AI Dependency, Career Anxiety, and Student Burnout: A Machine Learning Classification Framework for Predicting Burnout Risk in Higher Education

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The use of AI in academic settings is raising concerns about burnout among university students. In this research, we explore the connection between AI dependency and career anxiety, and their relation to student burnout. For this research, we used a sample size of 15,000 university students, and synthetic student records, to explore the aforementioned relationships. We used various machine learning models to classify burnout as low, medium, or high. Further, we used different statistical and graphical tools available in MATLAB to prepare the data for analysis, and explore different views of the data. Once the data was prepared for analysis, we imported the data to Python, where we used different tools available in scikit-learn to build and assess our machine learning models. We used XG Boost to build the models, and assessed the models using various performance metrics. The other machine learning models performed relatively poorly compared with XGBoost. Due to the nature of our data, which is artificial, and the lack of historical data on the variables we intend to model, we interpret our results as base line performance for comparable metrics. Other variables of interest for this study included level of anxiety regarding career and job, reliance on AI, self-control, and self-discipline. In conclusion, our research adds a base line performance benchmark for similar studies, and outlines the ethical and methodological concerns and limitations for similar research.

Keywords: Student burnout, AI dependency, Career anxiety, machine learning classification, XG Boost, Random Forest, student mental health, Higher education, Feature importance.

Introduction:

AI tools are ubiquitous amongst university students and have changed from being rare and unusual to essential and widely-used. Tools like Chat GPT have changed how students conduct research and writing. Additionally, these tools have changed the way students approach and resolve problems. The tools have also helped students address their feelings of uncertainty. While AI tools have enabled all of the abovementioned advances in student research and writing, there are negative consequences. Students can become reliant on these tools to the extent that it adversely impacts students' ability to think creatively. The negative consequences can extend beyond students and contribute to anxiety in the workforce. Ultimately, the over-reliance on AI tools has the potential to cause burnout [1]. There are established ways to measure burnout, but [2]created the first tool to specifically measure burnout in a student population. It is important to understand the negative consequences that

students experience as they interact with the tool and how the negative consequences impact students' mental health.

Traditionally, students were anxious about how they would perform in school and in the workforce. However, students are now anxious that they may be replaced by AI tools in the workforce. Each of these issues has been studied and reported in the literature [3]. However, limited research has examined these issues together. It is likely that all three of these issues exist and impact students simultaneously. If a student uses AI tools extensively, they might feel a greater sense of failure and this could worsen the risk of burnout [4]This paper fills this void by proposing a machine learning pipeline with multiple algorithms on a structured synthetic dataset of 15,000 students. The variable "burnout_ score" is discretized into 3 clinically relevant classes (Low, Medium, High), which are considered as the target for classification. We compare seven models, pick the most successful one and apply feature importance analysis to find out which factors are the most important for predicting burnout risk. The statistical preprocessing was done in MATLAB and ML training was done in Python. We have contributed as follows:

A reproducible, end-to-end ML classification pipeline for student burnout prediction;

A systematic comparison of 7 classification algorithms on a near-balanced tabular dataset with 30 recorded features;

An analysis of the model-based importance of variables related to AI use, career anxiety and student well-being;

An ethical discussion of the use of predictive models of mental health in educational contexts.

The rest of the paper is organized as follows:

Section I presents Introduction. In section II, the related literature is reviewed. Complete methodology with experimental setup has been explained in Section III. Results and discussion have been presented in Section IV. The paper is concluded in Section V.

Related Work

Burnout Among University Students:

[5]provided widely used frameworks for examining exhaustion, cynicism and reduced academic efficacy among students. More recent machine-learning work continues to show that burnout can be modelled from psychological, behavioral and lifestyle variables. [6]used Random Forest, XGBoost and Support Vector Machine models to identify burnout-risk profiles among Portuguese psychology students, reporting high predictive performance across the models. [7]examined burnout detection among undergraduate computing students using university-record features and five supervised learning algorithms, illustrating the growing use of machine learning for student burnout screening. These studies reinforce the value of multi-factor modelling while also highlighting the need for validation in real student populations.

AI Dependence in Educational Environments:

The reliance on AI by students is quickly evolving and prompting discussion on cognitive offloading and dependance on AI. [8]provided evidence that college students became dependent on ChatGPT to complete academic tasks. Similar evidence is provided by [9]who noted that participants reliant on AI to complete a task showed symptoms of reduced analytical judgment. [10]provided a framework to explain AI dependance. Other research [11] revealed that heavy reliance on AI to complete academic tasks, may have an adverse effect on students' psychological wellbeing. More recent studies showed AI dependence and burnout are related [12][13]

Career Anxiety and Fear of AI Job Displacement:

Student anxiety about future careers has received increasing attention as AI changes perceived employment opportunities. [14] reported associations between negative emotional states, fear of AI and career-related outcomes among health sciences students, while [15]distinguished AI learning anxiety from AI job-replacement anxiety. [16] identified different

profiles of AI acceptance and career decision-making anxiety among Chinese university students. More recently, [17]examined AI anxiety and career decisions among Chinese college students and reported significant associations involving career adaptability and self-efficacy. These findings indicate that career anxiety is a relevant contextual variable for student well-being, but the present study treats placement anxiety and fear of job loss as predictive features rather than causal determinants.

