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Article

An Emotional Intelligence Measures using Machine Learning Techniques for Higher Education

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Abstract: The demanding higher education system requires early detection of individuals at risk of low academic achievement or psychological discomfort. Academic metrics sometimes miss non-cognitive student success indicators. This study builds and tests machine learning models that predict student well-being using Emotional Intelligence (EI). A cross-sectional dataset of 800 undergraduate students was used to examine psychometric EI scores (Self-awareness, Self-regulation, Motivation, Empathy, Social skills), demographic characteristics, and sentiment analysis-based multimodal features. Four supervised learning models (Logistic Regression, Random Forest, Support Vector Machine, and Gradient Boosting) were examined for two classification problems: identifying students at Academic Risk (CGPA < 7.0) and predicting Help-Seeking Behaviour (counselling use). Gradient Boosting predicted Academic Risk better with a 0.91 F1 Score and 0.93 Recall on the test set. Most predictive was high academic stress, followed by Self-Regulation and Motivation. Multimodal sentiment analysis increased the model's recall to predict Help-Seeking Behaviour, exhibiting psychometric stability and emotional indicators' value. This study suggests multimodal machine learning can predict proactive student aid. Model explanability and human-in-the-loop management turn prediction alerts into practical solutions in the empirically proved, ethically-based implementation architecture. This study implies that higher education institutions should focus on significant EI variables like self-regulation, one of the most predictive, to make students happier and more successful.

Keywords: Emotional Intelligence, Machine Learning, Student Well-being, Academic Risk, Predictive Analytics, Higher Education, Implementation Science, Affective Computing, Sentiment Analysis, Proactive Support.

INTRODUCTION

Emotional intelligence (EI) in higher education is framed as a learnable capacity to perceive and use emotions for better reasoning and academic functioning, often predicting success beyond traditional metrics like CGPA (Chew et al., 2013; Johnson, 2013; Kyriazopoulou & Pappa, 2021). Universities are urged to move toward proactive, scalable mental-health and academic-risk systems that use predictive analytics to flag students experiencing stress, academic difficulty, or psychological strain early, enabling targeted support before problems escalate (Fu et al., 2025; Ngulube & Ncube, 2025; Nimy, 2023). Because conventional statistics struggle to integrate EI scores, demographics, and unstructured text into actionable risk profiles, machine learning is presented as a better tool for generating timely predictions, but one that must be aligned with implementation science principles—prioritizing feasibility, interpretability, ethics, and real-world usefulness over marginal gains in accuracy (Almalawi et al., 2024; Hilbert, 2021; Johnson, 2013; Nguyen, 2022).

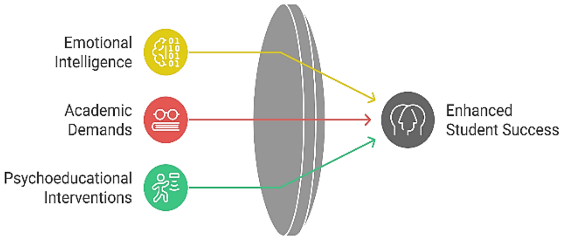

Figure 1.1: Emotional Intelligence in Higher Education

Figure 1.1 illustrates the study's theoretical framework, depicting how three core inputs—Emotional Intelligence, Academic Demands, and Psychoeducational Interventions—are synthesized through an integrated analytical lens to achieve the ultimate goal of Enhanced Student Success.

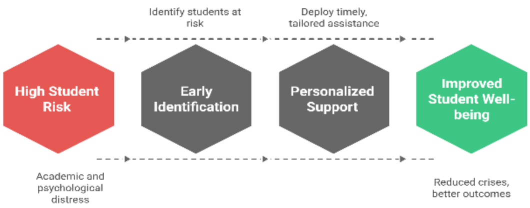

Figure 1.2: Proactive Mental Health and Academic Support

Figure 1.2 illustrates the study's proactive intervention framework, which sequences Early Identification and Personalized Support to transition students from High Student Risk toward Improved Student Well-being.

