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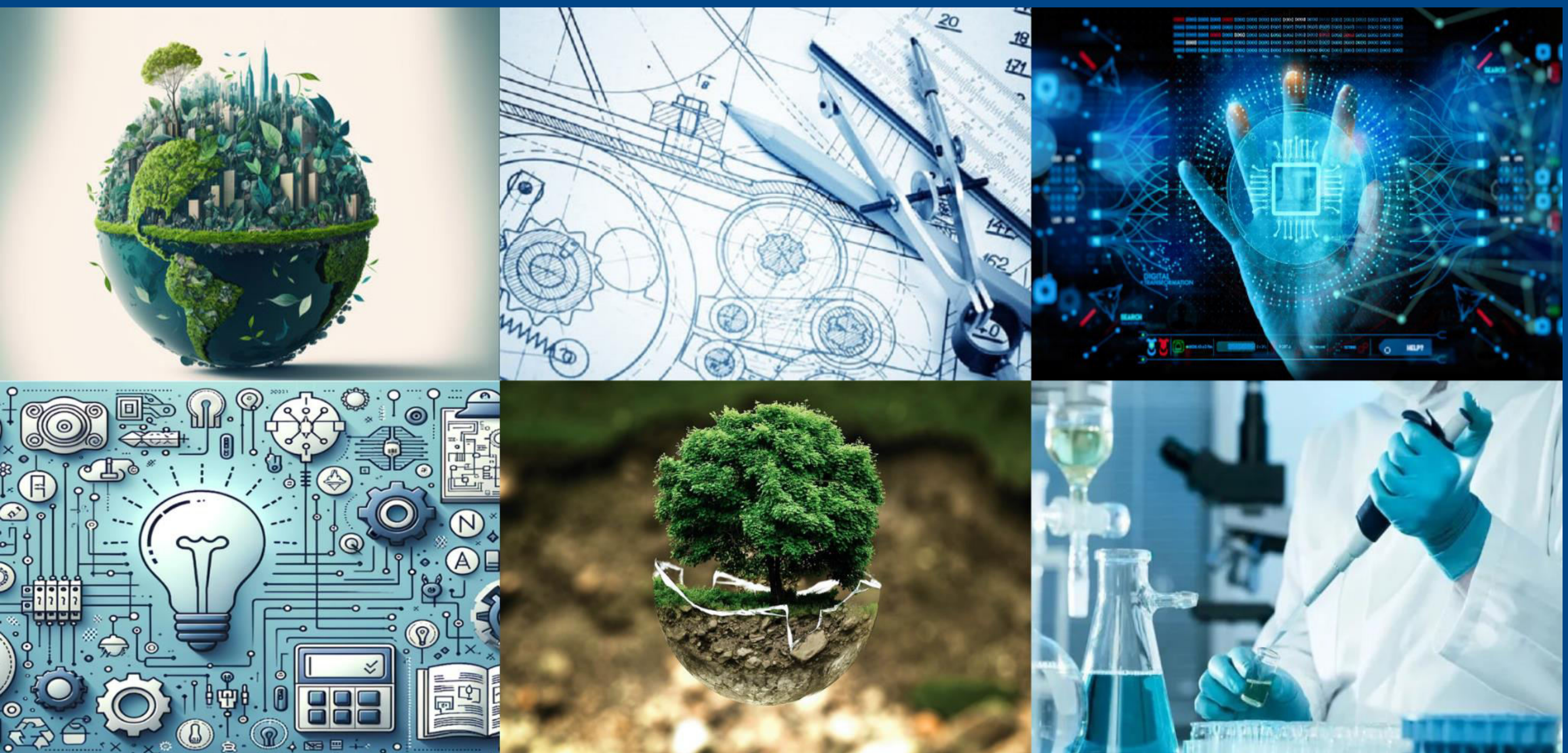

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AI-Based Emotional Health Risk Prediction Using Behavioural and Digital Activity Patterns

