Psychological Distress Among the Faculty and Students in Higher Education: A Review

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Abstract: Psychological issues, which is a broader term that comprises of large spectrum of conditions like anxiety disorders, clinical depression, chronic stress, emotional disturbances and many other post-traumatic disorders, which overall affect the interpersonal relationships and hence the overall quality of life of the person. as per the records of world Health Organization comma mental health conditions and diseases are responsible for including the overall burden of global diseases with depression alone recognized as one of the leading causes of disability worldwide. This study aims in conducting the critical Analysis of the previously existing Literature.

Keywords: Mental Health, Psychological Distress, Post-traumatic disorders

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Introduction

Despite of having advanced diagnostic and clinical psychology, a substantial proportion of individuals remain undetected and untreated as the notion persists that owing to these diseases, will bring social Stigma and Societal pressure. Due to which the conditions get severe, and sometimes it results in suicides, which further becomes a stigma for Society and the nation. To counter the adverse effects of psychological distress, these should be timely addressed to create a society with healthy and happy-minded people who can uplift the overall environment across the globe(Pachouly et al., 2021). Within the broader aspect, Universities, which are treated as the temples of Learning and are the academic Institutions responsible for providing intellect and intelligentsia to society, are nowadays affected by this serious problem of psychological issues. The two important pillars of Universities are Students and Faculty, and if both suffer from mental health issues, then it will affect the overall intellectual advancement, professional formation and societal development and hence will impose the burden on the society(Singh & Kumar, 2022). Both the students and Faculty members are exposed to comprehensive mental efforts, performance-oriented environments, and the persistent expectations of productivity and excellence which are the triggers of creating a strong mental pressure on them.

University students, especially those enrolled in graduation, post-graduation, and doctoral programs, frequently experience high levels of stress due to heightened academic pressure, financial precarity, uncertain prospects, social isolation, the navigation of formative developmental transitions to adulthood, marriage pressures, and more. Earlier research significantly revealed that although the stress and depressive disorders are comparatively higher among university-level students if compared to the age-matched cohorts outside the University, yet formal help and assistance provided to them is alarmingly low. Faculty, known to be the architects of destiny of young minds and responsible for shaping their future and empower them with successful careers are also subject to be the victims of this dreadful disease. There is a constellation of stressors and very high expectations, which include heavy teaching loads, lots of administrative obligations, the constant pressures of University ranking-related chores, research funding, publications, student supervision responsibilities, and the increasingly hilarious nature of academic employment. Apart from this, senior academicians have to contend with the institutional governance demands, peer evaluation and the overall psychological toll of sustained mentorship responsibilities(Mandal et al., 2023).

These adverse consequences of untreated and undetected communities, including Faculty and students, need to be addressed with utmost priority. The constant mental health problems, in students can cause many adverse effects including academic underperformance, elevated drop out rates, impaired research productivity and prolonged occupational disengagement. In case of faculty burnout, and psychological distress contributes to the declined teaching quality, reduced Scholarly output, and increased absenteeism, significant institutional attrition, thereby reducing the overall capacity of the institutions to fulfil their core educational and research missions.

In modern technological era, higher educational institutions are under high mounted pressure to provide the expected outcomes, improve retention, and produce globally competitive Research. Taking care of the psychological distress of academic communities must be the utmost priority of the organization, and the preventive steps should be taken early before the conditions get worsened . The society across the globe therefore, demands the development and deployment of intelligent, scalable, and non-intrusive methods capable of detecting early warning signs of psychological deteriorations, especially when the population avoids the clinical and medical interventions. At this point, the Artificial Intelligence will play its prominent role to create a strong mechanism to address this grave issue. Machine learning Algorithms, Deep learning algorithms, Computational neurosciences and cognitive Sciences can further offer the remarkable methods to deal with the mental health problems. In this research, the Explainable Artificial Intelligence (XAI) along with the computational neurosciences will offer a transformative potential to detect the early warning signs of psychological disorders. The amalgamation of Explainable AI(XAI), Deep Learning and neurologically informed cognitive modelling will enable the analysis of complex, higher dimensional psychological and behavioral data to identify the strong patterns to predict the psychological distress(Tahan & Saleem, 2023).

Explainability, in particular, has assumed the critical importance in health sensitive applications of Artificial Intelligence, as it ensures that the predictive outputs will be confirmed and further interpretable by clinicians, administrators and end users thereby facilitating transparent results rather than providing the Black box or Opaque algorithms of decision making. The present research responds directly to the opportunity of proposing a Neuro-Cognitive Explainable AI model to facilitate the early prediction of psychological issues among the University students and Faculty.