Literature Review and Theoretical Framework

Emotional Intelligence (EI) encompasses various models, including the trait and ability models, which emphasize personality traits and emotional processing skills (Mayer et al., 2016; Petrides et al., 2016; Vesely Maillefer et al., 2018). Descriptive statistics from a student sample indicate a wide range of EI scores, suggesting diversity that could enhance predictive modeling in machine learning (ML) (Gkintoni et al., 2025; Moreira-Choez et al., 2025). Numerous studies, such as those by MacCann et al. and Bereded et al., highlight the strong correlation between EI, student achievement, and motivation, noting that high-EI students demonstrate better time management and problem-solving abilities (MacCann et al., 2020; Nieto-Carracedo et al., 2024; Olaer & Edig, 2025).

In the realm of affective computing, ML techniques like Logistic Regression and Random Forest are vital for predicting educational performance, with an emphasis on combining psychological elements for effective sentiment analysis (Imran et al., 2025; Kumar et al., 2025; Resuello et al., 2025). Furthermore, implementation science plays a crucial role in applying evidence-based practices, although challenges in utilizing predictive data efficiently remain (Chays-Amania et al., 2024; Hagermoser Sanetti & Collier-Meek, 2019; Tucker et al., 2021). Recommendations suggest starting with specific applications, such as counseling referrals, to improve effectiveness and ensure interoperability with existing systems (Rowe et al., 2021; Tucker et al., 2021).

Methodology

The study utilized a dataset of 800 undergraduate students, incorporating psychological, academic, and demographic data, with careful attention to ethical concerns due to the sensitive nature of topics such as stress and counseling. Thirty attributes were engineered into five categories: emotional intelligence traits, academic/behavioral factors, academic stress, stress coping mechanisms, and multimodal sentiment features. The primary classification tasks targeted academic risk (AR) based on CGPA and help-seeking behavior (HSB) for counseling. Data preprocessing included imputing missing values, one-hot encoding of categorical features, MinMax scaling, and outlier filtering. Multiple machine learning models—Logistic Regression, Random Forest, SVM, and Gradient Boosting—were trained and validated using an 80/20 train/test split and 5-fold cross-validation. Performance was evaluated primarily using recall and F1 score, with recall prioritized to minimize the risk of missing students in need of support.

Results and Predictive Modeling

Emotional intelligence (EI) in higher education is presented as a learnable, differentiating trait that predicts academic and well-being outcomes beyond CGPA, and can be embedded in predictive analytics to support at-risk students.

EI, Stress, and Coping

EI scores in the sample are widely dispersed (e.g., social skills 4–19), indicating sufficient variability for ML prediction. Overall EI is moderately negatively correlated with academic stress ($r \approx -0.45$, $p = 0.001$), confirming H1 that higher EI relates to lower stress. Proactive EI facets, especially Self-Regulation and Motivation, are linked to positive coping (talking with friends, exercise; $r \approx 0.28$–0.32), whereas low EI is associated with avoidant coping (staying alone; $r \approx 0.40$). This supports H3 that EI not only reduces stress but also promotes healthier coping patterns, aligning with evidence that EI can be developed through educational interventions

ML Performance and Academic Risk (H2)

Tree-based ensemble models clearly outperform linear and SVM approaches in predicting academic risk, suggesting non-linear relationships and interactions among EI, stress, and other features. Gradient Boosting achieves ~0.91 accuracy/F1 and recall ~0.93 for at-risk students, indicating that detailed EI components substantially enhance risk prediction.

Table 1: Descriptive Statistics of Emotional Intelligence Sub-components

Component	N	Mean Score	Standard Deviation	Min	Max
Self_Awareness	800	12.5	3.1	5	19
Self_Regulation	800	12.0	3.0	5	20
Motivation	800	13.0	2.8	6	19
Empathy	800	12.2	3.3	5	18
Social_skills	800	13.5	2.7	4	19