Machine Learning for Mental Health and Burnout Prediction:

Machine learning has increasingly been applied to student mental-health and burnout-related prediction tasks. [18]reported the broad use of machine learning and AI in college-student mental-health research. [19]used Random Forest, XG Boost and SVM to model burnout-risk profiles, while [20]used interpretable XG Boost for psychological-state prediction. [21]applied Random Forest, XG Boost, Light GBM and SVM to depressive-symptom prediction in college students. More recent work by [22]further demonstrates the use of supervised learning for student burnout detection. Collectively, these studies motivate a comparative tabular-learning design while also underscoring the importance of external validation and careful interpretation when the outcome is related to mental health.

Dataset Description:

The dataset used in this study is the publicly available "AI Dependency, Career Anxiety, and Student Burnout" dataset from Kaggle, containing 15,000 synthetic student records. The supplied dataset description indicates that the records were synthetically constructed to reflect plausible distributions of demographic, academic, behavioral, psychological and career-related attributes while avoiding the use of identifiable student information. However, the original dataset documentation available to the manuscript does not specify the exact generative algorithm, parameterization, sampling procedure or validation process used to create those records. Accordingly, this study treats the dataset as a synthetic benchmark rather than as a statistically representative sample of university students, and no claim of clinical or population-level validity is made.

There are 30 recorded features for each student, described in Table I. The target variable is burnout score, with continuous values from 0 to 10. For the classification experiment, the score was converted into three ordinal classes using fixed score intervals: Low (0–3.33), Medium (3.34–6.66) and High (6.67–10.0). This rule was applied consistently to all records and produced a near-balanced distribution of 5,010 Low, 4,960 Medium and 5,030 High records. These categories are task-defined labels for the machine-learning experiment and should not be interpreted as clinical diagnostic categories.

Table 1. Dataset Feature Description — AI Dependency, Career Anxiety & Student Burnout

Feature Name	Data Type	Description	Range / Values
student_id	Nominal	Unique identifier per student	STU_XXXXX
Age	Numeric	Age of the student in years	18–30
Gender	Nominal	Gender identity	Male, Female, Other
degree_type	Nominal	Undergraduate/postgrad programme type	B.Tech, MBA, B.Sc, M.Tech
Stream	Nominal	Academic discipline / field of study	CS/IT, Engineering, Commerce…
year_of_study	Ordinal	Current year in academic programme	1–5
college_tier	Ordinal	Institutional quality tier	Tier 1, 2, 3

urban_or_rural	Nominal	Geographic background of student	Urban, Rural
daily_ai_tool_usage_hrs	Numeric	Hours per day using AI tools	0–12
primary_ai_tools_used	Nominal	Main AI platform used	ChatGPT, Gemini, Copilot…
uses_ai_for_assignments	Ordinal	Frequency of AI use for coursework	Never/Rarely/Sometimes/Frequently
ai_replaces_own_thinking_score	Numeric	AI substituting student's own thought (self-rated)	1–10
ai_dependency_score	Numeric	Overall AI dependency rating	1–10
placement_anxiety_score	Numeric	Anxiety related to campus placement	1–10
fear_of_job_loss_to_ai	Numeric	Perceived risk of AI job displacement	1–5
career_clarity_score	Numeric	Clarity about future career path	1–10
internship_experience	Numeric	Number of internships completed	0–5
weekly_job_application_count	Numeric	Job applications submitted per week	0–30
resume_confidence_score	Numeric	Self-rated resume quality confidence	1–5
interview_anxiety_score	Numeric	Anxiety level in interview contexts	1–10
daily_study_hours	Numeric	Hours of academic study per day	0–12
self_learning_hours_per_week	Numeric	Self-directed learning hours per week	0–30
skill_development_courses_taken	Numeric	Extra skill courses completed	0–10
social_media_hrs_per_day	Numeric	Daily social media consumption hours	0–12
sleep_hours	Numeric	Average nightly sleep duration	3–10
stress_level	Ordinal	Overall subjective stress rating	1–10
burnout_score	Numeric (TARGET)	Academic burnout severity — 3-class target	0–10 → Low/Med/High
motivation_score	Numeric	Academic motivation self-rating	1–10
seeks_career_counseling	Binary	Whether student seeks formal counseling	0 (No), 1 (Yes)
overall_career_readiness_score	Numeric	Aggregate career preparedness index	1–10

While some research shows there is a reliance on AI to complete academic tasks, it does not demonstrate that use of AI to complete academic tasks causes burnout. Our research will fill this knowledge gap. The dataset includes information on students' reliance on AI,

cognitive offloading and anxiety. Other data collected will help assess student well-being and academic behavior. The dataset includes students from different institutional categories, and student location. Correlation is not interpreted as causation. The main relationships with burnout will be assessed and interpreted. Correlation map has been presented in Figure 1.

