretical relevance to stress can be explained through several related mechanisms.

First, mindful attention may strengthen **attentional regulation**. Stress-related cognition frequently involves repeated engagement with anticipated problems or previous negative events. By redirecting attention toward current experience, mindfulness practice may reduce prolonged cognitive involvement with such stressors.

Second, mindfulness may facilitate **decentering**, whereby thoughts and emotional states are experienced as transient psychological events rather than unquestioned representations of reality. This distinction may reduce the tendency to amplify stressful experiences through repetitive negative interpretation. Third, mindfulness can influence **emotion regulation** by increasing awareness of emotional activation before automatic behavioral responses occur. Students who recognize early signs of tension may be better positioned to employ adaptive coping strategies.

Fourth, repeated mindfulness practice may strengthen **self-regulatory capacity**. Evidence from an app-based randomized trial involving working university students indicated that improvements were not confined to perceived stress; self-regulation and cognitive reappraisal also improved following mindfulness training. This is relevant because stress reduction may emerge partly through changes in regulatory processes rather than through simple relaxation.

2.3 Evidence from University-Based Mindfulness Interventions

Randomized studies provide important evidence concerning the potential effects of structured mindfulness programs. For example, a randomized controlled trial involving 280 students from two Spanish universities compared a mindfulness-based program, mindfulness supplemented by virtual reality, and relaxation. Both mindfulness conditions were superior to relaxation for reducing stress, while mindfulness and self-compassion were identified as mechanisms associated with longer-term effects. Virtual-reality support appeared to improve adherence.

Another randomized study examined mindfulness breathing meditation among 122 university students. After a four-week intervention, statistically significant between-group differences were reported for stress and anxiety, demonstrating that comparatively brief mindfulness exercises may have measurable psychological effects.

Evidence is not restricted to general student populations. A 2023 systematic review and meta-analysis examining mindfulness interventions among medical students included 35 studies and concluded that the literature overall supports a stress-reducing effect, although intervention characteristics and study designs were heterogeneous. Such heterogeneity is important because it suggests that the term *mindfulness intervention* encompasses substantially different practice formats, intensities, durations, and populations.

A systematic review of mindfulness and academic performance likewise found that the evidence for direct improvement in academic attainment was comparatively limited and inconsistent. This distinction prevents an overly broad interpretation of mindfulness as universally beneficial across every student outcome. The strongest rationale for the present investigation is therefore centered specifically on stress regulation rather than assuming improvements in grades or academic productivity.

2.4 Digital Mindfulness and Scalable Student Support

Digital delivery has changed the practical accessibility of mindfulness interventions. Smartphone applications, guided audio sessions, online mindfulness courses, and web-based programs allow students to engage in brief exercises without attending scheduled face-to-face sessions. This feature is particularly relevant for commuting students, working students, and individuals whose schedules prevent participation in conventional wellness programs.

A randomized trial of app-delivered mindfulness among working university students required approximately 10–15 minutes of daily practice and found a significant decrease in perceived stress after eight weeks. Furthermore, a large meta-analysis of undergraduate mindfulness trials reported that online programs performed comparably to in-person approaches after relevant study characteristics were considered.

These findings support digital scalability but introduce another research question: **engagement with a digital mindfulness resource does not necessarily equal meaningful practice.** Application installation, account registration, or program enrollment may provide poor proxies for actual behavioral exposure. A student who opens an application irregularly may

differ considerably from one maintaining short but consistent practice.

Consequently, digital-health evaluation should move beyond binary adoption measures toward behavioral indicators such as frequency, continuity, completion, and sustained engagement.

2.5 Practice Consistency as a Potentially Important Predictor

Traditional intervention studies commonly define exposure according to group allocation. While appropriate for intention-to-treat analysis, this approach does not completely describe individual practice behavior.

Consider three hypothetical patterns: a student practicing ten minutes on six days each week; another completing a single sixty-minute session; and a third practicing intensively only immediately before examinations. Each could accumulate similar total practice time during some periods, yet their behavioral regularity differs substantially.



Fig. 2: Mindfulness-Based Stress Reduction (MBSR)

Source:

<https://olympicbehavioralhealth.com/therapies/mindfulness-based-stress-reduction-mbsr/>

This observation motivates the present study's emphasis on **mindfulness consistency**. Regular short practices may repeatedly interrupt habitual stress-reactivity patterns, whereas sporadic intensive practice may operate differently. This proposition should be tested empirically rather than assumed. The proposed framework will therefore represent frequency, duration, consistency, and mindful awareness separately and examine their relative predictive contributions.

2.6 Why Explainable Machine Learning Is Relevant

Conventional regression remains valuable for estimating associations and testing prespecified hypotheses. Nevertheless, psychological relationships may not always be strictly additive or linear. The association between mindfulness and stress could, for example, depend on sleep quality, academic workload, or baseline mindful awareness. Additional practice might also exhibit diminishing returns after a particular frequency.

