AI-BASED EARLY DETECTION OF ACADEMIC STRESS AND BURNOUT AMONG UNIVERSITY STUDENTS: A REVIEW

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Abstract

Academic stress is an important issue in higher education and can occur as a result of the workload, examinations, deadlines, competition, financial problems, uncertainty, and adjustment to university life. If stress persists, it can lead to exhaustion, disengagement, decreasing effectiveness in studies, and burnout. The research proposal to which this review is based on states the necessity to develop scalable and ethical ways of detecting students with academic stress who risk moving to serious distress or burnout. In this research paper, AI and ML are proposed to be used for early detection of the risk. The review analyzes the recent evidence on academic stress and the burnout of students based on AI/ML detection and prevention technologies with special attention to the data sources, ML methods, multimodality, wearables, explanations and validation, privacy, ethical issues, and human oversight. The provided literature map shows the most common limitations including cross-sectional design, survey dependence, small or one-discipline samples, limited external validation, as well as the lack of reasoned connection between prediction and intervention. The study suggests that future investigations ought to progress from static categorization towards longitudinal forecasting through employment of academic, behavioral, psychological, digital-engagement, and, where ethical considerations permit, biological input. A responsible early warning system is expected to provide valid results, with temporal and external validation, internal calibration, subgroup fairness assessment, interpretable output, as well as ensuring privacy of personal information being processed. The paper wraps up the investigations with the provision of a concept research framework suitable for the higher education context and in line with the proposed contribution to students' welfare and quality education.

Keywords: academic stress; student burnout; artificial intelligence; machine learning; multimodal learning analytics; wearable AI; explainable AI; early warning systems; higher education; responsible AI.

1. Introduction

Academic stress is a multidimensional phenomenon affecting students across higher-education settings. The research template identifies workload, examinations, deadlines, competition, financial concerns, uncertainty and adjustment to university life as important sources of academic stress. Persistent stress may be accompanied by exhaustion, disengagement and declining academic functioning. Conventional screening is commonly questionnaire-based and often provides an episodic view of student well-being. The proposed research therefore explores whether AI/ML can combine heterogeneous indicators and provide earlier identification of changing risk.

The problem of the research is not just limited to classifying students as either stressed or not stressed. The primary goal of the institution is to find out certain patterns that signify a growing risk and channel that information into some type of support. The author of the supporting proposal outlines the system based on AI and including academic, behavioral, psychological, digital learning data and giving out certain risk levels and alerts. It also

proposes a scalable system that can be implemented across higher-education institutions and linked to SDG 3 and SDG 4.

An important methodological distinction is required between prediction and diagnosis. AI models identify statistical patterns associated with an outcome; they do not independently establish a psychological diagnosis or determine the cause of a student's difficulties. A responsible system should therefore function as decision support, with human review and clear safeguards against punitive or inappropriate use.

2. Review Scope and Method

The supplied review plan proposes a 2015–2026 publication window and includes university/college undergraduate and postgraduate populations; academic stress, psychological stress, student burnout, exhaustion and closely related distress outcomes; and AI, ML, deep learning, predictive analytics or multimodal computational approaches. Empirical peer-reviewed journal and conference studies with measurable model outputs, predictors/features or evaluation metrics are included. Conceptual papers, editorials, unrelated AI-for-tutoring studies, duplicates and studies without sufficient methodological information are excluded. The planned databases are PubMed/MEDLINE, Scopus, Web of Science, IEEE Xplore, ScienceDirect and SpringerLink.

The supplied research template contains a 20-study evidence map from 2024–2026 and identifies repeated research gaps. For this six-page paper, these studies are synthesized thematically rather than presented as an exhaustive systematic review. The paper should therefore be considered a structured narrative review unless a complete reproducible database search, deduplication, screening and formal risk-of-bias process is subsequently completed.

3. Evidence from Recent Literature

The evidence base demonstrates increasing use of machine learning for student stress and burnout. A 2024 systematic review of ML models for depression, anxiety and stress among undergraduate students identified 48 studies. The review reported that many studies achieved apparently strong accuracy, but 47 of the 48 studies relied only on internal validation and the certainty of evidence was rated very low. This discovery has an important value in the field which is that high internal accuracy doesn't necessarily mean that reliable performance can be achieved from new students or institutions. Wearable AI is another technologically advancing direction [1]. A 2024 systematic review and meta-analysis on stress detection using wearables among students indicated a pooled mean accuracy of 85.6 percent, and the pooled sensitivity and specificity of about 75 percent. Performance benchmarks were different for different stress types, wearable types and placement, dataset size, and the method of obtaining ground truth.