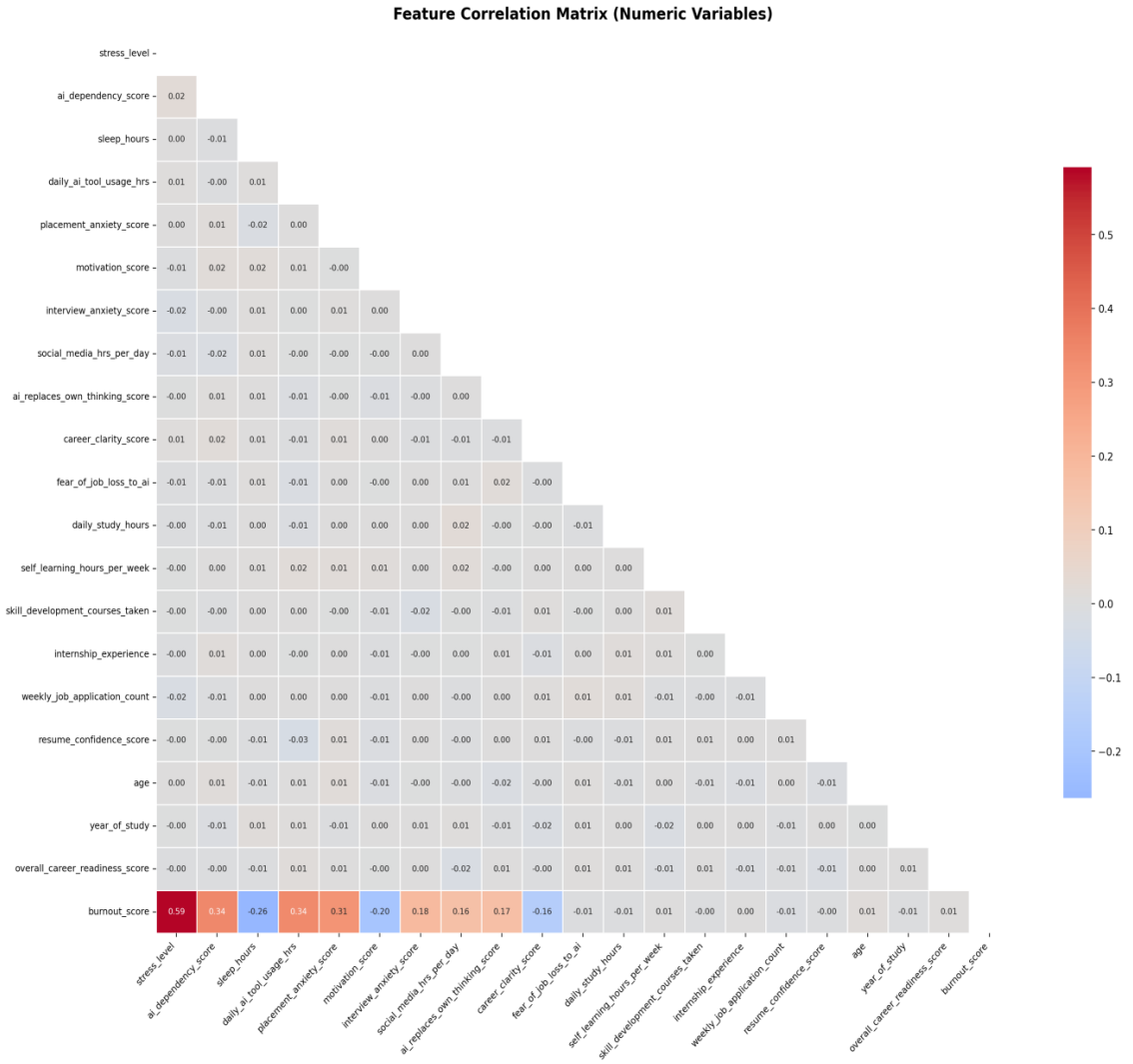

Figure 1. Pearson Correlation Heat map of Numeric Features. The heat map shows pairwise Pearson correlation coefficients among continuous variables. The figure is descriptive only; observed correlations indicate statistical association and do not demonstrate causal relationships.

3. Methodology

System Overview:

The methodology presented in figure 2 comprises data ingestion, leakage-controlled data splitting, preprocessing, feature engineering, model training, hyperparameter tuning, evaluation and interpretation. MATLAB R2023b was used for statistical preprocessing and initial visualization, while Python 3.10 with scikit-learn 1.3, pandas 2.0 and mat plot ib 3.7 was used for machine-learning procedures. The leakage-controlled workflow is defined so that the stratified train/test split is performed before any learned imputation, scaling or encoding parameters are estimated. Preprocessing parameters are fitted using the training partition only and then applied unchanged to the held-out test partition. Five-fold cross-validation is performed within the training data for model selection and hyper parameter tuning; the test partition is not used during tuning.