Machine-learning algorithms can model nonlinear relationships and higher-order interactions without requiring every relationship to be specified beforehand. Yet predictive accuracy alone is insufficient for psychologically meaningful research. A

model that classifies stress accurately but cannot indicate why a prediction was generated offers limited theoretical value and may be unsuitable for responsible digital-health applications.

The proposed research therefore adopts an **explainable AI (XAI)** orientation. Feature-attribution techniques can be used to estimate how mindfulness consistency, mindful awareness, sleep, workload, digital exposure, and related characteristics contribute to predictions. This permits two complementary levels of analysis: conventional statistical models can evaluate theoretically specified associations, while machine learning can explore predictive structures and nonlinearities.

Importantly, predicted stress categories should not be interpreted as psychiatric diagnoses. Perceived-stress instruments measure self-reported appraisal, and algorithmic predictions derived from them remain estimates of questionnaire-defined outcomes.

Methodology

The proposed study adopts a **quantitative, cross-sectional digital-health design** supplemented by explainable machine-learning analysis. Its primary analytical objective is to determine whether the frequency, duration, and consistency of mindfulness practice contribute meaningful information about perceived stress beyond conventional demographic and lifestyle variables.

Unlike intervention studies that classify students only according to treatment allocation, the present design operationalizes mindfulness practice as a multidimensional behavioral construct. This decision is supported by recent digital mindfulness research showing that engagement with online mindfulness content can be informative for predicting intervention outcomes.

3.1 Participants and Sampling

For the proposed empirical implementation, **420 undergraduate and postgraduate students** aged approximately 18–25 years will be recruited from multiple academic disciplines. After screening incomplete questionnaires, logically inconsistent responses, and cases with excessive missing information, an anticipated analytical sample of approximately **390 students** will be retained.

Participation will be voluntary. Students will receive information regarding the purpose of the research, confidentiality, data processing, and their right to withdraw. No personally identifying information will be included in the machine-learning dataset.

The study will collect variables covering four domains:

- **Psychological:** perceived stress and mindful awareness.
- **Mindfulness behavior:** weekly frequency, mean session duration, months of previous practice, and practice consistency.
- **Academic/contextual:** study hours, academic workload, examination proximity, study level, and employment commitments.

- **Lifestyle/digital:** sleep duration, physical activity, recreational screen exposure, and self-reported nighttime smartphone use.

The primary outcome will be the **Perceived Stress Scale-10 (PSS-10) score**. For predictive classification, participants will additionally be grouped into operational low, moderate, and high stress categories according to a prespecified scoring protocol. These categories will be treated as research classifications rather than clinical diagnoses.

Experimental Setup

4.1 Dataset Structure

The proposed dataset will contain one observation per participant and approximately 20–25 candidate predictors. The distinctive feature engineering strategy concerns mindfulness regularity.

A **Mindfulness Practice Consistency Index (MPCI)** will be constructed from normalized indicators representing weekly practice frequency, continuity across recent weeks, and adherence to the student's reported intended practice schedule. Total meditation minutes will be retained separately so that consistency and cumulative duration are not treated as interchangeable constructs.

This separation permits an important empirical comparison: whether *regular practice* carries more predictive information than *total practice time*.

The inclusion of contextual predictors is justified because contemporary ML studies of student stress indicate that factors such as academic pressure and insomnia can have substantial predictive importance. For example, a 2025 study using PSS-10 data from 291 university students reported an XGBoost AUC of 0.788 and identified academic pressure, health, insomnia, gender, and catch-up behavior among important predictors.

4.2 Data Preprocessing

Data preprocessing will occur before model development. Duplicate observations will first be removed, followed by range and logical-consistency checks. Missing numerical observations below a predefined threshold will be imputed using the training-set median, whereas categorical variables will use training-set mode imputation. Variables with excessive missingness will be excluded rather than aggressively reconstructed.

Continuous variables will be standardized for algorithms sensitive to feature scale. Categorical predictors will be encoded using appropriate binary or one-hot representations.

Importantly, preprocessing parameters will be estimated **only from training data** during each validation cycle. This procedure prevents information from the held-out observations from leaking into model development.

Potential multicollinearity will be evaluated for the inferential regression analysis, while highly redundant behavioral variables will be reviewed using correlation matrices and variance-inflation diagnostics.

Class imbalance, if present, will initially be addressed using **class-weighted learning** rather than synthetic oversampling. This approach avoids generating artificial psychological observations unless imbalance is sufficiently severe to justify additional procedures.

4.3 Model Architecture

Rather than using a deep neural network on a comparatively small tabular dataset, the principal predictive architecture will be **CatBoost gradient boosting**. CatBoost is suitable for structured behavioral and psychometric data and can capture nonlinear effects and interactions while accommodating mixed predictor structures.