The evidence map made available with the proposal specifies more recent studies on explainable decision trees, undergrad computing students' burnout, psychology students' burnout profiles, psychometric predictions, student interaction logs, multisource stress detection, and wearable monitoring. The limitations common to nearly all these studies include the size and scope of the populations studied, cross-sectional studies, survey-based evidence, limited longitudinal evidence and lack of external validation and incomplete translation from prediction to practice.

Recent research in explainable-ML shows the merit of combining prediction with explanation. Liu and Yu, for example, in the 2026 study, apply an enhanced decision tree method along with SHAP analysis of the most significant characteristics. Illustrating the model outputs to the stakeholders of the organization is valuable but one should remember that explainability should not be mistaken for validity [2].

4. Data Sources and Multimodal Detection

4.1 Psychological and Self-Report Data

Validated questionnaires remain important because they directly measure perceived stress, exhaustion, coping and related constructs. Their limitations include response burden, recall effects, social desirability and limited temporal resolution. The appropriate role of self-report is therefore as a validated outcome or complementary modality rather than something to be completely replaced [3].

4.2 Academic and Administrative Data

The educational record can provide indicators of academic performance, attendance, course load, turning in work and academic progress. This information may already exist and can be scaled. However, it is indirect. For example, changes in attendance or performance may not necessarily be rooted in psychological stress. Therefore, it is important for models to avoid interpreting any indication of academic behavior as sufficient evidence for the existence of burnout [4].

4.3 LMS and Digital-Engagement Data

Learning management systems can provide data such as how often learners log on, what resources are used, assignment submissions, attempts to take quizzes, participation in discussions, and how engagement changes over time. Interaction logs can be helpful for early warning, but behavior in the digital world is highly contextual. Constant monitoring may also raise privacy issues that make the need for purpose specification, data limitations, and governance very important[6].

4.4 Wearable and Physiological Data

Data from learning-management-system includes different metrics such as login frequency, resource access, assignment submissions, and general interactions[5]. Although interaction logs can support early warning, group processing is highly contextualized. Data gathering could become an issue considering certain limitations, its minimization and governance.

4.5 Multimodal Fusion

Learning-management-system data provide information regarding log-ins, resource accesses, assignment submission s, quiz attempts, participation within discussions, and engagement. Although interaction logs can help to flag early warnings, digital behavior is contextual. Continuous monitoring may also arise concerns regarding surveillance. Hence, purpose limitation, data minimization, and governance are needed [7-10].

5. AI/ML Techniques for Stress and Burnout Prediction

Nowhere does the literature identify one clearly superior algorithm. However, logistic regression is an interpretable baseline, while decision trees create auditable rules but are likely to overfit. Random forests are known to model nonlinear interactions. In addition, support vector machines (SVM) are well-suited for problems in medium-dimensional datasets. Gradient-boosting methods, for instance, XGBoost, are effective when modeling complex relationships. Neural networks and deep learning models can be applied in the context of larger, sequential or multimodal datasets; however, they have higher data and validation requirements.

In the proposed early warning application the need for temporal modeling arises. The system should implement monitoring rather than predicting a specific label for a specific time or event. It is better to split observations on the level of students and deadlines rather than making random splits in the events sample.

Class imbalance is crucial because really high-risk students may represent a small minority. Hence, accuracy could give misleading results. There is a need to report precision, recall, f1-score, roc and auc scores, calibration, and confusion matrices. The alert thresholds have to be assessed in connection with the institutional capacity to intervene because too many false alerts would overload the counselors and make them lose their trust.

6. Explainability, Validation and Responsible AI

The suggested framework incorporates the idea of explainability through the means of SHAP, LIME or feature-importance methods and indicates that there should be a mechanism of human review in place. This is necessary because faculty and counselors require an understanding of how the alert has been generated. The explanations should point out the factors showing changes in the observable features but should not be interpreted as proof or diagnosis of causation. Therefore case-based explanations must be given in terms of the indices that need to be verified rather than judgements on the motivation or mental status of the student in question.

Validation appears to be the most serious deficiency in terms of the current body of evidence. Internal cross-validation should be complemented with student-level holdout, time validation as well as, whenever possible, external validation performed on a different cohort, programme or institution. The generalizability should also be checked for appropriate student subgroups and academic contexts.