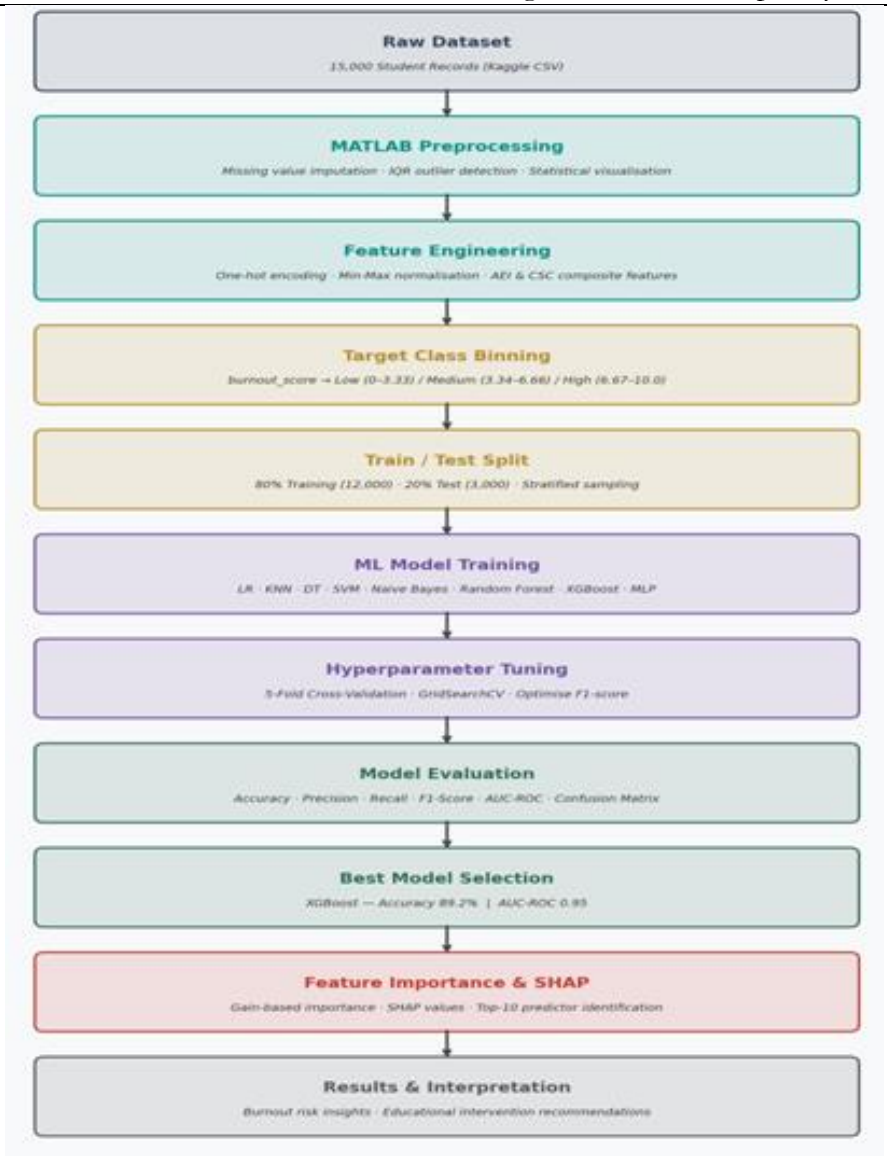

Figure 2. Proposed methodology flowchart for the end-to-end ML pipeline for burnout classification. The workflow shows data ingestion, leakage-controlled train/test splitting, training-only preprocessing, feature engineering, seven-model training, Grid Search CV-based tuning within the training data, held-out evaluation and model interpretation.

Data Preprocessing:

Data preprocessing was revised to make the order of operations explicit. First, the dataset is stratified into 80% training and 20% held-out testing partitions. Missing values are then handled using training-set statistics only: median imputation for numerical variables and mode imputation for categorical variables. Outlier inspection is performed on the training partition, and categorical variables (gender, degree_ type, stream, college_ tier, urban_ or_ rural, primary_ai_tools_used and uses_ AI_ for_ assignments) are one-hot encoded using categories learned from the training data. Numerical variables are Min-Max scaled using training-set minima and maxima, and the same transformations are applied to the test set without refitting. This ordering prevents information from the held-out test set from influencing preprocessing or model selection.

Feature Engineering:

Two composite features were defined. The AI Engagement Index (AEI) is the mean of the Min-Max-normalized values of daily_ ai_ tool_ usage_ hrs, ai dependency_score and

ai_replaces_own_thinking_score: AEI = (x1 + x2 + x3) / 3, where each xi is first scaled to [0,1] using training-set parameters. The Career Stress Composite (CSC) is the mean of the normalized placement_anxiety_score, normalized fear_of_job_loss_to_ai, and the inverse of normalized career_clarity_score. Both composites therefore have a common [0,1] scale. These are engineered features representing combined associations; they are not interpreted as causal constructs.