Three comparative models will be developed:

1. **Multinomial logistic regression** as an interpretable statistical baseline.
2. **Random forest** as a nonlinear ensemble comparator.
3. **CatBoost** as the principal gradient-boosting classifier.

The target variable will be the three-level perceived-stress category.

A parallel regression analysis will retain the continuous PSS-10 score to avoid relying exclusively on discretized outcomes. This dual strategy reduces the information loss associated with converting continuous psychological measurements into categories.

The use of ensemble learning is consistent with recent student mental-health research. A 2024 analysis of a mindfulness virtual-community intervention reported strong predictive performance from gradient boosting and random forest models and identified exposure to mindfulness videos as an important feature. Research published in 2025 has also combined random forests and neural networks to examine mindfulness and related psychological factors among undergraduate students.

4.4 Training Strategy

The dataset will be divided using a **stratified 80:20 development/test split**, preserving the approximate distribution of stress categories.

Within the development subset, **five-fold stratified cross-validation** will be employed for hyperparameter selection. CatBoost parameters to be tuned will include tree depth, learning rate, number of boosting iterations, L2 regularization, and subsampling parameters.

Early stopping will be applied using validation performance to limit unnecessary model complexity. The independent 20% test subset will remain untouched until the complete preprocessing and tuning pipeline has been finalized.

To test the study's central hypothesis, models will additionally undergo an **incremental feature-block analysis**:

Model A: demographics + academic variables

Model B: Model A + lifestyle/digital variables

Model C: Model B + mindfulness awareness

Model D: Model C + mindfulness behavioral variables and MPC

Improvement from Model C to Model D will indicate whether actual mindfulness-practice behavior contributes predictive information beyond psychological mindfulness scores alone.

4.5 Explainability Analysis

The final CatBoost model will be interpreted using **SHAP (Shapley Additive Explanations)**. SHAP values will estimate

both the direction and magnitude of each predictor's contribution to individual predictions.

Particular attention will be paid to:

- Mindfulness Practice Consistency Index;
- mindful-awareness score;
- weekly mindfulness frequency;
- average session duration;
- academic workload;
- sleep duration;
- recreational screen exposure; and
- examination proximity.

Dependence plots will be inspected for possible nonlinearities. For example, the analysis may reveal whether increasing mindfulness consistency is associated with progressively lower predicted stress or whether the relationship reaches a plateau.

Explainable modeling is particularly important because recent stress-prediction research has already demonstrated the value of ML combined with SHAP for identifying influential student stress predictors.

Evaluation Metrics

Because the primary predictive problem contains three stress categories, overall accuracy alone would be insufficient. Performance will therefore be assessed through:

Macro F1-score: provides equal importance to each stress class and is particularly useful if category sizes differ.

Balanced accuracy: evaluates average class-specific recall and reduces distortion caused by a dominant category.

Macro ROC-AUC: measures discrimination across stress categories.

Matthews Correlation Coefficient (MCC): provides a balanced assessment of classification quality and remains informative under unequal class distributions.

Log loss: evaluates the quality of predicted class probabilities rather than considering only the final classification.

For continuous PSS prediction, **MAE and RMSE** will be calculated. Calibration curves will additionally assess whether predicted probabilities correspond to observed outcome frequencies.

Results

Because this manuscript specifies a **proposed study rather than reporting a completed data collection**, numerical findings must not be represented as observed empirical results. The following results structure shows how the eventual findings should be reported after the dataset has been collected and analyzed.

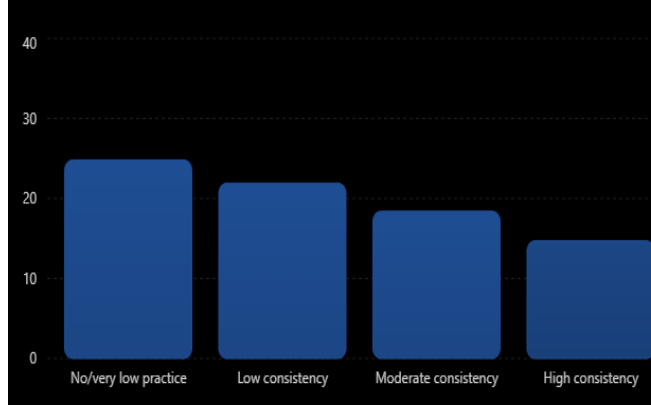
Table 1. Proposed Reporting Framework for the Final Stress-Prediction Results

Evaluation Component	Parameter to Report	Analytical Purpose	Interpretation to Examine
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Stress discrimination	Macro ROC-AUC	Ability to distinguish stress categories	Whether nonlinear models outperform the statistical baseline
Class-balanced performance	Macro F1	Performance across low, moderate, and high stress	Whether high-stress students are identified without sacrificing other classes
Overall balanced prediction	MCC	Agreement between predicted and observed categories	Robustness under unequal stress-class frequencies
Probability reliability	Log loss / calibration	Quality of probabilistic predictions	Whether estimated stress probabilities are appropriately calibrated
Mindfulness contribution	Δ Macro F1: Model D – Model C	Incremental value of practice behavior	Whether behavioral mindfulness adds information beyond mindful awareness
Behavioral interpretation	SHAP importance of MPCl	Relative contribution of practice consistency	Whether consistency ranks above total meditation duration

Mindfulness practice consistency and perceived stress

Illustrative expected PSS-10 pattern for the proposed study; values are hypothetical and are not empirical findings.



