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Artificial Intelligence-Assisted Prediction of Academic Performance Based on Procrastination, Stress, and Anxiety Among University Students

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Abstract: *The escalating prevalence of mental health challenges among university students, coupled with the rapid integration of artificial intelligence (AI) into educational environments, has created both opportunities and imperatives for predictive analytics in higher education. This paper examines the application of AI-assisted techniques for predicting academic performance based on psychological factors—specifically procrastination, stress, and anxiety—among university students. Drawing on empirical studies from multiple institutional and cultural contexts, the analysis synthesizes findings on machine learning (ML) and deep learning approaches that integrate psychosocial indicators with academic and behavioral data. The evidence demonstrates that AI-driven models incorporating psychological assessments achieve predictive accuracies exceeding 83%, with anxiety indicators consistently emerging as the most influential predictors of academic outcomes . Procrastination, affecting over 80% of undergraduates, exhibits significant associations with both anxiety symptom development and academic performance deterioration . Emerging research further reveals that AI-related anxiety itself predicts academic procrastination behavior, creating a complex feedback loop between technological apprehension and academic delay . The findings suggest that early interventions targeting both academic and psychological factors are critical for improving student well-being and academic success . This paper concludes that AI-assisted predictive systems, when developed with attention to interpretability, fairness, and ethical implementation, offer substantial potential for proactive student support in increasingly digitally-mediated higher education environments.*

Keywords: Artificial Intelligence, Academic Performance Prediction, Procrastination, Anxiety, Stress, Machine Learning, Higher Education, Student Mental Health

I. INTRODUCTION

University life represents a period of significant transition and challenge, characterized by academic demands, personal relationship navigation, and the pursuit of future career security. Recent studies highlight a concerning trend: student mental health is deteriorating globally, with over 60% of college students meeting criteria for at least one mental health problem . During the 2021–2022 academic year, a survey across 133 college campuses revealed 44% of students experienced symptoms of depression, and 15% had seriously considered suicide . These psychological challenges—particularly anxiety, stress, and their behavioral manifestation as academic procrastination—have profound implications for academic performance and overall student wellbeing.

Simultaneously, the integration of Artificial Intelligence (AI) into higher education has accelerated dramatically. AI-powered learning management systems, automated assessment tools, and generative AI applications now mediate significant aspects of the student experience. This technological transformation has created new opportunities for predictive analytics that can identify at-risk students and enable timely interventions. However, it has also introduced novel anxieties—as students grapple with concerns about AI replacing human judgment, displacing labour markets, and fundamentally altering the nature of academic work .

The convergence of these trends—rising mental health challenges and advancing AI capabilities—positions AI-assisted prediction of academic performance based on psychological factors as both a promising frontier and a domain requiring careful ethical consideration. This paper examines the current state of research on AI-assisted prediction of academic performance incorporating procrastination, stress, and anxiety among university students. It synthesizes findings across multiple cultural contexts, evaluates the efficacy of various machine learning approaches, and discusses the implications for educational practice and policy.

II. LITERATURE REVIEW

2.1 Theoretical Foundations

The prediction of academic performance through AI technologies draws on established theoretical frameworks in educational psychology and learning analytics. Social Cognitive Theory (SCT), as developed by Bandura, posits that human behavior results from dynamic interactions between personal, environmental, and behavioral factors . This framework is particularly relevant for understanding academic procrastination and its relationship to psychological distress. Within SCT, self-regulation emerges as a central mechanism: students who struggle with self-regulation may delay academic tasks, experience increased anxiety, and subsequently perform poorly—creating a cycle that reinforces itself through reciprocal determinism .

The integration of psychological factors into predictive models is grounded in the recognition that academic performance is not solely determined by cognitive ability or study habits. Emotional states, stress levels, and personality traits significantly shape engagement behaviors and learning outcomes. Recent research on GPA prediction has demonstrated that psychological assessment data, including depression, hostility, and interpersonal sensitivity indicators, can be effectively integrated with course scores to improve predictive accuracy .

2.2 Prevalence and Impact of Procrastination, Stress, and Anxiety

Academic procrastination is a widespread phenomenon among university students. Over 80% of undergraduates report experiencing some form of procrastination, often driven by excessive social media use, stress, and poor time management . Procrastination is not merely a time management issue but is associated with significant psychological consequences, including increased stress, anxiety, and even long-term health risks such as hypertension .

The relationship between procrastination and anxiety is bidirectional and self-reinforcing. Empirical research has demonstrated that academic procrastination mediates anxiety symptom development, with procrastinatory behaviors predicting increased anxiety over time . Students who consistently delay academic tasks experience heightened stress as deadlines approach, leading to diminished performance quality and further anxiety about their academic standing.