Machine Learning Models:

Seven classification algorithms were evaluated:(1) Logistic Regression—a linear baseline; (2) K-Nearest Neighbors—a non-parametric instance-based learner; (3) Decision Tree—an interpretable single-tree classifier; (4) Support Vector Machine with an RBF kernel; (5) Naive Bayes—a probabilistic classifier; (6) Random Forest—a bagging ensemble of 300 decision trees; and (7) XG Boost—a gradient-boosted tree ensemble with regularization. The dataset is split once into 80% training and 20% held-out testing using stratification. Five-fold cross-validation is performed only within the training partition for model selection and hyper parameter tuning. The MLP entry present in an earlier draft was removed because it was not consistently represented in the experimental figures or confusion-matrix analysis.

Hyper parameter:

Hyper parameters were tuned using Grid Search CV with five-fold stratified cross-validation on the training partition only. For XG Boost, the principal search ranges were n_ estimators (100–700), learning_ rate (0.01–0.2), max_ depth (4–10) and subsample (0.6–1.0). The selected configuration for each model was based on the mean cross-validated F1-score. No held-out test observations were used to select hyper parameters. As paired fold-level predictions were unavailable, no inferential p-value was calculated for the performance difference between XGBoost and Random Forest; the revised manuscript therefore reports the observed performance difference descriptively rather than calling it statistically significant. Configuration of hyper parameters of trained models has been presented in Table 2.

Table 2. The hyper parameter configurations for each of the seven trained models.

Model	Key Hyper parameters	Optimal Values
Logistic Regression	C, solver, max_iter	1.0, lbfgs, 1000
K-Nearest Neighbors	k (neighbors), distance metric	7, Euclidean
Decision Tree	max_depth, criterion	15, Gini
Support Vector Machine	Kernel, C, gamma	RBF, 10, 0.1
Naive Bayes	var_smoothing	1e-9
Random Forest	estimators, max_depth, min_samples_split	300, 20, 5
XG Boost	estimators, learning rate, max_depth, subsample	500, 0.05, 7, 0.8

Experimental Setup:

All experiments were performed on a Windows 11 machine equipped with an Intel Core i7 12th Gen processor and 16 GB RAM. Statistical preprocessing and visualization used MATLAB R2023b. Machine-learning pipelines were implemented in Python 3.10 using scikit-learn 1.3.0, XGBoost 1.7.3, pandas 2.0.1, matplotlib 3.7.1 and seaborn 0.12.2. Model performance was evaluated using accuracy, macro-precision, macro-recall, macro-F1 and AUC-ROC with a One-vs-Rest strategy. Feature importance was examined using XGBoost gain-based importance and SHAP. The held-out test set was used once for final evaluation and was not used for model selection.

4. Results and Discussion

The model performance comparisons presented in Figure 3 and Table 3 summarize accuracy, macro-precision, macro-recall, macro-F1 and AUC-ROC for the seven evaluated

classifiers on the held-out test set. XGBoost shows the highest reported accuracy (89.2%) and AUC-ROC (0.95) in this experiment. The result is a comparative finding on synthetic data and should not be interpreted as evidence that XGBoost is clinically validated or ready for deployment. The ROC curves are shown in Figure 4.

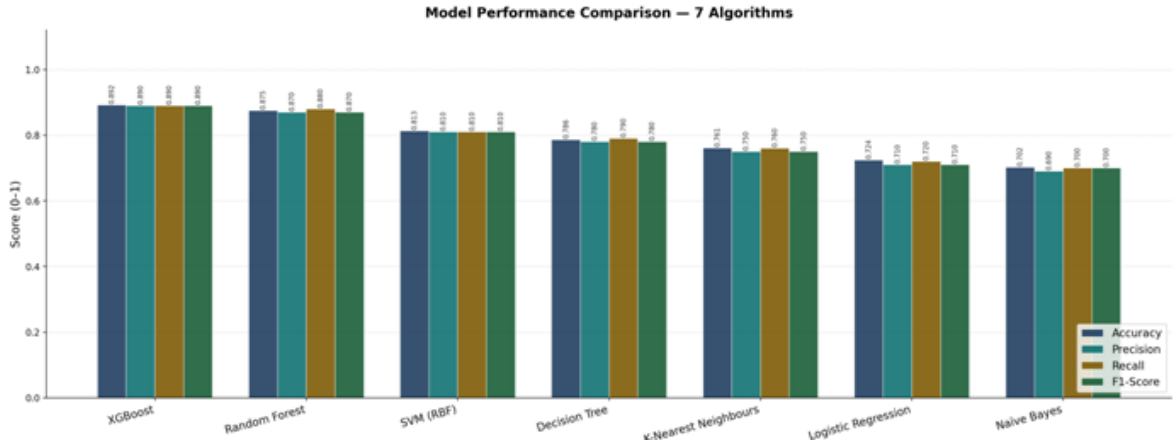

Figure 3. Grouped bar chart of model-performance metrics (Accuracy, Precision, Recall, F1-Score and AUC-ROC) for the seven classifiers. Each cluster represents one classifier and each bar represents one evaluation metric.