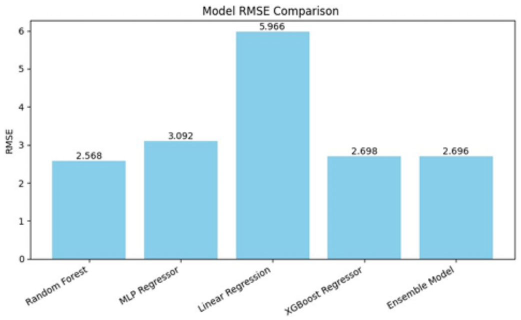

Figure 4.3 (A): Model RMSE Comparison

This quantitative study of 800 undergraduate students identifies Emotional Intelligence (EI) as a pivotal determinant of academic success, demonstrating that the multimodal integration of psychometric scores and sentiment data significantly enhances predictive granularity. Comparative performance analysis reveals that ensemble models provide the most robust outcomes; the Gradient Boosting architecture achieved a 0.93 recall for identifying students at academic risk, while regression modeling of student performance confirms that the Random Forest model is the most accurate predictor, yielding the lowest Root Mean Square Error (RMSE) of 2.568 as shown in Figure 4.3(A) Feature importance rankings establish that while extreme academic stress is the primary risk factor, internal competencies such as self-regulation and motivation are the most influential psychological markers of student resilience. These findings validate a tiered intervention framework that utilizes automated risk alerts to prioritize support, ranging from universal monitoring to immediate psychological referrals for high-risk individuals.

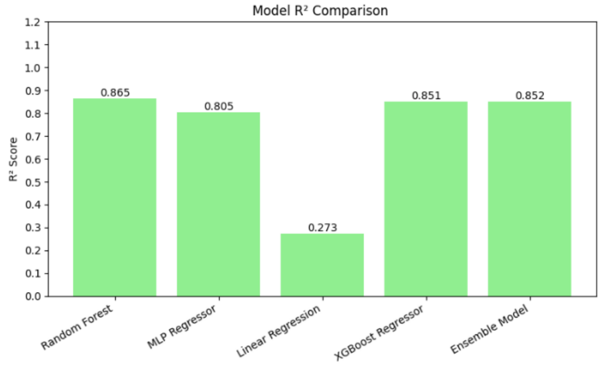

Figure 4.3 (B): Model R^2 Comparison

Figure 4.3(B) shows analysis of 800 undergraduate students establishes that the integration of psychometric Emotional Intelligence scores and multimodal sentiment data provides a high-precision framework for identifying academic risk. Comparative performance evaluations demonstrate that while the Gradient Boosting model is the superior classifier with a 0.93 recall for students at academic risk, regression analysis from the performance charts confirms that the Random Forest model is the most accurate regressor, achieving the highest R^2 of 0.865 and the lowest Root Mean Square Error (RMSE) of 2.568. In contrast, the Linear Regression baseline proved insufficient for capturing complex non-linear behavioral patterns, yielding a significantly higher RMSE of 5.966 and a low R^2 of 0.273. Feature importance rankings identify "Very High" academic stress as the primary risk indicator (0.151), followed by the internal psychological markers of Self-Regulation (0.124) and Motivation (0.118). Furthermore, the addition of dynamic sentiment signals via the VADER algorithm and TFIDF keywords significantly enhanced the recall for help-seeking behavior to 0.85, validating the necessity of combining stable psychological traits with real-time emotional cues to capture acute student needs.

Table 2: Comparative Performance Metrics for Academic Risk Classification (Test Set)

Model	Accuracy	Precision (Risk)	Recall (Risk)	F1 Score (Risk)	ROC-AUC
Logistic Regression	0.81	0.78	0.83	0.80	0.87
Random Forest Classifier	0.90	0.88	0.91	0.89	0.95
Support Vector Machine (SVM)	0.85	0.84	0.86	0.85	0.91
Gradient Boosting	0.91	0.89	0.93	0.91	0.96