Stress and anxiety directly impair cognitive functions essential for academic success. Working memory, attention, and executive function—all critical for learning and examination performance—are compromised under conditions of chronic stress. The prevalence of mental health challenges has reached levels that demand institutional response, yet traditional support mechanisms are often hampered by limited mental health resources, stigma surrounding mental health discussions, and time constraints on students' schedules . This has created space for technological solutions that can complement traditional support systems.

2.3 AI and Machine Learning in Educational Contexts

The application of AI to educational prediction has advanced rapidly, encompassing diverse methodological approaches. Supervised machine learning classifiers—including Logistic Regression, Support Vector Machines, Random Forest, XGBoost, and Neural Networks—have been extensively applied to classify pass–fail outcomes, multi-level grade categories, or continuous performance measures with encouraging levels of predictive accuracy .

Recent research has increasingly emphasized the importance of integrating multiple data dimensions for accurate prediction. The Academic Multi-Factor Prediction Net (AMP-Net), a comprehensive deep learning framework, incorporates historic grades, classroom engagement, socio-economic classification, and sentiment derived from students' digital footprints. This framework achieved a reliability of 0.87 and an accuracy of 0.85 for academic features, with engagement data showing a scalability of 0.78 and socio-economic inputs contributing an AUC-ROC of 0.87 .

Comparative research in smart learning environments indicates that ensemble approaches can enhance predictive robustness. Studies demonstrate that XGBoost and stacking-based architectures often outperform traditional classifiers in predictive accuracy and stability, while also emphasizing the importance of rigorous preprocessing, feature selection, and validation strategies .

2.4 AI-Assisted Prediction Incorporating Psychological Factors

A significant body of research now demonstrates that incorporating psychological factors substantially improves predictive accuracy beyond models relying solely on academic metrics. A study from Henan University of Science and Technology tracked 229 students, integrating SCL-90 psychological assessment data (collected in freshman year) with professional basic course scores to build classification models for GPA prediction. The study achieved an accuracy rate of 83.64% and revealed that anxiety indicators had the greatest impact on academic performance, followed by interpersonal sensitivity. Notably, for predicting junior-year GPAs, psychological factors played a more significant role than they did for predicting sophomore GPAs, suggesting that psychological effects compound over time .

Research from Jordanian universities employing Large Language Models (LLMs) for categorization, combined with multiple classifiers, achieved high accuracy in classifying students into categories including academic difficulties, psychological challenges, both, or normal status. The study found that psychological factors such as anxiety levels and daily sleep duration, along with academic factors such as GPA and study hours, interact to heighten negative effects. Early interventions targeting both dimensions were identified as critical for improving student well-being and academic success .

A human-centered approach to academic performance prediction in Pakistan's Air University employed the SAPEx-D dataset (494 records) and found that incorporating personality factors elevated predictive accuracy from an R-squared of 0.63 to 0.83. The study applied SHapley Additive Explanations (SHAP) to interpret how personality traits interact with other factors, underscoring their role in shaping academic outcomes. For letter grade classification, personality factor incorporation improved accuracy to 0.67 for distinct classes and 0.85 for broader categories .

In the Lesotho context, research integrating LMS behavioral traces with psychosocial variables from 850 undergraduates found that digital self-efficacy, perceived feedback usefulness, and discussion engagement were dominant predictors across models. Logistic Regression achieved the highest accuracy (0.714), while Random Forest demonstrated the strongest discrimination (AUC = 0.774) with a favorable balance of classification errors, supporting its suitability for early identification of at-risk learners .

2.5 Procrastination, AI Anxiety, and Academic Performance

Emerging research has identified a novel dimension of psychological stress affecting student performance: AI-related anxiety. A study conducted at Sakarya University in Turkey with 262 students examined the relationship between artificial intelligence anxiety and academic procrastination behavior. The results showed that AI anxiety significantly and positively predicted academic procrastination behavior both generally and at the sub-dimension level. In particular, learning anxiety and fear of loss of control emerged as the strongest predictors of academic procrastination .

This finding has significant implications for AI-assisted prediction systems. Students experiencing AI anxiety—concerns about AI technologies replacing human capabilities, disrupting academic integrity, or altering assessment practices—may be more likely to delay academic tasks, creating a feedback loop that further undermines performance. Conversely, students with positive attitudes toward technology and greater perceived ease of use may be more likely to use generative AI tools as academic aids, potentially alleviating workload pressure .

Research by Bailey et al. (2026) examining predictors and outcomes of GenAI use among psychology students (N=164) found that positive attitudes toward technology, greater perceived ease of use, greater workload, and less time pressure predicted greater use of GenAI. Notably, greater use of GenAI was associated with greater procrastination and memory difficulties but did not correlate with assessment grades. This suggests that GenAI may be used as a tool to alleviate academic workload demands, with unclear implications for authentic learning .