The principles of responsible AI must be integrated into the design process. Data on student welfare can be highly sensitive when information about academic performance is provided together with psychological and physiological data. Application of techniques such as data reduction, pseudonymization and de-identification where applicable, use of encryption, role-based access, audits, limits on data retention period and provision of informed consent should be planned. The system must also serve a specific purpose. There should be no shift from student support to student surveillance and punishment. Student support systems should keep human involvement on different levels. It is necessary to look at risk levels as triage mechanisms rather than diagnoses. Any alerts should be examined by qualified staff in order to view relevant context and decide on the possibility of further action. Solutions related to the system should be available to students and used only by authorized people with knowledge of retention period and possible consequences of alerts.

7. Research Gaps and Proposed Framework

Table 1: Table explains the research gap in all frameworks.

Research gap	Evidence pattern	Proposed response

Longitudinal evidence	Many studies are cross-sectional.	Repeated measurements and temporal prediction across semesters.
External validation	Internal validation dominates.	Temporal, cohort and multi-institution validation.
Multimodal integration	Studies often rely on one or two modalities.	Combine academic, behavioral, psychological and optional physiological data.
Outcome definition	Stress, anxiety, depression and burnout can be conflated.	Use clearly defined constructs and validated student measures.
Explainability	Interpretability is still uneven.	Use case- and model-level explanations with human review.
Intervention evidence	Prediction is rarely connected to measured support outcomes.	Evaluate referral, support uptake, alert burden and student outcomes.
Privacy/fairness	Continuous monitoring creates surveillance and bias risks.	Privacy-by-design, consent, subgroup evaluation and governance.

A working architecture can then be divided into six layers: (1) collecting data from validated questionnaires, academic information systems, LMS and optional wearables; (2) ensuring quality and privacy of the data; (3) conducting comparative predictive modeling; (4) performing explainability, calibration and fairness analysis; (5) achieving human-in-the-loop intervention; (6) evaluating results obtained. The results received should be an early warning signal and suggested support pathway rather than an automated diagnosis.

Thus, the novelty of the proposed solution can be seen through the lens of the research: proactive identification of problems before stress develops into burnout or academic failure; inclusion of different student data dimensions; combination of AI, educational analytics and mental health assessment; performing immediate or repeated early warning; the solution is scalable across the institution; reduction of institution's exposure to SDG 3 and SDG 4.

8. Discussion

The assessment of existing materials confirms the viability of students' stress and burnout prediction through the usage of AI, but the analyses show that the area is still in the process of moving from testing to the effective operating models. Therefore, the key contributions in the future are unlikely to be achieved through achieving only slightly better accuracy. Rather, research will prove its worth if it shows that predictions hold true over time and cohorts, explanations are useful for people making decisions, and alerts can be used for the provision of support in an ethical way without any unnecessary monitoring of people or false sense of safety. In the context of India, a dataset that could be constructed based on the longitudinal data of the institution may be significant if it encompasses a variety of academic programs and cohorts. Despite the strengths the institution's specificity can give, it still should be treated as both an advantage and a disadvantage, which means that the model trained in one

university may learn local patterns that are not transferable. In this case, external validation should be included in the research process from the very beginning of conducting studies.

This study must differentiate predictive correlation from causation. The correlation of sleep, emotional support, attendance, or school performance to increased predicted risk does not validate the causal nature of the correlation between the predictor and burnout. Therefore, any recommendations regarding interventions must be grounded in existing knowledge regarding student support methods and verified through empirical research.

9. Limitations of the Review

This document provides a structured narrative review and is primarily based on the provided research plan and research proposal and validated literature and authoritative guidance. It is not a comprehensive PRISMA systematic review and does not guarantee coverage of all publications in the period 2015-2026. Some studies in the evidence map utilized for the paper are included as part of the research background without the full-text verification in the current shortened version of the article. Prior to submission to the journal, a repeatable search of the database, duplicate removal,, risk of bias determination, and final references verification has to be done.

10. Conclusion

The use of AI/ML techniques for early identification of stress and burnout in students is a promising area for research in higher education. Previous studies show that academic, behavioral, psychological, digital, and physiological indicators could hold predictive information, while newer research papers pay more attention to explainable models. However, evidence of effectiveness is still limited due to such factors as lack of validation, cross-sectional method, small and biased samples, a variety of definitions of stress and burnout in different studies, and the absence of proof that useful predictions lead to improved outcomes.

The current approach can solve these issues with the construction of a longitudinal, explainable, multimodal framework that respects the privacy of students and has human oversight. The primary goal should be responsible risk assessment, not diagnosis, and measures of effectiveness should include not only accuracy, but also measures such as recall, F1, AUC, calibration, temporal and external validation, fairness, and operational workload. Finally, the system should be deemed effective provided it can provide timely assistance without violating the autonomy and privacy of a student.

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