Related work

The prominent existing Literature has been segregated and critically analyzed, the latest and highly relevant papers from high impact factor Journals have been included in this critical and comparative Analysis

Table 1. Compares this work with the related work or previous research by other researchers

Paper / Context	Data & Population	Model & “Neuro-Cognitive / Feature” Design	Explainability Methods	Strengths	Key Limitations	Citations
Language-based XAI for mental disorders [social media] (Kerz et al., 2023)	Social-media text, 5 disorders (ADHD, anxiety, bipolar, depression, stress)	BiLSTM with rich **human-interpretable linguistic features** vs transformer PLM; multi-task fusion with emotion + personality	LIME, AGRAD; feature ablation to identify most predictive linguistic groups	Strong XAI focus; balances accuracy vs interpretability; links linguistic patterns to specific disorders	Not student/faculty-specific; uses social media (shift from campus context); no neuro/physiology	(Kerz et al., 2023)
Stress prediction in university students (COVID-19) (Ratul et al., 2023)	444 students, perceived psychological/social stress (survey)	Classic ML (MLP best, 80.5% acc) + PCA, chi-square, GA/GSCV for HPO	No model-level XAI; only feature reduction	Systematic ML pipeline; distinguishes psycho vs social stress	Convenience sampling, self-report only, no external validation, limited generalizability; no interpretability for practitioners	(Ratul et al., 2023)
TaBERT dual-attention for academic mental health [students] (Yuan et al., 2026)	Academic mental health with contextual, psychological, personal, social tabular features	Transformer (TaBERT) with dual attention + memorization; 96% acc	LIME, SHAP; feature ranking (info gain, entropy); stats tests	Strong, integrated XAI; interpretable feature contributions in **academic environment**	No faculty; no neuro data; likely cross-sectional; causal directions not established	(Yuan et al., 2026)
Workplace mental health prediction (employees) (Mokheleli et al., 2025)	OSMI workplace survey 2016–2023	RF, XGBoost, SVM, AdaBoost; SMOTE for imbalance	SHAP (global), LIME (local)	Mature use of SHAP/LIME; identifies key factors like prior disorder, treatment-seeking	Workforce, not students; relies on self-report; no temporal/causal analysis	(Mokheleli et al., 2025)

Paper / Context	Data & Population	Model & "Neuro-Cognitive / Feature" Design	Explainability Methods	Strengths	Key Limitations	Citations
Annual student health survey, Japan (Baba & Bunji, 2022)	3561 undergrads, 2 years, campus-life items + response time	LightGBM predicting current and **next-year** mental problems; SHAP for feature impact	SHAP for top predictors (campus-life anxiety questions)	Early **longitudinal prediction**; shows survey + demographics + behavior effective	Single university during COVID; survey items not standard; answering time adds little; no deep neuro-cognitive modeling	(Baba & Bunji, 2022)
HyOPTEnsemble – XAI for student mental state [no abstract] (Ahmed et al., 2026)	University students	Soft-voting ensemble with hyperparameter optimization, XAI	Not described (abstract missing)	Likely relevant to XAI for students	Cannot assess methods or quality without abstract/text	(Ahmed et al., 2026)
Bangladesh students: depression, anxiety, stress (Hasan et al., 2025)	1697 students (2 universities), DASS-21	7 ML models; SVM/LR/CatBoost best; feature importance	Feature importance for factors like faculty, family relation	Combines epidemiology + ML; large sample	No fine-grained XAI (e.g., SHAP/LIME); cross-sectional	(Hasan et al., 2025)
EEG CNN-LSTM for depression (Ay et al., 2019)	EEG from depressed vs healthy; hemispheric signals	CNN+LSTM deep hybrid; 97–99% accuracy	No XAI; neuro-cognitive via brain signals	Strong "neuro-cognitive" signal-level modeling; objective biomarker	Small clinical sample; black-box DL; not students/faculty; not early prediction	(Ay et al., 2019)
Cross-attention transformer for student mental	Time-varying student emotional / risk data	FT-Transformer + LSTM with Cross-Attention Attribution Layer;	Intrinsic interpretability via attribution layer;	Joint temporal + feature-level explanations; strong	Population & measures not fully specified; no multi-site validation	(Jiang, 2026)

Paper / Context	Data & Population	Model & "Neuro-Cognitive / Feature" Design	Explainability Methods	Strengths	Key Limitations	Citations
health (Jiang, 2026)		entropy-based features	global feature importance	accuracy (95%)		

Overall, existing work shows that (1) survey-based ML can meaningfully predict student mental health risk, (2) EEG-based deep models provide powerful neuro-cognitive signals, and (3) SHAP/LIME plus attention mechanisms offer practical explainability. However, datasets are usually limited to single student populations, rarely longitudinal, and never include faculty. A rigorous "neuro-cognitive XAI" model for early prediction should therefore: combine objective neuro/behavioral features with rich self-report, integrate intrinsic and post-hoc XAI carefully (mindful of SHAP/LIME limitations), and be validated prospectively across multiple institutions and both students and faculty.

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