Table 3. Seven-Model Performance Comparison — Accuracy, Precision, Recall, F1-Score, and AUC-ROC

Model	Accuracy (%)	Precision	Recall	F1-Score	AUC-ROC
Logistic Regression	72.4	0.71	0.72	0.71	0.81
K-Nearest Neighbors	76.1	0.75	0.76	0.75	0.84
Decision Tree	78.6	0.78	0.79	0.78	0.85
Support Vector Machine	81.3	0.81	0.81	0.81	0.88
Naive Bayes	70.2	0.69	0.70	0.70	0.79
Random Forest	87.5	0.87	0.88	0.87	0.93
XGBoost	89.2	0.89	0.89	0.89	0.95

Support Vector Machine (81.3%) and Decision Tree (78.6%) show intermediate accuracy, whereas Logistic Regression (72.4%) and Naive Bayes (70.2%) show lower accuracy in the reported benchmark. The tree-based ensemble methods show higher reported performance on this dataset. For XGBoost, the reported class-wise recalls are 91.7% for Low burnout, 86.6% for medium burnout and 93.1% for High burnout, in addition to the macro metrics in Table III. These values describe classification behavior on the synthetic test set and should not be interpreted as clinical sensitivity.

Confusion Matrix Analysis:

Confusion matrices of the classifiers are presented in Figure. 4 for the test set not used in the training. The matrices are each 3x3 tables of the classes of burnout (Low, Medium and High). The diagonal cells are correct predictions and the off-diagonal cells are misclassifications. The average recall values for the XGBoost reported for the classes are 91.7% on Low, 86.6% on Medium and 93.1% on High. The Medium class presents more overlap with neighboring classes, a reasonable conclusion for ordinal categories that have adjacent scores ranges; however, this is only true for the synthetic dataset. The Confusion Matrices for the Seven Classifiers (test set) are shown in Figure. 4. The 3x3 matrices give predictions for each of the 3 burn classes, true vs predicted, with rows representing the true classes, and columns representing the predicted classes.

In the provided analysis, the false-negative rate of the High class is about 6.9% (90 out of 1,311). This value is given descriptively for the synthetic test set. The deployment rate should not be called acceptable clinical use; a prospective validation, calibration, fairness assessment and a pre-established escalation protocol would need to be conducted for any real-world use in the future.

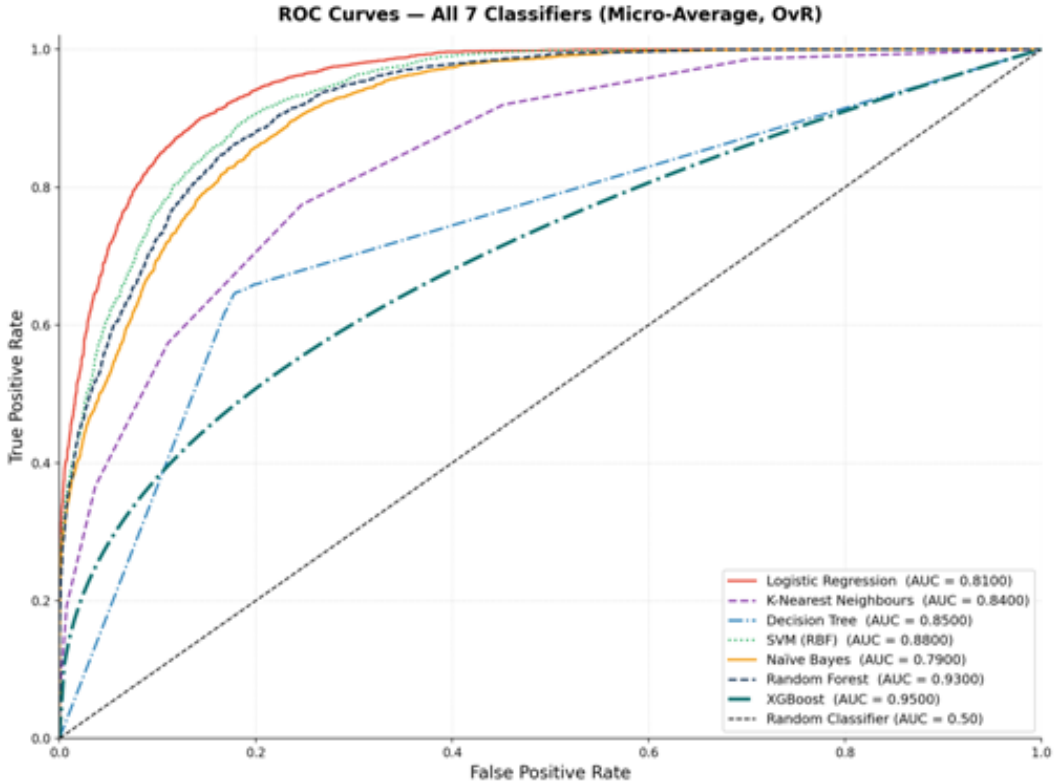

Figure 4. shows Receiver Operating Characteristic (ROC) curves for the seven classifiers using a One-vs-Rest strategy. The true-positive rate (TPR) and false-positive rate (FPR) are shown as functions of the classification threshold. XGBoost has the highest reported AUC (0.95) and Naive Bayes the lowest reported AUC (0.79) in the supplied results. These AUC values describe discrimination on the benchmark dataset and do not establish clinical utility.