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ABSTRACT: College students face rising rates of stress, anxiety, and burnout, yet institutional mental health screening remains infrequent and reactive rather than preventive. This paper presents a machine learning pipeline for early identification of student mental health risk using passively observable digital-behaviour features. A dataset of 500 college students, each described by eight behavioural predictors (daily screen time, app-switching frequency, sleep hours, notification count, social media time, focus score, mood score, and anxiety level), was used to derive a composite digital wellbeing score, which was discretised into High, Medium, and Low risk tertiles using quantile binning. Logistic Regression and Random Forest classifiers were trained on standardised features and evaluated using accuracy, per-class precision/recall/F1, confusion matrices, and five-fold cross-validation. Logistic Regression achieved a test accuracy of 87% and a cross-validation accuracy of 93.2%, outperforming Random Forest (82% test, 86.2% cross-validation). Class-level analysis shows the model attains its highest precision (100%) on the Low Risk class and its highest recall (94%) on the Medium Risk class, with the High Risk class reaching 94% precision and 87% recall. Feature importance analysis confirms that anxiety_level (30.3%) and sleep_hours (21.4%) together account for over half of predictive power, consistent with established sleep-and-anxiety research. The system is proposed strictly as a preliminary decision-support prototype to complement, not replace, professional counselling.

KEYWORDS: Emotional Health Risk Prediction, Digital Phenotyping, Machine Learning, Logistic Regression, Random Forest, Feature Importance, Student Wellbeing.

I. INTRODUCTION

Mental health difficulties among college students, including anxiety, chronic stress, and burnout, have become increasingly common, yet institutional mechanisms to detect them remain largely reactive: a single formal assessment per semester or a counselling referral triggered only after visible distress. By the time a student is seen, the underlying difficulty has frequently already escalated. Meanwhile, students generate a continuous stream of digital-behaviour data through their devices — screen time, app-switching, notification load, and social media usage — that is rarely examined for early warning signals.

This work investigates whether a compact set of everyday digital-behaviour indicators, combined with self-reported focus, mood, and anxiety scores, can predict a student's mental health risk category using standard supervised learning. The goal is not clinical diagnosis but a lightweight, interpretable triage signal that could help shift student support from a once-a-semester model toward continuous, preventive monitoring. The remainder of this paper is organised as follows: Section II reviews related work, Section III describes the dataset, methodology, and evaluation formulas used, Section IV reports results and discussion, and Section V concludes with future directions.

II. LITERATURE REVIEW

Passive smartphone sensing for mental health monitoring ("digital phenotyping") has been studied across several populations. Feng et al. [1] compared classical machine learning, deep learning, and large language model approaches

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for forecasting mental health states from smartphone sensing data, finding that passively captured behaviours such as sleep, mobility, and phone use often precede self-reported symptoms.

A UK feasibility study using the Mindcraft application [2] combined fourteen days of active and passive smartphone data from secondary-school students, applying contrastive pretraining and supervised fine-tuning; combined modalities outperformed passive-only models, and SHAP-based attribution highlighted behavioural signals as clinically meaningful predictors. A large Danish cohort study [3] combined objective night-time smartphone behaviour with self-reported sleep to predict stress and depressive symptoms across thousands of adults, while a cross-sectional university study [4] found objectively measured screen time associated with poorer sleep quality and duration.

Idiographic modelling of momentary stress in college students [5] showed app-usage type and phone-derived sleep proxies carry within-person stress information, though the smartphone–mental-health relationship varies across individuals. Broader reviews [6] emphasise that combining passive behavioural features with minimal active self-report consistently improves predictive performance over passive-only models. The present work builds on this line of research, focusing on a compact, interpretable feature set evaluated with classical, low-resource classifiers suitable for deployment in a resource-constrained college setting.

III. METHODOLOGY

Dataset Description:
The dataset comprises 500 college student records, each with eight behavioural predictors — daily_screen_time_min, num_app_switches, sleep_hours, notification_count, social_media_time_min, focus_score, mood_score, and anxiety_level — and a composite digital_wellbeing_score used only for label construction. No missing values were present across any of the 500 records.