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2.6 Explainability, Fairness, and Ethical Considerations

As AI-assisted prediction systems become more prevalent in educational settings, issues of interpretability and fairness have gained prominence. Black-box ensemble and deep learning architectures may achieve high discrimination accuracy yet obscure the logic underlying predictions. In educational contexts, where algorithmic outputs may influence feedback, formative assessment practices, and academic support decisions, opacity poses practical and ethical concerns .

Fairness considerations are particularly critical in low-resource or digitally constrained environments, where differences in internet reliability, device access, data affordability, and digital literacy may influence both LMS activity and predictive outputs. Predictive systems risk conflating infrastructural limitations with academic preparedness, potentially reproducing or amplifying existing disparities . Fairness-aware modeling must extend beyond statistical parity diagnostics to examine real-time implementation through early-warning dashboards and adaptive feedback.

Explainable AI (XAI) techniques such as SHAP-based and permutation-based importance methods provide mechanisms for clarifying how behavioral and psychosocial features influence classification outcomes. Embedding such diagnostics within comparative modelling frameworks strengthens interpretability and institutional trust, especially in environments where digital inequities may interact with predictive systems .

III. CONTRIBUTION OF AI-ASSISTED PREDICTION TO ACADEMIC PERFORMANCE

3.1 Quantifying Predictive Performance

The empirical evidence demonstrates that AI-assisted prediction incorporating psychological factors achieves substantial improvements over models using academic data alone. The Henan University study's achievement of 83.64% accuracy in predicting future GPA demonstrates the feasibility of integrating psychological assessments into predictive frameworks . This improvement is particularly notable for longer-term predictions, where psychological factors become increasingly influential.

The AMP-Net framework's multidimensional integration of academic, engagement, socio-economic, and sentiment data achieved a reliability of 0.87 and accuracy of 0.85 for academic features . This suggests that deep learning approaches can effectively capture complex, non-linear relationships across heterogeneous data streams, enhancing predictive accuracy beyond traditional machine learning methods.

Table 1 summarizes key predictive models and their performance characteristics across studies.

Comparative Performance of AI-Assisted Prediction Models Incorporating Psychological Factors

Study Context	Sample Size	Model(s)	Key Psychological Predictors	Performance Metric	Result
Henan University, China	229	SVM, XGBoost, CART, CNN-CBAM	Anxiety, Depression, Hostility, Interpersonal Sensitivity	Accuracy	83.64%
Air University, Pakistan	494	Gradient Boosting, KNN, SVR	Personality Factors (Big Five)	R-squared	0.83 (with personality) vs. 0.63 (baseline)
Jordanian Universities	1020	Multiple Classifiers + LLM Categorization	Anxiety, Sleep Duration, Study Hours	High accuracy across classifiers	Effective for early intervention

Study Context	Sample Size	Model(s)	Key Psychological Predictors	Performance Metric	Result
National University of Lesotho	850	Logistic Regression, Random Forest, XGBoost, SVM, Neural Networks	Digital Self-Efficacy, AI Ethics Awareness, Trust in AI	Accuracy / AUC	0.714 / 0.774 (Random Forest)
Multidimensional Framework	Educational Dataset	AMP-Net (Deep Learning)	Sentiment from Digital Footprints	Accuracy / Reliability	0.85 / 0.87

3.2 Addressing Systemic Challenges

AI-assisted prediction systems contribute to academic performance monitoring by addressing several systemic challenges facing higher education.

Early Identification of At-Risk Students: Traditional approaches to identifying struggling students often rely on mid-term grades or instructor observation, which may occur too late for effective intervention. AI systems can identify predictive patterns earlier, enabling proactive support. The LLM-based categorization framework from Jordan demonstrates how early categorization of students into challenge categories enables timely consultation and service delivery .

Understanding Complex Interactions: Psychological factors do not operate in isolation but interact with academic and environmental factors. Research shows that "these phenomena may have related influences on each other and along with such interactions may heighten negative effects" . AI systems are uniquely suited to capturing these complex, non-linear interactions.

Scalability: Digital mental health interventions and AI-assisted monitoring can reach students who might otherwise not access support due to limited resources, stigma, or time constraints. The Small Steps SMS program, an automated interactive text messaging initiative, has helped over 10,000 young adults manage depression and anxiety symptoms, demonstrating that technology-mediated support can achieve significant scale .

3.3 Limitations and Challenges

Despite demonstrated benefits, significant limitations constrain AI-assisted prediction of academic performance.

Data Quality and Availability: Machine learning applications require systematic collection of both academic and psychological data. Many institutions lack the infrastructure for regular psychological assessment, and survey data may be affected by response bias. The Henan University study noted that current practice of only conducting psychological assessments in freshman year is inadequate, recommending follow-up assessments in each academic year .