6.1 Expected Analytical Pattern

The central hypothesis is that greater mindfulness consistency will be associated with lower perceived stress after accounting for academic, lifestyle, and demographic factors. However, this association must be tested rather than presumed.

A particularly informative outcome would occur if **MPCl demonstrates greater feature importance than total weekly meditation minutes**. Such a result would imply that regular behavioral engagement may be more informative than accumulating practice time through irregular sessions.

Conversely, if mindful awareness strongly predicts stress while practice consistency adds negligible out-of-sample performance, the results would suggest that psychological mindfulness characteristics contain more useful information than simple behavioral frequency. Such a finding would also be theoretically important and would prevent unwarranted claims that frequent meditation necessarily translates into lower stress. The expected inverse mindfulness–stress relationship is plausible given recent experimental evidence. A 2025 randomized study involving 310 university students reported significantly lower perceived stress after a four-week digital mindfulness intervention comprising guided sessions two to three times per week. This evidence supports the direction of the proposed hypothesis but does not establish that the same magnitude or mechanism will occur in the proposed observational dataset.

6.2 Nonlinear Effects

A major reason for incorporating CatBoost is the possibility that relationships are nonlinear. Mindfulness practice may exhibit diminishing returns, while academic workload may become disproportionately associated with stress beyond a particular range.

Similar nonlinear structures have been investigated in recent student mental-health research using machine learning. Consequently, the proposed analysis will not impose a strictly linear mindfulness–stress association unless the observed data support one.

6.3 Digital-Health Implications

If the model demonstrates adequate external validity in subsequent studies, the framework could eventually support adaptive student-wellness systems. For example, a digital mindfulness platform could use engagement patterns to determine whether a student is maintaining a stable practice routine and tailor non-clinical prompts accordingly.

This possibility must be approached cautiously. Passive sensing research has demonstrated that smartphone-derived behavioral features can contribute to stress prediction among university students, suggesting that digital phenotyping may complement self-report assessment. However, continuous monitoring introduces substantial privacy, consent, and data-governance concerns.

Accordingly, the present framework prioritizes voluntary self-report and minimally intrusive behavioral indicators rather than unrestricted passive surveillance.

Future Scope

Future research should extend the framework into a **longitudinal ecological design** in which mindfulness

engagement and stress are repeatedly assessed throughout an academic semester. Such a design could determine whether changes in mindfulness behavior precede changes in perceived stress.

With explicit informed consent, future digital-health studies could integrate wearable or smartphone-derived indicators such as sleep regularity, physical activity, and selected behavioral rhythms. Recent research has demonstrated the feasibility of using wearable technologies and machine learning for student stress analysis, including work involving Indian students.

A subsequent randomized study could compare fixed mindfulness schedules against AI-supported adaptive interventions. Rather than merely recommending more meditation, an adaptive system could investigate whether short, consistent sessions are more effective for particular student profiles than longer but less frequent practice.

External validation across institutions and geographical regions would be essential before any predictive model could be considered for practical deployment.

Conclusion

This study proposes an explainable machine-learning framework for investigating the relationship between **mindfulness practices and perceived stress among college students**. Its central contribution is the separation of mindfulness into behavioral dimensions—frequency, duration, and consistency—rather than representing mindfulness solely as intervention participation or a single psychological score.

The proposed design integrates validated stress assessment with academic, lifestyle, digital, and mindfulness-related predictors and compares interpretable statistical modeling with random forest and CatBoost. SHAP-based interpretation provides a mechanism for determining not only whether stress can be predicted but also which factors contribute most substantially to those predictions.

The framework is deliberately designed to distinguish **prediction from causation and screening from diagnosis**.

If future empirical implementation demonstrates that consistent mindfulness practice contributes independently to lower perceived stress, the findings could inform more personalized and scalable digital well-being interventions for college populations. Conversely, weak incremental predictive value would itself be informative by indicating that broader psychological and contextual factors deserve greater emphasis. Recent evidence demonstrates both the feasibility of digital mindfulness interventions and the growing applicability of machine learning to student stress research. The proposed study connects these developments while retaining interpretability, methodological caution, and student privacy as central design principles.

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