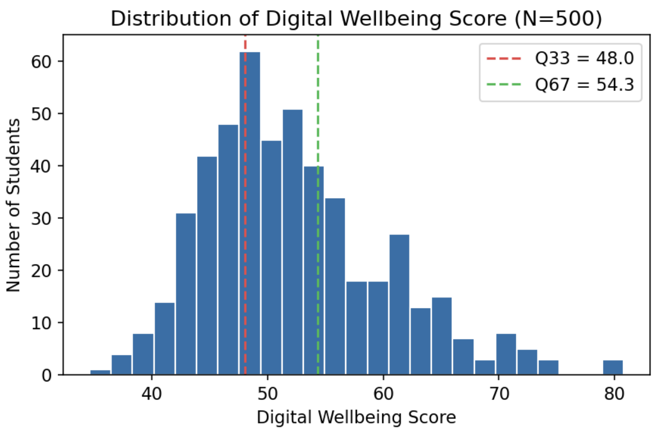

Figure 1: Distribution of the composite digital_wellbeing_score across 500 students, with quantile boundaries (Q33, Q67) marking the risk-tier cut points.

Target Variable Construction:
A quantile-based cut (pandas.qcut, q=3) was applied to digital_wellbeing_score to divide students into three tertiles. Because a higher digital_wellbeing_score corresponds to lower anxiety and better wellbeing (Pearson $r = -0.84$ between digital_wellbeing_score and anxiety_level in this dataset), the bottom tertile was labelled High Risk, the top tertile Low Risk, and the middle tertile Medium Risk. This produced 168 High Risk, 167 Medium Risk, and 165 Low Risk students (Q33 = 48.0, Q67 = 54.3), a naturally near-balanced split.

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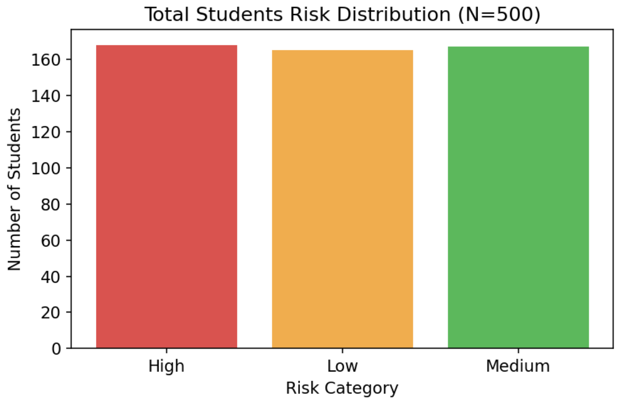

Figure 2: Final risk-category distribution across the 500-student dataset.

Preprocessing and Feature Scaling:
All eight features were standardised using the Z-score transformation, Eq. (1), fitted on the training split only to avoid data leakage:

$$z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j}$$

where x_ij is the raw value of feature j for student i, and μ_j, σ_j are the training-set mean and standard deviation of feature j. An 80:20 split (random_state = 42) yielded 400 training and 100 test records.

Logistic Regression Classifier:
A multinomial Logistic Regression model was trained under a one-vs-rest scheme. For K = 3 classes, the posterior probability of class k given feature vector x is given by the softmax function, Eq. (2):

$$P(y = k \mid \mathbf{x}) = \frac{e^{\mathbf{w}_k^\top \mathbf{x} + b_k}}{\sum_{c=1}^{K} e^{\mathbf{w}_c^\top \mathbf{x} + b_c}}$$

where w_k is the weight vector for class k and b_k its bias term. The model was trained with the L-BFGS solver (max_iter = 1000).

Random Forest Classifier:
A Random Forest ensemble of 100 decision trees (random_state = 42) was trained on bootstrapped samples, with node splits chosen to minimise Gini impurity, Eq. (3):

$$G(n) = 1 - \sum_{k=1}^{K} p_{nk}^2$$

Feature importance I_j for feature j is the total decrease in Gini impurity attributable to splits on feature j, summed across all trees, Eq. (4):

$$I_j = \sum_{t=1}^{T} \sum_{n \in N_t(j)} \Delta G(n)$$

Evaluation Metrics:
Both models were evaluated using accuracy, per-class precision, recall, and F1-score, Eqs. (5)–(6), along with five-fold cross-validation:

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$$\text{Precision} = \frac{TP}{TP + FP} \qquad \text{Recall} = \frac{TP}{TP + FN}$$

$$F_1 = 2 \cdot \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

IV. RESULTS AND DISCUSSION

Class-Level Performance:

Table 1 reports the class-level performance of the Logistic Regression model on the held-out test set.