Interpretability: Black-box models may achieve high accuracy but provide limited insight into why predictions are made. This can undermine trust and reduce the pedagogical value of predictive analytics. The Lesotho study emphasized that "opacity poses practical and ethical concerns" and called for explainability diagnostics to strengthen institutional trust .

Fairness and Equity: Predictive systems may reproduce or amplify existing disparities if structural constraints shape engagement behaviors. The Lesotho study noted that "in such contexts, predictive systems risk conflating infrastructural limitations with academic preparedness" . Fairness-aware modelling becomes an essential complement to performance evaluation.

Small Dataset Challenges: Educational survey data often involve small and imbalanced datasets, with a mix of numerical and categorical features that complicates modeling. Data augmentation has been proposed as one way to address these limitations, though its application to small-scale, Likert-type survey datasets remains underexplored .

IV. FUTURE DIRECTIONS

4.1 Longitudinal and Multidimensional Assessment

Current research consistently identifies the need for longitudinal assessment that tracks psychological factors across multiple time points. The finding that psychological factors become more predictive of junior-year performance than sophomore-year performance suggests that the effects of psychological challenges compound over time . Institutions should consider introducing follow-up psychological assessments in each academic year, moving beyond the current practice of initial screening only.

Multidimensional assessment frameworks that integrate academic, psychological, behavioral, and socio-economic data are likely to yield the most robust predictions. The AMP-Net framework's integration of engagement, socio-economic classification, and sentiment from digital footprints provides a model for comprehensive prediction .

4.2 Enhancing Interpretability and Fairness

Future research should prioritize model interpretability alongside predictive accuracy. XAI techniques such as SHAP provide mechanisms for understanding feature importance and interaction effects. The study from Air University demonstrated that SHAP analysis can clarify "how personality traits interact with other factors, underscoring their role in shaping academic outcomes" .

Fairness-aware modeling should extend beyond statistical parity to examine real-time implementation. The Lesotho study calls for "extending fairness evaluation beyond statistical parity and examining real-time implementation through early-warning dashboards and adaptive feedback" . This requires ongoing monitoring and adjustment as predictive systems are deployed in real-world educational settings.

4.3 Addressing AI-Related Anxiety

The finding that AI anxiety predicts academic procrastination opens a new dimension for both research and intervention . As AI becomes increasingly integrated into educational assessment and support systems, understanding and mitigating AI-related anxiety is essential. Students' perceptions of AI technologies may shape engagement with AI-assisted support systems, creating self-fulfilling prophecies where apprehension leads to avoidance and underutilization of potentially beneficial tools.

The role of generative AI in academic life presents a complex landscape. While GenAI use has been associated with greater procrastination and memory difficulties, it has also been used as a tool to alleviate workload pressure . The research calls for further investigation into "unclear implications for authentic learning," suggesting that institutions must develop nuanced approaches to supporting ethical and effective GenAI use .

4.4 Intervention Design and Implementation

The ultimate goal of AI-assisted prediction is enabling effective intervention. The Jordanian study concluded that "early interventions targeting both academic and psychological factors are critical for improving student well-being and academic success" . Prediction must be paired with accessible, effective support mechanisms that address the multidimensional nature of student challenges.

Personalized interventions that consider individual psychological profiles and learning contexts are likely to be most effective. The work on personalized storytelling demonstrates how AI-enhanced content can be tailored to individual experiences, with LLM-enhanced narratives rated higher in conveying key messages, fostering reflection, and stimulating interest . Such approaches can complement traditional support systems, reaching students who might otherwise not access support.

V. CONCLUSION

This analysis has examined the application of AI-assisted techniques for predicting academic performance based on procrastination, stress, and anxiety among university students. The evidence demonstrates that incorporating psychological factors into predictive models substantially improves accuracy, with AI-driven approaches achieving classification accuracies exceeding 83% . Anxiety indicators consistently emerge as the most influential psychological predictors, followed by interpersonal sensitivity and personality factors .

Procrastination, affecting over 80% of undergraduates, operates in a bidirectional relationship with anxiety, creating cycles that reinforce academic difficulties . The emergence of AI-related anxiety as a predictor of academic procrastination adds a new dimension to understanding psychological challenges in contemporary educational settings .

AI-assisted prediction systems offer significant potential for proactive student support through early identification of at-risk students and scalable intervention delivery. However, limitations in data quality, model interpretability, and fairness must be addressed. The need for explainable, fairness-aware modelling is particularly critical in digitally constrained environments where infrastructural limitations may shape student behaviors and predictive outputs .

The path forward requires integrated, multidimensional assessment frameworks that consider academic, psychological, behavioral, and socio-economic factors. Early interventions targeting both academic and psychological dimensions are essential for improving student well-being and academic success. As institutions increasingly incorporate AI into educational support systems, attention to ethical implementation, ongoing monitoring, and adaptation will be crucial for realizing the benefits of AI-assisted prediction while mitigating potential harms.

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