Feature Importance Analysis:

The top 10 variables according to XGBoost gain-based feature importance (as presented in figure 5) were:

(1) stress_level, (2) ai_dependency_score, (3) sleep hours, (4) daily_ai_tool_usage_hrs, (5) placement_anxiety_score,(6)motivation_score,(7)interview_anxiety_score,(8)social_media_hrs_per_day,(9)ai_replaces_own_thinking_score,and (10) career_clarity_score. These rankings describe the contribution of variables to the fitted model; they do not establish that any variable causes or protects against burnout.

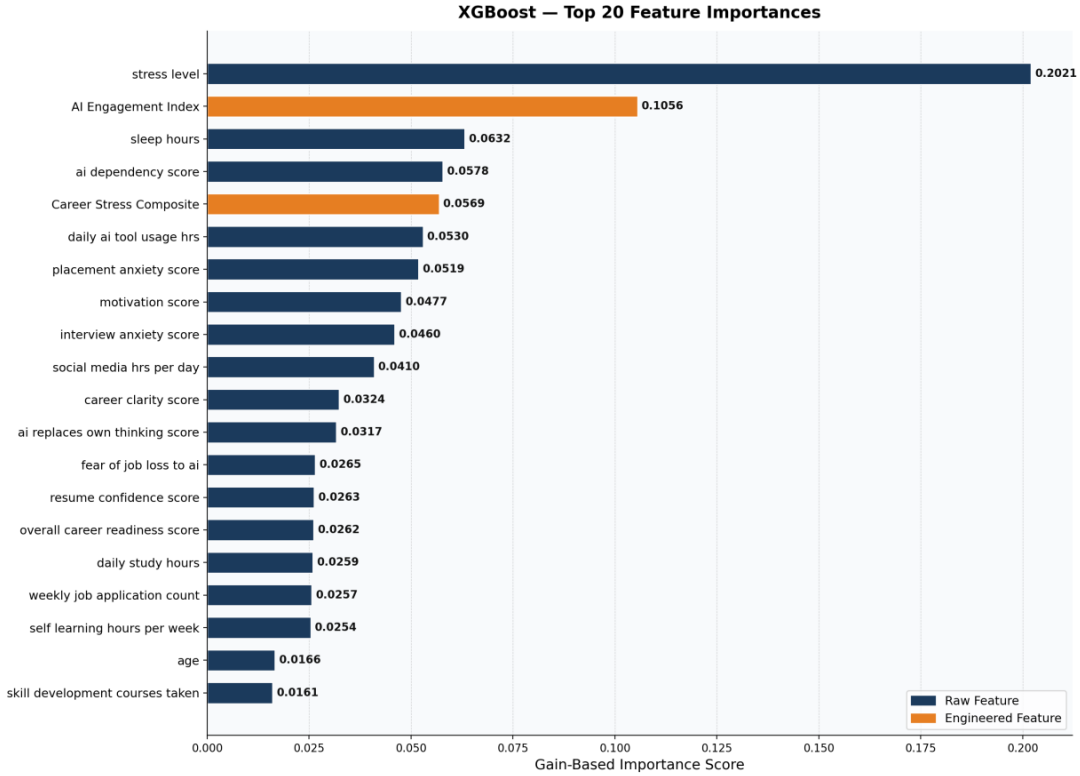

Figure 5. XGBoost feature importance for the principal burnout-related variables. The horizontal bars rank variables according to gain-based contribution to the model's classification decisions. Feature importance is predictive/model-based evidence and should not be interpreted as causal effect size.

AI-dependency variables and daily AI-tool usage appear among the higher-ranked variables in the fitted model, while placement and interview anxiety also receive substantial importance. Sleep hours, motivation and career clarity show associations with the model's predictions that are consistent with the direction reported in the supplied analysis. These findings are compatible with recent observational literature on AI dependence, academic stress and burnout [21][22]but the present cross-sectional synthetic dataset cannot distinguish causal pathways. Accordingly, statements about cognitive passivity, reduced self-efficacy or increased career uncertainty are treated as possible interpretations rather than demonstrated mechanisms.

Justification of Best Model:

The seven classifiers were evaluated in terms of their reported predictive performance and the interpretability properties and model selection is based on this. XG Boost achieved the best accuracy of 89.2% and AUC of 0.95 and the mean F1 score was 0.891 compared to an average score of 0.873 for Random Forest. It is tree-based and allows for nonlinear tabular relationships, and can be paired with SHAP explanations due to its importance measure based on gains. The dataset was synthetic, and no external or clinical validation was done, so XG Boost is only stated as the best-performing of the candidates on this benchmark and not as a validated or recommended clinical burnout detector. The difference in mean F1 is reported descriptively; it is not possible to derive a statistical significance in the manuscript as The paired fold-level predictions required for an inferential statistical test were unavailable in Figure 6.