Risk Class	Precision	Recall	F1-score	Support
High Risk	0.94	0.87	0.90	38
Low Risk	1.00	0.80	0.89	30
Medium Risk	0.73	0.94	0.82	32

Table 1: Class-level performance of Logistic Regression on the held-out test set (N = 100).

Overall Model Comparison:

Model	Test Accuracy	5-Fold CV Accuracy
Logistic Regression	87.0%	93.2%
Random Forest	82.0%	86.2%

Table 2: Overall accuracy comparison between the two trained classifiers.

Logistic Regression outperformed Random Forest on both test accuracy and cross-validation accuracy and was therefore adopted as the preferred model.

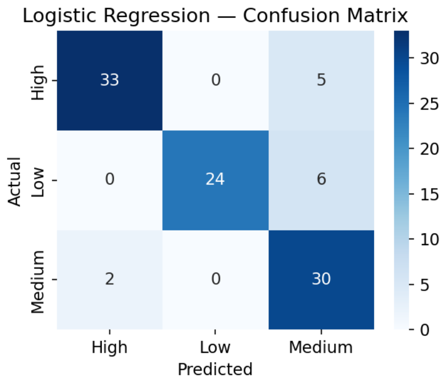

Figure 3: Confusion matrix for Logistic Regression on the 100-student held-out test set.

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Feature Importance:

Figure 4 shows Random Forest feature importances. anxiety_level (30.3%) and sleep_hours (21.4%) are, by a wide margin, the two most influential predictors, followed by focus_score (12.8%), notification_count (9.2%), social_media_time_min (8.5%), daily_screen_time_min (7.1%), mood_score (5.4%), and num_app_switches (5.3%).

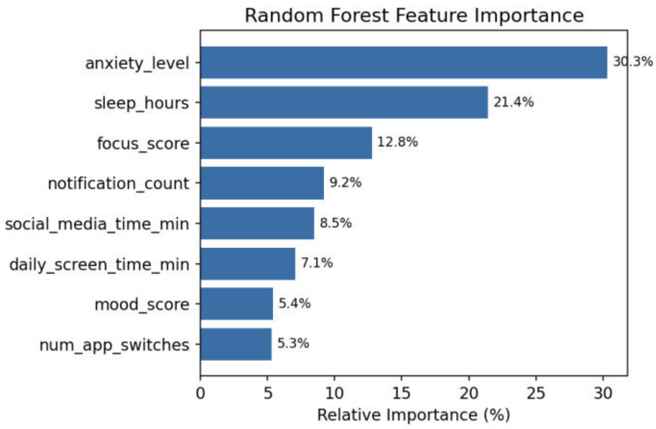

Figure 4: Random Forest feature importance across all eight predictors.

Discussion and Limitations:

The model is most precise (100%) when flagging a student as Low Risk, and most sensitive (94% recall) on the Medium Risk class. On the class that matters most operationally, High Risk, the model reaches 94% precision but only 87% recall, meaning some genuinely high-risk students are still missed — the gap most worth closing in future iterations, for example by lowering the High Risk decision threshold.

- Risk labels are derived from the dataset's own composite score via quantile binning, not a clinically validated instrument; the model predicts an engineered proxy label, not a diagnosis.
- The composite digital_wellbeing_score shares behavioural dimensions with the predictor set, and its exact formula is unpublished, so part of the reported accuracy may reflect a partially deterministic relationship.
- 500 records from a single (synthetic) source limit generalisability across institutions, cultures, and age groups.
- The system is a decision-support prototype only and must not substitute for professional clinical assessment.

V. CONCLUSION AND FUTURE WORK

This paper presented a machine learning pipeline for early student mental-health risk screening from eight digital-behaviour features. Logistic Regression achieved 87% test accuracy and 93.2% cross-validation accuracy, with anxiety_level and sleep_hours emerging as the dominant predictors. Future work includes independently verifying the digital_wellbeing_score construction to rule out label leakage, benchmarking gradient-boosted models such as XGBoost, validating on real consented student data, lowering the High Risk decision threshold to improve High Risk recall, and integrating longitudinal behavioural sequences via recurrent or attention-based models to capture risk trajectories over time.

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