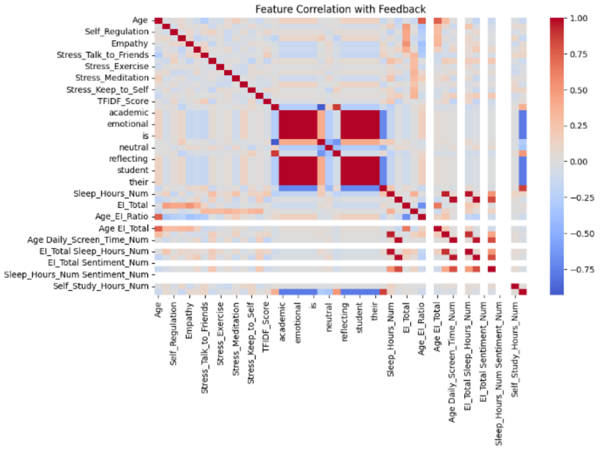

Figure 4.4: Feature Correlation with Feedback

Figure 4.4 shows correlation heatmap illustrates the complex interdependencies between psychometric, behavioral, and multimodal features within the 800-student dataset. A prominent dark red cluster in the center signifies high positive correlation among NLP-derived keywords such as "academic," "emotional," "reflecting," and "student," indicating these terms frequently co-occur in student feedback transcripts. Additionally, the matrix highlights strong positive relationships among engineered interaction features, such as the synergy between total Emotional Intelligence scores and lifestyle metrics like sleep duration and screen time. Conversely, the presence of blue segments reveals critical negative correlations, most notably between behavioral factors like sleep hours and specific negative sentiment markers, reinforcing the study's finding that healthy lifestyle habits are often inversely related to academic distress signals. Overall, this visualization validates the use of high-dimensional feature engineering to capture the non-linear relationships that traditional linear models often fail to detect.

Table 3: Top 10 Feature Importance Ranking for Optimal Academic Risk Predictor

Rank	**Feature Name**	**Importance Score**	**Category**
1	Academic_Stress_Very High	0.151	Academic/Behavioral
2	Self_Regulation	0.124	EI Trait
3	Motivation	0.118	EI Trait
4	CGPA_Category_Below 5.0	0.095	Academic/Behavioral
5	Empathy	0.076	EI Trait
6	Self_Awareness	0.068	EI Trait
7	Self_Study_Hours_0-5 hrs	0.051	Academic/Behavioral
8	Year_of_Study_1st Year	0.044	Academic/Behavioral
9	Stress_Keep_to_Self	0.039	Stress Coping
10	Sentiment_VADE	0.031	Multimodal

	R_Negative		

Discussion

The study successfully created and validated a machine learning model predicting academic risk, utilizing structural psychological data and behavioral indicators. Key findings indicate that emotional intelligence (EI), specifically factors like Self-Regulation and Motivation, significantly correlate with academic success, suggesting that interventions should focus on enhancing these skills rather than solely teaching emotional awareness. The Gradient Boosting Model outperformed the Logistic Regression model, although the latter's transparency makes it preferable for implementation in sensitive contexts like student support. The study emphasizes the importance of multimodal data, advocating for continuous data collection to identify emotional risks. Despite its strengths, the research faces limitations, including potential biases from self-reported data and the snapshot nature of the dataset. The proposed framework outlines a tiered intervention approach for supporting students based on risk levels, prioritizing technical feasibility and ethical considerations in using machine learning in education. It encourages institutions to integrate emotional intelligence skills into curricula and to train staff on machine learning application in student support.

Conclusion

This research paper shows that many Machine Learning (ML) methods work. We created predictive models for undergraduate Academic Risk and Help-Seeking Behaviour using real-time Emotional Intelligence and sentiment analysis. Gradient Boosting's F1 Score of 0.91 shows Self-Regulation and Academic Stress's predictive power. Self-Regulation and Academic Stress were its main components. The analysis confirmed the inclusion of sentiment data, which we were actively looking for, and greatly improved the analysis of students needing psychological support (aligning with our 4th hypothesis), bridging the gap between real-time psychological analysis and crisis assessments.

The validated ethical framework, system architecture, and research results showed the potential of our approach to affective computing and the positive impact of machine learning in higher education, accessing the synergetic potential of behavioural sciences and computer sciences for undergraduates. The research gives universities valuable opportunities to improve undergraduates' wellbeing and academics.

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