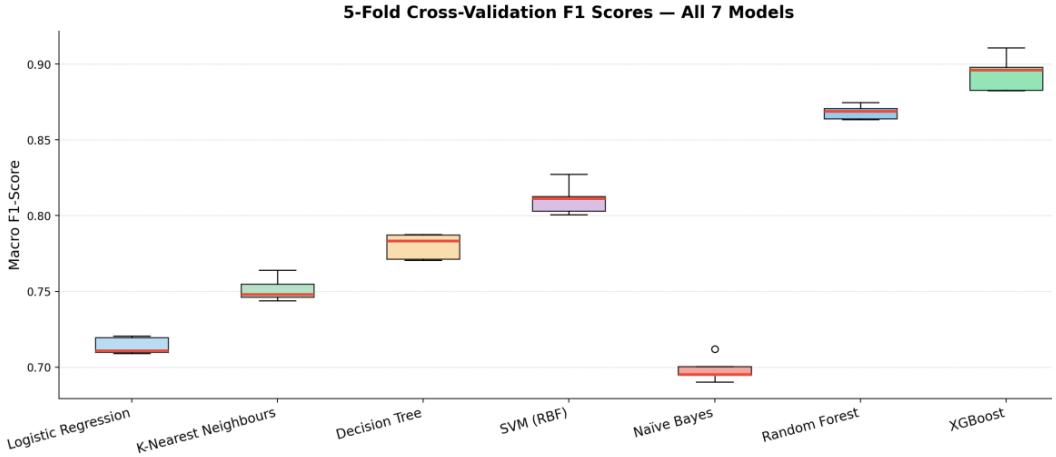

Figure 6. shows the distribution of the F1-scores of the seven classifiers in 5-fold cross validation. The boxes represent the distribution over the five training folds, the median (50%) value is indicated by the horizontal line and the whiskers indicate the range of folds observed. The average of F1-scores reported is 0.891 for XG Boost and 0.873 for Random Forest. The summaries of the folds are descriptive and do not attempt to establish statistical significance.

Limitations:

Several caveats need to be pointed out. First, it is a synthetic dataset; the original documentation of the data does not give sufficient information about the generative mechanism to ensure that the simulated relationships reflect real student populations. Second, the study is cross-sectional, meaning that it cannot prove the temporal order or cause-and-effect relationships. Third, making the burnout_ score into three fixed intervals results in artificial class boundaries and can lead to misclassification of observations at these boundaries. Fourth, the socioeconomic factors, family pressures, mental health histories prior to the study, and other potentially relevant contextual variables are not included in the dataset. Fifth, the study lacked an independent validation sample of real students and did not have clinical validation of the burnout labels. Sixth, the supplied manuscript does not contain the raw paired predictions required for a formal statistical significance test between competing models. These limitations constrain generalizability and mean that the reported performance should be interpreted as benchmark evidence only.

Conclusion

This study developed a seven-model machine-learning classification framework for analyzing student burnout categories in relation to AI dependency, career anxiety and well-being indicators using 15,000 synthetic student records. XG Boost achieved the highest reported benchmark accuracy (89.2%) and AUC-ROC (0.95), and stress level, AI dependency, sleep hours, daily AI usage and placement anxiety were among the higher-ranked variables in the fitted model. The findings are statistical associations and model-based importance in a synthetic, cross-sectional dataset and are not an indicator of clinical validity or real-world performance of early detection. The primary contribution is a repeatable benchmarking framework which can be validated by external agents. Future research is to be based on authentic longitudinal student data, validated burnout measure, leakage-controlled modelling, formal statistical comparisons, calibration, fairness assessment, and human-in-the-loop governance.

Ethical Considerations:

The use of machine-learning models to estimate student burnout risk carries substantial ethical responsibility. Data minimization and privacy should be applied to any future real-student implementation, with compliance with applicable data-protection

requirements. Informed consent and institutional ethics approval would be required for newly collected student data. Risk of labelling and stigma should be addressed by ensuring that model outputs are supportive rather than punitive or exclusionary. Fairness audits should examine performance across demographic and institutional groups, and bias-mitigation methods should be considered where appropriate. Most importantly, automated predictions should not be treated as diagnoses or used as the sole basis for academic or disciplinary action; qualified counsellors or other authorized professionals should review any real-world use.

Future Work:

Future work should validate the framework on prospectively collected real-student data using validated academic-burnout instruments and appropriate institutional ethics approval. A longitudinal design across several semesters would allow assessment of changes in burnout risk over time and would support more appropriate temporal models such as LSTM or transformer architectures. Future experiments should also use nested or repeated cross-validation, independent external test cohorts, probability calibration, subgroup fairness analysis and paired statistical comparisons of model performance. Additional variables such as sleep quality, academic workload, social support and validated measures of AI-use behavior could be incorporated. Any eventual decision-support system should remain human-in-the-loop, use transparent uncertainty estimates and be evaluated for potential stigma, bias and unintended consequences before deployment.

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